Naveen Jindal School of Management

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UT Dallas Author(s):

Indranil R. Bardhan
Zhiqiang Zheng

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RESEARCH ARTICLE

THE IMPACT OF HEALTH INFORMATION SHARING ON DUPLICATE TESTING[1]

Sezgin Ayabakan
Fox School of Business, Temple University, 1801 Liacouras Walk,
Philadelphia, PA 19122-6083 U.S.A. {ayabakan@temple.edu}

Indranil Bardhan and Zhiqiang (Eric) Zheng
Naveen Jindal School of Management, University of Texas at Dallas, 800 West Campbell Road,
Richardson, TX 75080 U.S.A. {bardhan@utdallas.edu} {ericz@utdallas.edu}

Kirk Kirksey
The University of Texas Southwestern Medical Center, 6303 Forest Park Road,
Dallas, TX 75390 U.S.A. {kirk.kirksey@utsouthwestern.edu}

Recent healthcare reform has focused on reducing excessive waste in the U.S. healthcare system, with duplicate testing being one of the main culprits. We explore the factors associated with duplicate tests when patients utilize healthcare services from multiple providers, and yet information sharing across these providers is fragmented. We hypothesize that implementation of health information sharing technologies will reduce the duplication rate more for radiology tests compared to laboratory tests, especially when health information sharing technologies are implemented across disparate provider organizations. We utilize a unique panel data set consisting of 39,600 patient visits from 2005 to 2012, across outpatient clinics of 68 hospitals, to test our hypotheses. We apply a quasi-experimental approach to investigate the impact of health information sharing technologies on the duplicate testing rate. Our results indicate that usage of information sharing technologies across health organizations is associated with lower duplication rates, and the extent of reduction in duplicate tests is more pronounced among radiology tests compared to laboratory tests. Our results support the need for implementation of health information exchanges as a potential solution to reduce the incidence of duplicate tests.

Keywords: Duplicate testing, health information sharing, health information exchange, quasi-experiment, radiology test, laboratory test

Introduction

On average, healthcare services in the United States cost twice as much as similar services in the Organization for Economic Cooperation and Development (OECD) countries. Annual healthcare spending in the United States amounted to $3.2 trillion, or 17.8% of gross domestic product (GDP) in 2015, and is projected to grow to 20.1% of GDP by 2025, if current trends continue (CMS 2016). It is estimated that 40% to 50% of U.S. healthcare spending amounts to waste, of which overuse of resources is a significant contributor (Bentley et al. 2008). The Congressional Budget Office estimates that around $700 billion per year, or 5% of the U.S. GDP, is expended on tests and treatments that do not actually improve health outcomes (Orszag 2008). Waste due to inefficient use of health resources can arise in many situations such

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The appendix for this paper is located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

as excessive antibiotic use for viral infections, avoidable hospitalizations for nursing home patients, unnecessary admissions of patients, and overuse of screening and imaging procedures (Bentley et al. 2008). The aim of the Affordable Care Act (ACA), enacted in March 2010, was to replace the current fee-for-service structure under which providers are paid more for ordering frequent tests and treatments with an accountable, value-based reimbursement 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 laboratory tests and imaging procedures related to the diagnosis and treatment of congestive heart failure (CHF) outpatients. A likely cause of the excessive use of laboratory and 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 only 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), thus increasing the possibility of incurring duplication in the future. The problem is exacerbated when patients switch care providers. In such instances, technological barriers are created when these healthcare providers do not have access to information sharing platforms that allow patient data to be shared across health systems in a standard format.

A unique aspect of our research is that we differentiate and contrast the impact of health information sharing on the duplication of radiology versus laboratory tests. Specifically, we estimate how interorganizational information sharing technologies impact the level of duplication of two types of tests: (1) radiology imaging tests that are typically processed, stored, and shared in a digital format, and (2) laboratory tests that are typically performed manually on patients, although the results might be processed and shared electronically.

We hypothesize that health information sharing technologies can reduce the duplication rate of radiology tests more than that of laboratory tests, due to differences in the data attributes and standards pertaining to these two types of tests. We empirically test our hypotheses using two data sources from the Dallas Fort Worth Hospital Council (DFWHC) Research Foundation, and the American Hospital Association (AHA) IT Supplement database. The DFWHC database provides a comprehensive dataset of more than 39,600 CHF patient visits to outpatient clinics across all non-Federal hospitals in North Texas since 2005. The AHA dataset provides additional data on the use of health information technologies to share patient health information across healthcare providers. We implement a quasi-experiment approach to study the change in the rate of duplicate testing with respect to implementation of health information sharing.

We find that interorganizational information sharing is associated with a higher level of reduction in the duplication rate of radiology imaging tests compared to laboratory tests. Our results suggest that health information sharing across healthcare organizations is most beneficial in reducing duplication among low volume, high cost digital radiology tests. On the other hand, its impact on high volume, low cost laboratory tests might be crimped by factors that preclude clinicians from using the results of previous laboratory tests for decision making. These factors include lack of data standards to accommodate the exchange of test results, which may be in unstructured data format across health systems, stringent requirements to adhere to clinical guidelines, and practice of defensive medicine. Our study provides a foundation to empirically demonstrate the value of health information exchanges (HIE) by estimating the costs attributed to duplicative outpatient tests resulting from the unavailability of a common health information sharing infrastructure among healthcare providers in the United States. Our study findings lend support to the context of the current debate on healthcare reform, and the need to reduce healthcare costs by minimizing redundant tests and procedures, through implementation of HIEs (Adjerid et al. 2015). Our study also highlights the necessity to adopt universally accepted data standards to enable more efficient and effective digital communication across disparate healthcare entities.

Background

A typical patient receives care from multiple, geographically disparate providers over the course of their treatment. Mobility of patients not only leads to more voluminous health data, but greater fragmentation and challenges for sharing information (Flanders 2009). This is because there exist significant organizational and technological barriers to sharing patient health information across disparate, and often competing, health providers in the present healthcare environment. In an ideal scenario, when a patient switches from one provider to another, her prior health data must follow. However, in a fee-for-service environment, healthcare providers lack incentives to share patient health information with other providers. They may also be reluctant to retrieve clinical

information from other providers because it can be cumbersome and time consuming; even if providers are willing to share, logistical barriers stemming from fragmented medical data across health systems may lead to inconsistencies and distortions to the patient medical record (Johnson et al. 2011). Further, patients may not always be able to accurately recall or communicate clinical information and treatment details from prior visits to their current healthcare provider.

When providers cannot easily access their patients' health information, such as diagnosis, allergies, medication history, and test results due to a lack of information sharing infrastructure, they tend to repeat diagnostic tests. LaBorde et al. (2011) observed that a lack of IT integration across healthcare providers could lead to duplicate diagnostic laboratory tests. Hillestad et al. (2005) argued that electronic medical records (EMRs) could greatly facilitate information flow among providers and estimate that EMRs can save $7.9 billion annually by reducing the need for redundant diagnostic tests. Hence, it is imperative to develop a better understanding of the impact of information sharing on the incidence of duplicate diagnostic testing (Johnson et al. 2011; LaBorde et al. 2011).

To accomplish this, we focus on the two main groups of diagnostic tests which are often over-utilized: radiology imaging and laboratory tests (Harendza et al. 2013, Winkens and Dinant 2002). Radiology imaging tests consist of low-volume, high-cost diagnostic tests such as CT scan, X-rays, and magnetic resonance imaging (MRI) (Bates 1998). Over-utilization and repeat testing of radiology imaging procedures range between 14.7% and 20.7% for different types of radiology tests (Lammers et al. 2014). It is reported that sharing imaging data across providers can decrease utilization of radiology services, with savings up to $86,700 per provider (Wang et al. 2003). On the other hand, laboratory tests represent high-volume, low-cost procedures, such as blood work and pathology tests. Bates et al. (1998) reported that 28% of laboratory tests were repeated before expiry of their test-specific, predefined time intervals, suggesting unnecessary and overutilization of these tests.

In this study, we contrast the impact of health information sharing technologies on the duplication rate of laboratory tests with that of radiology imaging tests. We argue that mobility of patient health data necessitates information sharing across organizational boundaries. We examine the potential benefits that may be accrued from implementation and usage of these technologies to develop a better understanding of their role in reducing the duplication rate of diagnostic tests. Such analyses provide supporting evidence and a benchmark to better inform policy makers and stakeholders who are considering funding the implementation and rollout of HIEs as a vehicle to reduce inefficiencies due to duplicate testing.

Technological Barriers of Sharing Test Results

Radiology and laboratory tests differ in terms of their processing structure, level of utilization, ordering frequency, reusability, and storage requirements. Differences in their IT infrastructure requirements and applications for data retrieval and sharing may substantially impact their reusability. Healthcare organizations share various types of patient data with each other, using widely accepted data standards and guidelines. These data standards govern the manner in which patient information is electronically stored and exchanged which, in turn, makes data stored in one location available and meaningful across a variety of clinical settings (Kim 2005). When a radiology test is performed, it is typically processed and stored in a digital format. It can then be shared with other providers using picture archival and communications systems (PACS). Data standards used to transmit diagnostic images are called Digital Imaging and Communications in Medicine (DICOM) (Branstetter 2007).

The method of reporting final radiology results to the ordering physician will depend on the technologies in place. In less digitally sophisticated delivery organizations, radiology results may be delivered via the radiology information system (RIS). However, for organizations with more advanced technologies, radiology results are delivered via the EMR. This result includes the radiologist's final report as well as a link to the diagnostic image. In these cases, the reporting of final results is closely linked to the computerized provider order entry (CPOE) function by virtue of linking an order with a fulfilled result. In the North Texas region, most major delivery systems have implemented an EMR with both results reporting and CPOE. Hence, CPOE and results reporting are closely linked in a single system: the EMR.

On the other hand, laboratory tests, such as pathology tests, may be processed manually with laboratory instruments, but the results can be digitized for storage and transmission. In ordering lab tests and transmitting lab results, the commonly used standard is the Logical Observation Identifiers Names and Codes (LOINC) (AHIMA Work Group 2013). Although both DICOM and LOINC standards facilitate data sharing and exchange across healthcare systems, a lack of widespread adoption of these standards and inconsistencies in their implementations hinder interoperability among healthcare entities and limit their ability to share test results.

Non-Technological Barriers of Sharing Test Results

There are many reasons behind the high rates of duplication in diagnostics tests and procedures (Dai et al. 2017). Some

duplicate tests are necessary because a patient's condition may change from one visit to another. A retest may be ordered to detect the changes or patients may specifically request a second opinion to retake certain tests. However, diagnostic tests may also be conducted unnecessarily for non-clinical and non-technological reasons. Overuse of tests can be attributed to a variety of reasons including pressure from patients (Oboler et al. 2002), the practice of defensive medicine, a term reflecting providers' tendency to overuse tests in order to prevent future litigation (Currie and MacLeod 2013), and financial reimbursements that are based on a fee-for-service environment, which incentivizes providers to conduct redundant tests (Cooke 2010, Kim et al. 2011).

Some intervention policies have been devised to mitigate overutilization, especially for laboratory tests. These policies include reducing reimbursement rates, active management of test utilization by laboratory staff, development of laboratory formularies, and elimination of clinically inappropriate duplicate tests that are ordered within specified time frames (Wilson 2015). There have been educational efforts directed at changing physician practices, which only had a temporary effect on reducing overuse of laboratory tests (May et al. 2006). Krasowski et al. (2015) suggest that tiered restrictions, such as requirements for preapproval from a pathologist before ordering certain types of lab tests via CPOE systems, may help to reduce the incidences of duplication among lab tests.

Duplicate Tests and Health Information Sharing

It is important to note that we focus on the determinants of duplicate testing in their own right and do not attempt to differentiate between whether a specific test is necessary or truly redundant. Determining whether a test is necessary or redundant is a subjective exercise and can vary from one patient to another, and from one physician to another. Nevertheless, prior studies have reported that 20% to 50% of high-tech diagnostic tests fail to provide information that improves patient diagnosis or treatment, and may be considered redundant or unnecessary (AHIP 2008).

A research study on the determinants of duplicate testing is an interesting, significant, and valid problem for the following reasons. First, the U.S. healthcare system suffers from excessive overuse of tests. Nationwide, it is estimated that approximately 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 were hard to justify across 200 hospitals, while the St. John Health System in Tulsa abused CT scans with a staggering duplication rate of 80% in 2008, resulting in $250,000 in unjustified Medicare charges (Bogdanich and McGinty 2011). Second, developing a better understanding of the drivers of duplication represents a first step toward helping policy makers, providers, payers, and consumers determine the factors that contribute to the duplication rate, so that appropriate steps can be implemented to reduce the extent of duplication. Third, our empirical analysis provides a baseline for policy makers to determine the severity of redundancy and, in fact, a policy based on duplication can be more easily operationalized than a redundancy-based one, since the savings from unnecessary duplicative testing might be used to help fund regional HIEs.[2]

The prevailing mode of healthcare reimbursement during the last several decades has been a fee-for-service (FFS) environment, wherein providers are reimbursed for services disbursed. In this environment, providers are reimbursed based on their case volume (which includes the number of services and tests). The magnitude of reimbursements is proportional to the number of tests and procedures performed. Hence, there is little incentive for care providers to actively reduce the volume of such tests and procedures, even if the same test/procedure was already conducted on the same patient by a different provider. Passage of the ACA marks a shift away from the current FFS landscape to a value-based reimbursement model, wherein reimbursements are no longer simply based on the quantity of services, but more on patient health outcomes and quality metrics. The value-based model also imposes a maximum limit (i.e. capitation) on reimbursements disbursed for patient care related to specific treatments (such a knee replacement surgery or a one-year treatment of a CHF patient). In this new landscape, providers are reimbursed based on the quality of care provided, rather than the number of tests and procedures. We believe that our research is very topical in the current context of payment reform, since it brings duplicate testing into sharper focus as providers try to reduce costs from duplicate procedures.

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 transactions was enabled through implementation of electronic data interchange (EDI) standards. Prior studies have reported significant business value of EDI in facilitating interorganizational information sharing (Barua and Lee 1997; Li et al. 2006). Interorganizational information sharing across the supply chain spans four dimensions of information: trans-

[2]For example, the ACA's readmission policy punishes hospitals with excessive 30-day readmission rates, without differentiating between preventable and non-preventable readmissions.

actional, operational, strategic, and competitive (Seidmann and Sundararajan 1998). The strategy literature has also highlighted the importance of information sharing among organizations. Information distortion and the lack of information sharing are important considerations in interorganizational process design (Carley and Lin 1997; Cohen and March 1986). Yang and Maxwell (2011) observed that interoperability across organizations enabled cross-boundary information sharing. Rather than relying on (often) imprecise narratives provided by patients, it is important to better understand prior procedures and tests already performed on the patients, in order to reduce the level of information distortion as they move from one healthcare provider to another.

Research Hypotheses

Health information technologies facilitate capturing, storing, sharing, and retrieval of patient health information. Accessing patients' medical and surgical histories, allergies, and current and past medication lists through health IT will allow providers to make better diagnosis and treatment decisions (Booth 2003). Electronic health records (EHRs) provide the technological foundation for sharing patient health information across organizational boundaries (Mishra et al. 2012). EHRs enable information sharing with more convenient access to digitized patient data on prior procedures, tests, and medical history (HealthIT.gov 2013). For example, Canada Health Infoway, a nationally interoperable EHR, was implemented in response to the problem of physicians having to reorder diagnostic imaging procedures due to patient referrals and transfers across various facilities (Mendelson et al. 2008). Yet, EHRs from different vendors have been criticized for not being able to communicate with each other, resulting in islands and silos of fragmented information (Ozdemir et al. 2011). DesRoches et al. (2013) observed that exchange of patient clinical summaries and laboratory and diagnostic test results with outside entities were among the least adopted functionalities of an EHR. The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which promotes adoption of EHRs through its meaningful use incentive program, defines a common data set for all patient summary of care records and requires that at least 55% of lab test results be incorporated into EHRs as structured data (Wright et al. 2013).

We now develop our hypotheses based on how various health IT systems are implemented, used, and integrated into hospitals' current EHRs to investigate the differential impact of health information sharing on duplicate testing of radiology versus laboratory tests.

Differential Impact of Information Sharing on Radiology and Laboratory Tests

EHRs facilitate communication between different health entities through various HIT applications such as PACS, RIS, and laboratory information systems (LIS). These applications enable viewing and sharing of radiology and laboratory tests with other entities inside and outside of the healthcare system. Reliable information sharing requires common data standards to accommodate communication across systems.

We draw on the rich literature in interorganizational information sharing theory (Galbraith 1973; Tushman and Nadler, 1978) to develop our hypotheses. Data integration refers to the standardization of data definitions and structures through common schema across data sources (Goodhue et al. 1992). Data integration ensures that data have the same meaning across users, making the data from different systems, collected across time, logically compatible (Martin 1982). Goodhue et al. (1992) argue that, in certain organizational contexts, the benefits of data integration are not enough to offset their costs, leading to the failure of such efforts. Further, the need for sharing information is greatest when there is a high degree of interdependence among business units. In such situations, information sharing systems serve as appropriate mechanisms to improve organizational communication and operational coordination between different organizational units (Goodhue et al. 1988).

In the context of healthcare, information sharing technologies offer potential to reduce the need to reorder radiology tests (Sodickson et al. 2011). The ability of providers to obtain timely and accurate access to prior radiology images is critical for them to determine whether another radiology imaging service is needed (Lu et al. 2012). Retrieval and sharing of digital radiology images are typically done through PACS applications which can be integrated into EMR systems (Branstetter 2007). However, successful sharing of radiology images across providers has been stalled by nonconformance to DICOM standards (Merge 2015). Non-DICOM images, and images stored in JPEG, PNG, GIFF, and TIFF formats, cannot be processed via PACS applications (Varma 2012), which poses a challenge to sharing these types of images across provider locations due to limitations associated with image size, resolution, compression, meta-data, and data format (Merge 2015). Therefore, health IT platforms that are capable of sharing unstructured and large image files play key roles in establishing interoperability across various providers and enabling reductions in radiology test utilization.

Sharing laboratory tests across providers is even more challenging. There are over 200,000 certified clinical labs in the

United States (ONC 2011). These labs are used extensively by healthcare providers either exclusively or to supplement internal clinical laboratory operations. Lack of interoperability among these labs and conformance to data standards has hindered sharing of lab test results across providers (ONC 2011). In 2012, only 58% of lab tests in the United States were sent electronically in structured format to the ordering provider's EHR (Swain and Patel 2014), due to nonconformance with LOINC standards. One difficulty in using LOINC to transmit laboratory test results lies in the poor mapping algorithms between LOINC procedure codes and local codes used in a healthcare provider's clinical database. Often, these clinical databases for procedural codes involve local, idiosyncratic, and sometimes redundant and/or ambiguous names (Abhyankar et al. 2012). Laboratory tests conducted at external labs are simply coded as "outside test" with the actual name included in the comment, or note due to mismatch between the LOINC algorithm and local codes used in the provider's database (Pan and Cimino 2015). In spite of recent advances in adoption and usage of EHRs by healthcare providers, electronic integration of lab results into patient health records still poses a significant challenge to sharing these results across multiple providers and health organizations.

Currently, the level of information sharing for laboratory tests lags behind that of radiology tests. Interoperability among LISs poses a bigger challenge for sharing laboratory tests, compared to more mature and widely adopted PACS that are integrated with DICOM standards. The American College of Radiology and National Electrical Manufacturers Association, the developers of DICOM standards, view DICOM as an essential standard to share digital image files regardless of device manufacturer, enabling PACS to interface with EMR systems so that radiology images and test reports can be shared across organizational boundaries (Chen 2012). On the other hand, the Office of the National Coordinator (ONC) for health IT has cautioned against the use of multiple standards for representing lab results by labs and hospitals, and encouraged adoption of LOINC codes in laboratories to better interface with the LIS/EHRs of hospitals (ONC 2011).

Moreover, lab tests involve a higher level of manual processing compared to radiology tests. Although simple lab tests (such as blood tests and urine samples) are standardized and data is recorded in a structured data format, other types of lab tests such as pathology and biologic smears, involve free-form text which results in unstructured data. Hence, sharing these types of test results across providers can be challenging and such unstructured data is often subject to misinterpretation. When physicians encounter difficulties in retrieving and interpreting prior tests, they are more likely to order a new lab test. The tendency to order a duplicate lab test is further exacerbated by the low cost and high volume nature of lab tests, even in the presence of health information sharing (Henricks 2000).

In view of these technological and nontechnological differences between radiology and laboratory tests, we focus on the relative impact of information sharing on the duplication rates of these two types of tests. We argue that, compared to lab tests, radiology tests are less likely to be duplicated in the presence of information sharing, since the images and reports are available in standard formats using universally accepted standards. Formally, we hypothesize that

H1: *Usage of information sharing technologies will reduce the duplication rate of radiology tests more than that of laboratory tests.*

Interorganization Information Sharing

Information sharing requires the ability to share data across EHRs operated by disparate healthcare organizations. This can occur at two levels: internal and external integration (Raghupathi and Tan 2002). Internal integration refers to the degree to which systems and technologies are integrated with another facility/business unit within an organization; whereas external integration goes beyond the enterprise boundary, and is especially important for achieving interoperability across different healthcare organizations. The ONC (2011) highlighted the importance of HIEs in facilitating information sharing "where patients often live in one jurisdiction and seek treatment in another will benefit from studying the regulations of neighboring states to foster consistency where patients' lab records cross state lines." Of particular interest is how such information sharing across organizational boundaries (of disparate healthcare providers) impacts the extent of duplicate testing of radiology and laboratory tests.

Information sharing across health systems is especially helpful when patients migrate between providers across disparate health organizations.[3] Walker et al. (2005) estimated that 13.7% of tests can be avoided (amounting to $31.8 billion in annual savings) if outpatient providers and independent laboratories had mutual access to a health information exchange.

[3]A healthcare organization is equivalent to a health system that may be comprised of one or more hospitals. For example, Texas Health Resources is a healthcare organization in North Texas which is comprised of 24 hospitals in the Dallas–Fort Worth region.

HIE participation is projected to reduce repeat radiology imaging procedures conducted on emergency room patients between 8.7% and 13.0% (Lammers et al. 2014). Recent adoption of cloud-based systems and web-based personal health records (PHRs) have emerged as potential solutions to foster interorganization information sharing (Mendelson 2011; Shrestha 2011). Such systems allow timely access to patient medical information such as previously performed imaging tests and reports from different locations, resulting in reduction in duplicate procedures (Shini et al. 2012).

Some software vendors have recently started providing enterprise-wide solutions to integrate various PACS across healthcare organizations (e.g., Centricity by GE and Intellispace by Phillips). Enterprise-wide implementation of PACS equips physicians and radiologists with instant access to radiology images, ease-of-view exam schedules and work-to-do lists, all of which are crucial to help reduce the overutilization of imaging procedures. Likewise, Internet-enabled image transfer systems have enabled greater interhospital information sharing. Flanagan et al. (2012) reported that implementation of an Internet-enabled image transfer system at Harborview Medical Center helped to reduce their imaging duplication rate by 8.1%. Enablement of point-to-point data exchange between heterogeneous information systems (integration of LIS into an EHR) will also facilitate the reuse of lab test results (Lober et al. 2009).

Overall, interorganization information sharing technologies help increase information availability, reduce latency, and subsequently reduce the extent of duplicate testing in radiology and laboratory services. Based on our earlier discussions of interorganizational information theory, we posit that the value of information sharing will be more pronounced at the interorganization level, since organizational and data integration barriers pose the greatest challenge to sharing patient data across healthcare organizations due to a lack of interdependence across disparate providers in a FFS environment. On the other hand, intra-organization information sharing takes place when health information is shared among hospitals or departments that belong to the same healthcare organization (or health system). Coupled with our earlier discussions on differences in data standards and data attributes between these two categories of tests, we posit that interorganization information sharing will benefit radiology tests more than laboratory tests, in terms of the reduction in their duplication rates.

H2: *The difference in duplication rates between radiology and laboratory tests is greater when interorganization information sharing technologies are used.*

Research Methodology

We obtained our research data from two primary sources: the DFWHC Research Foundation and the AHA IT Supplement database. We first describe the data and variables that we use to operationalize our conceptual research model.

Data

Our study focuses on CHF patients, since CHF is one of the two chronic diseases subject to the new ACA penalties on hospital-based readmissions, starting in 2011. We obtained a comprehensive dataset of 39,600 CHF patient visits to outpatient clinics of all 68, non-Federal hospitals belonging to 26 different health systems in North Texas. Utilizing 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. 2015). The REMPI allows us to track a patient's entire visit and diagnosis history, and study their patterns of care and diagnosis (including tests) received across multiple, outpatient clinics in the eighteen-county region. Our data consists of all care received by patients in the outpatient clinics of these hospitals and their affiliated health systems in North Texas. We only include patients with CHF as the principal diagnosis (i.e., patient admissions with ICD-9 code of "428.xx"). Focusing on the principal diagnosis alleviates possible patient heterogeneity arising from treatment procedures and imaging tests that may vary across different diagnoses. We focus specifically on outpatient visits because patients receive radiology imaging procedures and laboratory tests primarily in an outpatient setting, which accounts for the majority of these tests (Lee et al. 2012).

We first applied a cutoff window of 90 days to determine whether a radiology test can be considered as duplicate. This is because the typical life span of a radiology imaging test is about three months, and similar cutoff windows have been used in the prior literature. For example, Lu et al. (2012, p. 629) 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 four months." In addition, Lee et al. (2007) defined the time window of a repeat imaging test as seven months, but reported that a majority of repeat radiological imaging tests occur in the first two months after the initial exam.

For procedures involving lab tests, we focus on the top six hematology tests that are commonly performed in practice,

since they account for the majority of the lab tests for CHF patients (Dumitru 2016). These tests include complete blood count, hematocrit, prothrombin time, partial thromboplastin time, and fibrinogen tests. Similar to the radiology imaging tests, we applied a 90-day cutoff window for calculation of lab test duplication rates. We also conducted several robustness checks with different cutoffs including a much tighter, 30-day window in the "Results" section. All our main results turned out to be consistent.

In our analysis, we excluded the index visit since duplication rate is calculated with respect to the prior visit data. Based on these criteria, we focus on the visit history of 4,038 CHF outpatients who exhibited at least two (or more) outpatient visits during the study period. Hence, our dataset comprises a total of 9,403 consecutive visits, where the visits occur within 90 days (of the prior visit). Table 1 reports the descriptive statistics of our model variables.

Figure 1 provides an illustrative profile of the outpatient visit history for a 62-year old, non-white, female CHF patient along with all imaging tests performed during her visits. The first visit of this patient is treated as the index visit. Visits 4 and 7 fall outside the 90-day time window of their respective previous visits and, accordingly, both are treated as new index admissions. To calculate the duplication rate, we compared 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 with common procedure terminology (CPT) codes of 93220, 93307, and 93325, and one chest x-ray coded as 71010. We compared these CPT codes to the previous visits' CPT codes, and observed that 71010 had been performed 43 days ago, during visit 4. Therefore, this chest x-ray (coded as 71010 during visit 5) was flagged as a duplicate procedure and we increased the duplication count (*Duplicate_Count*) by one. Hence, the *Duplicate_Rate* was calculated as *Duplicate_Count* divided by the total number of imaging procedures performed during visit 5, and is equal to 25%.

We collected data on the extent of health information sharing between providers in our data set, from the AHA IT database. This database provides comprehensive, survey-based, health IT data gathered from providers across all hospitals and outpatient clinics. The sample questionnaire for 2012 is presented in Figure A1 in the appendix. Data on the extent and type (i.e., lab tests, radiology images) of health information sharing, within and across providers, was available for the years between 2008 and 2012 for both radiology and laboratory tests.

Variable Definitions

Clinical information on outpatient procedures is reported using CPT codes. For radiology tests, we tracked CPT codes for X-rays, CT scans, magnetic resonance imaging (MRI), and ultrasounds, which comprise a majority of the imaging procedures. For laboratory tests, we used CPT codes for CBC, hematocrit, prothrombin time, partial thromboplastin time, and fibrinogen, which comprise a majority of the laboratory tests. Table 2 lists the top radiology and laboratory tests included in our data sample.

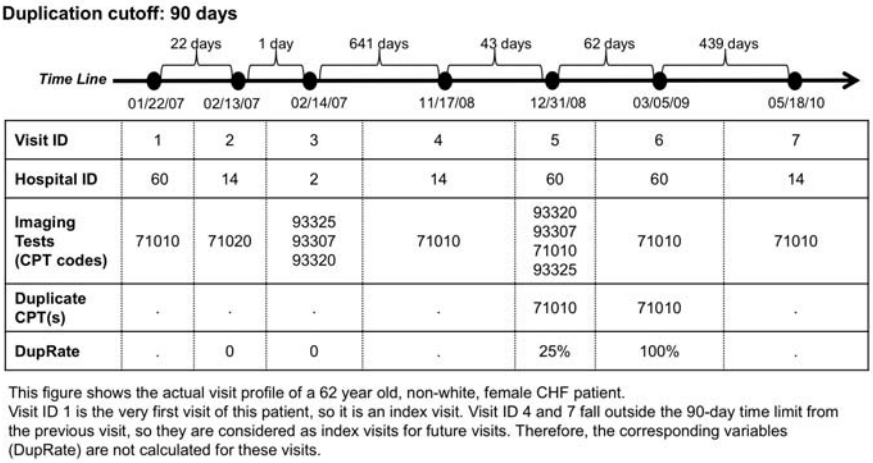
For each patient visit, we counted the number of duplicate tests for each CPT code that appeared on the current visit. We repeated this procedure for both radiology and laboratory tests and calculated *DupRateRad* and *DupRateLab* measures for each visit. Each CPT code was matched against the ones recorded across all prior visits that occurred within 90 days prior to the current visit. If the CPT code appeared in any of the prior relevant visits (i.e. , $\leq$ 90 days), it was flagged as a duplicate procedure and included in the count of the total number of duplicate procedures pertaining to the current visit. We then calculated *DupRateRad* (*DupRateLab*) as the ratio of the total number of radiology (laboratory) test duplicates to the total number of all CPT radiology (laboratory) procedures, for the current visit. Table 1 reports the visit-level averages for duplication count, procedure count, and duplication rate of radiology (laboratory) tests, which are 0.18 (0.46), 0.40 (0.64), and 15.35% (32.49%) respectively. To test hypotheses H1 and H2, in which we compare the relative reduction in *DupRateRad* compared to *DupRateLab*, we first standardized *DupRateRad* and *DupRateLab* with a mean of zero and a standard deviation of one. Then, we calculated the difference, Δ(DupRate) = *DupRateRad – DupRateLab,* and used it as our dependent variable in our estimation model.

Table 2 reports descriptive statistics for the top 10 duplicate imaging procedures and laboratory tests. We note that chest x-ray procedures exhibited the highest duplication percentages at the patient visit level. In our calculation of the duplication rate, we compared tests based on their CPT codes, so that the incidence of duplication is measured only if the same test (with same CPT code) is repeated within 90 days, for the same primary diagnosis. Similarly, we differentiated between the types of laboratory tests with respect to their distinct CPT codes. For instance, "complete cbc w/auto diff wbc" and "complete cbc automated" are treated as two distinct lab procedures (just as a frontal X-ray is treated differently than a lateral X-ray).

In order to capture the extent of health information sharing of radiology and laboratory results, we constructed a variable

Table 1. Descriptive Statistics of Variables

Variable	Variable Definition	Dim.		Mean	Std Dev	Min	Max
Admission Characteristics							
DupRate	Duplicate Procedures (percentage)	*%*	*RAD*	15.35	35.1	0	100
			LAB	32.49	45.65	0	100
DupCount	Duplicate Procedures (absolute)	*Count*	*RAD*	0.18	0.44	0	6
			LAB	0.46	0.74	0	5
ProcCount	Number of Procedures	*Count*	*RAD*	0.4	0.75	0	10
			LAB	0.64	0.91	0	6
Charge_ER	Binary (1 = if contains emergency charge)	*0 or 1*		0.23	0.42	0	1
Days_Between _Visits	Days Between Consecutive Visits	*days*		23.13	25.28	0	90
Admission Source							
Referral_Source	Binary(1 = if Admission Source is Physician)	*0 or 1*		0.91	0.29	0	1
Transfer_Source	Binary(1 = if Admission Source is Transfer)	*0 or 1*		0.001	0.05	0	1
Other_Source	Binary(1 = if Admission Source: Other)	*0 or 1*		0.09	0.28	0	1
Visit Type							
Emergency_Visit	Binary(1 = if Emergency or Urgent visit)	*0 or 1*		0.16	0.36	0	1
Elective_Visit	Binary(1 = Elective visit)	*0 or 1*		0.55	0.5	0	1
Other_Visit	Binary(1 = Other outpatient)	*0 or 1*		0.29	0.45	0	1
Patient Demographics							
Female	Binary (1 = Gender: Female)	*0 or 1*		0.52	0.5	0	1
White	Binary (1 = Race: White)	*0 or 1*		0.65	0.48	0	1
Age	Patient Age in years	*Contin's*		67.75	16.87	1	90
Hospital Characteristics							
CMI	Provider Case Mix Index	*Contin's*		1.67	0.26	0.93	3.08
Teaching	Binary(1 = if Teaching status)	*0 or 1*		0.4	0.49	0	1
Urban	Binary(1 = if Location: Urban)	*0 or 1*		0.66	0.47	0	1
Beds	Number of Beds	*Contin's*		491.38	304.97	0	1029
Insurance Type							
Private	Binary(1 = if Payer: Private)	*0 or 1*		0.03	0.16	0	1
Medicaid	Binary(1 = if Payer: Medicaid)	*0 or 1*		0.06	0.24	0	1
MedicareA	Binary(1 = if Payer: Medicare Part A)	*0 or 1*		0.45	0.5	0	1
MedicareB	Binary(1 = if Payer: Medicare Part B)	*0 or 1*		0.18	0.39	0	1
Selfpay	Binary(1 = if Payer: Self Pay)	*0 or 1*		0.07	0.26	0	1
Other_Insurance	Binary(1 = if Payer: Other)	*0 or 1*		0.2	0.4	0	1



Visit ID	1	2	3	4	5	6	7
Hospital ID	60	14	2	14	60	60	14
Imaging Tests (CPT codes)	71010	71020	93325 93307 93320	71010	93320 93307 71010 93325	71010	71010
Duplicate CPT(s)	.	.	.	.	71010	71010	.
DupRate	.	0	0	.	25%	100%	.

This figure shows the actual visit profile of a 62 year old, non-white, female CHF patient.
Visit ID 1 is the very first visit of this patient, so it is an index visit. Visit ID 4 and 7 fall outside the 90-day time limit from the previous visit, so they are considered as index visits for future visits. Therefore, the corresponding variables (DupRate) are not calculated for these visits.

Figure 1. Illustrative Example of Outpatient Visits and Radiology Imaging Tests

Table 2. Duplication Rate for Radiology and Laboratory Procedures

CPT Code	CPT Description	By Admission			By Patient		
		Total	Dup.	%	Total	Dup.	%
RADIOLOGY TESTS[†]							
71010	Radiologic examination, chest; single view, frontal	1428	970	67.9%	1076	708	65.8%
71020	Radiologic examination, chest, 2 views, frontal and lateral	1036	558	53.9%	845	449	53.1%
93306	Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, complete, with spectral Doppler echocardiography, and with color flow Doppler echocardiography	217	60	27.7%	204	56	27.5%
93307	Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, complete, without spectral or color Doppler echocardiography	148	21	14.2%	137	19	13.9%
93325	Doppler echocardiography color flow velocity mapping	135	19	14.1%	124	17	13.7%
93320	Doppler echocardiography, pulses wave and/or continuous wave with spectral display	124	14	11.3%	116	13	11.2%
71250	Computed tomography (CT), thorax; with contrast material(s)	38	10	26.3%	34	9	26.5%
93970	Duplex scan of extremity veins including responses to compression and other maneuvers; complete bilateral study	50	8	16%	48	8	16.7%
93308	Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, follow-up or limited study	31	7	22.6%	28	7	25%
71275	Computed tomographic angiography, chest (noncoronary), with contrast material(s), including noncontrast images, if performed, and image postprocessing	48	5	10.4%	47	5	10.6%
LABORATORY TESTS							
85025	Complete cbc w/auto diff wbc	2494	1910	76.6%	1639	1232	75.2%
85610	Prothrombin time	1705	1256	73.7%	970	661	68.1%
85027	Complete cbc automated	872	710	81.4%	481	405	84.2%
85730	Thromboplastin time partial	658	342	51.9%	543	286	52.7%
85379	Fibrin degradation quant	198	67	33.8%	179	58	32.4%
85014	Hematocrit	110	48	43.6%	94	43	45.7%

[†]For radiology procedures only top 10 imaging tests are shown with respect to the total number of occurrences.

All_Share_{ht} that combines the four relevant questions from the AHA IT Supplement survey (see Figure A1 for survey questions). Specifically, we first created four binary variables based on the respective AHA survey questions. If a provider exchanged radiology reports with other hospitals or ambulatory providers, in a given year *inside* their health system, we created an index variable with a value of one, and zero otherwise. We then followed the same procedure to create another index variable to indicate whether radiology reports are shared with other hospitals or ambulatory providers *outside* their health system. These two steps were repeated for laboratory results, yielding the other two index variables. Finally, variable All_Share_{ht} provides an aggregate measure of information sharing across these four index (binaries) variables, that is, it takes a value of one only when all four indices are one, and zero otherwise. Hence, All_Share_{ht} for hospital/clinic h at time t will be one only when it exchanges health information inside and outside the health system, for radiology reports and lab results.

As we are particularly interested in the interorganization information sharing, we constructed a variable $Inter\_Share_{ht}$ to index whether a hospital/clinic h at time t shared data with other hospitals or ambulatory providers *outside* its health system, both for radiology reports and laboratory results. The variable takes a value one only when both types of test results are shared across health systems, and zero otherwise.

Table 3 reports the percentage of providers that have exchanged radiology reports and lab test results electronically with all providers in their region, as well as with providers across other health systems. We observe that all-provider and interorganization health information sharing follow an increasing trend over time as more providers have started using health IT to exchange radiology reports and lab test results. For instance, the rate of all-providers (interorganization) information sharing of radiology and laboratory data rose from 23.5% (33.8%) in 2008 to 66.2% (67.6%) in 2012, for the providers in our data set.

We also account for the effect of several control variables, which include patient payer type, admission characteristics, demographics, and provider-specific factors. For each patient visit, the payer type can be categorized into one of the six insurance variables: Private, Medicaid, Medicare Parts A and B, Self-pay, and other. We use Medicare Part B as our baseline insurance variable because of our focus on 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 tracked patient-specific, demographic information on patient gender, age, race, and zip code. We also obtained provider information from the Centers for Medicare and Medicaid Services (CMS), which classifies providers based on their teaching status, geographic locations (urban, rural), patient case mix index (CMI), and facility size (of the hospital to which the outpatient clinic is affiliated). Table A1, in the appendix, provides the correlation matrix of our model variables.

Model Specification

We now describe our econometric models along with the estimation techniques.

Base Model: Quasi-Natural Experimental Setup

The first part of our econometric estimation examines the impact of health information sharing on duplicate testing. In order to study whether the usage of generic or interorganization information sharing systems has an impact on the duplication rate, we deploy a difference-in-difference (DID) specification which has been extensively used in the IS literature, within natural and *quasi-natural experimental* settings (Kumar and Telang 2012; Meyer 1995). A DID specification 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 specification allows us to handle potential confounding effects of unobserved factors and time-invariant features from treatment effects (Meyer 1995).

We focus on two groups of providers with respect to their usage of health information sharing technologies. The first group (control group) did not use an information exchange functionality between 2008 and 2012, while the second group (treatment group) started using these technologies between 2008 and 2012.[4] In order to test H2, we further differentiate between the types of information exchange, across all-providers or interorganization (with providers outside the health system). Thus, our assignment of observations to treatment and control groups creates the binary variable, *Treatment*, for all observations, where *Treatment* takes a value of one if a patient visit belongs to a provider in the treatment group. To compare treatment and control groups, during the pre- and post- treatment periods, a second binary variable has to be assigned to each observation. This binary

[4]The AHA IT database was only available starting in 2008.

Table 3. Percent of Providers with Interorganization and All-Provider Information Sharing

Variable/Year	2008	2009	2010	2011	2012
All-Provider Information Sharing	23.5%	29.4%	41.1%	45.6%	66.2%
Interorganization Information Sharing	33.8%	39.7%	45.6%	47.1%	67.6%

variable, *Post,* takes a value of one if we observe the instance after the treatment is applied.

Generally, quasi-experiments require two observations per subject, one receiving treatment and another that does not. To construct the *Post* variable for the control group, the reference time point is assumed to be the time when the treatment is rendered to the treatment group. However, complications may arise if providers in the treatment group use health information sharing functionalities in different years. To address this challenge, with respect to a provider in the control group, we identify the most similar provider (to the focal provider) in the treatment group and designate the implementation time of the treated provider as the corresponding time for the control provider. In other words, we match hospitals from the treatment group to the control group.

In observational studies where it is impossible to randomly assign subjects into treatment and control groups, due to ethical or practical reasons, an appropriate matching strategy is recommended (Rosenbaum 1989). Rather than applying a greedy algorithm, such as propensity score matching, we adopt the algorithm developed by Rosenbaum (1989), and used by Cram et al. (2009), to match providers between treatment and control groups. We adopt a one-to-many matching strategy, using the SAS macro developed by Mayo Clinic (Bergstrahl and Kosanke 1995), and include the provider controls *CMI*, *Beds*, *Teaching*, and *Urban* as matching covariates. Once matching is complete, we calculate the $Post_{ht}$ variables (1 or 0).

Control Function Estimation

Although the providers are matched using the Rosenbaum algorithm, there may still remain patient- and visit-level confounding factors that need to be controlled. Thus, we deploy a regression model that estimates the DID coefficients free of patient-, visit-, and provider-level effects. However, one may still argue that the $Treatment_h$ variable may be subject to potential endogeneity. For example, providers with higher duplication rates may be more likely to implement health information sharing technologies. To address the potential for endogeneity, our identification strategy adopts a control function estimation approach (Rivers and Vuong 1988; Wooldridge 2011). The control function approach disintegrates the correlation between endogenous explanatory variables and unobservables affecting the outcome using additional regressors that do not appear in the structural equation (Wooldridge 2010). Accordingly, we first estimate the residuals, $\bar{v}_2$, from the estimation equation specified in (1):

$$Treatment_h = \mathbf{z}\boldsymbol{\pi}_2 + v_2 \quad (1)$$

Where $\mathbf{z}$ includes all control variables as well as Age_Clinic_{ht}, $Age\_Clinic^2_{ht}$, Age_Clinic_{ht}*$Post_{ht}$, $Age\_Clinic^2_{ht}$*$Post_{ht}$ as exclusion restrictions to the second step regression. Finally, we regress $\Delta(DupRate)$ on $\mathbf{z}_1$, $Treatment_h$, and $\bar{v}_2$ using OLS to estimate equation (2).

$$\Delta(DupRate)_{it} = \alpha_1 Treatment_h + \alpha_2 Post_{ht} + \alpha_3 Treatment*Post_{ht} + \mathbf{z}_1\boldsymbol{\delta}_1 + \rho_1 \bar{v}_2 + e_1 \quad (2)$$

The variable $Treatment_h$ equals one if a patient i visits provider h that belongs to the *Treatment* group based on their information sharing status. $Post_{ht}$ equals one if patient i's visit at time t happens during the post-treatment period of provider h. Note that the coefficient estimate of $Treatment*Post_{ht}$ is of primary interest, since it captures the change in duplication rate after the provider implements information sharing technologies (all-providers or interorganization), relative to providers that did not. Here, vector $\mathbf{z}_1$ also includes all control variables, as well as patient, admission, and hospital-level factors, except the exclusion restrictions applied in model (1). We applied bootstrapping (200 repetitions) to obtain the robust standard errors in model (2). Additional details on the control function approach are presented in the appendix.

Results

We now present our DID estimation results, after accounting for endogeneity using the control function approach.

Difference-in-Difference Estimation

We first present the duplication rates between the *Control* and *Treatment* groups of clinics, across pre- and post-implementation periods in Tables 4 and 5, for all-providers

Table 4. Difference in Difference Analysis for Information Sharing across All Providers

Group		A: D(DupRate)			B: DupRateRad			C: DupRateLab		
		Pre-Impl	Post-Impl	First Difference Post – Pre	Pre-Impl	Post-Impl	First Difference Post - Pre	Pre-Impl	Post-Impl	First Difference Post – Pre
Control: NEVER	Mean	**-20.7**	**-21.2**	**-0.5** t = 0.12	**21.9**	**27.3**	**5.4*** t = 1.80	**42.6**	**48.5**	**5.9*** t = 1.69
	StdDev	55.3	50.4		40.3	40.9		47.2	45.7	
	N	624	252		624	252		624	252	
Treatment: IMPL'ED	Mean	**-18.3**	**-31.8**	**-13.5***** t = 5.45	**20.6**	**10.5**	**-10.1***** t = -5.59	**38.9**	**42.3**	**3.4** t = 1.46
	StdDev	47.8	52.7		39.7	30.0		47.7	47.1	
	N	1019	673		1019	673		1019	673	
Second Difference:		***Treatment - Control***		**-13.0***** t = -2.83	***Treatment - Control***		**-15.5***** t = -4.58	***Treatment - Control***		**-2.5** t = -0.58

Two-sided p-values, *p < 0.10, **p < 0.05, *** p < 0.01
Mean and StdDev are for duplication percentage per visit.
90-day time window for duplication

Table 5. Difference-in-Difference Analysis for Interorganization Information Sharing

Group		A: D(DupRate)			B: DupRateRad			C: DupRateLab		
		Pre-Impl	Post-Impl	First Difference Post – Pre	Pre-Impl	Post-Impl	First Difference Post - Pre	Pre-Impl	Post-Impl	First Difference Post – Pre
Control: NEVER	**Mean**	**-23.6**	**-15.2**	**8.4**** t = 2.18	**21.8**	**27.2**	**5.4*** t = 1.86	**45.4**	**42.4**	**-3.0** t = -0.89
	StdDev	55.1	50.9		40.4	40.8		47.3	45.8	
	N	558	302		558	302		558	302	
Treatment: IMPL'ED	**Mean**	**-12.7**	**-37.8**	**-25.1***** t = 9.26	**22.1**	**7.6**	**-14.5***** t = -7.24	**34.8**	**45.3**	**10.5***** t = 3.91
	StdDev	43.4	51.3		40.7	25.9		46.7	47.3	
	N	673	547		673	547		673	574	
Second Difference:		***Treatment - Control***		**-33.5***** t = -7.31	***Treatment - Control***		**-19.9***** t = -5.82	***Treatment - Control***		**13.56***** t = 3.15

Two-sided p-values, *p < 0.10, **p < 0.05, *** p < 0.01
Mean and StdDev are for duplication percentage per visit.
90-day time window for duplication

and interorganization information sharing cases, respectively. In both tables, Panel A presents the DID results of Δ(*DupRate*), the difference in the duplication rate between radiology and laboratory tests; whereas Panel B and Panel C present the DID results for *DupRateRad* and *DupRateLab* (i.e., the individual results of radiology and laboratory duplication rates), respectively. In each panel, the first column reports the average duplication rate in the "Pre-Implementation" period, while the second column reports the average duplication rate in the "Post-Implementation" period, and the third column represents the first difference of the post- and pre-implementation periods.

For the case of general information sharing across all providers, Panel A of Table 4 shows that there is no significant first difference across pre- and post-implementation periods for the control group, while the treatment group exhibit a -13.5% ($p < 0.01$) reduction in Δ(*DupRate*). The second difference between the treatment and control group is -13.0% ($p < 0.01$), meaning that health information sharing across providers helps to reduce duplicate radiology tests by 13% more than laboratory tests. A closer look at the results in Panel B (for radiology) suggests that there is a significant 15.5% ($p < 0.01$) decrease in *DupRateRad* between the control and treatment groups. However, Panel C (for laboratory tests) does not show a significant difference in terms of *DupRateLab,* compared to their counterparts in the control group.

Table 5 tabulates the DID estimates for the case of inter-organization information sharing. Panel A shows an increase of 8.4% ($p < 0.05$) for the control group across pre- and post-implementation periods, while the treatment group exhibits a 25.1% reduction ($p < 0.01$) in Δ(*DupRate*). The second difference coefficient, as shown in the last row of Panel A, indicates that providers who shared radiology reports electronically across different healthcare organizations exhibited a 33.5% ($p < 0.01$) greater reduction in duplication rate, compared to laboratory tests that were exchanged in a similar manner. The results in panels B and C of Table 5 lend further support to our findings in terms of the decrease in duplication rates of radiology versus lab tests.

Control Function Approach Results

We then report the estimation results of the control function approach, aggregated across radiology and laboratory tests, in Table 6. The detailed breakdown of the results for radiology and laboratory tests are separately presented in Table 7. Note that, since Δ(*DupRate*) is standardized with a mean of zero and standard deviation of one, the coefficients are interpreted as a product of their values with the standard deviation of the difference variable.

In estimating equation (2), we controlled for insurance type (*Selfpay, Private, Other_Insurance, MedicareA, Medicaid*), visit source (*Transfer_source, Other_source*), visit type (*Emergency_Visit, Other_Visit*), patient age (*Age*), gender (*Female*), race (*White*), days between consecutive visits (*Days_between_visits*), whether there was an emergency room charge (*ER_Charge*), and other provider characteristics (*CMI, Beds, Teaching, Urban*). In addition to these control variables, we used the instrument variables Age_Clinic_{ht}, $Age\_Clinic^2_{ht}$, $Age\_Clinic_{ht}*Post_{ht}$, and $Age\_Clinic^2_{ht}*Post_{ht}$ as exclusion restrictions.

Our estimation results, as reported in the second column of Table 6, suggest that compared to laboratory tests, the reduction in the duplication rate of radiology tests is not statistically significant, for the case of information sharing across all providers (i.e., $Treatment*Post_{ht}$ is negative but statistically insignificant with $\alpha_3^{all,\Delta} = -0.0182$). Thus, the results do not support hypothesis H1, after accounting for endogeneity. In Table 7, we separately analyze the radiology and laboratory test duplication rates, and observe that information sharing across all providers does not have a significant impact either on radiology or laboratory test duplication rates ($\alpha_3^{all,rad} = -0.0596$, $\alpha_3^{all,lab} = -0.0414$).

We then examine the impact of interorganization information sharing. The results are reported in the third column of Table 6. The interaction term, $Treatment*Post_{ht}$, is negative and statistically significant ($\alpha_3^{inter,\Delta} = -0.645,\ p < 0.01$), suggesting that radiology test duplication rates are reduced by 32.8% more than laboratory test duplication rates, in the presence of interorganization information sharing technologies. This impact is more pronounced than the all-provider case, which supports hypothesis H2. A closer examination of the differential impact of inter-organization information sharing on test duplication rates (Table 7, columns 4 and 5) reveals a negative impact on radiology test duplication rate ($\alpha_3^{inter,\ rad} = -0.396,\ p < 0.01$), whereas the impact turns positive for lab test duplication rate ($\alpha_3^{inter,\ rad} = 0.249,\ p < 0.05$).

The results for H1 and H2 taken together are intriguing. The value of information sharing is salient only for the case of inter-organization information sharing. The generic case of all-provider information sharing was not found to be effective in reducing the duplication rate of radiology or laboratory tests. Our results imply that, when providers share radiology and lab test results outside their health system, patients will experience reductions in the duplication rate only for radiology tests, while their lab test duplication rates may increase, thus widening the gap, Δ(*DupRate*). As we argued in H1 and H2, this difference can be partially attributed to technological barriers for sharing certain types of laboratory tests where the data is stored in unstructured data format, whereas radiology tests are less likely to be duplicated due to standardized data interfaces.[5]

Among the control variables in Table 6, the positive coefficient of *Emergency_Visit* suggests an increase in the relative duplication rate of radiology versus laboratory tests (11.7% for the all-providers case and 17.1% for the interorganization information sharing case), compared to elective visits. *ER charge* witnesses an increase in the relative duplication rate of radiology versus laboratory tests, suggesting an increase of 12.9% for all-providers and 7.9% for interorganization information sharing. With respect to Table 7, we observe that female patients tend to receive 5.1% and 5.2% fewer duplicate radiology tests, compared to their male counterparts for all-providers and interorganization information sharing cases, respectively. Compared to patients on Medicare B insurance plan, patients with Medicaid coverage experience 12.4% (all-providers case) and 15.7% (interorganization case) more duplicate radiology procedures; and similarly, these patients

[5]We thank an anonymous reviewer for this argument.

Table 6. Results of Control Function Approach across all Tests

	All-Providers *DV: D(DupRate)*		Interoganization *DV: D(DupRate)*	
Treatment	-0.214	(0.137)	0.146	(0.162)
Post	-0.056	(0.109)	0.243*	(0.131)
Treatment*Post	-0.018	(0.135)	-0.645***	(0.166)
Selfpay	0.133	(0.149)	0.107	(0.162)
Private	-0.064	(0.172)	-0.247	(0.225)
Other_Insurance	-0.128	(0.120)	-0.148	(0.141)
MedicareA	-0.252**	(0.121)	-0.239*	(0.130)
Medicaid	-0.00003	(0.147)	0.061	(0.172)
Emergency_Visit	0.226**	(0.093)	0.335**	(0.136)
Other_Visit	0.271***	(0.083)	0.168	(0.103)
Transfer_Source	0.777*	(0.451)	-0.032	(0.430)
Other_Source	-0.122	(0.206)	-0.419	(0.288)
Female	-0.068	(0.056)	-0.037	(0.054)
White	0.051	(0.062)	0.041	(0.059)
Age	0.001	(0.002)	0.0001	(0.002)
CMI	0.179	(0.171)	0.394**	(0.182)
Teaching	-0.338***	(0.125)	-0.033	(0.151)
Urban	0.254***	(0.096)	0.03	(0.173)
Log(Beds)	-0.022	(0.054)	-0.207***	(0.057)
Days_Between_Visits	0.004***	(0.0009)	0.004***	(0.001)
ER_Charge	0.250***	(0.059)	0.157**	(0.065)
Residuals	0.388***	(0.140)	0.212	(0.158)
Correlation Coef. (R^2)	0.087		0.095	
AIC	3.12		3.09	
LogLikelihood	-3984.77		-3197.99	
N	2568		2080	
Standard Dev(Y)	0.515		0.509	

Marginal effects at the mean values of the variables are reported.
Bootstrap standard errors (200 replications) are reported in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.0$

also experience 15.4% (all-providers case) and 35.3% (inter-organization case) greater duplication of laboratory tests.

Robustness Checks

We address several econometric concerns to ensure the robustness of our results**.** First, since the patients and providers in our sample are quite diverse in terms of their characteristics, we control for several sources of heterogeneity by including patient age, race, and gender, as well as provider size, teaching status, case mix index, and location (urban/suburban) in our estimation models. Second, we check for the presence of multicollinearity by reporting the correlation matrix in Table A1 in the appendix. The highest correlation is 0.94, which is between *Beds* and *Teaching*, with VIF values of 2.43 and 4.22, respectively. These low VIFs suggest low multicollinearity.

To examine the effect of time-window choice for a test to be considered as duplicate, we re-ran the same analysis with a shorter 30-day time window. The results of the control function estimation approach for Δ(*DupRate*) are reported in Table A2 in the appendix. Although we shorten the time window, which led to a reduction in the number of observations, the control function estimation results were largely consistent. As observed in Table A2, the coefficient of the interaction term, *Treatment*Post*, is insignificant for all-providers information sharing, but significant and negative for inter-organization information sharing.

Table 7. Results of Control Function Estimation Approach

	All-Providers		Interorganization	
	DV: DupRateRad	***DV: DupRateLab***	***DV: DupRateRad***	***DV: DupRateLab***
Treatment	-0.206* (0.125)	0.007 (0.110)	0.014 (0.147)	-0.132 (0.134)
Post	-0.032 (0.087)	0.024 (0.079)	0.062 (0.112)	-0.180** (0.089)
Treatment*Post	-0.06 (0.108)	-0.041 (0.101)	-0.396*** (0.143)	0.249** (0.126)
Selfpay	0.189 (0.156)	0.056 (0.122)	0.222 (0.175)	0.115 (0.127)
Private	-0.119 (0.171)	-0.055 (0.155)	-0.130 (0.200)	0.117 (0.190)
Other_Insurance	0.181 (0.112)	0.309*** (0.094)	0.218 (0.138)	0.366*** (0.111)
MedicareA	0.002 (0.115)	0.254*** (0.097)	0.096 (0.135)	0.334*** (0.111)
Medicaid	0.326** (0.141)	0.326*** (0.113)	0.414** (0.165)	0.353** (0.141)
Emergency_Visit	0.047 (0.070)	-0.179** (0.076)	0.109 (0.121)	-0.226** (0.112)
Other_Visit	-0.030 (0.064)	-0.301*** (0.065)	-0.053 (0.077)	-0.221*** (0.079)
Transfer_Source	0.583* (0.341)	-0.194 (0.213)	-0.025 (0.333)	0.006 (0.234)
Other_Source	-0.014 (0.198)	0.109 (0.146)	-0.392** (0.191)	0.026 (0.201)
Female	-0.134*** (0.039)	-0.066 (0.043)	-0.136*** (0.044)	-0.099** (0.044)
White	0.081* (0.045)	0.030 (0.048)	0.085* (0.051)	0.044 (0.049)
Age	0.003* (0.0015)	0.002 (0.002)	0.003 (0.002)	0.003 (0.002)
CMI	0.102 (0.131)	-0.077 (0.125)	0.395*** (0.141)	0.0002 (0.138)
Teaching	-0.002 (0.091)	0.336*** (0.097)	0.157 (0.149)	0.190 (0.126)
Urban	0.102 (0.082)	-0.152* (0.081)	-0.011 (0.148)	-0.041 (0.126)
Log(Beds)	-0.079* (0.046)	-0.057 (0.044)	-0.153*** (0.058)	0.054 (0.049)
Days_Between_Visits	0.001 (0.001)	-0.003*** (0.001)	0.001 (0.001)	-0.003*** (0.0001)
ER_Charge	0.990*** (0.058)	0.740*** (0.052)	0.999*** (0.067)	0.842*** (0.052)
Residuals	0.267** (0.119)	-0.121 (0.110)	0.109 (0.143)	-0.102 (0.129)
Correlation Coef. (R^2)	0.237	0.108	0.238	0.107
AIC	2.59	2.74	2.58	2.72
LogLikelihood	-3296.56	-3496.92	-2667.84	-2804.99
N	2568	2568	2080	2080
Standard Dev(Y)	0.380	0.473	0.379	0.471

Marginal effects at the mean values of the variables are reported.
Bootstrap standard errors (200 replications) are reported in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01

As a secondary check to address endogeneity concerns in our health information sharing variables, we ran a two-step Heckman approach (Bharadwaj et al. 2007) because our all-providers and interorganization information sharing variables are binary. In the first step, we obtain the inverse Mills ratio (λ) based on a first-stage probit model with an estimation equation $\Pr(y_2 = 1|X_2) = \Phi(X_2\beta_2)$ (Heckman 1976, 1979). Next, the inverse Mills ratio is introduced in the full treatment model (Mani et al. 2010), and estimated as shown in (3):

$$\hat{\lambda} = \lambda\left(X_2\hat{\beta}_2\right) = \frac{\phi\left(X_2\hat{\beta}_2\right)}{\Phi\left(X_2\hat{\beta}_2\right)} \quad \text{for } y_2 = 1 \text{ (treatment hospitals} \tag{3}$$

$$\hat{\lambda} = \lambda\left(X_2\hat{\beta}_2\right) = \frac{-\phi\left(X_2\hat{\beta}_2\right)}{\left(1-\Phi\left(X_2\hat{\beta}_2\right)\right)} \quad \text{for } y_2 = 0 \text{ (control hospitals)}$$

In the second stage, we obtained $\hat{\beta}_1$ and $\hat{\gamma}_1$ from the OLS estimation of $E\left(y_1|X_1, y_2 = 1\right) = X_1\beta_1 + \gamma_1\lambda\left(X_2\hat{\beta}_2\right)$. Incorporating the *inverse Mills ratio (λ)* into the second stage as a control variable, accounts for endogeneity (Wooldridge 2010). We note that inverse Mills ratios are prone to collinearity, leading to incorrect standard errors in the second stage (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 λs. This can be achieved by adding at least one exogenous explanatory variable to the selection model (Leung and Yu 1996). We introduce the four exogenous variables that were used in our control function approach, Age_Clinic_{ht}, $Age\_Clinic^2_{ht}$, Age_Clinic_{ht}*$Post_{ht}$, and $Age\_Clinic^2_{ht}$*$Post_{ht}$. We report the OLS estimation results using the two-step Heckman correction approach, in Table A3 of the appendix. Accordingly, only interorganization information sharing had a significant impact (-33.3%, $p < 0.01$) on Δ(*DupRate*), which is consistent with our main results.

We also performed a consistency check on the IT variables that we used in our main model (exchange of radiology and laboratory reports) and their relevance to reducing test duplication rate. Here, we conducted a falsification test and replaced our IT variable with another variable, *exchange of medication history* (where the exchange was operationalized in a similar manner as our information sharing variables). Our aim was to test whether the original IT variables (exchanging radiology and laboratory reports) were the driving forces behind our analysis, since the new IT variable (exchange of medication history) should not be associated with reductions in test duplication rates. The results on this falsification test are reported in the appendix in Table A4. The variable of interest, *Treatment*Control*, did not show any significant impact on the duplication rate across all-providers and interorganization information sharing cases. We conclude that our original IT variables are legitimate and accurately represent the information sharing construct.

Conclusion

In this study, we investigate the impact of health information sharing on the extent of duplicate testing, in the context of laboratory and radiology imaging tests, conducted on CHF patients in outpatient clinics of hospitals. Our main finding is that there is a differential impact of information sharing on the reduction in the rate of duplication. Electronic exchange of patient health information among healthcare providers only reduces the duplication rate of radiology tests, but not laboratory procedures. Our results further indicate that only interorganization information sharing is effective: duplication of radiology tests is reduced by 32.8% more than the duplication rate of lab tests in the presence of interorganization technologies. Hence, our findings indicate that the impact of health information sharing is more nuanced, and is significant only when radiology and lab tests are shared between different health organizations.

To the best of our knowledge, our study represents one of the first attempts to empirically explore the differential impact of electronic health information exchange on the duplication rate of two major categories of tests, radiology and laboratory, using a large panel of patient data tracked across a relatively long period of time. Although Lammers et al. (2014) explored the role of HIEs in reducing duplicate tests, our research is distinct due to several unique factors: (1) our data set comprises of patient visits across all ambulatory providers, whereas Lammers et al. only studied information exchange between ER departments; (2) we specifically track usage of health information sharing to exchange lab test results and radiology reports among providers, whereas they measured hospital enrollment in a HIE (without directly measuring the extent of HIE usage for exchanging radiology images); and (3) we conduct a granular analysis of duplicate testing at the ICD-9 level (while they aggregated imaging tests at the modality level which can lead to severe over-counting).

Policy Implications

Our analysis provides a straightforward approach to quantify the benefits of implementing a HIE as a means to reduce the overall duplication rate of diagnostic tests. Our findings suggest that, if providers affiliated with different healthcare organizations were able to communicate through a common, federated IT infrastructure, they could share data on patients' tests and procedures even when patients are mobile, and consequently reduce the extent of duplicate testing. One possible solution to this issue could be to promote implementation of regional HIEs, and common interoperability standards. Indeed, researchers have suggested that HIEs can reduce a significant portion of waste in the U.S. healthcare system through a higher level of information transparency (Adjerid et al. 2015; 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). A main pillar of an HIE system is the integration of universally accepted data standards which enable communication across disparate applications and healthcare entities. With this research, we show that there is a need to improve and expand the current data standards being used to communicate across various laboratory information systems. This result also echoes the suggestion of ONC to expand the use of LOINC across laboratories and other healthcare providers (ONC 2011).

Based on our data, we estimate that the cost of duplicate imaging tests for CHF patients amounts to $1,120,914 in the North Texas region, which is equal to an average, additional cost of $300 for every CHF outpatient treated. In this study, we only focus on CHF patient visits to outpatient clinics and impose a time window of 90 days to define the incidence of duplication. Therefore, our estimates of projected cost

savings are very conservative. According to Walker et al. (2005), the 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 stakeholders. Thus, our research complements the extant healthcare IT literature by showing that a lack of information sharing and the resulting unavailability of information can lead to higher levels of duplicate testing. Our research also addresses the call from Dixon et al. (2010) who highlight the rarity of published studies for evaluating the business value for HIEs.

Limitations and Future Work

Our study does have a few limitations. First, we do not have any procedure-level information (or access to physician notes) that can identify whether a duplicate procedure is truly redundant or an essential one. There is a lack of consistent 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). However, we contend that restricting 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 the literature and our communication with radiologists. Second, our results only reflect the duplication rates of laboratory and imaging procedures for outpatients with CHF as their principal diagnosis. For a generic view of overall duplication, other chronic illnesses should also be taken into account, such as pneumonia, asthma, and COPD, since CHF patients are typically afflicted with some of these comorbidities. Third, the decision maker for ordering tests is primarily the physician, and our study does not take into account physician-specific attributes such as training, workload, or experience, in terms of their impact on duplicate testing. However, we believe that our consideration of clinic/facility size and CMI can serve as a proxy for some of the variations that explain these physician-specific attributes. Fourth, the AHA survey does not provide additional information on how these test results are shared (i.e., extent of exchange), with whom they share, whether providers are able to receive and interpret the test, etc. Nevertheless, we believe that our study provides a starting point to address these types of issues related to the role of information systems in reducing duplication and waste across healthcare systems.

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About the Authors

Sezgin Ayabakan is an assistant professor in the Management Information Systems Department at Temple University's Fox School of Business. He graduated from the University of Texas at Dallas with a Ph.D. in Management Science in 2014. Sezgin received his M.S. degree in Industrial and Systems Engineering from the University of Florida in 2008, and a B.S. degree in Industrial Engineering from Bilkent University, Turkey. His broader research interests focus on the impact of health information technology and analytics on the cost and quality of healthcare delivery, as well as the business value of information systems on firm performance.

Indranil Bardhan is a professor in the Naveen Jindal School of Management at the University of Texas at Dallas. His research and teaching interests focus on applications of healthcare IT and analytics to improve the effectiveness of healthcare organizations. His research has been supported by grants from the National Science Foundation and the UT Health System, and has received several Best Paper awards at major journals and international conferences. He serves as a senior editor at *MIS Quarterly*, and has previously served as associate editor for several major journals and international conferences. He holds a Ph.D. in Management Science from the McCombs School of Business at UT Austin.

Zhiqiang (Eric) Zheng is a professor in information systems at the University of Texas at Dallas. He received his Ph.D. in information systems from the Wharton school at the University of Pennsylvania. His current research interests include healthcare IT, social media analytics, and financial analytics. He has published papers in *Management Science*, *Information Systems Research*, *MIS Quarterly* and *Informs Journal on Computing*. He currently serves as a senior editor at *Information Systems Research*, and is on the editorial board of *Informs Journal on Computing* and several other journals.

Kirk Kirksey serves as the Vice President of Information Resources for the University of Texas Southwestern Medical Center at Dallas, and the Senior Chief Information Officer for Zale Lipshy and Clements University Hospitals. With an operating budget over $80m, his 500 + employee organization oversees computing for the clinical, educational, research and administrative missions of the organization as well as an extensive data/telephony, data center disaster recovery, and support infrastructure. In 2009, Kirksey was appointed the UT System Fellow for Health Information Technology. He holds a Master's degree from UT Arlington.

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RESEARCH ARTICLE

THE IMPACT OF HEALTH INFORMATION SHARING ON DUPLICATE TESTING

Sezgin Ayabakan
Fox School of Business, Temple University, 1801 Liacouras Walk,
Philadelphia, PA 19122-6083 U.S.A. {ayabakan@temple.edu}

Indranil Bardhan and Zhiqiang (Eric) Zheng
Naveen Jindal School of Management, University of Texas at Dallas, 800 West Campbell Road,
Richardson, TX 75080 U.S.A. {bardhan@utdallas.edu} {ericz@utdallas.edu}

Kirk Kirksey
The University of Texas Southwestern Medical Center, 6303 Forest Park Road,
Dallas, TX 75390 U.S.A. {kirk.kirksey@utsouthwestern.edu}

Appendix

Though our quasi-experiment approach (described in the "Results" section), using a treatment-to-control matching algorithm, is a well-accepted methodology to purge out confounding effects, one may still argue that the $Treatment_h$ variables might still be subject to potential endogeneity. For example, providers with higher duplication rates may be more likely to implement health information sharing technologies. To address the concern of endogeneity, we adopted a control function estimation approach as discussed in Wooldridge (2011) and Rivers and Vuong (1988). The control function approach disintegrates the correlation between endogenous explanatory variables and unobservables affecting the outcome using additional regressors that do not appear in the structural equation (Wooldridge 2010). Suppose y_1 refers to the outcome variable, y_2 refers to endogenous explanatory variable, and $\mathbf{z}$ is the $1 \times L$ vector of exogenous variables, where $\mathbf{z_1}$ is a $1 \times L_1$ strict subvector of $\mathbf{z}$. Then model becomes

$$y_1 = \mathbf{z_1}\boldsymbol{\delta_1} + \alpha_1 y_2 + u_1 \tag{4}$$

with the orthogonality condition of $E(\mathbf{z}'u_1) = 0$. To correct for the endogeneity issue in y_2, we apply a linear projection of y_2 on all other exogenous variables. The reduced form of y_2 can be expressed as

$$y_2 = \mathbf{z}\boldsymbol{\pi_2} + v_2 \tag{5}$$

again with the orthogonality condition of $E(\mathbf{z}'v_2) = 0$. Endogeneity becomes an issue if and only if u_1 is correlated with v_2 which can be expressed as in this linear projection:

$$u_1 = \rho_1 v_2 + e_1 \tag{6}$$

where $\rho_1 = E[v_2 u_1]/E[v_2^2]$. Plugging (6) into (4) gives us the control function model for a probit model

$$y_1 = \mathbf{z_1}\boldsymbol{\delta_1} + \alpha_1 y_2 + \rho_1 v_2 + e_1 \tag{7}$$

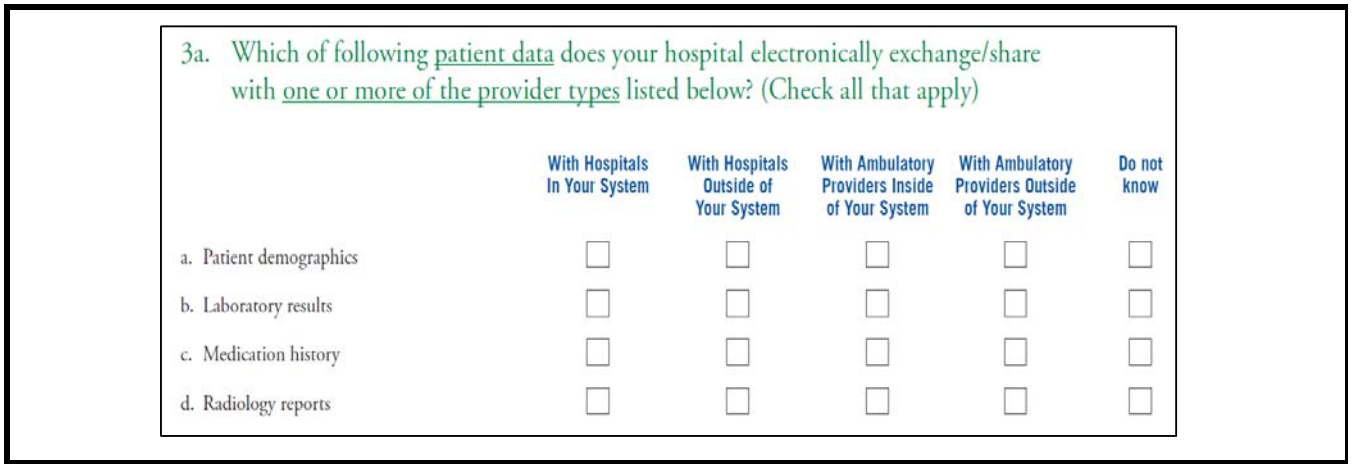
where v_2 is treated as a regressor. Since $E[\mathbf{z_1} e_1] = 0$, $E[v_2 e_1] = 0$ and $E[y_2 e_1] = 0$, model (7) can be estimated in a simple two-step procedure (Wooldridge 2010, 2011). In the first step, we regress y_2 on $\mathbf{z}$, which includes additional regressors that are excluded from $\mathbf{z_1}$. These additional

regressors in **z** will help to breakdown the correlation between u_1 and v_2. Then we estimate the residuals from the first step, $\overline{v_2}$, and plug them into model (7). Finally, we regress y_1 on $\mathbf{z_1}, y_2$ and $\overline{v_2}$ using OLS. The robust standard errors in model (7) can be obtained by bootstrapping to account for first stage estimation (Wooldridge 2011). We estimate model (7) for generic-, intra-, and interorganization information sharing, and include controls for patient payer type, visit type, admission source, age, gender, race, and other provider characteristics.

It remains to be determined as to which variables are to be included in **z** as part of the first stage estimation. Potential candidates should explain the variation in our endogenous variables (i.e., $TreatmentGeneric_h$, $TreatmentIntra_h$, and $TreatmentInter_h$), while they should not be systematically co-determined with *Duplicate_Rate* (Kumar and Telang 2012). One possible variable is the age of a hospital in terms of the number of years that it has been in operation (Age_Clinic_{ht}).[1] Relatively new providers would be more likely to implement health information sharing technologies, while older providers are usually slow adopters of such systems due to the difficulty of replacing legacy systems. At the same time, the age of a provider clinic/facility may not be systematically co-determined with its duplication rate.

We use the two variables, Age_Clinic_{ht}, $Age\_Clinic^2_{ht}$, and the interactions $Age\_Clinic_{ht}*Post_{ht}$, $Age\_Clinic^2_{ht}*Post_{ht}$ as additional variables in the first stage for all three cases, generic-, intra-, and interorganization information sharing. Since the control function approach resembles two-stage least squares (2SLS) estimation, we first check if these additional variables also satisfy the exogeneity and relevance properties of instrument variables in 2SLS (Greene 2011). The exogeneity assumption implies that IVs should be uncorrelated with the error term and the relevance assumption implies that IVs should be correlated with the independent variables (Greene 2011). To test the exogeneity of IVs, we use a test of over-identifying restrictions via Hansen's (1982) commonly employed Hansen-Sargan test. The Sargan statistic is distributed as χ^2 with degrees of freedom equal to the number of exclusion restrictions less the number of endogenous variables. Accordingly, we obtain $\chi^2_{(3)} = 5.474$ with $p = 0.14$, $\chi^2_{(3)} = 0.068$ with $p = .99$, and $\chi^2_{(3)} = 0.371$ with $p = 0.94$ respectively for generic, intra-, and interorganization information sharing variables. These statistics fail to reject the null hypothesis and implies that the instruments that we have selected are valid.

To test the relevance assumption, we employ a weak identification test on the IVs using the Anderson canonical correlations likelihood-ratio test statistic in which the null hypothesis suggests that the model is under identified or instruments are weak. Overall, the statistic is distributed as chi-squared with degrees of freedom equal to number of instruments less the number of regressors plus one. We report the statistics as $\chi^2_{(4)} = 600.9$ with p = 0.00, $\chi^2_{(4)} = 215.9$ with $p = 0.00$, and $\chi^2_{(4)} = 497.0$ with $p = 0.00$ respectively for generic-, intra-, and interorganization information sharing variables. Our results suggest that the IVs are not weak.



3a. Which of following patient data does your hospital electronically exchange/share with one or more of the provider types listed below? (Check all that apply)

	With Hospitals In Your System	With Hospitals Outside of Your System	With Ambulatory Providers Inside of Your System	With Ambulatory Providers Outside of Your System	Do not know
a. Patient demographics	☐	☐	☐	☐	☐
b. Laboratory results	☐	☐	☐	☐	☐
c. Medication history	☐	☐	☐	☐	☐
d. Radiology reports	☐	☐	☐	☐	☐

Figure A1. AHA IT Supplement 2012 Data Questions on Radiology and Laboratory Tests

[1]We manually collected information on the age of the outpatient clinic, measured as the number of years it had been in operation.

Table A1. Correlation Matrix

Variable	V#	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14
DupRateRad	***V1***	1													
DupRateLab	***V2***	0.31	1												
InsuranceType†	***V3***	-0.04	-0.05	1											
VisitType†	***V4***	-0.38	-0.19	0.05	1										
AdmissionSource†	***V5***	0.12	0.06	0.01	0.39	1									
Female†	***V6***	-0.08	-0.04	0.07	0.11	-0.03	1								
White†	***V7***	-0.13	0.002	0.12	0.28	-0.06	0.09	1							
Age	***V8***	-0.1	-0.01	0.40	0.13	0.03	0.21	0.43	1						
CMI	***V9***	0.02	-0.07	0.01	0.06	-0.02	-0.19	-0.41	-0.24	1					
Teaching†	***V10***	0.10	-0.05	-0.11	-0.11	0.18	-0.30	-0.59	-0.50	0.77	1				
Urban†	***V11***	0.23	-0.11	0.004	-0.37	0.29	-0.29	-0.62	-0.50	0.66	0.59	1			
Log(Beds)	***V12***	-0.07	-0.11	-0.005	0.18	-0.07	-0.08	-0.28	-0.16	0.56	0.94	0.17	1		
Days_Between_Visits	***V13***	0.07	-0.06	0.009	-0.13	0.13	-0.13	-0.20	-0.15	0.25	0.41	0.53	0.1	1	
ER_Charge†	***V14***	0.53	0.35	-0.10	-0.91	0.22	-0.16	-0.40	-0.27	0.01	0.34	0.55	-0.05	0.21	1

†These variables are categorical variables, as shown below.

InsuranceType: *MedicareB*, *Selfpay*, *Private*, *Other_Insurance*, *MedicareA*, *Medicaid.*

VisitType: *Elective_Visit*, *Emergency_Visit*, and *Other_Visit.*

AdmissionSource: *Referral_source*, *Transfer_source*, and *Other_source.*

Between continuous variables, Pearson correlations are reported.

Between continuous and categorical variables, polyserial correlations are reported.

Between categorical variables, polychoric correlations are reported.

Correlations > 0.4 are highlighted in grey boxes.

Table A2. Results of Control Function Approach (30-Day Time Window)				
	All-Providers		Interorganization	
Treatment	-0.136	(0.190)	0.130	(0.193)
Post	0.118	(0.134)	0.200	(0.163)
Treatment*Post	-0.111	(0.173)	-0.618***	(0.224)
Selfpay	0.00801	(0.212)	0.0695	(0.214)
Private	-0.0337	(0.244)	-0.178	(0.267)
Other_Insurance	-0.161	(0.173)	-0.187	(0.163)
MedicareA	-0.357**	(0.169)	-0.307*	(0.166)
Medicaid	0.161	(0.229)	0.227	(0.197)
Emergency_Visit	0.275**	(0.126)	0.455**	(0.182)
Other_Visit	0.379***	(0.115)	0.334***	(0.119)
Transfer_Source	0.874*	(0.478)	-0.155	(0.494)
Other_Source	-0.444*	(0.257)	-0.688**	(0.288)
Female	-0.120*	(0.0656)	-0.109*	(0.0658)
White	0.0157	(0.0859)	0.0269	(0.0817)
Age	0.00451*	(0.00272)	0.00367	(0.00300)
CMI	0.0497	(0.191)	0.256	(0.220)
Teaching	-0.415**	(0.182)	0.0629	(0.188)
Urban	0.331**	(0.140)	0.114	(0.186)
Log(Beds)	0.0183	(0.0826)	-0.172**	(0.0752)
Days_Between_Visits	0.000209	(0.00364)	0.000673	(0.00449)
ER_Charge	0.305***	(0.0819)	0.204**	(0.0960)
Residuals	0.509***	(0.190)	0.434**	(0.189)
Correlation Coef. (R^2)	0.116		0.119	
AIC	3.13		3.10	
LogLikelihood	-2353.15		-1907.83	
N	1518		1246	
Standard Dev(Y)	0.513		0.502	

Marginal effects at the mean values of the variables are reported. Bootstrap standard errors (200 replications) are reported in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.0

Table A3. Heckman Correction Results with Mills Ratio Estimation

	All-Providers		Inteorganization	
Treatment	-0.178	(0.123)	0.238*	(0.133)
Post	-0.0387	(0.104)	0.253**	(0.125)
Treatment*Post	-0.0545	(0.132)	-0.654***	(0.155)
Mills_Ratio	0.211***	(0.0703)	0.0647	(0.0789)
Selfpay	0.122	(0.155)	0.155	(0.154)
Private	-0.0689	(0.181)	—	—
Other_Insurance	-0.137	(0.123)	-0.108	(0.113)
MedicareA	-0.261**	(0.121)	-0.191*	(0.112)
Medicaid	-0.00852	(0.157)	0.108	(0.156)
Emergency_Visit	0.226**	(0.0963)	0.345***	(0.128)
Other_Visit	0.262***	(0.0843)	0.189*	(0.0970)
Transfer_Source	0.784*	(0.418)	-0.00710	(0.402)
Other_Source	-0.109	(0.199)	-0.392	(0.276)
Female	-0.0667	(0.0485)	-0.0349	(0.0540)
White	0.0464	(0.0594)	0.0222	(0.0641)
Age	0.00104	(0.00200)	0.000257	(0.00214)
CMI	0.186	(0.165)	0.428**	(0.176)
Teaching	-0.327***	(0.121)	-0.0173	(0.153)
Urban	0.264**	(0.108)	0.00754	(0.156)
Log(Beds)	-0.0293	(0.0526)	-0.217***	(0.0601)
Days_Between_Visits	0.00393***	(0.000964)	0.00427***	(0.00105)
ER_Charge	0.251***	(0.0625)	0.165**	(0.0704)
Constant	-0.340	(0.354)	0.183	(0.391)
Correlation Coef. (R^2)	0.087		0.095	
F Statistic	3.12		3.09	
N	2568		2080	
Standard Dev(Y)	0.515		0.509	

First stage involved probit estimation using additional variables Age_Clinic_{ht}, $Age\_Clinic2_{ht}$, Age_Clinic_{ht}*$Post_{ht}$, $Age\_Clinic2_{ht}$*$Post_{ht}$ as exclusion restriction.

Robust standard errors are reported in parentheses.

*p < 0.10, **p < 0.05, ***p < 0.0

Table A4. Results of Control Function Estimation with Information Sharing of Patient Medication History

	All-Providers		Interorganization	
Treatment	-0.138	(0.110)	-0.124	(0.106)
Post	0.127	(0.0827)	0.142*	(0.0820)
Treatment*Post	-0.120	(0.131)	-0.136	(0.121)
Selfpay	0.103	(0.106)	0.102	(0.102)
Private	-0.394***	(0.108)	-0.390***	(0.118)
Other_Insurance	0.101	(0.0807)	0.101	(0.0831)
MedicareA	-0.176**	(0.0694)	-0.174**	(0.0749)
Medicaid	0.138	(0.109)	0.134	(0.108)
Emergency_Visit	0.383***	(0.0695)	0.390***	(0.0647)
Other_Visit	0.249***	(0.0652)	0.247***	(0.0696)
Transfer_Source	0.235	(0.305)	0.232	(0.344)
Other_Source	-0.339***	(0.0978)	-0.349***	(0.0929)
Female	0.0484	(0.0318)	0.0483	(0.0294)
White	0.0731*	(0.0432)	0.0745*	(0.0438)
Age	-0.00492***	(0.00131)	-0.00496***	(0.00151)
CMI	0.178	(0.154)	0.194	(0.160)
Teaching	-0.727***	(0.0733)	-0.734***	(0.0704)
Urban	0.406***	(0.100)	0.396***	(0.0936)
Log(Beds)	0.132***	(0.0349)	0.130***	(0.0350)
Days_Between_Visits	0.00144**	(0.000696)	0.00145**	(0.000704)
ER_Charge	0.361***	(0.0598)	0.366***	(0.0566)
Residuals	0.134	(0.124)	0.119	(0.117)
Correlation Coef. (R^2)	0.12		0.103	
AIC	3.08		3.08	
LogLikelihood	-8959.80		-8929.93	
N	5828		5811	
Standard Dev(Y)	0.497		0.497	

Marginal effects at the mean values of the variables are reported. Bootstrap standard errors (200 replications) are reported in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.0

Table A5. Glossary of Acronyms	
ACA	Affordable Care Act
AHA	American Hospital Association
CBC	Complete blood count
CHF	Congestive heart failure
CMI	Case mix index
CMS	Center for Medicare and Medicaid
COPD	Chronic obstructive pulmonary disease
CPOE	Computerized provider order entry
CPT	Current Procedural Terminology
CT	Computed tomography
DFWHC	Dallas–Fort Worth Hospital Council
DICOM	Digital imaging and communications in medicine
DID	Difference in difference
ECG	Echocardiography
EDI	Electronic Data Interchange
EHR	Electronic health record
EMR	Electronic medical record
ER	Emergency room
FFS	Fee-for-service
HIE	Health information exchange
HITECH	Health Information Technology for Economic and Clinical Health Act
ICD	International Classification of Diseases
LIS	Laboratory information systems
LOINC	Logical observation identifiers names and codes
MRI	Magnetic resonance imaging
OECD	Organization for Economic Cooperation and Development
ONC	Office of the National Coordinator
PACS	Picture archival and communication systems
PHR	Personal health records
REMPI	Regional master patient index
RIS	Radiology information systems
VIF	Variance inflation factor

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