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# Health Information Technology Investments, Patient Experience, and Hospital Bad Debt

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**ABSTRACT:** In this study, we examine the effect of health information technology (HIT) investments on hospital bad debt via improved patient experience. Using data from California Hospital Reports and Definitive Healthcare, we first expect and find that HIT investments decrease hospital bad debt. Next, following Baron and Kenny's (1986) approach and the bootstrap approach of Zhao, Lynch, and Chen (2010), we study whether patient experience mediates the relationship between HIT investments and hospital bad debt. We find that HIT improves patient experience which, in turn, reduces bad debt at hospitals. Taken together, our findings provide evidence that patient experience is important as a means to affect the relationship between HIT investments and hospital bad debt.

**Keywords:** health information technology investments; patient experience; hospital bad debt.

## I. INTRODUCTION

Bad debt is a chronic issue for hospitals (Mariarty 2020). Concern about bad debt has intensified since the enactment of the Affordable Care Act of 2010 because hospital charity care has plunged and more patients have accessed healthcare services via high

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deductible and coinsurance/copayment health plans (Reiter, Noles, and Pink 2015). As a result, patient payment responsibility has increased, and hospital bad debt has risen. Hospital bad debt is the result of patients not paying their deductibles and coinsurance/copayments. When a patient enters a hospital and requests healthcare services, the hospital staff evaluate the patient's ability to pay based on the hospital policies and the personal information provided by the patient. The patient will be deemed a charity case or be billed for services.[1] If the patient is determined to qualify for charity care, he/she receives a free or reduced-price service, and the unreimbursed cost of the services is recorded in the charity care account. Otherwise, the patient is billed for services. If the patient does not pay the bill, the uncollected payment is recorded in the bad deb account. Thus, bad debt relates to patients who are, at least initially, deemed able to pay (Beck, Gilstrap, Rippy, and Vansant 2020). Spoden (2019) reports that there are three main reasons why patients are not willing to pay their bills. First, the patient does not realize he/she will receive bills in the first place. Second, the patient is confused by the bills (e.g., the patient may receive multiple bills from the physician, the facility, the lab, and the anesthesiologist in surgical cases). Third, the patient cannot afford to pay the whole bill at once. In addition, some patients may just "not want to pay" rather than "cannot pay." Given the increased patient payment responsibility and inefficient bad debt collection in hospitals, collecting patient payments to reduce bad debt is increasingly important to hospitals.

Pesce (2003) proposes that health information technology (HIT) can facilitate hospitals to reduce bad debt. HIT allows hospitals to improve coverage and documentation related to pre-authorizations, medical necessity, advance beneficiary notices, insurance eligibility, patient estimates, and availability of government and charity programs to cover the cost of medical services (Lavin, Harper, and Barr 2015). For instance, by using HIT, hospital staff could accurately tell the patients in advance about their insurance coverages and what bills they will receive; thus, the patients will anticipate their bills and adjust their budgets for the bills. Thus, we expect that HIT investments reduce hospital bad debt.

In other industries, besides the direct association between information technology (IT) investments and firm performance, researchers often study how IT investments impact firm performance via business processes, such as customer service (for a review, see Dehning and Richardson [2002]). In this study, we further investigate whether HIT improves patient experience, which in turn reduces bad debt at hospitals. HIT could improve patient experience for several reasons. First, patients often have difficulties in understanding their prognosis, purpose of care, expectations, and involvement in treatment due to medical terminology and jargon (Ha and Longnecker 2010). The providers can use HIT, such as video presentations and images, to provide information in a way that patients can understand their conditions, tests, and procedures (Dontje, Corser, and Holzman 2014). Second, HIT can facilitate patients to be better informed and educated (Doyle, Lennox, and Bell 2013), and hence increase patient engagement in the entire care span (Roberts, Chaboyer, Gonzalez, and Marshall 2017). Third, the providers can use HIT to provide customized communication for each patient, which could reduce information overload and aid patient decisions (Ansari and Mela 2003). Patient experience is enhanced when they feel acknowledged, cared about, listened to, and important, such as when information is customized, personal, and contextual to their own situations (Roberts et al. 2017). Prior research in other industries finds that better customer experience leads to higher willingness to pay and secure

[1] Uninsured patients are most likely eligible for charity care (Kwon, Stoeberl, Martin, and Bae 1999); i.e., uncollected payments from uninsured patients are recorded in the charity care account rather than the bad debt account.

revenues with better accounts receivable turnover and a higher speed of cash flow (Rust, Moorman, and Dickson 2002). Similarly, when patients have unhappy experiences during their hospitalizations, they would be less likely to pay their deductibles and coinsurance/copayments. Therefore, we expect that HIT investments reduce hospital bad debt via improved patient experience.

To empirically test our expectations, we use data from California Hospital Reports and Definitive Healthcare for the period from 2013 to 2016. We develop the regression models to investigate (1) whether HIT investments affect hospital bad debt, and (2) whether patient experience mediates the relationship between HIT investments and hospital bad debt. Consistent with our expectations, we find evidence that HIT investments are negatively associated with hospital bad debt. Furthermore, following Baron and Kenny's (1986) approach and the bootstrap approach of Zhao, Lynch, and Chen (2010), we find that the effect of HIT investments on hospital bad debt is mediated by patient experience. Our findings demonstrate that patient experience is important as a means to affect the relationship between HIT investments and hospital bad debt. In the supplementary analyses, we conduct "change" analyses to reinforce the causality in the main analyses. We also re-estimate our models using the balanced panel data, and find that the results persist.

This study makes two contributions to the extant literature on HIT and hospital financial performance. First, because hospital financial and HIT data are scarce relative to the comprehensive datasets in other industries, researchers have to use outdated data in their studies. Since the enactment of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, hospitals have made much greater use of HIT. We use more recent data to study the effects of HIT under the current environment in hospitals. Second, our study points to the importance of patient experience as a mediating mechanism for the relationship between HIT investments and hospital bad debt.

The remainder of this paper proceeds as follows: In Section II, we review relevant prior research examining the effects of HIT on hospital financial performance, hospital bad debt, and patient experience. Then we present our hypotheses. Section III details our research design, including the sample-selection procedure and the empirical methods that we use to test our hypotheses. Section IV presents the results of the empirical tests. Section V details supplementary analyses. Section VI presents our concluding comments.

# II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

## HIT and Hospital Financial Performance

Prior research finds evidence that the adoption and utilization of HIT are beneficial to clinical outcomes (e.g., Dykes and Collins 2013; King, Patel, Jamoom, and Furukawa 2014; McCullough, Parente, and Town 2016; Truitt, Thompson, Blazey-Martin, Nisai, and Salem 2016) and administrative efficiency (Bardhan and Thouin 2013) at hospitals. However, research on the association between HIT and hospital financial performance is inconclusive. Based on the theories and/or estimated savings, some researchers argue that HIT could improve hospital profitability, enhance productivity, and save costs (e.g., Melville, Kraemer, and Gurbaxani 2004; Hillestad et al. 2005; Wang and Biedermann 2010). A handful of empirical research examines the accounting/ financial benefits associated with HIT, and finds mixed results. On the one hand, some studies are not able to find an association between HIT and financial performance (e.g., Wang, Wan, Burke, Bazzoli, and Lin 2005; Kazley and Ozcan 2007; Agha 2014; Smith and Coustasse 2014; Collum, Menachemi, and Sen 2016). On the other hand, some studies provide evidence of a positive association between HIT and financial performance (Devaraj and Kohli 2000; Menachemi, Burkhardt, Shewchuk, Burke, and Brooks 2006; Bardhan and Thouin 2013; Baker, Song, and Jones 2017). All these studies use outdated hospital data. For example, both Collum et al. (2016) and Cho, Ke, Atems, and Chang (2018) use the 2010 American Hospital Association survey data, and Baker et al. (2017) use 1998–2004 HIMSS Analytics data. In 2009, only 12 percent of U.S. hospitals were using HIT systems (Charles, Gabriel, and Searcy 2015). Because the HITECH Act of 2009 boosts the adoption and use of HIT in hospitals, 96 percent of hospitals had certified HIT systems in 2017 (Office of the National Coordinator for Health Information Technology 2017; hereafter, ONC). HIT data used in those studies have become obsolete. The only paper that uses more recent hospital HIT data is T. Wang, Y. Wang, and McLeod (2018). We use the same HIT data as theirs in our paper.

## Hospital Bad Debt

U.S. healthcare spending grew 4.6 percent in 2018, reaching $3.6 trillion or $11,172 per person. As a share of the nation's gross domestic product, health spending accounted for 17.7 percent (Hartman, Martin, Benson, and Catlin 2020), which is nearly twice as much as the average in the OECD countries (Tikkanen and Abrams 2020). Over 30 percent of that amount was spent on hospital services (Fay 2019), which were the largest component of healthcare costs (Gee 2019). It is widely believed that HIT could lead to major healthcare cost savings (Hillestad et al. 2005). Prior research finds that HIT can reduce general operating costs (Borzekowski 2009), adverse patient safety event costs (Encinosa and Bae 2011), administrative costs (Cutler, Wikler, and Basch 2012), and redundant costs (Bardhan and Thouin 2013).

However, to the best of our knowledge, little research studies whether HIT could reduce hospital bad debt that is an increasing burden for hospitals. Definitive Healthcare defines hospital bad debt as "the difference between what was billed to patients and the amount patients actually paid" (Mariarty 2020).[2] In other words, hospital bad debt results from *patients* not paying their deductibles and coinsurance/copayments. When a patient enters a hospital and requests healthcare services, hospital staff evaluate the patient's ability to pay based on the hospital policies and the personal information provided by the patient. If the patient is deemed a charity case, services are provided free of charge or at a reduced price, and then the unreimbursed cost of the services is recorded in the charity care account. Otherwise, the patient is billed for services. If the patient does not pay the bill, the uncollected payment is recorded in the bad deb account. Thus, bad debt relates to patients who are, at least initially, deemed able to pay (Beck et al. 2020). Patients are not willing to pay their bills because most of the time they do not realize they will receive bills in the first place, are confused by the bills (e.g., patients may receive multiple bills from

[2] The redefinition of bad debt was effective on December 15, 2018, based on FASB Topic 606. According to FASB Topic 606, hospitals can only report bad debt if there was an adverse event—such as unemployment or bankruptcy—that prevented a patient from being able to pay the expected amount. Many healthcare providers will see a dramatic drop in the bad debt expense and a new contra revenue account to capture implicit price concessions in their financial statements (Parde and Pavona 2019). Many hospitals simply switch out the term bad debt for another one: implicit price concession, which refers to effectively the same thing (Bannow 2018). Researchers who conduct research on bad debt after 2018 will use both bad debt and implicit price concessions accounts, which are the same bad debt data as we use in our paper. Therefore, the evidence our findings provide in our paper is still valid. The redefinition of bad debt does not diminish the contribution of our paper.

the physician, the facility, the lab, and the anesthesiologist in surgical cases), or cannot afford to pay the whole bill at once (Spoden 2019). In addition, some patients may just "not want to pay" rather than "cannot pay."

Hospitals have been wrestling with bad debt collection for many decades. They make "reasonable collection efforts" before Medicare partially reimburses bad debts. In some cases, nonprofit hospitals engage in overly aggressive debt collection efforts, which could jeopardize their tax-exempt status (e.g., the Hamot Medical Center case in Erie, Pennsylvania). In general, bad debt collection in hospitals is inefficient. In a 2018 survey, half of 100 hospital C-suite executives and finance leaders said they only expect to recover up to 10 percent of their bad debt (Gooch 2019). Concern about bad debt has intensified since the enactment of the Affordable Care Act of 2010. First, although the Affordable Care Act of 2010 decreases the number of uninsured people, many newly insured patients are now accessing healthcare services via high deductible and coinsurance/copayment health plans and are unable to pay the deductibles, coinsurance, and/or copayments (Reiter et al. 2015). For example, Sweeney (2017) reports that Illinois' largest hospital network saw its uncollectible accounts increased more than 22 percent in 2016, to $269.5 million, or about 5 percent of its overall revenue. Swedish Covenant Hospital watched its bad debt skyrocket by 71 percent, to $11.2 million, in 2015. Bad debt at Lurie Children's Hospital increased 22 percent, to $11.5 million, in 2015. The spike in bad debt was related to an increase in deductibles and overall patient financial responsibility under today's insurance plans. Second, charity care has plunged since the enactment of the Affordable Care Act of 2010 (Sweeney 2017). These two factors work in tandem, causing patients to face a substantial increase in average out-of-pocket costs and hospitals to face a significant rise in bad debt. Specifically, U.S. hospital bad debt rose from $3.14 billion in 2012 to $3.69 billion in 2016, a 17 percent increase (O'Brien 2018). In a survey to hospital C-suite executives and finance leaders in 2018, about one-third of hospitals had $10 million or more in bad debt. Twenty percent of these hospitals had between $10 and $30 million in bad debt, and another 10 percent reported between $30 and $50 million in bad debt. Approximately 59 percent of participants indicated that high patient copayments, greater deductibles, and other health insurance reforms were the largest drivers of hospital bad debt (LaPointe 2018).

Given the increased patient payment responsibility and inefficient bad debt collection, collecting patient payments to reduce bad debt is increasingly important to hospitals. Pesce (2003) proposes that hospitals could invest in HIT to reduce bad debt. HIT allows hospitals to improve coverage and documentation related to pre-authorizations, medical necessity, advance beneficiary notices, insurance eligibility, patient estimates, and availability of government and charity programs to cover the costs of medical services (Lavin et al. 2015). Using the comprehensive information from HIT systems, hospital staff could accurately tell the patients in advance about their insurance coverage and what bills they will receive; thus, the patients will anticipate their bills and adjust their budgets for the bills. Furthermore, hospital staff could use HIT, such as a financial assistance screening system, to identify the alternative funding sources that a patient is most likely to qualify for. For instance, when a patient schedules a healthcare service in advance, hospital staff use HIT to access the patient's historical data and insurance information. If the procedure is covered by insurance and the patient paid medical bills in the past, the hospital will perform the procedure because it is a low risk that the patient does not pay. However, if the procedure is not covered by insurance and/or the patient did not pay medical bills in the past, HIT can flag potential bad debt. The hospital can check if the patient qualifies for Medicaid or agrees to an interest-free loan program. Thus, HIT facilitates the hospital to ensure payments and still deliver appropriate care to the patient (Dazley 2020). This could be an important benefit of HIT related to bad debt in hospitals. Therefore, we propose the following hypothesis:

**H1:** HIT investments are negatively associated with hospital bad debt.

## Patient Experience as a Mediator

Mediation analysis investigates the mechanisms that underlie an observed relationship between an independent variable and a dependent variable, and examines *how* they relate to a third intermediate variable, the mediator. Rather than hypothesizing only a direct causal relationship between the independent and dependent variables, a mediational model hypothesizes that the independent variable causes the mediator variable, which in turn causes the dependent variable. The mediator variable then serves to clarify the nature of the relationship between the independent and dependent variables (MacKinnon 2008). In the seminal paper, Baron and Kenny (1986, 1173) state that failure to properly use mediation analysis results in "missed opportunities to probe more deeply into the nature of casual mechanisms." According to Baron and Kenny (1986), the mediation effect we expect is validated if the following three conditions are met. First, the independent variable must affect the dependent variable. Second, the independent variable must affect the presumed mediator. Third, the mediator must affect the dependent variable in the presence of the independent variable. If this final condition holds, then the effect of the independent variable on the dependent variable is reduced or eliminated in the presence of the mediator. Many prior studies have examined the association between HIT investments and hospital financial performance, but we investigate an underlying mechanism for this association. If HIT investments can improve patient experience, and enhanced patient experience can reduce hospital bad debt, we have uncovered a previously unidentified path from HIT investments to hospital financial performance.

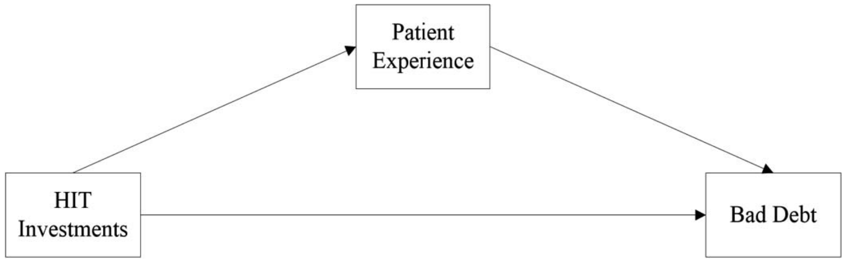
Patient experience encompasses the range of interactions that patients have with the healthcare system (Agency for Healthcare Research and Quality 2017; hereafter, AHRQ). It has been a long-lasting topic in healthcare research, but most prior research has focused on its clinical outcomes (e.g., Manary, Boulding, Staelin, and Glickman 2013; Doyle et al. 2013; Bentley, Trevaskis, Woods, Guest, and Watt 2018). There is no unanimous agreement on which interactions should be included in patient experience metrics. California Hospital Reports assess patient experience with nine items[3] complying with CMS HCAHPS: Patients' Perspectives of Care Survey. Four of the nine items might be associated with HIT, including "Nurses communicated well," "Doctors communicated well," "Staff explained medicine," and "Received information and education." In this study, we use these four items to measure patient experience.[4]

HIT can promote patient experience in various ways. First, patients often poorly understand their prognosis, purpose of care, expectations, and involvement in treatment due to medical terminology and jargon (Ha and Longnecker 2010). The providers work with HIT, such as video presentations and images, to provide information in a way that patients can understand their

[3] The nine items include "Would recommend hospital," "Received information and education," "Nurses communicated well," "Doctors communicated well," "Help received," "Pain well controlled," "Staff explained medicine," "Patient room and bathroom was clean," and "Quiet at night."

[4] We acknowledge that the items relate to "communication," but we use the "patient experience" label because that is the label used by the HCAHPS Survey.

**FIGURE 1**
**Mediation Model**




conditions, tests, and procedures (Dontje et al. 2014). Second, HIT facilitates patients to be better informed and educated (Doyle et al. 2013). Thus, patients could be actively involved in decision-making, and feel more engaged in the care process (Roberts et al. 2017). Third, HIT enables hospitals to customize their communication with each patient, such as tailored messages to reflect the patients' personal situation and information needs. Patients are more accepting of the tailored communication as information is perceived to be useful and relevant. Customized communication could reduce information overload and aid patient decisions (Ansari and Mela 2003). Patient experience is enhanced when they feel acknowledged, cared about, listened to, and important, such as when information is customized, personal, and contextual to their own situations (Roberts et al. 2017). Thus, HIT allows hospitals to improve patient experience.

Prior research in other industries suggests that better customer experience leads to higher willingness to pay (Gilmore and Pine 2002; Mascarenhas, Kesavan, and Bernacchi 2006) and secures revenues (Rust et al. 2002). Similarly, when patients have unhappy experiences during their hospitalizations, they would be less likely to pay their deductibles and coinsurance/copayments. Taken together, HIT investments might improve patient experience, which in turn reduces bad debt at hospitals, illustrated by the Mediation Model in Figure 1.

Hence, we posit our H2 as follows,

**H2:** Patient experience mediates the relationship between HIT investments and hospital bad debt.

# III. RESEARCH DESIGN

## Sample Selection

We use Definitive Healthcare data to measure hospital HIT investments and hospital bad debt and California Hospital Report data to measure patient experience. Due to the time for data gathering and processing, there is a two-year delay in the reports. Cynosure Health provides us California Hospital Reports from 2013 to 2016. After merging California Hospital Reports and Definitive Healthcare data, we exclude the observations that lack valid data to calculate the control variables. Our final sample includes 696 observations from 208 unique California hospitals between 2013 and 2016.

## Empirical Model

To test H1, we develop Model (1) as follows:

$$\begin{aligned} BadDebt_{i,t} = {} & \beta_0 + \beta_1 HIT\_INV_{i,t-1} + \beta_2 MCI_{i,t} + \beta_3 MedicareMix_{i,t} + \beta_4 MedicaidMix_{i,t} + \beta_5 CMI \\ & + \beta_6 Charity\_Care + \beta_7 Size_{i,t} + \beta_8 Leverage_{i,t} + \beta_9 Teaching_{i,t} + \beta_{10} Gov_{i,t} \\ & + \beta_{11} For\text{-}profit_{i,t} + \beta_{12} Urban_{i,t} + \beta_{13} Network_{i,t} + Year_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $BadDebt_{i,t}$ is defined as bad debt scaled by lagged net patient revenue in hospital *i* in year *t*. We define HIT investments, $HIT\_INV_{i,t-1}$, as total HIT expense scaled by net patient revenue in year $t-1$. We combine HIT capital expense and operating expense into total HIT expense because they are complementary in HIT usage.[5] A negative and significant $\beta_1$ would suggest that HIT investments reduce hospital bad debt.

We follow prior studies to include the control variables. Gapenski, Vogel, and Langland-Orban (1993) find several determinants of hospital performance, including patient-mix (i.e., Medicare/Medicaid mix) and organizational characters (i.e., size, teaching status, and network). Molinari, Alexander, Morlock, and Lyles (1995) find that size, location, network, and ownership of a hospital are significantly associated with hospital performance. Some studies also use the market concentration index as a control variable for market competition (e.g., Collum et al. 2016; Goes and Zhan 1995; Alexander, Weiner, and Griffith 2006), but they demonstrate mixed evidence. In this study, the control variables include the market concentration index (*MCI*), Medicare-mix (*MedicareMix*), Medicaid-mix (*MedicaidMix*), Case Mix Index (*CMI*), Charity Care Charges (*Charity_Care*), hospital size (*Size*),[6] hospital leverage (*Leverage*),[7] government hospital (*Gov*), for-profit hospital (*For-profit*), medical school affiliation (*Teaching*), hospital location (*Urban*), and networked hospital (*Network*).[8]

We anticipate the directions of the control variables. Prior research finds mixed results about *MCI* on hospital financial performance. The relationship between *MCI* and bad debt is unknown. Regarding Medicare and Medicaid, Kwon et al. (1999) argue the following:

> Medicare has furnished only limited payments for bad debt. It has reimbursed only the deductible and coinsurance amounts owed, but unpaid, by Medicare patients where providers have made reasonable collection efforts (Sutter 1994). However, the percentage of total Medicare payments attributable to Medicare bad debt was traditionally so small that bad debt seldom received serious attention from the Medicare Administration. Similar findings have been reported by Saywell et al. (1989), Zollinger

[5] In an untabulated robust test, we use HIT capital expense and HIT operating expense scaled by net patient revenue in year *t*–1, respectively, as the independent variables. The results persist.

[6] In an untabulated test, we define *Size* as log Total Assets. The results persist.

[7] We add *Leverage* as a control variable according to the comments from the 2018 AAA Annual Meeting. It is not included in prior healthcare studies. In untabulated analyses, (1) we re-estimate the regression models *without* controlling *Leverage*, and (2) we define *Leverage* as long-term liability scaled by beginning of year total assets in year *t*, respectively. The results persist.

[8] Some prior research includes "uncompensated care costs" as a control variable (e.g., Wang et al. 2018). "Uncompensated care costs" is the item that includes both bad debt and charity care. In this paper, our dependent variable is bad debt, which is highly correlated with "uncompensated care costs." Therefore, we do not include "uncompensated care costs" as a control variable.

> et al. (1991), and Weissman et al. (1992). Accordingly, a negative relationship is expected between Medicare and hospital bad debt. (Kwon et al. 1999, 18)
>
> Numerous studies indicate that most, if not all, patients who left their bills unpaid had some form of insurance coverage. It is implied that those who left bills unpaid were probably underinsured . . . Hospitals with an unusually high proportion of Medicaid population are usually located in areas where the community income is lower than average . . . A positive relationship is expected between them (Medicaid and hospital bad debt). (Kwon et al. 1999, 19)

Thus, we expect that *MedicareMix* (*MedicaidMix*) is negatively (positively) associated with bad debt.

Prior research finds mixed results on the relationship between hospital size and hospital financial performance, based on different hospital financial performance measures. Cleverley and Harvey (1992a, 1992b) show a statistically significant and positive relationship between size and profitability among urban hospitals, but a significant and negative relationship between them among rural hospitals. Gapenski et al. (1993) also find that hospital size is negatively related to two pre-tax profitability measures: basic earning power and pre-tax return on assets. McCue (1991) and McCue, Clement, and Hoerger (1993) find that hospital size is not related to total profit margin. The findings of these studies also appear to have been supported by Vogel, Langland-Orban, and Gapenski (1993). Regarding bad debt, larger hospitals may have more resources to provide better mechanisms to collect payments. Empirically, Kwon et al. (1999) and Chang et al. (2012) find a negative association between hospital size and bad debt. Thus, we expect that *Size* is negatively associated with bad debt.

Because the intensity of patient CMI may influence the scale of the hospitalization costs and the resulting amounts of bad debt, we include CMI as a control variable. In an extreme case, Cleveland Clinic focuses predominantly on organ transplant cases and has a marginal revenue of $50,000 per patient—substantially higher than most other hospitals. Its uncollectible copay amounts would likely be correspondingly higher as a result. On the other hand, CMI tends to be stable over time, and thus the association between CMI and bad debt may not be significant. The association between CMI and bad debt is unknown. When the ACA comes into being, hospitals might move their charity care to bad debt expense. Thus, we expect that charity care should be negatively associated with bad debt.

Cleverley (1990) indicates that the relationship between hospital leverage and financial performance is complex. The use of debt could raise a hospital's return on equity, but if returns from its debt-financed assets are less than interest costs, profitability decreases. Because bad debt is an item in hospital financial performance, we expect that the association between *Leverage* and bad debt is unknown.

Schuhmann (2008) finds that nonteaching hospitals have better financial performance than teaching hospitals. Teaching hospitals incur more uncompensated care because they take in patients with a variety of disease conditions. The patients provide educational value to the medical graduates, and the medical education payments from Medicare help offset some of the uncompensated care expenses. They also are more likely to be larger than nonteaching hospitals and are located in urban and economically depressed inner-city areas (HCIA Inc. 1997). Empirically, Chang et al. (2012) find that teaching hospitals have higher bad debt than nonteaching counterparts in California. We expect that *Teaching* is positively associated with bad debt. Government hospitals tend to offer more unprofitable services than other types of hospitals (Horwitz 2005). We expect that *Gov* is positively associated with bad debt.

Buczko (1994) argues that for-profit hospitals show a lower percentage of bad debt than not-for-profit hospitals. However, Shukla, Pestian, and Clement (1997) and Kwon et al. (1999) do not support that proposition, and find that the percentage of bad debt in for-profit hospitals is slightly higher than that in not-for-profit hospitals. The relationship between *For-profit* and bad debt is unknown. Mick and Morlock (1990) find that urban hospitals have a lower percentage of bad debt than rural hospitals. We expect that *Urban* is negatively associated with bad debt. Broyles, Brandt, and Biard-Holmes (1998) find that networked hospitals reported better financial performance (lower operating/labor costs and nonlabor expenses) than non-networked ones. We expect that *Network* is negatively associated with bad debt.

To test our H2, we follow Baron and Kenny (1986) to develop Models (2) and (3) as follows:

$$PatExperience_{i,t} = \alpha_0 + \alpha_1 HIT\_INV_{i,t-1} + \Sigma Controls + Year_t + \varepsilon_{i,t} \tag{2}$$

$$BadDebt_{i,t} = \gamma_0 + \gamma_1 HIT\_INV_{i,t-1} + \gamma_2 PatExperience_{i,t} + \Sigma Controls + Year_t + \varepsilon_{i,t} \tag{3}$$

where $PatExperience_{i,t}$ is patient experience for hospital *i* in year *t*, which is a single underlying factor score from loading the four items, "Nurses communicated well," "Doctors communicated well," "Staff explained medicine," and "Received information and education," in California Hospital Reports. Because all the four items are intended to capture the same underlying construct (patient experience), we load the four items on a single underlying factor, *PatExperience*. The factor analysis indicates that the factor loadings of the four items are 0.9179, 0.8319, 0.7967, and 0.8411, respectively, on a single factor with an eigenvalue of 2.877.

*BadDebt* and *HIT_INV* are the same definitions as those in Model (1). Haley et al. (2016) find that as the level of competition in the healthcare market increases, the level of patient experience increases. We expect that *MCI* is positively associated with patient experience. We expect that *MedicareMix* and *MedicaidMix* are negatively associated with patient experience because the beneficiaries of Medicare and Medicaid, i.e., seniors and people living under welfare, might face more challenges in communicating with the providers due to education or experience. Sharma, Chandrasekaran, and Bendoly (2020) find that hospitals with higher CMI demonstrate greater patient experience improvements. We expect that CMI is positively associated with patient experience. Several studies find a negative relationship between the hospital proportion of low-income patients and patient experience scores (Gilman et al. 2015; Chatterjee, Joynt, Orav, and Jha 2012; Liu, Wen, Mohan, Bae, and Becker 2016). Low-income patients are more likely uninsured, which results in more charity care. Thus, we expect that charity care is negatively associated with patient experience. Elliott et al. (2010) find that small hospitals are the most likely to score in the top quartile for patient experience survey measures. We expect that *Size* is negatively associated with patient experience. Hospitals with financial constraints might have limited staff training resources, which may result in lower patient experience. We expect that *Leverage* is negatively associated with patient experience. Lehrman et al. (2010) find that teaching hospitals are more likely to have better patient experience. We expect that *Teaching* is positively associated with patient experience.

Jha, Orav, Zheng, and Epstein (2008) report that for-profit hospitals receive lower patient perception scores than other hospitals. They attribute lower patient experience in for-profit hospitals to the difference in the patient population, including expectations. This finding is also supported by Lehrman et al. (2010). We expect that *For-profit* is negatively associated with patient experience. Betts, Balan-Cohen, Shukla, and Kumar (2016) find that patient experience is lower in government hospitals than in not-for-profit hospitals. We expect that *Gov* is negatively associated with patient experience. In HCAHPS, patients report better experiences with rural hospitals (Jha et

**TABLE 1**

**Descriptive Statistics**

| Variables | n | Mean | Std. Dev. | 1st Quartile | Median | 3rd Quartile |
|---|---|---|---|---|---|---|
| $HIT\_INV_{t-1}$ | 696 | 0.04 | 0.01 | 0.04 | 0.04 | 0.05 |
| $BadDebt_t$ | 696 | 0.09 | 0.09 | 0.03 | 0.06 | 0.11 |
| *PatExperience* | 696 | 0.00 | 0.95 | −0.43 | 0.11 | 0.57 |
| *MCI* | 696 | 0.17 | 0.21 | 0.03 | 0.09 | 0.25 |
| *MedicareMix* | 696 | 0.33 | 0.13 | 0.24 | 0.32 | 0.43 |
| *MedicaidMix* | 696 | 0.16 | 0.11 | 0.08 | 0.13 | 0.23 |
| *CMI* | 696 | 1.59 | 0.26 | 1.43 | 1.58 | 1.72 |
| *Charity_Care* | 696 | 0.06 | 0.09 | 0.01 | 0.03 | 0.08 |
| *Size* | 696 | 272.47 | 262.44 | 98.80 | 195.50 | 365.78 |
| *Leverage* | 696 | 0.69 | 0.61 | 0.30 | 0.55 | 0.84 |
| *Teaching* | 696 | 0.14 | 0.35 | 0.00 | 0.00 | 0.00 |
| *Gov* | 696 | 0.15 | 0.36 | 0.00 | 0.00 | 0.00 |
| *For-profit* | 696 | 0.32 | 0.47 | 0.00 | 0.00 | 1.00 |
| *Urban* | 696 | 0.92 | 0.28 | 1.00 | 1.00 | 1.00 |
| *Network* | 696 | 0.78 | 0.42 | 1.00 | 1.00 | 1.00 |

All continuous variables are winsorized at the 1st and 99th percentiles.

al. 2008). We expect that *Urban* is negatively associated with patient experience. Networked hospitals may have more network-shared resources and then provide better services. We expect that *Network* is positively associated with patient experience.

To meet the three conditions of Baron and Kenny (1986), first, *HIT_INV* must affect *BadDebt* in Model (1). Second, *HIT_INV* must affect the presumed mediator, *PatExperience*, in Model (2). Third, the mediator, *PatExperience*, must affect *BadDebt* in the presence of the *HIT_INV* in Model (3). If the final condition holds, the effect of *HIT_INV* on *BadDebt* is reduced or eliminated in the presence of the mediator, *PatExperience*. Moreover, we acknowledge that Baron and Kenny's (1986) causal step regression has come under criticism in recent years (Hayes 2009; Zhao et al. 2010). Zhao et al. (2010) suggest a superior test approach (i.e., the "bootstrap" approach proposed by Preacher and Hayes 2004) for the mediation test. Therefore, we further conduct a bootstrap approach analysis following Zhao et al. (2010).

In all regression models, we include year fixed effects, *Year*, to control for temporal variations. Because all observations are in the same industry and the same state, we do not control industry or state fixed effects. We winsorize all continuous variables at the 1st and 99th percentiles to fix the outlier issue. We use the *r* and *cluster* options of the regress function in Stata to ensure standard errors are robust and clustered at the hospital level. We provide the definitions of all variables in Appendix A.

# IV. RESULTS

## Descriptive Statistics

Table 1 reports the descriptive statistics of the variables used in our main analyses. For the full sample (696 observations), the mean (median) of *HIT_INV* in California hospitals is 0.04 (0.04), and the mean (median) of *BadDebt* is 0.09 (0.06). The mean and standard deviation for *PatExperience* are 0.00 and 0.95,[9] respectively. The means for most control variables in our sample are consistent with prior research. For example, *MedicareMix* and *MedicaidMix* are consistent with those in Collum et al. (2016). The means of *Teaching* and *MCI* are different because our sample only includes the hospitals in California from 2013 to 2016, while Collum et al. (2016) use data of national hospitals from 2007 to 2011 (n = 11,602). The means of *Gov, Urban*, and *Network* are consistent with those in Cho et al. (2018).

## Bivariate Correlations

Table 2, Panels A and B, presents the Pearson and Spearman correlations between variables. Consistent with our expectations, we find that *HIT_INV* is negatively correlated with *BadDebt* ($p < 0.001$) and is positively correlated with *PatExperience* ($p < 0.05$). The correlations between the dependent variables, *BadDebt* and *PatExperience*, and the control variables also match our predications or prior research.

## Multivariate Regression Results

Column (1) in Table 3 presents the results from estimating Model (1). Consistent with our H1, the estimated coefficient $\beta_1$ on *HIT_INV* is negative (−1.183) and significant at the 5 percent level, suggesting that one unit increase in *HIT_INV* reduces 1.183 units of *BadDebt*. Recall that both *HIT_INV* and *BadDebt* are defined as scaled by net patient revenue. The economic magnitude of the results shows that one dollar increase in total HIT investments reduces $1.183 hospital bad debt on average.

Columns (2) and (3) in Table 3 present the results from estimating Models (2) and (3). Consistent with our expectations, the estimated coefficient $\alpha_1$ on *HIT_INV* is positive (1.414) and significant ($p = 0.047$) in Column (2), suggesting that the second condition in Baron and Kenny's (1986) approach is met. In Column (3), the estimated coefficient $\gamma_1$ on *HIT_INV* is insignificant ($p = 0.355$), and the coefficient $\gamma_2$ on *PatExperience* is negative (−0.022) and significant ($p < 0.001$), suggesting that the third condition is met. Recall that we find that *HIT_INV* decreases *BadDebt* significantly, suggesting that the first condition is met. Taken together, the results demonstrate that the effect of *HIT_INV* on *BadDebt* is eliminated in the presence of the mediator, *PatExperience*; i.e., the mediating effect of patient experience on the relationship between HIT investments and hospital bad debt is a full mediation.

Besides the results we documented using Baron and Kenny's (1986) approach, the bootstrap approach (Zhao et al. 2010) also shows a full mediation using 5,000 bootstrap samples (Sobel test value = −0.055; SE = 0.007; Z = −3.455; p = 0.022. The bootstrap results are not tabulated.)

Figure 2 presents the results of the mediation model analysis linking HIT investments, patient experience, and hospital bad debt. We observe that when patient experience is included in Model (1), *HIT_INV* loses its statistical significance. Specifically, the coefficient $\beta_1$ for the direct path from *HIT_INV* to *BadDebt* is significant when the mediator is *not* included in the model. The coefficient $\gamma_1$ for the direct path from *HIT_INV* to *BadDebt* is insignificant when the mediator is included in the model. Our findings have meaningful contributions to accounting literature because prior research

[9] *PatExperience* is a single underlying factor score using factor analysis. The computed factor scores are standardized with a mean of 0 and have a standard deviation of 1 (DiStefano, Zhu, and Mindrila 2009). That means the loaded factor score, *PatExperience*, should be distributed as a standardized normal distribution (i.e., the mean is 0 and the standard deviation is 1).

**TABLE 2**

**Pearson and Spearman Correlation Coefficients**

**Panel A: (1)–(8)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) *HIT_INV* | 1.0000*** | −0.1835*** | 0.0308** | 0.0590 | −0.0370 | −0.0097 | −0.0234 | 0.0007 |
| | 0.0000 | 0.0000 | 0.0417 | 0.1201 | 0.3293 | 0.7983 | 0.5379 | 0.9849 |
| (2) *BadDebt* | −0.2664*** | 1.0000*** | −0.3296*** | −0.0127 | −0.0165 | 0.1868*** | −0.3707*** | −0.0256 |
| | 0.0000 | 0.0000 | 0.0000 | 0.7379 | 0.6634 | 0.0000 | 0.0000 | 0.5003 |
| (3) *PatExperience* | 0.0597** | −0.3136*** | 1.0000*** | 0.2817*** | −0.0608 | −0.3038*** | 0.2896*** | −0.0190 |
| | 0.0115 | 0.0000 | 0.0000 | 0.0000 | 0.1092 | 0.0000 | 0.0000 | 0.6171 |
| (4) *MCI* | 0.1177*** | −0.0609 | 0.1991*** | 1.0000*** | 0.2915*** | −0.1320*** | −0.0703* | −0.0841** |
| | 0.0019 | 0.1082 | 0.0000 | 0.0000 | 0.0000 | 0.0005 | 0.0638 | 0.0265 |
| (5) *MedicareMix* | 0.0661* | −0.0235 | −0.0466 | 0.3353*** | 1.0000*** | −0.461*** | 0.0399 | −0.2382*** |
| | 0.0812 | 0.5368 | 0.2199 | 0.0000 | 0.0000 | 0.0000 | 0.2932 | 0.0000 |
| (6) *MedicaidMix* | −0.0675* | 0.1342*** | −0.3084*** | −0.0558 | −0.4763*** | 1.0000*** | −0.2376*** | 0.2518*** |
| | 0.0752 | 0.0004 | 0.0000 | 0.1411 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| (7) *CMI* | −0.0722* | −0.2773*** | 0.3352*** | −0.0822** | 0.0611 | −0.2769*** | 1.0000*** | −0.0922** |
| | 0.0568 | 0.0000 | 0.0000 | 0.0301 | 0.1075 | 0.0000 | 0.0000 | 0.0149 |
| (8) *Charity_Care* | 0.3080*** | −0.1889*** | −0.0804** | −0.0864** | −0.2694*** | 0.2576*** | −0.1139*** | 1.0000*** |
| | 0.0000 | 0.0000 | 0.0340 | 0.0226 | 0.0000 | 0.0000 | 0.0026 | 0.0000 |
| (9) *Size* | 0.1018*** | −0.2640*** | −0.2678*** | 0.0821** | −0.1478*** | −0.0647* | 0.5512*** | 0.0362 |
| | 0.0072 | 0.0000 | 0.0000 | 0.0303 | 0.0001 | 0.0883 | 0.0000 | 0.3406 |
| (10) *Leverage* | 0.2258*** | 0.1498*** | −0.1368*** | −0.1364*** | −0.0684* | 0.0695* | −0.0956** | 0.0119 |
| | 0.0000 | 0.0001 | 0.0003 | 0.0003 | 0.0715 | 0.0669 | 0.0117 | 0.7538 |
| (11) *Teaching* | 0.1944*** | 0.0605 | 0.0859** | −0.0453 | −0.2274*** | 0.1502*** | 0.2680*** | 0.2055*** |
| | 0.0000 | 0.1105 | 0.0235 | 0.2325 | 0.0000 | 0.0001 | 0.0000 | 0.0000 |
| (12) *Gov* | 0.3448*** | 0.1890*** | −0.0091 | 0.0241 | −0.1855*** | 0.1791*** | −0.1781*** | 0.1937*** |
| | 0.0000 | 0.0000 | 0.8102 | 0.5257 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| (13) *For-profit* | −0.0290 | 0.1845*** | −0.4000*** | −0.1815*** | 0.0266 | 0.1040*** | −0.1635*** | −0.0174 |
| | 0.4450 | 0.0000 | 0.0000 | 0.0000 | 0.4842 | 0.0060 | 0.0000 | 0.6466 |
| (14) *Urban* | −0.0866** | −0.0976** | 0.0714* | −0.3125*** | −0.1267*** | −0.0081 | −0.0833** | 0.0761** |
| | 0.0224 | 0.0100 | 0.0596 | 0.0000 | 0.0008 | 0.8310 | 0.0280 | 0.0446 |
| (15) *Network* | −0.1432*** | −0.0605 | 0.0098 | −0.0178 | 0.0892** | −0.1701*** | 0.1262*** | −0.0620 |
| | 0.0002 | 0.1107 | 0.7966 | 0.6386 | 0.0186 | 0.0000 | 0.0009 | 0.1022 |

*(continued on next page)*

## TABLE 2 (continued)

**Panel B: (9)–(15)**

| | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|
| (1) *HIT_INV* | 0.1452*** | 0.2396*** | 0.1784*** | 0.2838*** | −0.0015 | −0.0878** | −0.0906** |
| | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.9687 | 0.0206 | 0.0168 |
| (2) *BadDebt* | −0.3877*** | 0.1821*** | 0.1447*** | 0.1424*** | 0.2221*** | −0.1006*** | −0.0394 |
| | 0.0000 | 0.0000 | 0.0001 | 0.0002 | 0.0000 | 0.0079 | 0.2990 |
| (3) *PatExperience* | −0.2824*** | −0.1806*** | 0.0984*** | −0.0182 | −0.3886*** | 0.0770** | 0.0302 |
| | 0.0000 | 0.0000 | 0.0094 | 0.6317 | 0.0000 | 0.0423 | 0.4269 |
| (4) *MCI* | 0.0212 | −0.1009*** | −0.0361 | 0.1428*** | −0.2611*** | −0.1606*** | −0.0827** |
| | 0.5765 | 0.0077 | 0.3422 | 0.0002 | 0.0000 | 0.0000 | 0.0291 |
| (5) *MedicareMix* | −0.1705*** | −0.0555 | −0.2218*** | −0.1676*** | 0.0102 | −0.1387*** | 0.0986*** |
| | 0.0000 | 0.1436 | 0.0000 | 0.0000 | 0.7892 | 0.0002 | 0.0093 |
| (6) *MedicaidMix* | −0.0183 | 0.0906** | 0.1561*** | 0.1700*** | 0.1085*** | −0.0079 | −0.1318*** |
| | 0.6291 | 0.0168 | 0.0000 | 0.0000 | 0.0042 | 0.8348 | 0.0005 |
| (7) *CMI* | 0.5637*** | −0.1791*** | 0.2154*** | −0.1948*** | −0.1596*** | −0.0283 | 0.0671* |
| | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.4568 | 0.0768 |
| (8 *Charity_Care* | 0.1632*** | 0.0540 | 0.1191*** | 0.0075 | −0.0058 | 0.1120*** | −0.0154 |
| | 0.0000 | 0.1545 | 0.0016 | 0.8425 | 0.8790 | 0.0031 | 0.6856 |
| (9) *Size* | 1.0000*** | 0.1664*** | 0.3948*** | 0.0217 | −0.3659*** | −0.0626* | −0.0336 |
| | 0.0000 | 0.0000 | 0.0000 | 0.5669 | 0.0000 | 0.0990 | 0.3767 |
| (10) *Leverage* | 0.123*** | 1.0000*** | 0.0381 | 0.1787*** | −0.0062 | −0.0304 | −0.1040*** |
| | 0.0011 | 0.0000 | 0.3159 | 0.0000 | 0.8694 | 0.4236 | 0.0060 |
| (11) *Teaching* | 0.4087*** | 0.0020 | 1.0000*** | 0.2026*** | −0.1728*** | 0.0049 | 0.0420 |
| | 0.0000 | 0.9585 | 0.0000 | 0.0000 | 0.0000 | 0.8965 | 0.2680 |
| (12) *Gov* | 0.0501 | 0.1006*** | 0.2026*** | 1.0000*** | −0.2882*** | 0.0121 | −0.3594*** |
| | 0.1868 | 0.0079 | 0.0000 | 0.0000 | 0.0000 | 0.7509 | 0.0000 |
| (13) *For-profit* | −0.3071*** | −0.0125 | −0.1728*** | −0.2882*** | 1.0000*** | 0.1603*** | 0.2376*** |
| | 0.0000 | 0.7416 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| (14) *Urban* | −0.1301*** | −0.0290 | 0.0049 | 0.0121 | 0.1603*** | 1.0000*** | −0.1114*** |
| | 0.0006 | 0.4454 | 0.8965 | 0.7509 | 0.0000 | 0.0000 | 0.0032 |
| (15) *Network* | −0.0823** | −0.0153 | 0.0420 | −0.3594*** | 0.2376*** | −0.1114*** | 1.0000*** |
| | 0.0300 | 0.6876 | 0.2680 | 0.0000 | 0.0000 | 0.0032 | 0.0000 |

*, **, *** Indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.
Two-tailed p-values appear under the coefficients. Pearson correlations are below the diagonal and Spearman correlations are above the diagonal.
All variables presented are defined in Appendix A.

**TABLE 3**

**Regression Results of Models (1)–(3)**

| Variables | Model (1) $BadDebt_t$ | Model (2) *PatExperience* | Model (3) $BadDebt_t$ |
|---|---|---|---|
| $HIT\_INV_{t-1}$ | −1.183** | 1.414** | −0.321 |
| | (0.027) | (0.047) | (0.355) |
| *PatExperience* | | | −0.022*** |
| | | | (0.000) |
| *MCI* | −0.009 | 0.898*** | −0.011 |
| | (0.669) | (0.005) | (0.577) |
| *MedicareMix* | −0.008 | −1.141** | −0.016 |
| | (0.865) | (0.016) | (0.729) |
| *MedicaidMix* | 0.011 | −2.053*** | 0.034 |
| | (0.809) | (0.000) | (0.429) |
| *CMI* | −0.025 | 0.793*** | −0.008 |
| | (0.253) | (0.001) | (0.717) |
| *Charity_Care* | −0.066 | −0.273 | −0.060 |
| | (0.400) | (0.571) | (0.415) |
| *Size* | −0.000** | −0.000 | −0.000** |
| | (0.016) | (0.532) | (0.019) |
| *Leverage* | 0.011 | −0.129* | 0.008 |
| | (0.198) | (0.063) | (0.300) |
| *Teaching* | 0.011 | 0.081 | 0.013 |
| | (0.368) | (0.565) | (0.263) |
| *Gov* | 0.041*** | −0.022 | 0.040*** |
| | (0.002) | (0.876) | (0.001) |
| *For-profit* | 0.034*** | −0.603*** | 0.021* |
| | (0.006) | (0.000) | (0.074) |
| *Urban* | −0.007 | −0.168 | −0.011 |
| | (0.478) | (0.454) | (0.293) |
| *Network* | −0.000 | 0.073 | −0.002 |
| | (0.989) | (0.585) | (0.884) |
| Constant | 0.086* | 0.738 | 0.070 |
| | (0.056) | (0.157) | (0.120) |
| Observations | 696 | 696 | 696 |
| Adjusted $R^2$ | 0.257 | 0.314 | 0.288 |
| Year | Yes | Yes | Yes |

*, **, *** Indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.
Standard errors are robust and clustered at the hospital level. All continuous variables are winsorized at the 1st and 99th percentiles.
All variables are defined in Appendix A.

only draws a direct causal relationship between HIT investments and hospital financial performance. Although we find the direct relationship between HIT investments and hospital bad debt from the results of Model (1), we probe more deeply into the causality between them. Using a mediational model, we provide evidence that HIT investments cause enhanced patient

**FIGURE 2**
**Results of the Mediation Model Analysis with Patient Experience as a Mediator**

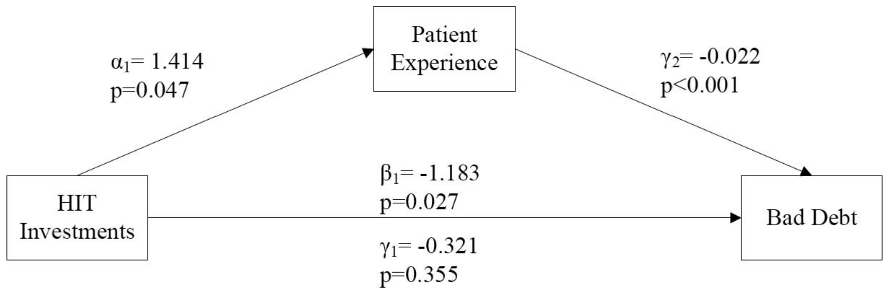





**TABLE 4**
**Regression Results of Change Analyses**

**Panel A: Change Analyses**

| Variables | Model (1) Δ_BadDebt | Model (2) Δ_PatExperience | Model (3) Δ_BadDebt |
|---|---|---|---|
| *Δ_HIT_INV* | −0.279** | 4.687* | −0.253 |
| | (0.035) | (0.054) | (0.630) |
| *Δ_PatExperience* | | | −0.096** |
| | | | (0.040) |
| *MCI* | −0.003 | 0.009 | −0.003 |
| | (0.669) | (0.915) | (0.665) |
| *Δ_MedicareMix* | −0.019 | −0.348 | −0.021 |
| | (0.878) | (0.641) | (0.866) |
| *Δ_MedicaidMix* | 0.072* | −0.157 | 0.071* |
| | (0.091) | (0.643) | (0.096) |
| *Δ_CMI* | −0.082** | 0.132 | −0.082** |
| | (0.033) | (0.628) | (0.032) |
| *Δ_Charity_Care* | −0.048 | −0.523** | −0.045 |
| | (0.319) | (0.038) | (0.352) |
| *Δ_Size* | −0.000 | −0.000 | −0.000 |
| | (0.918) | (0.237) | (0.871) |
| *Δ_Leverage* | 0.003 | −0.022 | 0.003 |
| | (0.749) | (0.607) | (0.739) |
| *Teaching* | 0.009 | 0.017 | 0.009 |
| | (0.197) | (0.680) | (0.191) |
| *Gov* | 0.014* | −0.030 | 0.014* |
| | (0.056) | (0.521) | (0.061) |
| *For-profit* | 0.016*** | −0.033 | 0.015*** |
| | (0.002) | (0.399) | (0.002) |
| *Urban* | −0.004 | −0.093 | −0.003 |
| | (0.496) | (0.105) | (0.562) |

*(continued on next page)*

**TABLE 4 (continued)**

| Variables | Model (1) Δ_*BadDebt* | Model (2) Δ_*PatExperience* | Model (3) Δ_*BadDebt* |
|---|---|---|---|
| *Network* | −0.009* | 0.030 | −0.009* |
| | (0.080) | (0.466) | (0.087) |
| Constant | 0.020** | 0.071 | 0.020** |
| | (0.020) | (0.398) | (0.023) |
| Observations | 468 | 468 | 468 |
| Adjusted $R^2$ | 0.055 | 0.047 | 0.055 |
| Year | Yes | Yes | Yes |

*, **, *** Indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.
Standard errors are robust and clustered at the hospital level. All continuous variables are winsorized at the 1st and 99th percentiles.
All variables are defined in Appendix A.

**Panel B: Descriptive Statistics for Three Main Variables in Change Model**

| Variables | n | Mean | Std. Dev. | 1st Quartile | Median | 3rd Quartile |
|---|---|---|---|---|---|---|
| Δ_*BadDebt* | 468 | 0.0204 | 0.0564 | −0.0031 | 0.0086 | 0.0309 |
| Δ_*HIT_INV* | 468 | −0.0003 | 0.0068 | −0.0028 | 0.0000 | 0.0026 |
| Δ_*PatExperience* | 468 | −0.0558 | 0.3930 | −0.1748 | −0.0438 | 0.2614 |

All three variables are winsorized at the 1st and 99th percentiles.

experience (the mediator variable), which in turn causes bad debt reduction, rather than only a direct causal relationship between HIT investments and bad debt.

In all regression results, the directions of the coefficients on the control variables meet our expectations and/or match with prior research, suggesting our models are robust.

The multivariate regression results support our expectations. We document that patient experience mediates the relationship between HIT investments and hospital bad debt.

# V. SUPPLEMENTARY ANALYSES

## Change Analyses

Although our previous analyses control for a variety of hospital characteristics that might account for the effect of HIT investments on hospital bad debt, reverse causality is always a concern. One may argue that a hospital with less bad debt has more cash on hand, thus can invest more in HIT. One way to address the potential reverse causality concern is to conduct a "change" analysis (Allison 2009). We replace the continuous variables in Models (1)–(3) with the changes in these variables.[10] For example, Δ_*BadDebt* is the difference between *BadDebt* in year *t* and year *t*−1. Panel A of Table 4 presents the results, which are consistent with those in our main analyses in Table 3. Thus, reverse causality does not drive the association between HIT investments and

[10] *MCI* is a continuous variable, but it does not change over the sample period. We keep using *MCI*, rather than Δ_*MCI*, in the models.

**TABLE 5**

**Regression Results of Models (1)–(3) Using the Balanced Panel Data**

| Variables | Model (1) *$BadDebt_t$* | Model (2) *PatExperience* | Model (3) *$BadDebt_t$* |
|---|---|---|---|
| *$HIT\_INV_{t-1}$* | −1.512** | 2.393** | −0.206 |
| | (0.018) | (0.026) | (0.660) |
| *PatExperience* | | | −0.023*** |
| | | | (0.000) |
| *MCI* | −0.008 | 0.695** | −0.024 |
| | (0.741) | (0.031) | (0.306) |
| *MedicareMix* | −0.007 | −1.565*** | −0.042 |
| | (0.911) | (0.003) | (0.499) |
| *MedicaidMix* | 0.005 | −1.999*** | −0.040 |
| | (0.924) | (0.000) | (0.431) |
| *CMI* | −0.014 | 0.816*** | 0.004 |
| | (0.637) | (0.005) | (0.894) |
| *Charity_Care* | −0.002 | −0.054 | −0.001 |
| | (0.984) | (0.929) | (0.993) |
| *Size* | −0.000* | −0.000 | −0.000* |
| | (0.068) | (0.743) | (0.067) |
| *Leverage* | 0.017 | −0.193** | 0.012 |
| | (0.132) | (0.012) | (0.225) |
| *Teaching* | 0.009 | 0.214 | 0.014 |
| | (0.411) | (0.166) | (0.175) |
| *Gov* | 0.041** | −0.090 | 0.043** |
| | (0.022) | (0.548) | (0.011) |
| *For-profit* | 0.048*** | −0.667*** | 0.033** |
| | (0.001) | (0.000) | (0.014) |
| *Urban* | −0.004 | −0.097 | −0.006 |
| | (0.730) | (0.705) | (0.585) |
| *Network* | −0.004 | 0.063 | −0.003 |
| | (0.763) | (0.684) | (0.845) |
| Constant | 0.077 | 0.497 | 0.065 |
| | (0.199) | (0.405) | (0.264) |
| Observations | 520 | 520 | 520 |
| Adjusted $R^2$ | 0.254 | 0.362 | 0.283 |
| Year | Yes | Yes | Yes |

*, **, *** Indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.
Standard errors are robust and clustered at the hospital level. All continuous variables are winsorized at the 1st and 99th percentiles.
All variables are defined in Appendix A.

bad debt. Moreover, the results demonstrate that investing more in HIT in the current year than the previous year can ensure higher patient experience, which in turn reduces more bad debt.

### Balanced Panel Data

Due to data availability, some data are missing in our sample. Thus, our sample is unbalanced panel data, which may be an issue if the missing data are not random. We re-estimate Models (1)–(3) using the balanced panel data, i.e., only keeping the hospitals with all variables available for the analyses in all four years. The balanced panel dataset contains 520 hospital-year observations, which cover 130 unique California hospitals. We report the results in Table 5, which are consistent with those in our main analyses. This finding further supports that our main results are robust.

## VI. CONCLUSION

Due to the Affordable Care Act of 2010, hospital charity care has plunged, and more patients have high deductible and coinsurance/copayment health plans. Consequently, patient payment responsibility increases, and hospital bad debt rises. In this study, we examine whether HIT investments affect patient experience to reduce hospital bad debt. Prior research relating to HIT investments and hospital financial performance has faced a challenge, partially due to data availability and accessibility (Schmitt and Wofford 2002). We use more recent Definitive Healthcare and California Hospital Report data to examine the effect of HIT under the current healthcare environment. We expect and find that HIT investments reduce hospital bad debt. Further, we provide evidence that patient experience mediates the relationship between HIT investments and hospital bad debt.

We recognize that our study is subject to some limitations. We use four-year data from California Hospital Reports to measure patient experience. The regional data may result in a moderate sample size, and limit the generalizability of our findings. Another limitation is the measure of patient experience. As we discussed, no unanimous agreement exists on how to measure patient experience. Many people believe that patient experience should include clinical outcomes. The measures of patient experience in California Hospital Reports do not include any clinical outcomes. Researchers can use other patient experience reports, including clinical outcomes, to investigate the associations among HIT investments, patient experience, and bad debt if data are available.



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## APPENDIX A

### Variable Definitions

| Variable | Definition |
|---|---|
| Independent Variable in Models (1), (2), and (3) | |
| $HIT\_INV_{i,t-1}$ | Hospital IT budget scaled by net patient revenue in year $t-1$. |
| Dependent Variable in Models (1) and (3) | |
| $BadDebt_{i,t}$ | Hospital bad debt scaled by lagged net patient revenue in year $t$. |
| Dependent Variable in Model (2) | |
| $PatExperience_{i,t}$ | A single underlying factor score from loading four items, including "Nurses communicated well," "Doctors communicated well," "Staff explained medicine," and "Received information and education," in California Hospital Reports in year $t$. |
| Control Variables | |
| $MCI_{i,t}$ | Hospital market concentration index in year $t$. |
| $MedicareMix_{i,t}$ | Hospital Medicare mix, which is the percentage of Medicare discharge in total patient discharges, in year $t$. |
| $MedicaidMix_{i,t}$ | Hospital Medicaid mix, which is the percentage of Medicaid discharge in total patient discharges, in year $t$. |
| $CMI_{i,t}$ | Hospital overall case mix index in year $t$. |
| $Charity\_Care_{i,t}$ | Hospital charity care charges in year $t$. |
| $Size_{i,t}$ | Hospital net patient revenue (in million) in year $t$. |
| $Leverage_{i,t}$ | Hospital total liabilities scaled by lagged total assets in year $t$. |
| *Teaching* | An indicator variable that is set equal to 1 if *Medical School Affiliation* is "Graduate" or "Major," and 0 otherwise. |
| *Gov* | An indicator variable that is set equal to 1 if *Ownership* is "Governmental," and 0 otherwise. |
| *For-profit* | An indicator variable that is set equal to 1 if *Ownership* is "For-profit," and 0 otherwise. |
| *Urban* | An indicator variable that is set equal to 1 if *Geographic Classification* is "Urban," and 0 otherwise. |
| *Network* | An indicator variable that is set equal to 1 if *Network* is present, and 0 otherwise. |
| *Year* | An indicator variable that is set equal to 1 if an observation's year is equal to one fiscal year. |