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Discrepancies in Hospital Financial Information: Comparison of Financial Data in State Data Repositories and the Healthcare Cost Reporting Information System

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Abstract

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Keywords

data and information quality, Medicare Cost Report, financial statement, state data repository, hospital

Comments

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ABSTRACT

High-quality financial data are important to stakeholders in the healthcare sector but are difficult to obtain. The two data sources most often used are hospital financial statements (HFSs) and Medicare Cost Reports (MCRs). Applying an analytical framework of data information quality dimensions, we compare a sample of 34,728 instances of 12 financial statement items extracted from HFSs and MCRs filed from 2007 through 2011. Our comparison shows a nontrivial frequency of missing items, widespread discrepancies across financial items, and a materiality of discrepancies that is significant in both sources. We also find many avoidable computational errors and significant absolute relative discrepancies between the sources. Additionally, we perform replications of two prior studies to test the believability of HFS and MCR data. Although we cannot conclude which source is more accurate, we do alert users of hospital financial data to the comparative potentials and limitations of these two major sources.

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I. INTRODUCTION

The size and impact of the hospital sector in the U.S. economy (at 17.4 percent of GDP in 2013, according to the Bureau of Economic Analysis [2015]) have increased the demand for data needed to analyze the operational and financial performance of hospitals. At present, hospital financial statements (HFSs) found in state data repositories (SDRs) and Medicare Cost Reports

(MCRs) stored in the Healthcare Cost Reporting Information System (HCRIS) are two major public sources of hospital financial information for various users, including policymakers, healthcare insurance companies, independent rating agencies, researchers, and other stakeholders (hereinafter referred to as "users" collectively). However, both of these sources of hospital financial information present challenges to users of the data.

While the financial statements filed by hospitals are publicly available from some SDRs, not all states collect them and/or allow public access to them. As of 2015, 18 states collect HFSs and make them publicly available in their SDRs. However, many of those HFSs are missing balance sheet and income statement information, lack a unique identifier, or differ in their presentation of data—all of which impair financial data comparability across hospitals.[1] As an alternative, MCRs are available for all hospitals in all 50 states and U.S. territories, and the data in MCRs are standardized in their format. Many users extract financial statements embedded in MCRs as their primary source of hospital financial data due to the accessibility, breadth of coverage, and standardized formatting of MCRs (e.g., Zeller, Stanko, and Cleverley 1996; Das 2013; Brickley and Van Horn 2002; Bai and Anderson 2015; Lamboy-Ruiz, Cannon, and Watanabe 2017; Paul, Quosigk, and MacDonald 2017).

Some existing literature, however, claims that financial statement items in MCRs are not only limited relative to those in HFSs, but they are also inaccurate (Kane and Magnus 2001; Ozmeral, Reiter, Holmes, and Pink 2012). In its letter commenting on revisions to the MCR form proposed in 2010 by the Centers for Medicare and Medicaid Services (CMS), the Medicare

[1] For example, Indiana and Texas information users can only obtain limited financial statements; Connecticut, Iowa, and Maryland, among others, do not report Medicare provider number, making it difficult to assess at what entity level an HFS is presented (i.e., hospital system or individual hospital); Florida, Iowa, and Minnesota, among others, only report a year of the filing (but not fiscal-year-end month or day), making it difficult to match entities with the same fiscal year end.

Payment Advisory Commission (MedPAC) states that "[a]ccurate information on hospital costs [...] is important for the operation of the Medicare program and for development of sound public policy. In our view, the proposed changes to the cost report would substantially improve the accuracy and completeness of the cost data hospitals report" (MedPAC 2009, 1).[2] However, in the same document, MedPAC also notes that despite the changes proposed by the CMS, several additional changes to the cost report are needed to address specific policy issues, particularly to make "reporting of hospitals' overall financial condition more *consistent* [italics added] with their audited financial statements" (MedPAC 2009, 1). The views expressed by MedPAC confirm that one purpose of MCRs is to provide information useful for assessing hospitals' financial condition, but, at the same time, material discrepancies may exist between data reported in MCRs and the corresponding data found in HFSs.

Although prior research has addressed data discrepancies between these two sources of hospital financial data, there are some limitations to those studies. For instance, the most recent study (Ozmeral et al. 2012) examined financial data only for critical-access hospitals, excluding non-critical-access community hospitals, which represent at least 62 percent of hospitals in the U.S.[3] The most cited study (Kane and Magnus 2001) collected samples of hospital reports from mid-1985 through 1995, which are now decades old. The main objective of our study is to fill the gaps left by prior literature by examining a recent, large sample of hospitals for the quality of data reported in the HFSs and MCRs.

In order to assess the quality of data, we adopt a framework of data information quality

[2] MedPAC is an independent congressional agency established by the Balanced Budget Act of 1997 (P.L. 105-33) to advise the U.S. Congress on issues affecting the Medicare program.
[3] The American Hospital Association (AHA) defines community hospitals as all non-federal, short-term general, and other special hospitals. Critical-access hospitals are rural community hospitals that receive cost-based reimbursement from Medicare. Those hospitals represented only 38 percent of all U.S. community hospitals in 2016 (AHA 2013).

(DIQ) dimensions developed by Wang and Strong (1996). In forming their framework, Wang and Strong (1996) relied on the rankings of DIQ dimensions that were most important to users of the data. In our study, we discuss SDRs and the HCRIS and empirically analyze data from these information sources with respect to all of Wang and Strong's DIQ dimensions. For our empirical analysis, we focus on the completeness, accuracy, relevancy, and believability of hospital data. We collect the HFSs of 655 hospitals from six SDRs for fiscal years 2007–2011.[4] To maintain our level of analysis at the same entity level, we match those hospital-year reports to the corresponding MCRs using Medicare provider number and fiscal year. We then identify 12 financial statement items (six income statement and six balance sheet items) aggregated at the high level and examine discrepancies between HFSs and MCRs using a total of 34,728 financial items.

First, with respect to completeness, we find a nontrivial number of missing financial statement items in HFSs and MCRs, with overall completeness rates below 94 percent. Second, in assessing the accuracy of hospital financial data, we find that, independent of the magnitude of differences, only 27.7 percent of data items, on average, are matched. When we turn our attention to absolute relative discrepancies between HFSs and MCRs, we find both mean and median discrepancies to be statistically different from zero.[5] Overall, our analysis of relative discrepancies suggests failings in data accuracy, yet we cannot ascertain whether HFSs or MCRs present the more accurate data. Third, we assess the accuracy of HFSs and MCRs independently by examining the frequency of avoidable computational errors (i.e., we check the equality of the

[4] While 18 states submit hospital financial data to their SDRs, 4 states do not have income statement or balance sheet data, and 8 more states do not disclose Medicare provider number or fiscal year end, which limits the scope of our analysis from 18 states to 6: Arizona, California, Maine, New Jersey, Nevada, and Washington.
[5] To vary the exposition, we use the terms *discrepancies* and *differences* interchangeably to indicate a difference between HFS and MCR line items where we focus on the magnitude of such difference. We refer to differences between HFSs and MCRs as *mismatches* when we focus simply on HFS and MCR line items that are not equal, without any reference to the magnitude of the difference.

accounting equation or whether reported total assets, total liabilities, and other financial items are zero or negative). Our avoidable error analysis suggests serious internal inconsistencies in the data, independent of any baseline for comparison.

Fourth, we evaluate the relevancy of reported data by examining the materiality of documented mismatches between HFSs and MCRs. Relevancy is a contextual data quality. Therefore, it is difficult to assess outside the context of a particular decision maker's task. However, we posit that if differences between two data sources were immaterial, then such differences would not affect the relevancy of data and vice versa. While we document that mismatches between HFSs and MCRs occur on average between 43.6 percent and 80.3 percent for the financial statement items we examine, material mismatches range from 31.8 percent to 66.6 percent. Furthermore, differences between mismatches and material mismatches are statistically significant from zero for all financial statement items examined, and range from 7.2 percent to 18.5 percent. We argue that the prevalence of material mismatches between the two data sources is large enough to affect the relevancy of hospital financial data reported.

Fifth, to assess the believability of hospital data empirically, we perform a replication of two empirical archival studies that focused on earnings quality. Specifically, we replicate a study of accrual earnings management (Leone and Van Horn 2005) and a study of earnings persistence (Dichev and Tang 2009) by using data from HFSs and MCRs and find results similar to those reported in the original studies regardless of the data source used. Whereas our other empirical analyses identify significant discrepancies between HFSs and MCRs, our replications offer evidence that users of hospital financial data can benefit from using MCRs if HFSs are not publicly available or are practicably unusable.[6]

In addition to our empirical analysis of the completeness, accuracy, relevancy, and believability of HFS and MCR data, we also discuss the other DIQ dimensions of the Wang and Strong (1996) framework. We argue that both HFSs and MCRs are comparable with respect to interpretability, ease of understanding, objectivity, timeliness, reputation, and access security. We also note that we can assess neither the value-added dimension nor the appropriate amount of data dimension, as these characteristics are contextual. Finally, we argue that MCRs are more accessible for large-sample studies and have higher representational consistency, while HFSs in some states may present financial statement data more compactly than MCRs, which provides the benefit of having a more concise representation.

Our study makes several contributions to the literature. First, we offer a means to assess hospital data quality by utilizing an established analytical framework (Wang and Strong 1996; Neely and Cook 2011). Second, compared with earlier studies that examined hospital data (Kane and Magnus 2001; Ozmeral et al. 2012), we use a more recent and more representative sample of U.S. hospitals. Third, we document the frequency of significant data omissions and discrepancies between MCRs and HFSs, notably after considering materiality thresholds used by financial statement auditors. Fourth, we show that despite existing data discrepancies, academic users may be able to use either HFSs or MCRs to draw inferences for answering broad research questions such as those concerning earnings quality.

[6] The inferences we draw from the replications may seem contrary to our concerns that large discrepancies between HFSs and MCRs may have a significant impact on the users of HFSs. But the users of these datasets bring different purposes to them. While the accuracy of data reported may be more important for some users, academic researchers often make simplifying assumptions and accept models with low coefficients of determination (R^2s) when explaining the average effect in a sample of firms (Dontoh, Radhakrishnan, and Ronen 2004). In contrast, state or federal enforcement agencies may rely on their ability to identify outliers that warrant detailed examination for potential material errors and/or fraud. For funding agencies, such as Medicare or Medicaid, the accuracy of reported numbers is crucial for determining whether federal or state resources are being misused. Hence, it is essential for users of hospital data to understand the nature and extent of discrepancies between the two data sources.

The remainder of the paper is organized as follows. Section II reviews relevant prior research and articulates the motivation for our study. Section III explains our process of sample selection and our descriptive statistics. Section IV presents our statistical analyses and empirical findings. Section V concludes.

II. BACKGROUND AND THEORY

For the for-profit setting, Neely and Cook (2011) provide a DIQ literature review documenting the demand for and the importance of sources of financial data that are accurate, timely, and complete. Other studies have reported data discrepancies between firms' filings and alternative data sources, particularly Compustat (e.g., Chychyla and Kogan 2015; Kern and Morris 1994; Kinney and Swanson 1993; Rosenberg and Houglet 1974; San Miguel 1977; Tallapally, Luehlfing, and Motha 2011). For instance, Chychyla and Kogan (2015) document data discrepancies between financial items reported in the SEC 10-K filings and in Compustat, two of the most popular sources of financial data used by practitioners and academics.

Although many studies have examined the sources of financial data for publicly traded firms, examinations of quality for sources of healthcare data have been comparatively limited. With respect to the healthcare sector, Kane and Magnus (2001), Chen, Stoner, Makhanu, Minikus, and Mueller (2004), and Ozmeral et al. (2012) explore several sources of hospital data and do observe discrepancies between the information contained in HFSs and MCRs. However, Kane and Magnus's (2001) sample is dated, exploring data between 1985 and 1995, and so does not reflect the current status of healthcare financial reporting quality. Chen et al. (2004) and Ozmeral et al. (2012) examine financial data from a restricted sample of hospitals (i.e., hospitals located in rural areas and/or classified as critical-access hospitals), representing less than 40 percent of the entire U.S. hospital population, which limits the generalizability of their studies.

To our knowledge, there is no study that utilizes a recent, large sample of hospital data for all types of U.S. hospitals.

Financial Data in Healthcare

As any other business entity does, U.S. hospitals prepare financial statements in accordance with U.S. Generally Accepted Accounting Principles (GAAP). At the demand of stakeholders,[7] most HFSs are also audited by certified public accountants. These audited financial statements are then perceived by hospital stakeholders to be the main source of financial data for the hospital sector (Kane and Magnus 2001; MedPAC 2004). While audited financial statements are a credible source of financial information about hospitals, their availability in a machine-readable format and their degree of comparability with hospitals in other states is limited.

At present, only 18 U.S. states make HFSs publicly available online through their SDRs. Of these states, even fewer report comprehensively both the income statement and the balance sheet information. Not all states collect hospital financial information, allow public access to SDRs for such information, and/or report comprehensive HFSs. Hence, as an alternative source of hospital financial data, many hospital stakeholders use MCRs archived by the HCRIS, which operates under the umbrella of the CMS. However, MCRs have not been used extensively in the financial accounting literature as the main source of hospital financial data and have sometimes been perceived as a source of inaccurate financial data (Kane and Magnus 2001; Ozmeral et al. 2012). In the following subsection, we review the concerns addressed in prior studies regarding the quality of financial data in HFSs and MCRs. (An enumeration of these concerns, with relevant passages quoted from the original publications, is provided in Appendix A.)

[7] Hospital stakeholders include, but are not limited to, managers, suppliers, creditors, government agencies, financial institutions, physicians, employees, patients, local community, and insurance companies.

Issues in Hospital Financial Data

Although not so frequently and thoroughly as in the setting of publicly traded firms, prior literature has characterized some data discrepancies between HFSs and MCRs as follows:

a) Operating incomes aggregated across states and by year were reported at different values in MCRs and audited financial statements, including an instance of a positive number in an MCR and a negative number in an HFS for the state of California for the period from 1985 to 1987 (Kane and Magnus 2001, 93).

b) The degree of discrepancies in major financial items (e.g., total assets and total liabilities) was lower than the degree of discrepancies in items that are *part of* the major financial items (e.g., current assets and current liabilities) for hospital reports in the period from 2007 through 2009 (Ozmeral et al. 2012).

c) There was a significant number of discrepancies in the financial ratios computed using MCRs and HFSs for fiscal years 1997–1999 (Chen et al. 2004).

d) The discrepancies observed were not associated with characteristics of the hospitals examined (e.g., hospital size and ownership type) (Chen et al. 2004; Kane and Magnus 2001; Ozmeral et al. 2012).

These studies argue that the discrepancies between HFSs and MCRs are random errors that may have the following causes:

1) inconsistencies in the operational definitions of financial items examined, such as HFS "other revenue," that must be manually computed using 15 line items from the MCR form (Ozmeral et al. 2012, Kane and Magnus 2001);

2) the lack of specificity in reporting instructions (Ozmeral et al. 2012);[8] and
3) differences in reporting entity (e.g., information contained in individual hospitals' MCRs may be collectively reported in one HFS of a multihospital system) (Magnus and Smith 2000).

Notably, some of the above arguments were untested—in particular, the argument that the discrepancies resulted from comparing "apples with oranges" by matching different reporting-entity levels within the same macro-organization (e.g., hospital system). However, such a problem can be solved by using a unique identifier to match hospital entities at the same level.

The discrepancies between HFSs and MCRs have led to a perception by some (e.g., Kane and Magnus 2001) that financial data in MCRs are "wrong" and that data in HFS are "correct," even though the CMS requires that hospitals prepare an MCR based on the trial balance produced by the hospital's accounting system, which is also used in the creation of an HFS. Further, Ozmeral et al. (2012) point out that MCRs are audited by fiscal intermediaries, implying that MCRs are not entirely unverified reports. Moreover, the CMS requires that each MCR submitted electronically include form CMS-339, which stipulates that audited financial statements must be submitted to the CMS with the MCR; plus, MCR reports not filed electronically must also include a copy of audited financial statements (CMS 2009). These instructions imply that a verification of MCRs against audited financial statements takes place.[9]

[8] As an example of lack of specificity, Ozmeral et al. (2012, 423) quote the instructions for the balance sheet in the MCR: "prepare these worksheets from your accounting books and records." In our opinion, however, if the hospital's accountants are to rely on their books and records for MCR preparation, the major line items in the balance sheet of the HFS (prepared using the same books and records) should match the same major line items in the balance sheet of the MCR.

[9] In fact, the CMS (2009, 32), in its *Medicare Financial Management Manual* states,

> [w]hile the Medicare auditor does not express an opinion on financial statements, he/she is responsible for collecting sufficient and competent evidential data as a basis for drawing conclusions about the Medicare

Additionally, the concerns raised in the studies about the quality of MCR data are peculiar in light of the recent integration of the database that contains MCRs by Wharton Research Data Services, a major provider of machine-readable data used in much academic research in finance, accounting, and other business fields.[10] Essentially, the quality of HFS data relative to MCR data remains an empirical question contextualized by use.

Considering the above context, we believe it is challenging to determine which data source provides "correct" numbers based on the information available to the public. We, therefore, follow a different approach in our examination of discrepancies between HFSs and MCRs. We do not intend to make explicit statements about which data source *overall* is correct or incorrect. Instead, as benchmarks for evaluating the two data sources, we adopt the DIQ dimensions framework of Wang and Strong (1996) and offer a data quality profile that users of hospital financial data may apply when considering each data source for their research. We first outline the DIQ dimensions that users find to be important. Next, we review the DIQ dimensions in the context of comparing HFSs and MCRs. Finally, we empirically evaluate a subset of the DIQ dimensions. Specifically, we focus on those DIQ dimensions that can be empirically evaluated by any practitioner, academic, or other user of hospital data without having to rely on additional private or proprietary information for verification.

Data and Information Quality (DIQ) Dimensions

Wang and Strong (1996) developed a framework for characterizing data quality by surveying data consumers about the dimensions of data quality that are important to them. The

cost report. Ensure that evidence obtained during the course of the in-house or field audit is sufficient to enable the auditor to support conclusions, adjustments, and recommendations. Make sure that there is enough factual and convincing evidence so that a prudent person can arrive at the same conclusion of fact as the auditor. In addition, evidence must be competent and relevant. That is, evidence must be valid and reliable and have a logical relationship to the issue/subject under review.

[10] Wharton Research Data Services offers HCRIS-sourced MCR data though their AHA subscription database: http://www.whartonwrds.com/wp-content/uploads/2016/09/AHA.pdf.

researchers defined and ranked 15 DIQ dimensions and later classified them into four target categories of data quality: (1) intrinsic = {believability, accuracy, objectivity, and reputation}, (2) contextual = {value-added, relevancy, timeliness, completeness, and appropriate amount of data}, (3) representational = {interpretability, ease of understanding, representational consistency, and concise representation}, and (4) accessibility = {accessibility and access security}. Neely and Cook (2011, 84) argue that "[w]hen considering DIQ with respect to AIS [accounting information systems], it is important to consider the multiple dimensions of quality" as opposed to focusing on a single dimension such as accuracy, for example. The main objective of our study is to compare the data in HFSs and MCRs, particularly those financial data that can be procured from these two data sources using the DIQ dimensions. Therefore, our broad research question can be stated as follows:

> **RQ**: Are the financial data in HFSs and MCRs different with respect to data information quality?

In comparing HFSs and MCRs using the Wang and Strong (1996) framework, we examine some of the DIQ dimensions empirically while others we assess only qualitatively based on our knowledge of SDRs, the HCRIS, the presentation of HFSs, and the format of the MCR, as well as by reviewing the relevant academic and practitioner literature. We present our comprehensive review of all fifteen DIQs in Appendix B, sorted from most important to least important per Wang and Strong. Because many of the DIQ dimensions are contextual or require an assessment of data sources (i.e., SDRs and the HCRIS) rather than the data themselves, we perform our statistical tests only on those dimensions that we can assess empirically, namely, accuracy, relevancy, completeness, and believability. Accordingly, with respect to our statistical analysis, we restate our broad research question in a more focused manner: Do the differences of financial data in HFSs and MCRs affect the accuracy, relevancy, completeness, and believability dimensions of data quality?

III. RESEARCH METHOD

Financial Statement Items Selected for Examination

For our main analysis, we follow the approach taken by Chychyla and Kogan (2015) and select the 12 most common financial items that have been used in prior research examining hospitals (e.g., Eldenburg and Krishnan 2008; Eldenburg, Gunny, Hee, and Soderstrom 2011; Krishnan and Yetman 2011; Ozmeral et al. 2012; Vansant 2016) and that are available in both HFSs and MCRs at the most aggregate levels.[11] Due to their high level of aggregation, these are the items for which we expect to observe the most convergence in the financial information presented, or the smallest number of differences; thus we follow a conservative approach in selecting items for examination. Specifically, we choose six financial items that are reported on the balance sheet: 1) *Total Current Assets*, 2) *Total Assets*, 3) *Total Current Liabilities*, 4) *Total Liabilities*, 5) *Total Fund Balance*, and 6) *Total Liabilities and Fund Balance*.[12] The other six financial items are reported in the income statement: 7) *Gross Patient Service Revenue* (similar to the accounting construct "gross sales revenues"), 8) *Total Deductions from Revenue*, 9) *Net Patient Service Revenue* (similar to "net sales revenues"), 10) *Total Operating Expenses*, 11) *Net Income from Service to Patients*, and 12) *Net Income*.[13]

[11] Due to the design of our study, which focuses on hospitals and is limited by the items disclosed in MCRs, we could not examine other financial data that Chychyla and Kogan (2015) include in their analysis: operating, investing, and financing cash flows; increase/decrease in cash; basic earnings per share (EPS) and diluted EPS; adjusted retained earnings and retained earnings; cost of goods sold; and gross profit.

[12] *Total Fund Balance* is a financial statement item equivalent to "total equity" or "total net assets"; *Total Liabilities and Fund Balance* is a financial statement item equivalent to "total liabilities and equity" or "total liabilities and net assets."

[13] *Net Income from Service to Patients* is defined as net patient revenues minus total operating expenses related to patient care; it is the accounting construct separately reported in the MCR most analogous to operating income. For HFSs we compute *Net Income from Service to Patients* by subtracting reported total operating expenses from

Data Collection, Matching, and Sample Selection

Due to the data limitations of MCRs (i.e., worksheets for the MCR do not include a statement of cash flows), we restrict our examination to financial items reported in the balance sheet and the income statement. We searched the Internet to identify the U.S. states that provide HFSs in their SDRs.[14] Of the 50 states and the District of Columbia, only 18 states publish online the financial statements of the hospitals under their jurisdiction. Of those 18 states, 14 have SDRs with HFS data available for both the income statement and the balance sheet.[15]

To properly match HFS and MCR entities, we need a unique identifier for each hospital and fiscal year end. Prior studies that have examined data discrepancies between HFSs and MCRs offer only limited details about their matching process for comparing financial items between the two data sources.[16] We use Medicare provider number in our matching process. Medicare provider number is a unique identifier intended to distinguish the smallest reporting entity offering hospital services (CMS 2007).[17] Our requirement for an assigned Medicare provider number in HFSs decreases the number of hospitals available for our examination, but it

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reported net patient revenue.

[14] Specifically, we employed two research assistants in 2015 to independently search and download from the Internet publicly available hospital financial information. We then checked search results for consistency.

[15] The SDRs with data for the balance sheet and the income statement are Arizona, California, Connecticut, Florida, Indiana, Minnesota, New Jersey, North Carolina, Oregon, Pennsylvania, Rhode Island, Texas, Vermont, and Washington. Other SDRs disclose data predominantly in the income statement or in the balance sheet, but not both comprehensively (i.e., Iowa, Maine, Maryland, and Nevada).

[16] Kane and Magnus (2001, 91) state, "we compared the MCR's Schedule G income statements with those of matched, audited financial statements." Ozmeral et al. (2012, 419) state that "[f]or each hospital in the sample, the AFS [audited financial statement] was matched to its corresponding MCR […] by hospital name, city, state, and fiscal year end to ensure comparison of coordinating data." Krishnan and Yetman (2011) use name and zip code to match hospitals.

[17] Hospital financial statements often do not include Medicare provider number and, in many instances, cover the financial items of more than one reporting entity in a consolidated disclosure (MedPAC 2009). Hence, HFSs may represent the consolidated financial statements of several entities with different Medicare provider numbers. The CMS *Provider Reimbursement Manual*, Part 1, Chapter 24 § 2414.5 states that "[i]nstitutions which have multiple facilities but only one provider number, or one provider number with sub-provider numbers for its related cost entities, are required to submit one cost report under that principal provider number together with the sub-provider numbers, if any." These hospitals file their financial statements combined in one MCR but may report financial statements separately to their SDRs. For such hospitals we do not have a match between MCR provider number and HFS, and thus we exclude them from our final sample.

allows us to control for discrepancies that would result from comparing financial items that cover different reporting entities. To increase the accuracy of the matching process, we also restrict our sample to HFSs that contain the fiscal year end, and not just reporting year. Consequently, our initial sample of raw data includes HFSs collected from the websites of six SDRs: Arizona, California, Maine, New Jersey, Nevada, and Washington, for a total of 7,347 report-years. The earliest year for which all necessary data are available is 2007, and the latest is 2011,[18] restricting our sample of HFSs to 3,946 report-years. Table 1 summarizes the process by which we selected our sample.

[Insert Table 1 here]

MCR data for years 2007–2011 are gathered from the HCRIS.[19] We eliminate MCRs covering fiscal periods with more or fewer than twelve months. These reports are usually issued by hospitals for initiating/ending their contract with the CMS, changing their fiscal year period, or changing their ownership type (Research Data Assistance Center 2013). After applying this criterion, we are able to identify only one report per hospital per year, resulting in 111,562 MCR-year observations. Next, we restrict our MCRs to only those states where hospitals report the 12 financial items examined in this study, yielding 13,980 report-year observations. Further, we limit our MCR sample to the years 2007–2011, ending up with 4,166 report-year observations.

Our subsequent step in data matching is to eliminate reports from both data sources (HFSs and MCRs) missing a Medicare provider number, resulting in 3,682 and 4,098 report-year observations, respectively. Afterwards, we exclude multiple reports with the same Medicare

[18] In 2010, MCR format changed, primarily to offer more instruction on how to fill out the MCR. Most hospitals started using the new format beginning in fiscal year 2011 (Lamboy-Ruiz et al. 2017), which is part of our sample period. However, mere change in MCR format should not affect the line items we examine in this study. Nevertheless, in untabulated tests, we re-estimate our empirical analysis after excluding 2011 from our sample, and our inferences remain unchanged.
[19] Data files are available at https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/index.html.

provider number occurring in the same fiscal year, resulting in 3,495 and 4,074 report-year observations, respectively.[20] Finally, we match HFSs and MCRs by Medicare provider number and fiscal year end, and after eliminating non-matches, we obtain 2,895 report-year observations. As a last check, we remove one observation that has different hospital names in the HFS and MCR under the same provider number and fiscal year, thus ending up with a final total of 2,894 report-year observations and 34,728 financial statement items (2,894 × 12) from 655 unique hospitals.

IV. EMPIRICAL RESULTS

Descriptive Statistics

Figure 1 depicts bar graphs with average dollar values (in thousands) of financial items reported in HFSs and MCRs. Financial items are listed in order of appearance in the balance sheet in the top panel and the income statement in the bottom panel. At first glance, most financial items show average values for HFSs and MCRs that are proximate to each other. However, *Net Income from Patient Revenue* and *Net Income* reveal a distinctive pattern of discrepancies in average dollar values. *Net Income from Patient Revenue* in MCRs presents an average amount (–9,283) that is roughly three times lower than the average amount reported in HFSs (–2,922). Although both data sources report positive dollar amounts of *Net Income*, the average amount reported in MCRs is almost half that reported in HFSs.

[Insert Figure 1 here]

[20] Note that in the case of duplicates, we do not eliminate duplicated observations to retain at least one report per fiscal year; rather, we remove all report-years that occur more than once per fiscal year with the same Medicare provider number. With this approach, we are able to eliminate cases where two reports are issued for the same year (e.g., a report for the first three months of the year and a separate report for the last nine months of the year). Further, we eliminate duplicates even if both reports cover the same 12-month period because we cannot identify with certainty which report is the correct one.

In Table 2, we present the descriptive statistics of financial items extracted from HFSs and MCRs. The mean values in Panels A and B are the same values reported in Figure 1. On average, the distribution of hospitals' balance sheet and income statement items (with the exception of *Net Income from Patient Revenue*) is skewed toward larger values, with median values consistently lower than mean values. Alarmingly, we identify minimal negative balance sheet values for both HFSs and MCRs. We also observe hospitals with zero *Gross Patient Revenues*, as well as negative *Net Patient Revenues.*

[Insert Table 2 here]

Analysis of Selected DIQ Dimensions

Completeness

Note that, in Table 2, the number of observations (*N*) for each of the 12 financial items is not equal to the expected number of matches (2,894), implying that for each of the financial items, whether in HFSs or MCRs, there are missing values. The number of missing financial items in each data source (*N Missing*) is our first evidence of incompleteness in each dataset. Overall, HFSs have a 94.6 percent completeness rate (32,862/34,728) while MCRs have only a slightly higher completeness rate of 95.1 percent (33,012/34,728) when all 12 financial items are considered at once. At the level of an individual financial item, completeness rates range from 93.1 percent for *Total Deductions from Revenue* in HFSs (2,695/2,894) to 95.4 percent for *Total Operating Expenses* in HFSs (2,761/2,894). Taken together, frequency rates for missing items that range from 4.6 to 6.9 percent are, we argue, nontrivial amounts for datasets that have already been subjected to considerable scrutiny through our sample selection procedure.[21]

[21] We want to caution the reader about the high incidence of missing values in MCRs, which may imply missing data. When a financial item is not listed or has a zero balance in the accounting trial balance, MCR filers do not enter zero values in the respective fields in the cost report worksheets used to prepare the MCR. This non-action

Next, having noticed missing financial items in both HFSs and MCRs, we continue our examination with an assessment of data completeness across the two sources simultaneously. Column A of Table 3 reports the frequency of financial item values that are missing in either HFSs or MCRs or both. The rate of such missing values ranges from 5.7 percent to 8.0 percent, with an average of 6.5 percent. Column B summarizes only items that are missing in both datasets for each hospital-year report. The balance sheet items have a slightly higher rate of missing items: 4.1 percent compared with 3.2 percent to 4.2 percent of missing values among the income statement items. Columns C and D show the frequency of missing items in HFSs only and MCRs only, respectively. Column E presents the frequency of differences between the two columns (i.e., column C – column D). We perform the chi^2 test for equality of items missing in HFSs only and MCRs only, that is, equality of values reported in columns C and D. For all financial items except for *Gross Patient Revenue*, there are more missing values in HFSs than there are in MCRs, even though the magnitude of the differences is relatively small, ranging from 0.2 percent to 1.6 percent. Nevertheless, it seems that HFSs are less complete than MCRs with respect to the 12 financial items that we examine.

[Insert Table 3 here]

Accuracy

We assess the accuracy of the data reported in HFSs and MCRs in several ways. First, we examine the frequency of financial statement items that are not equal as reported in HFSs and MCRs (i.e., mismatches) relative to matched and missing values across the two data sources. We measure the difference for each financial item for each hospital by subtracting the value of a

creates missing values automatically in the MCR for values that are intended to be zero. Following the underlying hierarchy of disclosures in financial accounting (e.g., total current assets = sum of all financial items listed as current in the assets section of the balance sheet), users of MCRs can identify zero-value financial items, and replace them accordingly if the aggregated amounts are equal to the sum of all of the respective components.

financial item found in an MCR from the value of the same financial item reported in an HFS. Therefore, a difference with a positive (negative) value indicates that the value of a financial item is higher (lower) in the HFS than in the MCR. We round the value of each financial item to the nearest thousand dollars to control for small discrepancies that might occur due to rounding in HFSs, which often disclose amounts rounded to the nearest thousand (000s).

Table 4 presents the frequency of items that are an exact match (i.e., difference is equal to zero) and indicates that such frequency is the highest for *Gross Patient Revenue* (50.6 percent) and the lowest for *Net Income from Patient Revenue* (14.0 percent) closely followed by *Total Operating Expenses* (14.8 percent).

[Insert Table 4 here]

All financial items except for *Gross Patient Revenue* exhibit frequencies of mismatches significantly greater than that of matches.[22] The highest frequency of mismatches is reported for *Net Income from Patient Revenue* (80.3 percent) and *Total Operating Expenses* (79.6 percent) while the lowest frequency of mismatches is reported for *Gross Patient Revenue* (43.6 percent). The average proportion of mismatches (relative to a total number of reports) is 65.8 percent. Although these mismatches do not take into account the magnitude of differences, the average rate of 65.8 percent, with the highest rate being 80.3 percent, is large and provides initial evidence suggesting a lack of overall accuracy for the two data sources. We cannot, however, assess *which* data source is inaccurate based on differences in data alone.

Because a large (small) *number* of discrepancies does not necessarily result in a larger

[22] As a validity test, we check the accuracy of the data compilation process done by SDRs. For the states of California and Indiana, we compare the reports that each hospital filed individually against the report compiled by the SDR. We find no evidence that the mismatches between MCRs and HFSs are caused by errors in the compilation process done by SDRs. For the states of California and Indiana, results show less than 0.1 percent of mismatches attributable to the compilation process.

(smaller) *amount* of discrepancies, we also examine the magnitude of discrepancies by calculating the absolute relative discrepancy between HFSs and MCRs (i.e., *Absolute Relative Discrepancy* = |(MCR – HFS)| / |(HFS)|). We focus our analysis on absolute values of differences because positive and negative relative differences may offset each other, resulting in underestimated mean values of relative discrepancies.

[Insert Table 5 here]

Panel A of Table 5 reports the descriptive statistics of absolute relative discrepancies. The mean absolute relative discrepancies range from 12.5 percent for *Operating Expenses* to 625.0 percent for *Net Income from Patient Revenue*. For illustrative purposes, we also depict the mean and median absolute relative discrepancies in Figure 2. Note the four financial items with average values of absolute relative differences greater than 100 percent: *Net Income* (267.8 percent), *Net Income from Patient Revenue* (625.0 percent), *Total Fund Balances* (126.3 percent), and *Total Current Liabilities* (130.6 percent).

[Insert Figure 2 here]

Table 5, Panel B summarizes statistical tests comparing mean and median absolute relative discrepancies to zero. All mean and median absolute relative discrepancies are statistically significantly greater than zero (all p-values < 0.1, one-tailed test).[23] Despite large mean absolute discrepancies and nontrivial median relative discrepancies, we cannot make definitive claims as to which data source is more accurate, as we do not have a baseline of data

[23] In untabulated tests, we compute signed relative discrepancies as follows: *Signed Relative Discrepancy* = (MCR – HFS) / |(HFS)|. The means of signed discrepancies are lower than the means of absolute relative discrepancies, ranging from –171.6 percent (*Net Income from Patient Revenue*) to 102.7 percent (*Total Fund Balance*). Most median signed relative discrepancies are zero, with the exception of *Total Operating Expenses* (0.03 percent) and *Net Income from Patient Revenue* (–0.1 percent). Zero medians may appear as somewhat odd. However, we find that there are a number of positive and negative relative discrepancies occupying the tails of the distribution of each financial item with a center of the distribution being represented by a zero discrepancy value. Thus, neither HFSs nor MCRs report systematically higher or lower values.

that is validated to be accurate with certainty. So far, our results suggest that significant differences exist between the two data sources in terms of the dollar amount (i.e., magnitude).

In order to investigate the accuracy of each data source independently, we next focus our attention on avoidable computational errors within HFSs and MCRs. Computational errors are one of the most important data quality issues in the financial reporting process that affect DIQ dimensions such as accuracy, reliability, and consistency (Debreceny, Farewell, Piechocki, Felden, and Graning 2010; Divorski and Scheirer 2001). Debreceny et al. (2010) examine mathematical computation errors (e.g., a value of the reported financial item does not match the sum of its related components: $A \neq B + C + D$) in interactive data filings to the SEC. They find 75 percent of the filings to be free from errors, with the remainder having an average of 1.8 errors per 10-Q filing. We follow the approach in Debreceny et al. and determine the computational errors of financial data extracted from HFSs and MCRs separately.

The computational errors can be easily identified due to the nature of HFSs and MCRs. In financial accounting, both the balance sheet and the income statement contain account balances or account changes, which are added and/or netted in order to present a total amount according to the predetermined structure of each statement given the accounting framework. We identify 18 potential computational errors based on the 12 financial items examined in the previous section. We begin with the most unexpected error: the inequality of the accounting equation (i.e., *Total Assets ≠ Total Liabilities + Total Fund Balance*). We next examine whether *Total Liabilities and Fund Balance ≠ Total Liabilities + Fund Balance*. We also check whether *Net Patient Revenue ≠ Gross Patient Revenue – Deductions from Revenue* and whether *Net Income from Patient Revenue ≠ Net Patient Revenue – Total Operating Expenses*. Lastly, we check for so-called nonsensical values that are usually eliminated during the sample selection stage of most empirical accounting studies: e.g., *Total Assets* = 0 (< 0), *Gross Patient Revenue* = 0 (< 0), *Net Patient Revenue* = 0 (< 0), *Total Current Assets* = 0 (< 0), *Total Liabilities and Fund Balance* = 0 (< 0), etc.

Table 6 presents the frequency of avoidable computational errors separated by each data source. The top three most common computational errors found in HFSs are Error #3 (19.96 percent, *Net Patient Revenue* ≠ *Gross Patient Revenue* – *Total Deductions from Revenue*) followed by Error #1 (2.86 percent, *Total Assets* ≠ *Total Liability and Fund Balance*) and Error #16 (1.10 percent, *Total Liabilities* < 0). For MCRs, the top three errors are Error #16 (3.03 percent, *Total Liabilities* < 0), followed by Error #14 (2.63 percent, *Total Current Liabilities* < 0) and Error #12 (1.68 percent, *Total Current Assets* < 0).

[Insert Table 6 here]

It is possible for a few hospitals in our sample to legitimately report zero *Gross Patient Revenue* or *Total Assets* during a liquidating year. However, the inequality of the accounting equation, or *Net Patient Revenue* that is not equal to *Gross Patient Revenue* minus *Total Deductions from Revenue*, points toward more serious issues with data accuracy. These results indicate that state staffs who oversee filings of HFSs either do not carefully perform computational checks or, if they do, do not request that their filers rectify data errors before making financial data publicly available. Although the frequency of the majority of computational errors seems low given that they occur in less than 2 percent of the filings, two errors (i.e., Errors #3 and #1) have occurrence rates that suggest greater issues with HFSs than with MCRs. Overall, our analysis of data accuracy shows that both HFSs and MCRs suffer from avoidable computational errors, suggesting that data in the two sources are often irreconcilable.

Relevancy

The relevancy dimension of data quality, while contextual in nature, also depends on the materiality of the financial information (Wang and Strong 1996; FASB 2010). If the discrepancies between HFSs and MCRs raise concerns about the accuracy of data and are considered to be material, such discrepancies would be related not only to the accuracy dimension but also to the relevancy dimension of data quality. To assess the relevancy dimension in the light of materiality, we examine the mismatches that are material.

We follow the arguments outlined by Leslie (1985) and Eilifsen and Messier (2015) and adopt a balance sheet materiality threshold of 0.5 percent of total assets and an income statement materiality threshold of 5 percent of net income. Table 7 reports the number and frequency of material mismatches between HFSs and MCRs in column B. For the purpose of comparison, column A also provides the number and frequency of mismatches presented in Table 4. Overall, the material mismatches represent more than half (52.7 percent) of the 34,728 financial items examined in this study, ranging from 41.4 percent (*Total Fund Balance*) to 66.6 percent (*Total Operating Expenses*). Column C summarizes the differences between mismatches and material mismatches. *Total Deductions from Revenue* (7.2 percent) shows the smallest difference, whereas *Net Income from Patient Revenue* (18.5 percent) displays the largest difference. All differences are statistically significant, indicating that they are different from zero. In summary, the discrepancies between HFSs and MCRs are not only common but also material; all 12 items show more than 30 percent of material discrepancies, and 7 of them are greater than 50 percent.

[Insert Table 7 here]

Believability

A user perceives data as believable when they are true, real, and credible (Wang and Strong 1996). Pipino, Lee, and Wang (2002, 214) state that "among other factors, it may reflect an individual's assessment of the credibility of the data source, comparison to a commonly accepted standard, and previous experience." In accounting research, it is common to rely on published studies first to validate (replicate) existing results and then to extend the literature stream by adding a unique contribution (e.g., Kothari, Leone, and Wasley 2005). From the perspective of data believability, we posit that the extent to which values reported in HFSs or MCRs can replicate the behavior documented in published studies that used similar data, the more believable the data source is. Therefore, to examine the potential impact of the discrepancies between HFSs and MCRs, we replicate a portion of the accrual-based earnings management study reported in Leone and Van Horn (2005) and an earnings persistence study by Dichev and Tang (2009).

Replication of earnings management study (Leone and Van Horn 2005). Leone and Van Horn (2005) find evidence that hospital administrators manage earnings toward zero and also manage earnings to avoid losses. They use multiple measures of discretionary accruals, which are discretionary adjustments to earnings that are allowed under U.S. GAAP. The financial data used in their study are obtained from the Van Kampen Merritt database, which is privately owned and includes hospitals with public debt financing. As is customary in accounting research in the healthcare industry, they obtain data for other hospital characteristics from the MCR (e.g., number of occupied beds per year and number of patient days).

We follow the sample selection procedure of Leone and Van Horn. Our sample period is 2007 to 2011 while their period is 1996 to 2002, and our sample includes hospitals from six states while they do not disclose their sample composition. Following Leone and Van Horn, we estimate discretionary accruals using the model in Jones (1991). We match hospital financial data in the MCR with the corresponding data in the HFS for the same hospital and the same fiscal year. We then construct two samples: one for HFSs and another for MCRs. Controlling for common hospitals helps us to eliminate unknown factors that might influence the results of the test (Kern and Morris 1994). Each sample includes 797 hospital financial reports per year for the period from 2007 to 2011. Table 8 shows the results of the ordinary least squares (OLS) estimations of model (1), which we have reproduced from Leone and Van Horn in Appendix C.

[Insert Table 8 here]

Panel A of Table 8 shows the descriptive statistics of the variables used in Table 2 of Leone and Van Horn (2005, 829). A comparison of the values for these variables indicates that mean *Earnings Before Discretionary Accruals* (*EBDA*) and median *Operating Income* (*INCOME*) are statistically different between HFSs and MCRs. However, *Discretionary Accruals* (*DA*) are not statistically different between samples. These results may suggest that the magnitudes of the mismatches are not large enough to alter the relationship between operating accruals and changes in net revenues and, hence, the estimation of discretionary accruals. On the other hand, it is also possible that the filters used to create the samples with non-missing values for the variables included in the Jones (1991) model result in dropping observations that are driving the significant differences documented in Tables 2 through 7 (e.g., we remove observations with a negative or zero value of total assets).

Panel B of Table 8 reports the results of our OLS estimation of model (1). Consistent with Leone and Van Horn (2005),[24] the coefficient on *EBDA* is negative and statistically significant for discretionary accruals in columns B and C (β_1 = –0.760 and –0.599,

[24] Leone and Van Horn (2005) define *EBDA* as *Operating Income* minus *DA*. Due to the nondisclosure of *Operating Income* in the MCR sample, we use *Net Income* instead. In untabulated analysis, we also replicated the results in Table 8 using *Net Income from Patient Revenue* as the level of earnings, and we obtain similar results.

respectively).[25] Note also that the estimated coefficient of the control variable, lagged operating income ($INCOME_{t-1}$), is positive and statistically significant in the HFS and MCR samples as documented in the previous study.[26] In addition, the adjusted R^2 for estimations are 55 percent and 68 percent, which implies the good fit of the models.

Overall, the results reported in Table 8 confirm earlier findings by Leone and Van Horn (2005), who argue that hospital managers use discretionary accruals to approach a zero earnings benchmark. The results reported in Table 8 also show that we can replicate Leone and Van Horn's findings with either source of data: HFSs or MCRs. Our findings are consistent with the argument that regardless of the discrepancies observed between HFSs and MCRs, inferences from research studies using financial items from HFSs can be replicated using data for the same items extracted from MCRs. Though the above findings support good levels of believability in both data sources, a higher value of adjusted R2 for the HFS regression may suggest a higher degree of believability with respect to HFSs.

Replication of earnings persistence study (Dichev and Tang 2009). Earnings levels are arguably one of the most examined financial items during yearly financial analysis performed by firms in all industries, including hospitals and state governments. The accounting literature has defined the quality of earnings in many ways, including the degree of persistence of current earnings (Dichev and Tang 2009). The higher the earnings persistence is, the better the quality of reported earnings. To determine the potential effects of differences between HFSs and MCRs on financial analysis and the decision-making process, we compare the earnings persistence of *Net*

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[25] A test of difference of the *EBDA* coefficients in Panel B of Table 8 for the matched samples (column C) shows that β_{1HFS} and β_{1MCR} are statistically different (chi^2 = 6.33 and p = 0.012).

[26] Although the coefficients for lagged discretionary accruals from Leone and Van Horn (2005) and both of our HFS samples are negative and statistically significant, they are not significant for the MCR sample. Lagged discretionary accruals are used as a control variable in the model, and its lack of significance does not affect the main inferences drawn from these results: managers adjust accruals toward a zero earnings benchmark.

Income reported in HFSs versus the persistence of Net Income reported in MCRs. We adopt the model introduced by Dichev and Tang because it requires only financial items that we examine in this study (i.e., *Net Income* and *Total Assets*). The model imposes a restriction on each hospital to have at least three consecutive years of non-missing values for *Net Income* and *Total Assets*. Hence, our sample used in this analysis was decreased from 2,894 to 1,433 hospital reports. Table 9 documents the results of the OLS estimations of model (2), which we have reproduced from Dichev and Tang (2009) in Appendix C.

[Insert Table 9 here]

Panel A of Table 9 shows the statistically significant coefficients of earnings persistence for HFSs ($\beta_{1HFS} = 0.583$, $p < 0.001$) and MCRs ($\beta_{1MCR} = 0.551$, $p < 0.001$) for pooled regressions. A test for difference in persistence coefficients shows that β_{1HFS} and β_{1MCR} are not statistically different ($chi^2 = 0.23$, $p = 0.629$). The magnitudes of reported β_{1HFS} and β_{1MCR} coefficients are similar to β as reported in Dichev and Tang. Therefore, this finding provides evidence that both data sources exhibit levels of quality of earnings similar to those documented in previous research.

For comparative purposes, we also replicate (partially) Panel B of Table 2 reported in Dichev and Tang (2009, 165) by estimating model (2) using observations from the highest and lowest earnings volatility quintiles. We present this replication in Panels B and C of Table 9, respectively. The results also show the statistically significant coefficients of persistence for both HFSs and MCRs, which are not significantly different from each other. Similar to Dichev and Tang, our results reveal a strong and monotonic relation between the volatility of earnings and earnings persistence when using both data sources. The above findings support good levels of believability for both data sources, but as in the previous replication, higher values in adjusted R^2

for HFS regressions may suggest a greater degree of believability for HFSs than for MCRs.

V. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

The U.S. hospital industry represents a large and growing part of the U.S. economy that relies heavily on federal and state funds from Medicare and Medicaid reimbursements. In order to maintain accountability for Medicare funds received, U.S. hospitals annually submit MCRs reporting information about their operations. Although MCRs are a seemingly valuable source of data for hospitals' stakeholders, the use of MCRs has been limited and the quality of their data criticized or deemed unreliable (e.g., Kane and Magnus 2001; Ozmeral et al. 2012; U.S. Government Accountability Office 2008). As an alternative to MCR hospital data, users may utilize HFSs, which are often claimed to contain more credible data because HFSs undergo an audit by public accountants. However, it is unclear whether the criticisms of MCRs in existing literature remain valid and whether HFSs are indeed a superior source of hospital financial data.

In this study, we examine the quality of hospital financial data presented in MCRs and HFSs. Using a large sample of U.S. hospitals that filed MCRs and HFSs from 2007 to 2011, we examine 12 common financial items. Our sample covers six states, 655 unique hospitals, and 34,728 total financial statement items. For our analysis, we employ the DIQ framework developed by Wang and Strong (1996) and supported by Neely and Cook (2011). The DIQ framework is appealing as an analytical construct because it was developed from users' own assessments of data quality dimensions. We apply the framework to hospital data reported in HFSs and MCRs and discuss the quality of the data based on DIQ dimensions: believability, accuracy, objectivity, reputation, value-added, relevancy, timeliness, completeness, appropriate amount of data, interpretability, ease of understanding, representational consistency, concise representation, accessibility, and access security. In our empirical tests of data quality for HFSs and MCRs, we focus on the DIQ dimensions of completeness, accuracy, relevancy, and believability.

We find a nontrivial amount of missing values in the income statement and the balance sheet for both MCRs and HFSs, suggesting a lack of data completeness (overall data completeness for both sources is only 93.5 percent). We also find statistically significant mean and median absolute relative discrepancies between MCR and HFS reported items. Specifically, such discrepancies range from 13.2 percent to 625.0 percent. Further, we observe a considerably large number of easily avoidable computational errors in HFSs and MCRs. Taken together, these two findings suggest a shortcoming of accuracy in the two data sources. In addition, we examine the materiality of differences between HFS and MCR reported values and observe rates of material discrepancies ranging from 31.8 percent to 66.6 percent, with an average rate of 52.7 percent. Because the relevancy of data often depends on the materiality of potential inconsistencies in the data, the prevalence of material mismatches we find between the two data sources indicates diminished relevancy. Lastly, to assess the believability of data, we perform an analysis to investigate the potential effects of observed discrepancies on research. To do this, we replicate earnings management (Leone and Van Horn 2005) and earnings persistence (Dichev and Tang 2009) studies using data from HFSs and MCRs. We find similar results leading to the same inferences as those made in the original studies, suggesting a fair degree of believability in both data sources.

In Appendix B, we review the DIQ dimensions that we are able to assess qualitatively and find that both HFSs and MCRs are comparable with respect to data interpretability, ease of understanding, objectivity, timeliness, reputation, and access security. Our review suggests that MCRs are more accessible for large-sample studies and have higher representational consistency, whereas HFSs present financial data in a more compact manner. It is noteworthy that we are unable to assess contextual DIQ dimensions such as value-added or appropriate amount of data because they depend on the context and nature of the tasks that users perform with the data. For instance, cross-state examinations of hospitals are possible with MCRs but not with HFSs due to the lack of availability of HFSs for many states.

With our findings, users can better understanding the nature and extent of discrepancies between the data reported in MCRs and those found in HFSs and be able to select the data source better suited to their tasks. Our findings support the notion that users of hospital financial data can benefit from using MCRs where HFSs are not publicly available. We also argue that researchers may benefit from using MCRs as an alternative to HFSs for hospital data if they seek data that are standardized, comparable across states, longitudinal, and cross-sectional. We do not advocate the use of one data source over the other in all cases; rather, we caution researchers about the discrepancies between these two main sources of hospital financial data. We leave it to future research to determine which source of hospital financial data definitively provides higher quality information.

We also encourage future researchers to investigate potential causes for discrepancies between HFSs and MCRs. For instance, future studies could examine whether the discrepancies are associated with the ownership structure of the hospital (i.e., for-profit, nonprofit, or governmental) or the type of hospital (i.e., teaching, rural, or affiliated with a religious organization). Additionally, academics may want to explore the possibility of whether discrepancies in financial data are more prevalent in hospitals that experience financial distress and therefore are constrained in their resources. Further, future research can examine which state-level characteristics influence the quality of SDRs and related HFSs. Academics may focus their attention on states' legal, enforcement, regulatory, and political regimes to examine whether these factors influence the frequency and severity of discrepancies between MCRs and HFSs.

Although our findings are agnostic about the relative superiority of the two sources, they are decisive about the many internal discrepancies of hospital financial data. Thus we urge hospital administrators to pay close attention to avoidable computational errors in their hospital's external filings and to develop processes that ensure such computational errors are minimal. To improve the quality of hospital financial data, we also recommend that state and federal policymakers encourage the adoption of standardized reporting formats such as eXtensible Business Reporting Language (XBRL) by the CMS and the agencies that oversee the management of SDRs. XBRL is a standardized method for preparing and exchanging business and financial information, which uses tags to identify each piece of financial data to make it machine readable and thus allows users such as analysts, investors, and regulators to access and analyze the data more easily. Existing research finds benefits to adopting XBRL (e.g., Kim, Lim, and No 2012; Li, Ni, and Lin 2012; Boritz and No 2013). If HFSs and MCRs were tagged with XBRL, users in need of hospital financial information could obtain comparable data from interoperable resources to use in their financial analysis and business decision-making.

As with any study, there are limitations to consider when interpreting our findings. Our sample included hospital financial data from only six states because HFSs from other states that would meet our minimum data requirements were not available. Plus, we examined only 12 common financial items for the period between 2007 and 2011. Therefore, our results may not reflect the practices of hospitals in other states or the consistency of other financial items in other years.

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Appendix A

Arguments against Using HFSs or MCRs in Research

We found the following arguments against using data from MCRs:

i. Magnus and Smith (2000, 70) in referencing Ashby (1993) and Johnsson (1991): "According to proponents of using audited financial statements instead of the MCR, the MCR tends to overstate costs and to present a negative slant on profitability since hospitals aim to maximize cost recovery."

ii. Kane and Magnus (2001):

   a. p. 83, "All of the Schedule G elements were designed prior to the publication of the first AICPA audit guide, so they do not comply with recent hospital accounting standards. Schedule G omits basic statements, such as a cash flow statement, and critical financial details, such as the hospital's provision of charity care; it suffers from inconsistent and erroneous reporting; and it does not undergo rigorous independent auditing."

   b. p. 92, "Relative to the audited financial statements, the MCR can either underestimate or overestimate hospitals' operating margins (operating income/total operating revenue). For instance, in the period 1985–1989 it underestimated hospitals' cumulative operating margin by 69 percent in New Jersey but overestimated it by 66 percent in Massachusetts, 280 percent in California, and 330 percent in Maine."

iii. Chen et al. (2004, 1): "A comparison of MCR and FS data shows considerable agreement for most hospital time-point measurements, especially when arrayed around a line of perfect agreement in a visual presentation. However, some hospital time-point measurements do not agree well. Specifically, in either report, the financial margins are quite small, so a difference will mean that a positive margin in one report, say the MCR, may be a negative margin in the other."

iv. U.S. Congressional Budget Office (2006, 11): "Although the Medicare Hospital Cost Report includes some information on uncompensated care, CBO did not analyze those Cost Report-based data because of concerns over the quality and consistency of the data. Nancy M. Kane and Stephen A. Magnus present a detailed description of the limitations of the Medicare Cost Report, especially financial measures contained in the cost report's worksheet G and uncompensated care in worksheet S-10."

v. Ozmeral et al. (2012):

   a. p. 416, "Other revenue and net income were consistently lower on the MCR and IRS 990, and depreciation was often higher on the MCR."

   b. p. 416, "The majority of total assets and fund balance (equity) values matched across the 3 reports, suggesting differences in classification among detailed accounts were more common than variances between the component totals (total assets, total liabilities, and fund balance)."

vi. MedPAC (2009, 3): "Schedule G was designed more than 25 years ago, and it is not consistent with the format and content of providers' audited financial statements, nor does it fully comport with generally accepted accounting principles that audited financial statements follow…"

Appendix B

Assessment of SDRs and the HCRIS with the Full DIQ Framework

In this appendix, we review each of the 15 DIQ dimensions in the order that they were ranked by Wang and Strong (1996) from highest to lowest. Where appropriate, we refer the reader to the empirical tests that we perform and discuss in section IV.

1. Believability

Believability is defined as "the extent to which data are accepted or regarded as true, real, and credible" (Wang and Strong 1996, 31). From this definition of believability, we posit that the data source is more believable to the extent to which values reported in HFSs or MCRs can replicate the findings documented in published studies that used similar data. To examine the potential impact of the discrepancies between the two data sources, we replicate a portion of the accrual-based earnings management study reported by Leone and Van Horn (2005) and the earnings persistence study presented by Dichev and Tang (2009) wherein we use HFSs and MCRs separately.[27] While a replication is one of the ways that we can assess the believability of data, we must acknowledge that in the event that all of the data sources contain similar types of errors or omissions, our replication would lead to an inference of believability that is flawed.[28] We also acknowledge that believability may be contextual in the sense that each user determines what degree of believability is acceptable or not based on a set of personal error tolerances.

2. Value-Added

Wang and Strong (1996, 31) define value-added as "the extent to which data are beneficial

[27] We chose the topic of earnings management/quality because it is a contemporaneous accounting behaviour that is comprehensively studied in the accounting literature using samples from the for-profit setting of publicly traded firms and recently in the nonprofit healthcare setting (e.g., Eldenburg et al. 2011; Vansant 2016).

[28] We thank an anonymous reviewer for bringing this issue to our attention.

and provide advantages from their use." Value-added data quality is contextual. Because tasks that data consumers perform depend on time and context, one way to achieve high contextual data quality is to offer data that match specific users' tasks at hand. For instance, if a user needs information about cash inflows and outflows from various hospital activities (i.e., operating, investing, or financing), the user would benefit from having the information contained in the statement of cash flows, which presently may only be provided in HFSs. On the other hand, if a user is interested in the community benefits (or charity care) offered by nonprofit hospitals, the user may have difficulty obtaining such data from states that do not require reporting of charity care (Hilltop Institute 2017a, 2017b), while MCR Form S-10, which all hospitals are required to file, offers detailed information about charity care costs. Furthermore, if a user is interested in comparing hospital performance, costs, or other financial metrics across states, he or she would be unable to do so using HFSs, due to the limitation of data availability, but would be able to perform cross-state analysis using MCRs. Therefore, we are unable to argue definitively whether HFSs or MCRs are better according to the value-added data quality dimension without a specific context.

3. Relevancy

Relevancy, according to Wang and Strong (1996, 31), is "the extent to which data are applicable and helpful for the task at hand." Stated alternatively, relevant information is capable of making a difference in a user's decision (FASB 2010). Relevancy is listed as a subcategory under contextual data by Wang and Strong, but in comparing HFSs and MCRs, we cannot definitively designate one data source as more relevant than the other because relevancy is also related to the concept of materiality. Stated differently, if the information gained from the data is immaterial, it would also be irrelevant to decision makers. Applying the same logic, if the differences between HFSs and MCRs are immaterial, the user can use either source of hospital data and apply specific criteria within the context of the task at hand to evaluate the data. However, if the differences are material, the user cannot rely on either source of hospital data with confidence and needs to subject the data to further scrutiny to make a reliable decision. Thus, to assess the relevancy dimension of the DIQ framework, we analyze the materiality of discrepancies in the financial items reported in HFSs and MCRs.

4. Accuracy

Accuracy is "the extent to which data are correct, reliable, and certified free from error" (Wang and Strong 1996, 31). Furthermore, the FASB (2010, QC15) declares information to be free from error when "there are no errors or omissions in the description of the phenomenon, and the process used to produce the reported information has been selected and applied with no errors in the process. In this context, free from error does not mean perfectly accurate in all respects." However, in the context of this study, we examine financial statement items reported by the same hospital entities in the same fiscal years and produced using the same accounting information systems. Hence, we deem data inaccuracy to be anything short of an exact match. In particular, we investigate accuracy by evaluating differences in major financial items reported in HFSs and MCRs as well as instances of computational errors that can be avoided by a hospital in any given year. For example, we check, among other items, whether assets equal the sum of liabilities and fund balances.

5. Interpretability

Interpretability is "the extent to which data are in appropriate language and units and data definitions are clear" (Wang and Strong 1996, 31). Assuming that the users of hospital financial data are familiar with the operational structure of hospitals and related terminology with respect to revenues and costs, both HFSs and MCRs present financial data with a similar degree of interpretability. HFSs include notes to financial statements to provide more information on the financial data, while the CMS offers manuals, which explain how the MCR worksheets have to be filled out. Both sources of data are also clear about the units used for financial data.

6. *Ease of Understanding*

Ease of understanding is "the extent to which data are clear without ambiguity and easily comprehended" (Wang and Strong 1996 32). Notably, Wang and Strong separate "ease of understanding" and "interpretability," although these two dimensions seem nearly synonymous. We believe that the emphasis of the sixth-ranked DIQ dimension is on the ease of comprehension. Given that an HFS and an MCR for the same hospital present basic financial data in the same units and with similar terminology, the ease of comprehension depends on one's ability to easily identify necessary data in both datasets. Within the task of identifying information in the balance sheet and the income statement, MCRs and HFSs are fairly comparable. Unlike MCRs, HFSs do not report an item termed *Net Income from Patient Revenue*, and thus users need to compute it as the difference between *Net Patient Revenue* and *Total Operating Expenses*. Other major balance sheet and income statement items are reported clearly on the respective statements in HFSs and in worksheets G and G3 of MCRs, and they both offer similar degrees of understandability.[29]

7. *Accessibility*

Accessibility in the Wang and Strong (1996, 32) framework "is the extent to which data

[29] It is worth pointing out that beyond the simple balance sheet and income statement presentation, the MCR may offer some additional challenges for extracting more detailed data. For example, Lamboy-Ruiz et al. (2017) have to combine information from MCR worksheets G3, G2, and A in order to create a more detailed hospital statement of revenues and expenses that segregates "Total patient care costs" from "Other indirect patient care expenses" as well as "Contributions, donations, bequests" and "Government appropriations" in the "Other income" section of the income statement. Furthermore, an ability to extract similar income statement items from HFSs depends on the level of reporting detail that the state requires and may not be consistent across all reporting states.

are available, or easily and quickly retrievable." At a given state level, HFSs are easily accessible and retrievable via online download. However, a user who is in need of comprehensive hospital information for all U.S. states and territories would be unable to obtain such data in HFS format for many states. Even in a data analysis limited to states offering hospital data online, the user must take the additional step of downloading the data from different repositories and combining them into one dataset. In contrast, the user can gather all hospital data in MCRs from the HCRIS. Therefore, we argue that MCRs are more accessible than HFSs.

8. Objectivity

Objectivity "is the extent to which data are unbiased (unprejudiced) and impartial" (Wang and Strong 1996, 32). We see no reason to expect that either data source would offer more or less biased information. Theoretically, both data sources present information from the same accounting information system with some variation in disaggregation within a document (HFS or MCR) for each hospital. However, such variations should not affect the degree of bias in reported information. One may argue that the differences, which we observe for financial items that should be the same in HFSs and MCRs, may be driven by managerial intent to obfuscate information or to "manage" reported financial performance, and that such earnings management would be more feasible with MCRs, which are allegedly unaudited by independent accountants. This argument, in itself, presents an empirical question, and we leave it to future research. In the absence of existing empirical evidence showing that the format of reported hospital data affects the neutrality of financial reporting, we claim that both HFSs and MCRs offer a similar degree of data objectivity.

9. Timeliness

Timeliness "is the extent to which the age of data is appropriate for the task at hand"

(Wang and Strong 1996, 32). MCRs have to be filed on or before the last day of the fifth month after the fiscal year end, so approximately 150 days after the fiscal year end. For the states that we examine, the deadline to submit annual reports (i.e., HFSs) to SDRs ranges from 30 days after each quarter end date (Nevada) to 180 days after the fiscal year end (Maine) or June 30th of the next calendar year (New Jersey). Washington and California require annual reports to be filed 120 days after a hospital's fiscal year end, while in Arizona, similar to the CMS requirements, hospitals must file their annual reports 150 days after the fiscal year end. Four out of six states also require quarterly reporting of financial data (California, New Jersey, Nevada, and Washington). One can argue that quarterly reporting is timelier than annual reporting, and thus some states provide more timely data to users. However, quarterly data are unaudited and may present fewer financial statement items than the annual report. With respect to annual reporting, only Nevada seems to offer significantly timelier HFSs than other states when compared to MCRs.

10. Completeness

Completeness exists when the data are "of sufficient breadth, depth, and scope for the task at hand" (Wang and Strong 1996, 32). This DIQ dimension is also of a contextual nature. Therefore, whether HFSs or MCRs offer sufficient breadth and depth of data ultimately depends on the task that a user performs. As we mentioned before, a detailed analysis of charity care costs is possible with MCRs but is unlikely to include every state that publishes hospital financial data due to a limitation in charity care reporting by state. In this study, we empirically assess the most basic aspect of completeness by comparing the frequency of missing data in HFSs and MCRs for major financial statement items.

11. Reputation

Reputation is "the extent to which data are trusted or highly regarded in terms of their source or content" (Wang and Strong 1996, 32).[30] We assess the perceived reputation of HFSs and MCRs based on an examination of positive and negative explicit statements made publicly by consumers of these data sources regarding their use in research. In our review of the literature, we found more negative arguments against using data from MCRs than arguments against using HFSs. We list selected arguments against both sources in Appendix A.

The arguments against MCRs include issues related to the quality of the data themselves (e.g., inaccuracies/errors) and the lack of equity and cash flows data. The arguments against using HFSs are not based on inaccuracies or the lack of specific data items but, instead, are based on the lack of data availability at the national level and aggregation issues with the data already available. As we discuss under the next dimension, we find that many SDRs, unlike the HCRIS, do not include unique hospital identifiers that can be used to combine data with other databases.

It is worthwhile to mention that our analysis of claims against the quality of MCR data reveals that researchers' subjective assessments were based on the historical reputation of the data quality. Some of the arguments against using MCRs seem to be rooted in Kane and Magnus (2001) and passed along to other potential users (i.e., U.S. Congressional Budget Office 2006).[31] As another argument against the reputation of MCR data, Magnus and Smith (2000) discuss

[30] The reputation dimension is often closely related to the number of errors or inaccuracies identified in the data (del Pilar Angeles and García-Ugalde 2012). The higher the number of errors, the lower is the perceived reputation of the data. Because accuracy is a DIQ dimension that we address in this study as a separate category, here we focus on an assessment of reputation that relies on different criteria.

[31] In an untabulated partial replication of Table 1 of Kane and Magnus (2001, 93) using our current sample for years 2007–2011, we find that state-aggregated values for *Net Income* using MCRs are lower than the values reported by HFSs. This finding is opposite to the trend documented in Kane and Magnus in a sample from 1985 through 1987. Contrary to Kane and Magnus, who do their analysis at the state level, we also compare average values for hospitals' annual *Net Income*, which are the values used in most research studies examining hospitals. We find the same pattern as in the state-aggregated values, and the values are not statistically different between HFSs and MCRs. The average values for hospitals' *Net Income* (000s) in the state of California are $11,609 for MCRs and $12,206 for HFSs. Therefore, our analysis provides evidence supporting the view that some of the inaccuracies reported in Kane and Magnus no longer exist in more recent data.

issues with cost overestimations found in MCR worksheets used by the CMS to reimburse hospitals for their provision of healthcare to the Medicare-insured population before 1983. We note that, in 1983, the CMS changed the reimbursement methodology from a cost-plus to a fixed fee-for-service model based on the patient's diagnosis, therefore nullifying the above-mentioned argument about overestimated costs in MCRs.

Further, the U.S. Government Accountability Office (GAO) used HFSs to examine trends in charity care provided by hospitals during 2008. While the GAO states in its report that the CMS has collected data on the provision of charity care since 2004, the GAO considers the data to be unreliable (U.S. GAO 2008). However, a year after the GAO report, the CMS, among other things, improved the MCR worksheet that reports charity care data by requiring separate reporting of payments received from patients approved for uncompensated care and another separate reporting of the bad expense component of uncompensated care costs. Overall, based on our analysis of arguments against MCR data quality, which are unrelated to the *accuracy* of data presented in HFSs and MCRs, we find many criticisms of MCRs to be outdated due to the revised MCR format and content requirements, and other arguments are valid only in a specific context and are related more to the completeness of data than to their reputation.

12. Representational Consistency

Wang and Strong (1996, 32) define representational consistency as "the extent to which data are always presented in the same format and are compatible with previous data." Despite the fact that MCR format is occasionally updated (most recently in 1996 and 2010) and some changes are made to the instructions, MCRs consistently contain a unique provider identifier, and the financial statement information is presented in comparable and standardized worksheets. On the other hand, hospitals have flexibility when presenting data in HFSs, and the consistency of presentation across hospitals and states may vary. We argue that MCR data offer greater representational consistency.

13. Concise Representation

Concise representation is "the extent to which data are compactly represented without being overwhelming" (Wang and Strong 1996, 32). We interpret the compactness of data representation to mean database structures that are usable with minimal manipulations. Based on our experience with the CMS and the HCRIS, CMS-provided data require significantly more pre-processing to be usable for financial statement analysis, among other things, due to the particular way that the CMS provides MCR reports and labels financial data.[32] On the other hand, HFSs are available in a more condensed form with financial statement items titled more intuitively.[33] From the standpoint of compact presentation, HFSs may be more compact and convenient than MCRs, but either data source can be overwhelming if we consider states that report a significant number of data items such as California.

14. Access Security

Access security is "the extent to which access to data can be restricted and hence kept secure" (Wang and Strong 1996, 32). From the viewpoint of users, access security would relate to assurance: that is, publicly available data in either MCRs or HFSs are not accessed by unauthorized third parties and altered, added, or removed. We are unaware of any such risks existing for MCRs or HFSs or having been documented by the popular press or existing academic research.

15. Appropriate Amount of Data

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[32] For more information on understanding MCR data structure, see https://www.resdac.org/resconnect/articles/11.

[33] See, for example, https://www.doh.wa.gov/DataandStatisticalReports/HealthcareinWashington/HospitalandPatientData/HospitalFinancialData/YearEndReports/2015HospitalYearEndReports, for Washington hospital reports.

Appropriate amount of data refers to "the extent to which the quantity or volume of available data is appropriate" (Wang and Strong 1996, 32). This data quality characteristic is also classified as contextual. Therefore, the question of which dataset (HFSs or MCRs) is more appropriate depends on the task that each user performs. For instance, California hospital reports are one of the most comprehensive hospital reports in the U.S., and likely for that reason, many researchers in accounting who use healthcare data have relied on (and limited) their studies to an examination of California hospitals (e.g., Eldenburg and Krishnan 2008; Eldenburg et al. 2011; Bai 2013; Vansant 2016).[34] On the other hand, MCR reports are suitable for users who seek to examine hospital characteristics and performance across states, (e.g., Lamboy-Ruiz et al. 2017).

[34] It is also worth noting that California has a large population, and therefore California hospitals provide data samples with sufficient size for statistical analysis with necessary statistical power.

Appendix C

Models of Discretionary Accruals and Earnings Persistence for Assessing Data Believability

Leone and Van Horn's (2005) model

To replicate Leone and Van Horn (2005), we estimate the following OLS regression for our multivariate tests of the zero profit hypothesis:

$$DA_{it} = \lambda_0 + \lambda_1 EBDA_{it} + \lambda_2 INCOME_{it-1} + \lambda_3 DA_{it-1} + \varepsilon_{it} \quad (1)$$

DA_{it} is the Jones discretionary accruals of hospital i in period t scaled by total assets at period $t-1$. The Jones (1991) model is the most commonly used method in the accounting literature to estimate discretionary accruals: $ACC_{it} / TA_{it-1} = \delta_{0t} / TA_{it-1} + \delta_{1t}\, \Delta NET\_REVENUE_{it} / TA_{it-1} + \delta_{2t}\, PPE_{it} / TA_{it-1} + \omega$, where ACC = total accruals calculated as the change in non-cash current assets minus the change in current liabilities from year $t-1$ to year t minus current depreciation expense; $\Delta NET\_REVENUE$ = change in net revenue from year $t-1$ to year t; PPE = net property, plant, and equipment as of the end of year t; TA = total assets as of the end of year t. The residuals from the Jones model are used as our measure of discretionary accruals.

$EBDA_{it}$ is the earnings before discretionary accruals (operating income minus discretionary accruals) for hospital i in period t scaled by total assets in period $t-1$. $INCOME$ is operating income scaled by total assets at the beginning of the period. DA_{it-1} is the Jones discretionary accruals of hospital i in period $t-1$ scaled by total assets at period $t-2$.

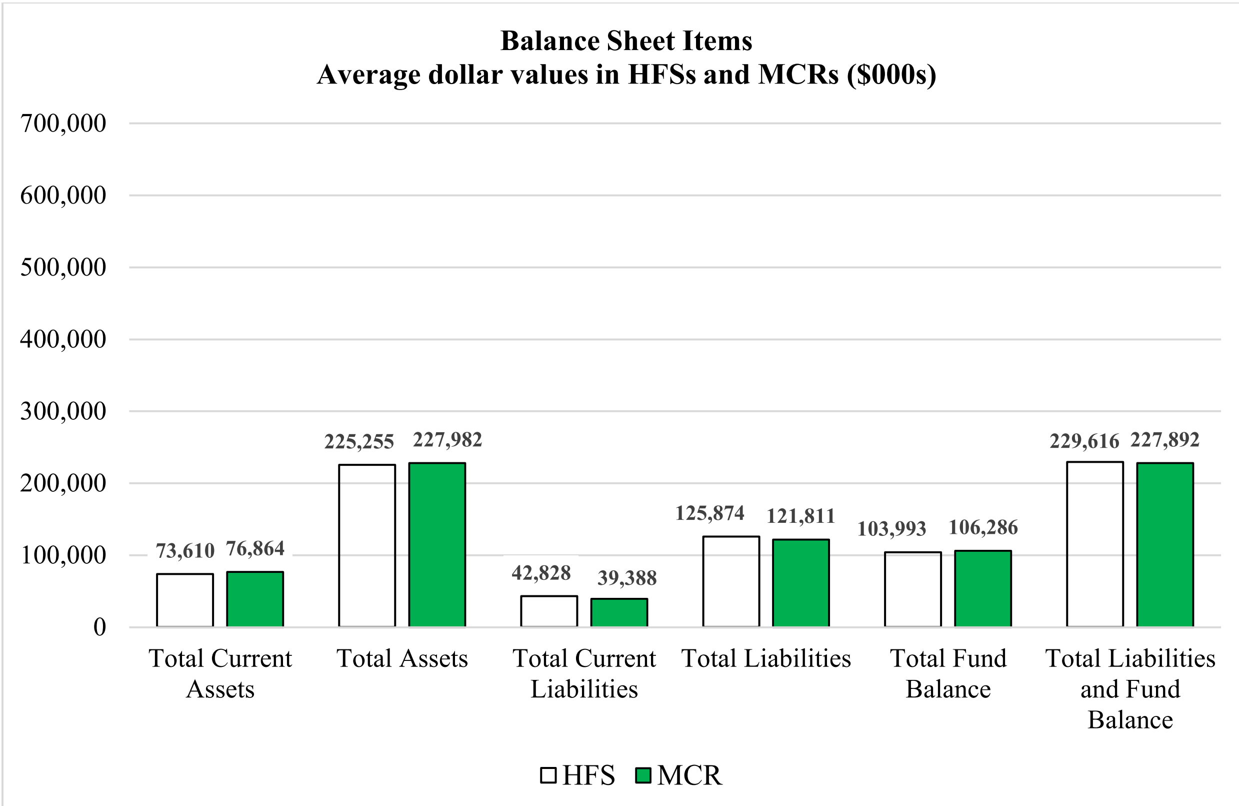
Dichev and Tang's (2009) model

Following Dichev and Tang (2009), our analysis of earnings persistence relies on commonly used regressions of current earnings on one-year lagged earnings:

$$Earnings_{it} = \alpha + \beta\, Earnings_{it-1} + \varepsilon_{it} \quad (2)$$

Earnings$_{it}$ are defined as *Net Income* in the current year deflated by *Total Assets* at the beginning of the year. Similarly, *Earnings*$_{it-1}$ are *Net Income* of the previous year deflated by *Total Assets* at the beginning of the previous year.

Figure 1. Trends of Dollar Values in Financial Items from HFSs and MCRs



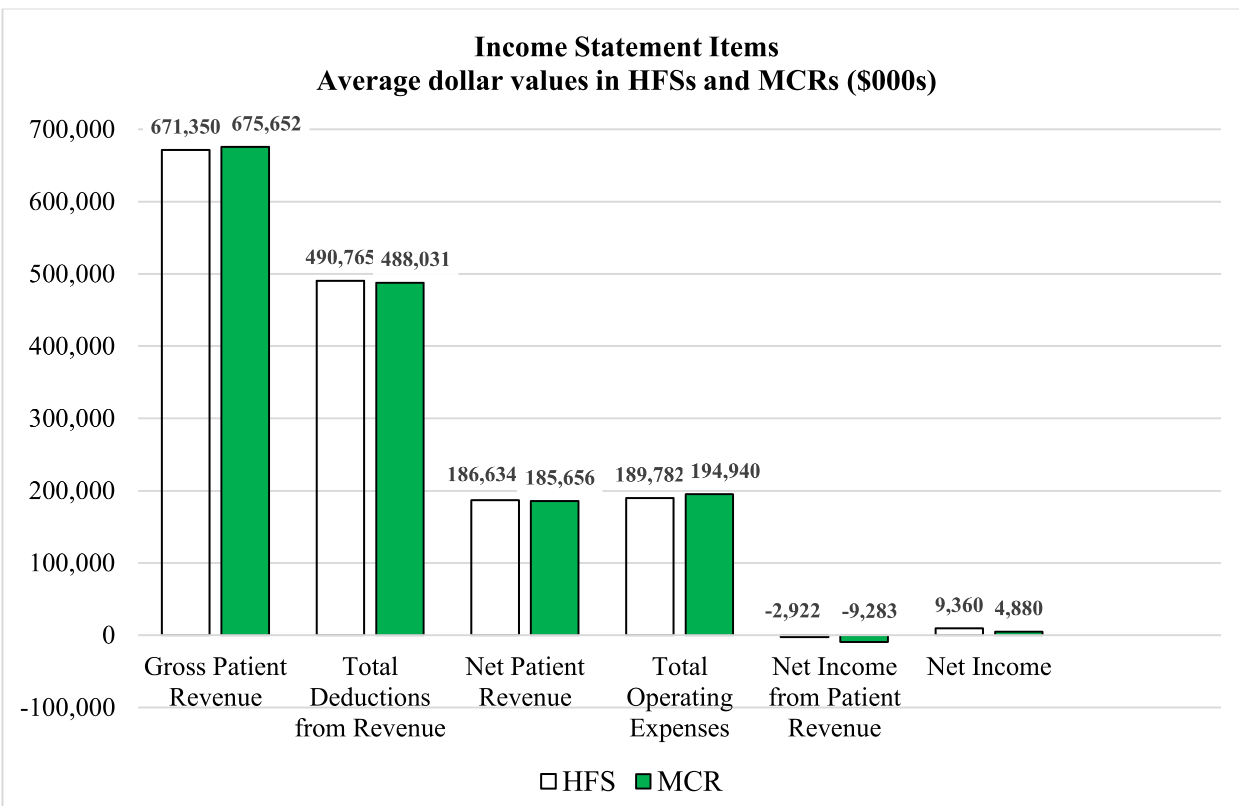
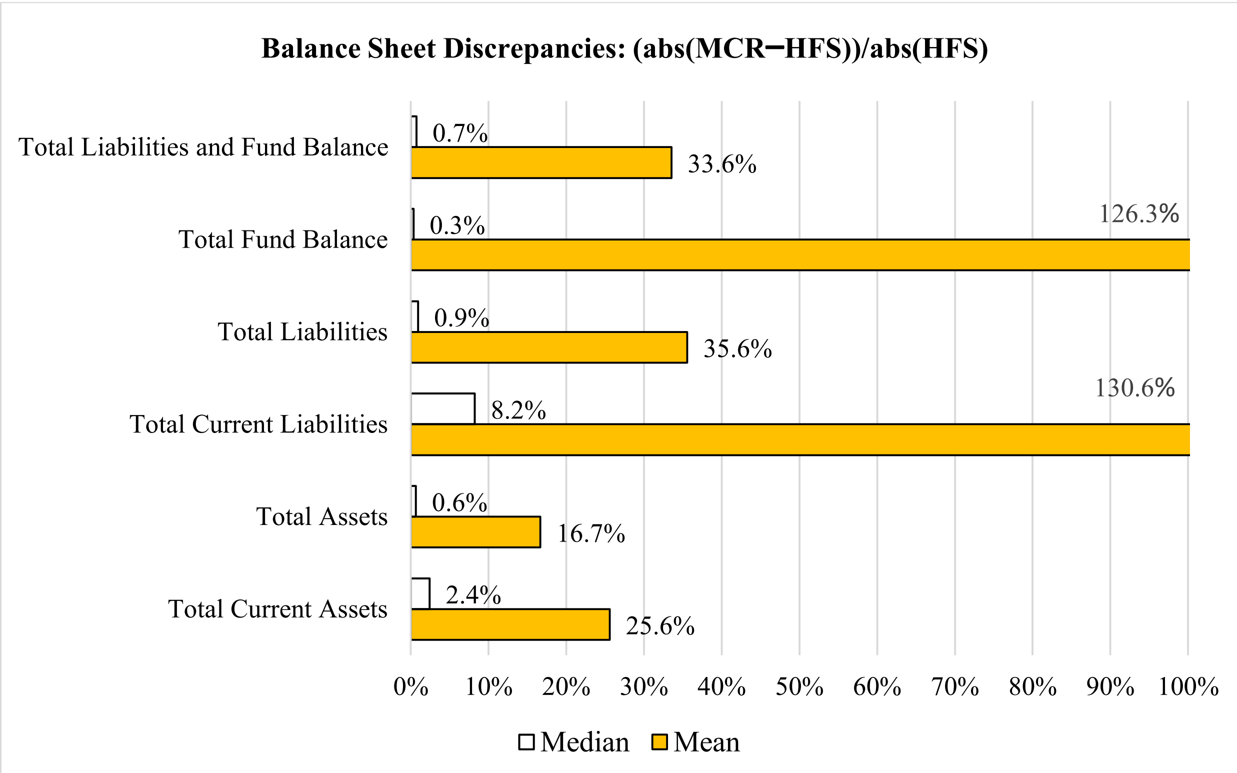


Figure 2. Descriptive Statistics of Relative Absolute Differences between HFS and MCR Items



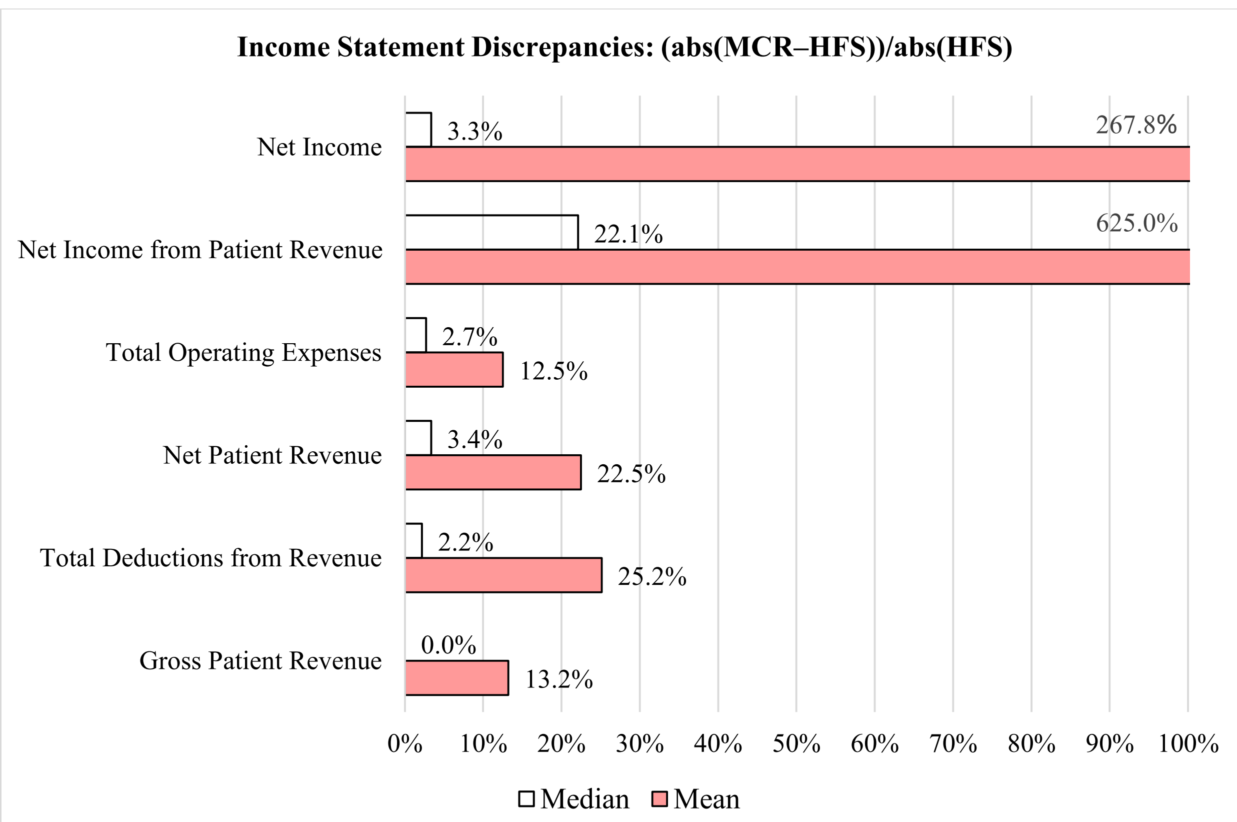


Table 1. Sample Selection

Data Source	**SDR**	**HCRIS**
Document Type	**HFS**	**MCR**
All MCRs available from all states	-	115,562
Less: reports from states that do not have all 12 Income Statement and Balance Sheet items in the HFS	-	(101,582)
All reports available from states that disclose Income Statements and Balance Sheets, fiscal year ends, and Medicare provider numbers (states retained: AZ, CA, ME, NJ, NV, WA)	7,347	13,980
Less: reports not occurring in both data sources in each year prior to 2012 (years retained 2007–2011)	(3,401)	(9,814)
Less: reports without Medicare provider number	(264)	(68)
Less: multiple reports with the same Medicare provider number in the same fiscal year	(187)	(24)
Less: reports not matched between two data sources by Medicare provider number and fiscal year	(600)	(1,179)
	2,895	2,895
Less: matched report with different hospital names in HFS and MCR	(1)	
Final hospital-year-level sample	2,894	
Times 12 financial items examined	×12	
Total number of financial items examined	34,728	

HCRIS (Healthcare Cost Report Information System), HFS (hospital financial statement), and MCR (Medicare Cost Report), SDR (state data repository)

Table 2. Descriptive Statistics of Major Financial Items from HFSs and MCRs

Panel A: Descriptive statistics of items extracted from HFSs (000s)

	Financial Line Items	N	N Missing	Mean	Median	STD	25%	75%	Min	Max
Balance Sheet	*Total Current Assets*	2,734	160	73,610	31,308	115,809	11,285	85,378	–11,149	1,238,763
	Total Assets	2,731	163	225,255	94,933	338,412	28,431	272,535	–29,387	3,232,684
	Total Current Liabilities	2,734	160	42,828	19,824	73,992	6,019	49,230	–192,918	846,545
	Total Liabilities	2,734	160	125,874	52,864	191,535	14,709	153,191	–192,918	1,711,571
	Total Fund Balance	2,729	165	103,993	30,120	184,919	4,587	131,793	–277,400	1,521,114
	Total Liabilities and Fund Balance	2,732	162	229,616	96,292	342,164	28,850	278,198	–61,363	3,232,684
Income Statement	*Gross Patient Revenue*	2,759	135	671,350	389,012	823,877	94,390	1,006,932	0	8,988,724
	Total Deductions from Revenue	2,695	199	490,765	265,552	624,317	50,567	738,932	–6,629	6,814,871
	Net Patient Revenue	2,760	134	186,634	111,870	224,679	39,127	257,862	–6,293	2,174,905
	Total Operating Expenses	2,761	133	189,782	114,551	228,755	39,582	257,882	2,048	2,163,429
	Net Income from Patient Revenue	2,760	134	–2,922	–402	33,568	–4,824	4,863	–545,826	184,469
	Net Income	2,733	161	9,360	2,623	30,038	–515	12,471	–181,531	291,634
Total		32,862								

Table 2 (continued)

Panel B: Descriptive statistics of items extracted from MCRs (000s)

	Financial Line Items	N	N Missing	Mean	Median	STD	25%	75%	Min	Max
Balance Sheet	*Total Current Assets*	2,743	151	76,864	30,278	131,429	10,669	86,393	–107,577	1,685,731
	Total Assets	2,743	151	227,982	94,006	347,329	27,217	274,194	–83,788	3,688,622
	Total Current Liabilities	2,740	154	39,388	18,025	70,756	5,242	46,717	–218,880	1,019,809
	Total Liabilities	2,741	153	121,811	51,230	188,565	13,501	151,201	–219,258	1,711,866
	Total Fund Balance	2,740	154	106,286	30,975	196,350	4,862	132,595	–138,134	1,976,756
	Total Liabilities and Fund Balance	2,743	151	227,892	93,862	347,450	27,103	274,194	–120,372	3,688,622
Income Statement	*Gross Patient Revenue*	2,741	153	675,652	398,546	824,216	94,702	1,010,463	0	8,987,972
	Total Deductions from Revenue	2,741	153	488,031	268,198	618,483	49,142	738,932	–1,132,890	6,595,466
	Net Patient Revenue	2,770	124	185,656	111,328	234,833	38,624	255,847	–1,339,485	2,760,416
	Total Operating Expenses	2,770	124	194,940	119,663	231,076	41,154	266,437	0	2,385,919
	Net Income from Patient Revenue	2,770	124	–9,283	–638	90,432	–6,750	4,479	–1,339,485	2,117,925
	Net Income	2,770	124	4,880	2,336	71,275	–792	11,554	–1,340,462	1,281,474
Total		33,012								

Panel A presents summary statistics of the major income statement and balance sheet items extracted from HFSs (hospital financial statements) in SDRs (state data repositories).

Panel B shows summary statistics of the major income statement and balance sheet items reported in MCRs (Medicare Cost Reports) provided by the CMS (Centers for Medicare and Medicaid Services). *N* is the number of observations for each financial statement item. *N Missing* is the number of missing financial items in HFSs or MCRs.

Table 3. Assessment of Completeness—Missing Values in HFSs and MCRs

	Financial Line Items	N	Column A (HFS or MCR or Both) n (%)	Column B (Both) n (%)	Column C (HFS Only) n (%)	Column D (MCR Only) n (%)	Column E (Difference) n (%)	
Balance Sheet	*Total Current Assets*	2,894	192 (6.6%)	119 (4.1%)	41 (1.4%)	32 (1.1%)	9 (0.3%)	***
	Total Assets	2,894	195 (6.7%)	119 (4.1%)	44 (1.5%)	32 (1.1%)	12 (0.4%)	***
	Total Current Liabilities	2,894	195 (6.7%)	119 (4.1%)	41 (1.4%)	35 (1.2%)	6 (0.2%)	***
	Total Liabilities	2,894	194 (6.7%)	119 (4.1%)	41 (1.4%)	34 (1.2%)	7 (0.2%)	***
	Total Fund Balance	2,894	200 (6.9%)	119 (4.1%)	46 (1.6%)	35 (1.2%)	11 (0.4%)	***
	Total Liabilities and Fund Balance	2,894	194 (6.7%)	119 (4.1%)	43 (1.5%)	32 (1.1%)	11 (0.4%)	***
Income Statement	*Gross Patient Revenue*	2,894	169 (5.8%)	119 (4.1%)	16 (0.6%)	34 (1.2%)	–18 (–0.6%)	***
	Total Deductions from Revenue	2,894	231 (8.0%)	121 (4.2%)	78 (2.7%)	32 (1.1%)	46 (1.6%)	***
	Net Patient Revenue	2,894	164 (5.7%)	94 (3.2%)	40 (1.4%)	30 (1.0%)	10 (0.4%)	***
	Total Operating Expenses	2,894	164 (5.7%)	93 (3.2%)	40 (1.4%)	31 (1.1%)	9 (0.3%)	***
	Net Income from Patient Revenue	2,894	164 (5.7%)	94 (3.2%)	40 (1.4%)	30 (1.0%)	10 (0.4%)	***
	Net Income	2,894	186 (6.4%)	99 (3.4%)	62 (2.1%)	25 (0.9%)	37 (1.2%)	***
	Total (Average)	34,728	2,248 (6.5%)	1,334 (3.8%)	532 (1.5%)	382 (1.1%)	150 (0.4%)	

***, **, * indicate the significance from the chi^2 test of the equality of financial statement items missing in HFS only (column C) and MCR only (column D) at the 0.01, 0.05, and 0.10 levels, respectively.

N is the number of observations for each financial statement item. *HFS or MCR or Both* is the number of items missing in HFS or MCR or both data sources (column A). *Both* is the number of items missing in both HFS and MCR (column B). *HFS Only* is the number of items missing in HFS only (column C). *MCR Only* is the number of items missing in MCR only (column D). *Difference* is the number of differences between HFS only and MCR only (i.e., column C – column D).

Table 4. Assessment of Accuracy: Matched, Mismatched, and Missing Items between MCRs and HFSs

	Financial Line Items	N	Matched Items n (%)	Mismatched Items n (%)	Missing Items n (%)
Balance Sheet	*Total Current Assets*	2,894	740 (25.6%)	1,962 (67.8%)	192 (6.6%)
	Total Assets	2,894	908 (31.4%)	1,791 (61.9%)	195 (6.7%)
	Total Current Liabilities	2,894	540 (18.7%)	2,159 (74.6%)	195 (6.7%)
	Total Liabilities	2,894	874 (30.2%)	1,826 (63.1%)	194 (6.7%)
	Total Fund Balance	2,894	1,117 (38.6%)	1,577 (54.5%)	200 (6.9%)
	Total Liabilities and Fund Balance	2,894	886 (30.6%)	1,814 (62.7%)	194 (6.7%)
Income Statement	*Gross Patient Revenue*	2,894	1,463 (50.6%)	1,262 (43.6%)	169 (5.8%)
	Total Deductions from Revenue	2,894	605 (20.9%)	2,058 (71.0%)	231 (8.0%)
	Net Patient Revenue	2,894	594 (20.5%)	2,136 (73.8%)	164 (5.7%)
	Total Operating Expenses	2,894	428 (14.8%)	2,302 (79.5%)	164 (5.7%)
	Net Income from Patient Revenue	2,894	406 (14.0%)	2,324 (80.3%)	164 (5.7%)
	Net Income	2,894	1,053 (36.4%)	1,655 (57.2%)	186 (6.4%)
Total / Average		34,728	9,614 (27.7%)	22,866 (65.8%)	2,248 (6.5%)

The table shows the number and relative percentage of discrepancies between the two data sources (MCR and HMS). For each of the 12 financial items, the total number of observations (*N*) is distributed among those values that are equal between the two databases (*Matched Items*), those values that are unequal (*Mismatched Items*), and those that are missing in either HFS or MCR or both (*Missing Items*). The sum of matched items, mismatched items, and missing items adds to 2,894 for each data item.

Table 5. Assessment of Accuracy: Discrepancies between MCR and HFS Line Items

	Financial Line Items	Absolute Relative Discrepancies abs(MCR–HFS) / abs(HFS)							
		N	**Mean**		**Median**		**STD**	**25%**	**75%**
Balance Sheet	*Total Current Assets*	2,686	25.6%	***	2.4%	***	1.4	0.0%	16.6%
	Total Assets	2,683	16.7%	***	0.6%	***	2.0	0.0%	5.3%
	Total Current Liabilities	2,683	130.6%	*	8.2%	***	43.5	0.3%	31.1%
	Total Liabilities	2,684	35.6%	***	0.9%	***	4.6	0.0%	9.1%
	Total Fund Balance	2,678	126.3%	**	0.3%	***	32.9	0.0%	10.1%
	Total Liabilities and Fund Balance	2,686	33.6%	**	0.7%	***	7.6	0.0%	5.9%
Income Statement	*Gross Patient Revenue*	2,725	13.2%	***	0.0%	***	2.0	0.0%	1.0%
	Total Deductions from Revenue	2,661	25.2%	***	2.2%	***	4.9	0.0%	7.2%
	Net Patient Revenue	2,730	22.5%	***	3.4%	***	2.2	0.0%	9.8%
	Total Operating Expenses	2,730	12.5%	***	2.7%	***	0.8	1.7%	8.1%
	Net Income from Patient Revenue	2,729	625.0%	***	22.1%	***	90.4	1.7%	100.0%
	Net Income	2,706	267.8%	***	3.3%	***	36.0	0.0%	53.4%

***, **, * indicate the significance of the t-test (Wilcoxon rank-sum test) for means (medians) at the 0.01, 0.05 and 0.10 levels, respectively.

The table provides summary statistics of absolute relative discrepancies between MCR and HFS values for 12 financial items in percentage terms.

Table 6. Assessment of Accuracy: Avoidable Computational Errors

Error	Description	HFS		MCR	
		N	N Errors (%)	N	N Errors (%)
#1	*Total Assets ≠ Total Liabilities + Total Fund Balance*	2,730	78 (2.86%)	2,743	9 (0.33%)
#2	*Total Liabilities & Fund Balance ≠ Total Liabilities + Total Fund Balance*	2,728	4 (0.15%)	2,738	0 (0.00%)
#3	*Net Patient Revenue ≠ Gross Patient Revenue – Total Deductions from Revenue*	2,695	538 (19.96%)	2,741	0 (0.00%)
#4	*Net Income from Patient Revenue ≠ Net Patient Revenue – Total Operating Expenses*	NA	NA NA	2,770	0 (0.00%)
#5	*Total Assets = 0*	2,731	16 (0.58%)	2,743	0 (0.00%)
#6	*Total Assets < 0*	2,731	3 (0.11%)	2,743	17 (0.62%)
#7	*Gross Patient Revenue = 0*	2,759	1 (0.00%)	2,741	4 (0.15%)
#8	*Gross Patient Revenue < 0*	2,759	0 (0.00%)	2,741	0 (0.00%)
#9	*Net Patient Revenue = 0*	2,760	1 (0.04%)	2,770	30 (1.09%)
#10	*Net Patient Revenue < 0*	2,760	1 (0.04%)	2,770	5 0.18%)
#11	*Total Current Assets = 0*	2,734	16 (0.59%)	2,743	1 (0.04%)
#12	*Total Current Assets < 0*	2,734	5 (0.18%)	2,743	46 (1.68%)
#13	*Total Current Liabilities = 0*	2,734	16 (0.59%)	2,740	1 (0.04%)
#14	*Total Current Liabilities < 0*	2,734	26 (0.95%)	2,740	72 (2.63%)
#15	*Total Liabilities = 0*	2,734	1 (0.04%)	2,741	16 (0.58%)
#16	*Total Liabilities < 0*	2,734	30 (1.10%)	2,741	83 (3.03%)
#17	*Total Liabilities & Fund Balance = 0*	2,732	0 (0.00%)	2,743	14 (0.51%)
#18	*Total Liabilities & Fund Balance < 0*	2,732	9 (0.33%)	2,743	19 (0.69%)

The table presents 18 common avoidable computational errors discovered in HFSs and MCRs. *N* is the number of observations with non-missing values for the variables used to calculate each error. *N Errors* is the number of observations with identified errors. Note that Error #4 does not apply to HFS because we compute *Net Income from Patient Revenue* for all HFSs. Therefore, there would be no computational error by design.

Table 7. Assessment of Relevancy: Comparison of Material and Non-Material Differences between HFSs and MCRs

	Financial Line Items	N	Column A (Mismatch) n	(%)	Column B (Material Mismatch) n	(%)	Column C (Difference) n	(%)	
Balance Sheet	*Total Current Assets*	2,894	1,962	(67.8%)	1,514	(52.3%)	448	(15.5%)	***
	Total Assets	2,894	1,791	(61.9%)	1,418	(49.0%)	373	(12.9%)	***
	Total Current Liabilities	2,894	2,159	(74.6%)	1,728	(59.7%)	431	(14.9%)	***
	Total Liabilities	2,894	1,826	(63.1%)	1,369	(47.3%)	457	(15.8%)	***
	Total Fund Balance	2,894	1,577	(54.5%)	1,198	(41.4%)	379	(13.1%)	***
	Total Liabilities and Fund Balance	2,894	1,814	(62.7%)	1,447	(50.0%)	367	(12.7%)	***
Income Statement	*Gross Patient Revenue*	2,894	1,262	(43.6%)	920	(31.8%)	342	(11.8%)	***
	Total Deductions from Revenue	2,894	2,058	(71.1%)	1,849	(63.9%)	209	(7.2%)	***
	Net Patient Revenue	2,894	2,136	(73.8%)	1,843	(63.7%)	293	(10.1%)	***
	Total Operating Expenses	2,894	2,302	(79.5%)	1,927	(66.6%)	375	(12.9%)	***
	Net Income from Patient Revenue	2,894	2,324	(80.3%)	1,788	(61.8%)	536	(18.5%)	***
	Net Income	2,894	1,655	(57.2%)	1,294	(44.7%)	361	(12.5%)	***
Total		34,728	22,866	(65.84%)	18,295	(52.68%)	4,571	(13.16%)	

***, **, * indicate the significance from the chi^2 test of the equality of financial statement items that have a mismatch and a material mismatch at the 0.01, 0.05, and 0.10 levels, respectively.

N is the total number of observations for each financial statement item. *Mismatch* (column A) shows the number of non-missing items whose values are different between HFS and MCR and the percentage of the items relative to *N*. *Material Mismatch* (column B) presents the number of non-missing items whose values are materially different between HFS and MCR and the percentage of the material items relative to *N*. Balance sheet materiality is defined as a threshold of 0.5% of HFS total assets, and income statement materiality is defined as 5% of HFS net income. *Difference* (column C) is the outcome of subtracting materially mismatched items from all mismatched items (i.e., column A – column B) and the difference between the percentage of mismatches and the percentage of material mismatches.

Table 8. Assessment of Believability: Comparison of Discretionary Accruals Analysis

Panel A: Descriptive Statistics

Variable	HFS Data			MCR Data			Difference	
	N	Mean	Median	N	Mean	Median	Mean	Median
Total Assets$_t$ ($000)	797	308,530	189,922	797	305,093	192,881	3,436	–2,959
Discretionary Accruals$_t$	797	–0.004	–0.001	797	–0.005	–0.004	0.001	0.003
Earnings Before Discretionary Accruals$_t$	797	0.004	–0.002	797	0.015	0.003	–0.001	–0.005 *
Operating Income$_{t-1}$	797	–0.009	–0.002	797	0.004	0.002	–0.013 **	–0.004
Discretionary Accruals$_{t-1}$	797	0.000	0.001	797	–0.002	–0.002	0.002	0.003

Panel B: Association of Discretionary Accruals and Pre-Managed Earnings

Variable	Column A (Leone & Van Horn 2005)	Column B (HFS Matched Sample)	Column C (MCR Matched Sample)
Intercept (β_0)	0.005 ***	0.003	0.003
Earnings Before Discretionary Accruals$_t$ (β_1)	–0.444 ***	–0.760 ***	–0.599 ***
Operating Income$_{t-1}$ (β_2)	0.236 ***	0.660 ***	0.512 ***
Discretionary Accruals$_{t-1}$ (β_3)	–0.090 ***	–0.058 ***	–0.066
Adjusted R^2	0.39	0.68	0.55
Number of Observations	8,179	797	797

***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: *Discretionary Accruals$_t$* are estimated using the Jones (1991) model, which is $ACC_{it} / TA_{it-1} = \delta_{0t} / TA_{it-1} + \delta_{1t}\, \Delta NET\_REVENUE_{it} / TA_{it-1} + \delta_{2t}\, PPE_{it} / TA_{it-1} + \omega$, where *ACC* is total accruals calculated as the change in non-cash current assets minus the change in current liabilities from year $t-1$ to year t minus current depreciation expense; *ΔNET_REVENUE* is the change in net revenue from year $t-1$ to year t; *PPE* is the net property, plant, and equipment as of the end of year t; *TA* is total assets. The residuals from the Jones model are our measure of discretionary accruals. *Earnings Before Dis cretionary Accruals$_t$* are operating income minus discretionary accruals for hospital i in period t scaled by total assets in period $t-1$. *Operating Income$_{t-1}$* is operating income from the previous year scaled by total assets at the beginning of the previous period.

Panel B: Column A presents the results of estimated discretionary accruals by Leone and Van Horn (2005, 829, Table 2). Columns B and C present our replication of Leone and Van Horn's results using data from HFSs and data from MCRs, respectively.

Table 9. Assessment of Believability: Comparison of Earnings Persistence Analysis

Panel A: Regression Results for the Full Sample

Variable	Dichev & Tang (2009)		HFS			MCR		
	Coef.	t-stat	Coef.	t-stat		Coef.	t-stat	
Earnings$_{t-1}$	0.652	NA	0.583	11.89	***	0.551	8.23	***
Adjusted R^2	0.398		0.341			0.232		
N	9,102		1,433			1,433		
Chi^2 *(Difference between HFS and MCR)*			0.23 (p = 0.629)					

Panel B: Regression Results for the Highest Earnings Volatility Quintile

Variable	Dichev & Tang (2009)		HFS			MCR		
	Coef.	t-stat	Coef.	t-stat		Coef.	t-stat	
Earnings$_{t-1}$	0.507	NA	0.423	6.40	***	0.363	3.89	***
Adjusted R^2	0.296		0.171			0.106		
N	1,820		285			286		
Chi^2 *(Difference between HFS and MCR)*			0.34 (p = 0.562)					

Panel C: Regression Results for the Lowest Earnings Volatility Quintile

Variable	Dichev & Tang (2009)		HFS			MCR		
	Coef.	t-stat	Coef.	t-stat		Coef.	t-stat	
Earnings$_{t-1}$	0.934	NA	0.957	18.03	***	0.92	8.26	***
Adjusted R^2	0.704		0.868			0.805		
N	1,820		287			289		
Chi^2 *(Difference between HFS and MCR)*			0.10 (p = 0.757)					

***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Each panel presents the results of replicating the earnings persistence relationship as reported in Table 2 of Dichev and Tang (2009, 165). The dependent variable is *Earnings*$_t$ = net income scaled by the beginning of the year total assets. *Earnings*$_{t-1}$ = net income from the previous year scaled by the beginning of the previous year total assets. Earnings volatility is the firm-specific three-year standard deviation of the earnings scaled by the beginning of year assets. Standard errors are clustered by hospital.