Sharing is Caring: The Role of Health Information Exchange on Patient Care*

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Abstract

Healthcare has been transformed by health information technology over the past two decades, but the impact of such digital technologies on health outcomes remains a long-standing and controversial question. In this project, we focus on the role of Health Information Exchange (HIE), an innovation designed to improve communication between healthcare systems and one that has been heavily subsidized and promoted as a way to improve quality of care. Using a newly compiled database of annual, state-level health information exchange laws, we show these laws strongly influence the adoption of HIE. Instrumental variable estimates that exploit state law changes show that HIE adoption reduces county-level mortality rates from flu and pneumonia by 18%. Hospital-level readmission rates for common conditions also fall by 4-5%. Given that the proportion of hospitals with HIE capability rose by 50 percentage points over the period in which we find these effects, we estimate that this diffusion saved 27,000 lives per year. We attribute the health improvements to enhanced public health response to infectious disease and improved care coordination.

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1 Introduction

Health information technology (HIT) has transformed the landscape of healthcare over the past two decades. Pioneering advances such as the application of artificial intelligence for diagnostics, the integration of robots in surgical procedures, and the utilization of telemedicine for remote treatments exemplify this technological revolution. Central to these innovations is the widespread adoption of Electronic Health Record (EHR) systems, which grew substantially in the US after the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 allocated $30 billion in federal funds to accelerate implementation. Despite this substantial investment and early optimism (Hillestad et al., 2005), research has generally found modest effects of EHR adoption alone on clinical outcomes (Bronsoler, Doyle, and Van Reenen, 2022). Beyond mere technology adoption, health information exchange (HIE)—the sharing of patient information across healthcare organizations—has emerged as a potentially critical and understudied factor in realizing the full potential of HIT to improve healthcare delivery and patient outcomes.

Provider participation in HIE has grown dramatically over time, though significant gaps still remain. In 2019, 74% of hospitals participated in Regional Health Information Organizations (RHIOs)—entities that facilitate information sharing across different healthcare organizations—up from 17% in 2007. Over the same time period, hospital exchange of patient information across organizational boundaries similarly rose. Despite this progress, 32% of patients in 2019 still reported experiencing information exchange gaps when visiting providers (ONC, 2019), and 64% of physicians lacked access to their patients' medical information from external sources (ONC, 2022). These statistics highlight the imperfect, though improving, state of information exchange despite substantial investments and ongoing policy initiatives.[1]

This paper studies the effect of health information exchange on health outcomes, addressing a question crucial for evaluating public investments in health information technology and informing current policy debates. We investigate whether increased information sharing can improve healthcare quality and patient health through two potential mechanisms: (1) improved care coordination between providers, which may enhance continuity and delivery of care, and (2) enhanced communication between providers and public health agencies, which may strengthen public health response capabilities, particularly for infectious diseases. Both mechanisms appear to be valued by stakeholders—over 80% of physicians believe HIE im-

[1] One notable ongoing initiative is the federal Trusted Exchange Framework and Common Agreement (TEFCA), which aims to establish a nationwide health information exchange network. With the first organizations approved to join TEFCA in December 2023, its impact on improving HIE and healthcare delivery remains to be seen.

proves care quality and coordination (ONC, 2022), while 86% of RHIOs surveyed in 2023 exchanged patient data with public health authorities (Rosenthal et al., 2024).

We focus on hospital participation in these RHIOs as our primary measure of HIE due to our ability to consistently measure it over time and these organizations' ability to facilitate information sharing across providers as well as with public health agencies. Combining hospital data from the American Hospital Association IT Survey with health outcomes from the National Vital Statistics System and the Centers for Medicare and Medicaid Services Hospital Compare database, we examine the effect of RHIO participation on two categories of outcomes: (1) county-level deaths per capita from influenza (flu) and pneumonia, and (2) hospital readmission rates for the common conditions of pneumonia, heart failure, and acute myocardial infarction (AMI). These measures allow us to investigate both proposed mechanisms, as readmission rates reflect hospital quality and potentially the degree of care coordination for often complex patients, while infectious disease mortality captures potential benefits of communication between providers and with public health agencies. Recognizing that information exchange benefits may materialize gradually over time as users adapt to evolving systems, we estimate these relationships using a long-differences specification from 2009 (just before the HITECH Act subsidies) to 2019 (the final year of our data).

We then use a two-stage least squares (2SLS) identification strategy, instrumenting for hospital RHIO participation with state-level laws regarding HIE in order to address endogeneity concerns inherent in hospital RHIO participation decisions. We construct a novel, comprehensive panel database of state HIE laws across multiple legal dimensions from 2000 to 2019, building on procedures established by Schmit et al. (2018). To navigate the challenge of choosing which legal dimensions are the best predictors of HIE, we implement two complementary approaches: (1) selecting as our instrument a single dimension—opt-out patient consent laws for participation in HIE—which we predict may strongly influence hospital utilization of HIE (Schmit et al., 2018; Apathy and Holmgren, 2020), and (2) employing a least absolute shrinkage and selection operator (LASSO) to more systematically identify the most predictive legal dimensions. First stage results for both approaches demonstrate that these laws significantly impact hospital RHIO participation, with the LASSO-selected instruments creating a stronger first stage than the opt-out patient consent law alone.

We ultimately find that hospital participation in information exchange organizations substantially improves health outcomes. Our preferred LASSO 2SLS specification estimates that a 10 percentage point increase in hospital RHIO participation reduces county flu and pneumonia deaths by 2.1 per 100,000 people (3.6% of the mean) and decreases both pneumonia and heart failure hospital readmission rates by 0.2 percentage points (1% and 0.8% of the means,

respectively). While we do not find any significant effect on AMI readmission rates, the point estimates are typically negative. These results are robust to various specification checks including controlling for various county-level characteristics, winsorizing outlier observations, varying our LASSO instrument selection procedure, and estimating these relationships with a two-way fixed effects panel specification instead of long-differences. We also find that restricting to a shorter time period (e.g., 2009-2015) yields slightly smaller estimates of the effect of HIE on health outcomes, suggesting that the full potential of information exchange may take time to materialize. This result is consistent with prior studies that find the effects of HIT also materialize gradually over time as providers require time to learn how to effectively use their new electronic tools (Bronsoler, Doyle, and Van Reenen, 2022)

Given the nationwide increase in hospital RHIO participation of over 50 percentage points from 2009 to 2019, our estimates suggest this change produced substantial health benefits: reducing county-level flu and pneumonia deaths by more than 10.6 per 100,000 people (18%) and decreasing hospital readmission rates for pneumonia and heart failure patients by more than 0.8 percentage points each (4-5%). Using standard estimates of the value of a statistical life (Federal Emergency Management Agency, 2020), we calculate that the reduction in flu and pneumonia mortality alone saved approximately 27,560 lives annually, which is equivalent to $206.7 billion.

Related Literature This paper contributes to two strands of literature. First, we build upon the literature examining technological diffusion, particularly in healthcare. Costs, complexity, competition, and complementary factors such as human capital are often leading drivers of technological adoption (Hall, 2005), and health information technology in the healthcare sector is no exception (Bronsoler, Doyle, and Van Reenen, 2022). For example, organizational aspects play a particularly crucial role in the adoption of technologies across industries as employee engagement represents a key component of effective management practices (Bloom and Van Reenen, 2007), and healthcare provider acceptance has proven essential for successful HIT implementation (Cohn, 2009; Hardiker et al., 2019).[2] Market structure also matters greatly, with weak competition among both healthcare providers and HIT vendors potentially dampening innovation incentives (Cutler, 2011; Bloom et al., 2015).

More unique to healthcare are barriers to technological adoption related to the concerns regarding patient safety (Harrington et al., 2011; Raposo, 2015) and patient privacy (Adler-Milstein and Pfeifer, 2017) as well as the fragmentation of providers and healthcare delivery

[2]Clinician resistance, especially among physicians with high human capital and organizational influence, can present significant barriers to adoption.

(Cebul et al., 2008; Agha et al., 2023). Several studies also have demonstrated that the legal environment surrounding HIT significantly influences provider adoption and usage of such technology, though many of these studies have relied on case studies, cross-sectional analyses, or the examination of limited policy dimensions (Miller and Tucker, 2009; Adjerid et al., 2015; Schmit et al., 2017; Schmit et al., 2018; Apathy and Holmgren, 2020). We contribute to this literature by incorporating comprehensive longitudinal data on multiple dimensions of HIE regulations and demonstrating the substantial impact of legal frameworks on HIE adoption (Bronsoler, Doyle, Schmit, and Van Reenen, 2022). We then leverage this legal variation as a source of quasi-random variation to identify the causal effect of HIE on health outcomes.

Second, we extend the literature on the effects of HIT and HIE on healthcare performance and patient outcomes. In an extensive review of both economic and medical papers, Bronsoler, Doyle, and Van Reenen (2022) synthesize evidence suggesting that HIT generally improves clinical outcomes and can lower healthcare costs. However, these effects are typically modest and highly heterogeneous across settings. Economic studies (e.g., McCullough et al., 2010; Miller and Tucker, 2011; Agha, 2014; McCullough et al., 2016; McCullough et al., 2021) tend to find more modest benefits than the medical literature (e.g., Chaudhry et al., 2006; Goldzweig et al., 2009; Buntin et al., 2011; Kruse and Beane, 2018; Lin et al., 2018). Further, effects appear to materialize gradually over time as providers learn to effectively integrate new electronic tools into their workflows.[3] Later studies typically find larger effects, likely reflecting this necessary adjustment period.

We contribute to this literature in several important ways. First, we incorporate substantially more recent data than most previous studies, which predominantly examined the period before and immediately following the 2009 HITECH Act. Second, we employ a long-differences specification across an extended time period. We expect it takes time for providers to learn how to employ new data-sharing capabilities, and a long-differences specification better captures the adjustment periods necessary for realizing clinical benefits. Most existing studies use cross-sectional designs or short panels that cannot adequately account for such learning. Given the revolution in HIT adoption, long-differences estimates using more recent outcomes may better capture the benefits of these changes. Third, we focus specifically on HIE rather than technology adoption alone—addressing the critical distinction between possessing electronic capabilities and effectively utilizing them to improve patient care. The mere adoption of HIT does not guarantee information exchange between providers or with public health authorities, which are the mechanisms through which care coordination benefits actually materialize. Our focus

[3]The healthcare sector often faces substantial adjustment costs when changing technologies and processes. Providers and organizations may require several years to learn how to use new systems effectively, creating a long and variable lag between adoption and improved outcomes (Bronsoler, Doyle, and Van Reenen, 2022).

on the utilization of HIE thus provides insights into the value of HIT that adoption-focused studies may not capture. Finally, we address endogeneity concerns that have challenged many previous papers by instrumenting for hospital HIE using quasi-random changes in state-level laws governing HIE. This approach provides a more robust source of plausibly exogenous variation than many prior identification strategies, allowing us to more convincingly estimate the causal impact of information exchange on health outcomes.

Outline The remainder of the paper is structured as follows: Section 2 describes our data, the growth in information technology and exchange in healthcare, and the evolution of the legal environment surrounding HIE. Section 3 details our empirical strategy for identifying the causal effect of HIE on health outcomes, which uses state-level law changes as instruments for changes in HIE. Section 4 presents our findings and then quantifies the magnitude of estimated effects and discusses potential mechanisms. Section 5 concludes.

2 Data & Setting

2.1 Data

We use three main types of data in this paper: (1) data on hospital characteristics including participation in HIE, (2) data on health outcomes at both hospital and county levels, and (3) hand-collected data on state laws regarding HIE.

Data on Hospitals Our primary data sources for information on hospitals and their usage of health information technology are the American Hospital Association (AHA) Annual Survey and the AHA IT Survey from 2005 to 2019. Distributed to all hospitals in the US, the Annual Survey contains detailed information on hospital characteristics while the IT survey documents hospital health IT capabilities and usage. The IT Survey consistently measures health information sharing capabilities, including hospitals' abilities to exchange data electronically with entities inside and outside their systems, and their participation in regional health information exchange organizations (RHIOs)—metrics that are central to our analysis.

Data on RHIOs We supplement our primary datasets on health information exchange with survey data that records characteristics of regional health information organizations (RHIOs) collected by Adler-Milstein et al. (2016). Administered between December 2014 and April 2015, the survey targeted all community and state organizations in the US that facilitated

clinical data exchange between independent entities as of December 1, 2014.[4] Of the 158 RHIOs meeting inclusion criteria, 127 completed the survey, yielding a response rate of 80 percent.[5] The survey collected information on organizational characteristics (e.g., number and types of participants involved in data exchange), types of data exchanged, ability to meet meaningful-use criteria, engagement in delivery and payment reform, funding sources, and barriers to development.[6] Critically for our analysis, the survey asked whether public health departments provided data to and received data from each RHIO. Among operational RHIOs, 44 percent reported that public health departments provided data to their network and 56 percent reported that public health departments received data from their network.

Data on Health Outcomes To assess how HIE usage affects patient health outcomes, we use two primary outcomes data sources: (1) hospital-level quality metrics from the Centers for Medicare and Medicaid Services (CMS) Hospital Compare database from 2009 to 2019, and (2) county-level mortality data from the National Vital Statistics System (NVSS) from 2000 to 2019. The Hospital Compare data provide quarterly risk-adjusted quality measures including 30-day mortality and readmission rates for multiple conditions. These measures are calculated using claims from a pooled 3-year sample of fee-for-service Medicare and Veterans Health Administration patients, with a one-year reporting lag. We focus specifically on readmission rates for three commonly measured conditions: acute myocardial infarction (AMI), heart failure, and pneumonia. The most recent available data at the time of our analysis were 2018 for AMI and heart failure readmission rates and 2017 for pneumonia readmission rates.[7,8,9] For county-level analysis, we use NVSS individual-level mortality records containing cause of death, demographic characteristics, and county identifiers, combined with Census Bureau population estimates to calculate county-level mortality rates. We focus particularly on deaths from influenza (flu) and pneumonia because they are common causes of death that may benefit from

[4]The survey identified 202 potential RHIOs based on prior surveys and web searches. Of these, 37 did not meet inclusion criteria (17 were defunct and 20 never pursued HIE between independent entities), and 7 had merged with others on the list. Details on the survey methodology are available in Adler-Milstein et al. (2016).

[5]We assess representativeness by comparing our RHIO survey data with AHA IT data. In 2015, 2,148 of 3,591 hospitals (59.8%) in the AHA IT survey reported participating in a RHIO. Of these 2,148 hospitals, 1,873 (87.2%) were located in counties with at least one RHIO in our survey dataset. This confirms that while our dataset does not capture the universe of RHIOs, it covers the vast majority of RHIOs in which hospitals participate.

[6]The survey also collected information on other stakeholder types including hospitals, physician practices, long-term care providers, public and private payers, independent imaging facilities, and independent labs.

[7]We use data from the last quarter of each year and assign the year of measurement as the first year in which each readmission rate is calculated to avoid capturing historical quality. Given the pooled 3-year sample with a 1-year lag, this results in 2017 and 2018 being the last years available.

[8]These readmission rates require at least 10 patients in the denominator for each measure, resulting in some hospitals not consistently appearing in the sample.

[9]Doyle et al. (2019) validates these CMS quality measures, finding that random assignment to better quality hospitals (as measured by the CMS Hospital Compare) results in better patient outcomes.

care coordination and improved public health surveillance (Rao et al., 2025).

Data on Legal Environment To investigate the role of state policy environments in HIE, we construct a novel panel database of state-level HIE laws from 2000 to 2019. Building upon Schmit et al. (2018), we systematically identify and code relevant laws as they existed on the last day of each year. Our data collection involved comprehensive searches of historical Westlaw databases using two approaches: (1) tracking laws previously identified in 2016 by Schmit et al. (2018), and (2) conducting additional keyword searches to capture both repealed and newly enacted legislation. A coding team, consisting of an experienced policy surveillance legal scholar and research assistants, categorized each law using a structured protocol with validation procedures such as redundant coding and comprehensive reviews. Further details on database construction are available in Appendix A.

The resulting database tracks state-level HIE policies across four broad categories: (1) governance structures for HIE operation, (2) financial sustainability mechanisms, (3) specifications for authorized HIE users and uses, and (4) data protection provisions for privacy and security.[10] Table 1 presents the 12 specific dimensions that we code within these categories, each representing a distinct aspect of how state laws may facilitate or impede information exchange. For each dimension, we establish an ex-ante prediction of its likely impact on HIE usage based on theory and existing research (e.g., Schmit et al., 2018).

We predict that laws governing patient consent models for data sharing will be among the most important dimensions in our database (Schmit et al., 2018; Apathy and Holmgren, 2020). Some states adopt "opt-in" systems requiring active patient consent for inclusion in HIE networks, while others implement "opt-out" frameworks where patients are included by default unless they specifically request exclusion. Given the large effects of defaults found in other settings—such as retirement savings (Madrian and Shea, 2001) and organ donations (Davidai et al., 2012)—we expect these patient consent defaults to significantly impact HIE participation. Other potentially key dimensions include provisions authorizing formal governance structures, specifying funding mechanisms, and establishing immunity protections for HIE participants. By tracking these dimensions over time, our database provides one of the first longitudinal and comprehensive views of the evolving legal landscape for HIE across the US, allowing us to examine how specific policy choices affect HIE adoption and usage.

[10]The governance category tracks laws about the state's role in creating and operating viable regional HIEs. Financial sustainability includes dimensions addressing funding sources and liability protections for HIE participants. The users and uses category tracks laws about who can access shared information and for what purposes, including mandated provider participation and authorized public health authority access. The data protections category encompasses provisions for privacy, confidentiality, and security of patient data.

2.2 Digital Revolution in Healthcare

The past two decades have witnessed a remarkable digital transformation in healthcare delivery driven by the newly widespread adoption of advanced Electronic Health Record (EHR) systems. This adoption grew substantially following the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which focused on increasing HIT usage by subsidizing $30 billion of EHR acquisition costs, changing Medicare reimbursement rules, and providing technical support for hospitals and physician offices. Critically, these HITECH incentives were contingent on providers attesting to their "meaningful use" of EHRs according to regulatory standards that included basic requirements for electronic HIE.[11] The subsequent rise in HITECH-certified EHR adoption has been impressive. Figure 1 shows that fewer than 5% of US hospitals had certified EHR systems in 2007; this share jumped to almost 80% by 2018. The diffusion pattern follows a traditional sigmoid function, with an inflection point after the implementation of the HITECH Act.

The growth in hospital EHR adoption parallels growth in hospital HIE. Figure 1 plots these trends using two measures of hospital HIE derived from the AHA IT Survey: (1) whether hospitals participate in any state, regional, or local health information exchange or health information organization (i.e., Regional Health Information Organization or RHIO), and (2) an index of HIE with other hospitals outside of each hospital's own hospital system (i.e., HIE Out Index). We construct the latter index using five questions from the AHA IT Survey regarding hospitals' abilities to electronically exchange data on patient demographics, laboratory results, medication history, radiology reports, and clinical records. The HIE Out Index represents the average of indicators for these five external-sharing capabilities (i.e., a hospital receives a value of 1 if it can exchange all 5 types of data, 0.8 if it can exchange 4 types, etc.).[12,13] Both measures show substantial growth over time: hospital RHIO participation rises from 17% in 2007 to 74% in 2019, while the average hospital's HIE Out Index increases from 9% in 2007 to 60% in 2015, the last year in which this index is measurable.[14] These patterns highlight the dramatic expansion of HIE capabilities in US hospitals over the past decade.

[11] Healthcare organizations that adopted advanced EHR systems with decision support capabilities and utilized these systems at the point of care for their patients fulfilled the "meaningful use" thresholds and thus qualified for HITECH subsidies.

[12] We focus on health information sharing outside of hospital systems because it is less clear whether or how laws on HIE would impact internal uses of patient health information.

[13] For hospitals that completed the survey but left HIE-related questions blank, we code those missing values as zeros. All of the following analyses are robust to leaving these responses as missing.

[14] 2015 is the last year in which the five questions comprising the HIE Out Index are asked in the AHA IT Survey. To attempt to see how our index would trend through 2019, we can construct a proxy for the index from 2009 to 2019 by incorporating survey questions that are available for later years. When we do so, we find that the HIE Out Index continues to grow from 2015 to 2019 at a similar rate as the observed growth in RHIO participation.

2.3 Correlation Between HIE and COVID-19 Mortality

The rapid growth in hospital HIE may yield significant benefits for health outcomes. Given that healthcare is a knowledge-intensive industry with fragmented sources of information, improved information exchange could enhance care coordination across providers and facilitate better communication between healthcare providers and public health agencies—potentially enabling more effective infectious disease tracking and targeted interventions. Figure 2 provides cross-sectional evidence supporting this hypothesis. Counties with higher capabilities for HIE—measured as each county's average hospital HIE Out Index in 2015, weighted by hospital bed size—experienced significantly lower COVID-19 death rates per capita in 2021 (Panel A), despite having similar COVID-19 case rates (Panel B).[15] This negative correlation between HIE and COVID-19 mortality persists even after controlling for various county-level socioeconomic characteristics and COVID-19 mortality in 2020, as shown in Appendix Figure B1. While these associations are suggestive of healthcare quality gains from data sharing, they remain cross-sectional correlations rather than causal evidence. To establish causality and address potential endogeneity in HIE adoption, we require a longer panel and a source of plausibly exogenous variation, which we find in the evolving legal environment for HIE described in the next subsection.

2.4 Evolution of HIE Legal Environment

The substantial expansion of HIE across US hospitals over the past two decades occurred alongside dynamic changes in the policy environment for HIE. Starting in 2005, Panel A of Figure 3 shows that an average of 6.5 states change their HIE laws each year through 2019. This legislative activity peaks in 2011, coinciding with the implementation of federal funding under the HITECH Act. While many states have implemented and revised their HIE laws, regulatory approaches vary considerably across jurisdictions. Panel A of Figure 3 illustrates this variation by also plotting the share of states that have adopted two different types of patient consent models over time: opt-in laws requiring active patient consent for inclusion in HIE networks, and opt-out laws where patients are included by default unless they specifically request exclusion. Both types of laws start gaining traction around the passage of the HITECH Act in 2009. By 2019, 30% of states have opt-out laws in place while 12% have opt-in laws, with the remaining 58% leaving patient consent procedures unspecified.

Most states have become more permissive toward HIE over time, though the magnitude

[15] 2015 is the last year in which the HIE Out Index is measurable in the AHA IT Survey. Correlations between the HIE Out Index and COVID-19 outcomes using a proxy for this index in 2019 yield similar results.

and direction of these changes vary considerably. To quantify this evolution, we construct a simple summary HIE Legal Index that sums indicators for the 12 HIE legal dimensions recorded in Table 1. Dimensions are normalized such that laws predicted to favor HIE are coded as +1, while those predicted to hinder HIE are coded as -1.[16] Panel B of Figure 3 maps the change in this index from 2009 to 2019 separately for each state. Only three states became less permissive toward HIE during this period, while 30 states became more permissive and 17 remained unchanged. This pattern reveals substantial variation in policy changes across states, even within geographic regions. Figure 4 further highlights the cross-sectional differences in state-level HIE legal environments as of 2019. No state had laws that positively addressed more than 8 of the 12 dimensions, while 13 states had none. The most pro-HIE legal frameworks appear in the Upper Midwest and Texas, while the least supportive environments are in parts of the Southeast, Mountain West, and Great Lakes. However, significant differences exist even within these regions, with no obvious systematic patterns driven by economic or political factors. This creates variation that we leverage to identify the causal effects of HIE on health outcomes.

3 Empirical Strategy

3.1 Overview

In this section, we aim to estimate the causal effect of HIE on health outcomes at both hospital and county levels. Hospitals self-select into participation in RHIOs, and such self-selection may be correlated with unobservable hospital differences that also affect health outcomes. For example, hospitals with increasing financial resources might more readily adopt HIE while simultaneously improving health outcomes through those same resources, potentially biasing OLS estimates towards overestimating health improvements due to HIE. Conversely, hospitals experiencing deteriorating health outcomes might implement HIE as a remedial measure, potentially biasing OLS estimates towards underestimating HIE health effects. Given the plausibility of both scenarios, the direction of this endogeneity bias is thus theoretically ambiguous.

To address this endogeneity concern, we instrument for hospital participation in RHIOs using state-level legal environments for HIE. Instrumenting with legal frameworks presents challenges due to the multitude of potential legal dimensions available. As detailed in Section 2, we track 12 distinct legal dimensions of HIE over time. These laws, as well as their potential interactions, could all influence HIE adoption. However, naively incorporating all of these dimensions as instruments risks exacerbating finite-sample bias in 2SLS estimation when some

[16] Since 2 of the 12 dimensions are predicted to hinder HIE, the maximum possible value of this HIE Legal Index is 10 and the minimum is -2.

instruments lack explanatory power (i.e., it increases the probability of weak instruments; Angrist and Krueger, 1999).

We therefore implement two complementary approaches to instrument for HIE using the legal environment. Our first approach is to select as a single instrument the legal dimension that we ex-ante predict will be the most influential and interpretable: whether the state has implemented an opt-out legal framework where patients are automatically included in HIE unless they explicitly request exclusion.[17] Based on the substantial effects of defaults observed in other contexts, we anticipate that an opt-out patient consent default will significantly increase HIE participation among both patients and hospitals.[18] However, we acknowledge that selecting this instrument involves discretion and that one legal dimension alone may not independently have sufficient power to statistically significantly predict HIE adoption.

Our second approach is to employ a least absolute shrinkage and selection operator (LASSO) to systematically identify relevant instruments. Since the first stage prediction of an endogenous variable can be viewed as a pure prediction problem, we select from potential HIE legal dimensions using a post-LASSO estimation procedure similar to that introduced by Belloni et al. (2011). We define the set of potential instruments W_{st} as the levels of our 12 legal dimensions for state s in year t.[19] We then apply LASSO to select the relevant dimensions in this set with a penalty on the absolute number of predictors and a tuning parameter chosen by 10-fold cross-validation. Following Belloni et al. (2011), we also constrain LASSO to select a maximum of three legal dimensions as instruments.[20] To address LASSO's shrinkage bias, which biases non-zero coefficient estimates toward zero, we subsequently run OLS on the LASSO-selected instruments. We report conventional standard errors (clustered at the state level).[21,22]

[17] The alternatives are for states to have an opt-in legal framework requiring active patient consent for inclusion in HIE or for states to not specify patient HIE consent procedures.

[18] We predict hospitals will be more likely to engage in HIE if the time and effort cost of enrolling their patients is lower.

[19] We also estimate versions where the set of potential instruments also includes all two-way interactions of the legal dimensions as well as all possible lags of the legal dimensions. Our results are always quite similar no matter the starting set.

[20] We constrain the number of chosen instruments in order to increase precision. We explore robustness to this decision in Section 3.4.

[21] Belloni et al. (2011), as well as Cattaneo et al. (2018), show that conventional standard errors are appropriate as long as the number of selected instruments is not close to the sample size.

[22] This methodological approach also closely resembles those used by Gilchrist and Sands (2016) and Derenoncourt (2022).

3.2 Estimating Equations

First Stage For the first stage of our 2SLS specification, we estimate the relationship between HIE and the HIE legal environment using the following hospital-level long-differences regression:

$$\Delta \text{RHIO}_h = \alpha + \delta \, \Delta Z_{s(h)} + \gamma \, \Delta X_{h,c(h)} + \varepsilon_h. \tag{3.1}$$

Here, RHIO_h indicates whether hospital h participates in any state, regional, or local health information exchange or health information organization (i.e., Regional Health Information Organization), $Z_{s(h)}$ represents the set of chosen state-level legal instruments (either the opt-out legal dimension or the LASSO-chosen legal dimensions), and $X_{h,c(h)}$ comprises control characteristics for hospital h and its county $c(h)$. Our baseline controls include county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. We use RHIO participation as our primary endogenous variable rather than our HIE Out Index because the index is only measurable through 2015, and we aim to incorporate more recent data.[23] RHIOs also typically facilitate information sharing both across providers and between providers and public health agencies, whereas our HIE Out Index only measures the former capability. The coefficient δ represents our main parameter of interest. We cluster standard errors at the state level, corresponding to the level at which HIE legal environments change, and we weight hospitals by their baseline bed sizes. For county-level outcomes of interest in the second stage, we estimate a parallel specification:

$$\Delta \text{RHIO}_c = \alpha + \delta \, \Delta Z_{s(c)} + \gamma \, \Delta X_c + \varepsilon_c. \tag{3.2}$$

In this equation, RHIO_c represents the average RHIO participation among hospitals in county c, weighted by their baseline bed sizes. All other terms remain analogous to those in the hospital-level equation. We continue to cluster standard errors at the state level, and we weight counties by their baseline populations.

We employ a long-differences specification to account for the potentially long adjustment periods between (1) initial hospital RHIO participation and subsequent benefits for patient health outcomes, and (2) the enactment of laws and resulting changes in provider behavior. Research on HIT adoption consistently demonstrates that clinical improvements materialize gradually, as providers require time to effectively integrate new electronic tools enabled by the digitization of healthcare records (Bronsoler, Doyle, and Van Reenen, 2022). We thus antic-

[23] Our estimates are robust to this choice. When we substitute RHIO_h with a proxy version of HIE Out Index_h that incorporates survey questions available for later years to extend HIE Out Index_h through 2019, we observe similar results, though these tend to be noisier due to the measurement error introduced by the proxy.

ipate a learning period before RHIOs can be effectively utilized to improve health outcomes. Consequently, in both Equations 3.1 and 3.2, Δ denotes the change from 2009 (just before HITECH Act subsidies and most developments in the HIE legal environments) to 2019 (the final year in our data). For example, ΔRHIO_h measures the change in RHIO participation for hospital h across this decade. This long-differences approach implicitly controls for hospital (or county) fixed effects. We check for robustness using two-way fixed effects versions of these first stage equations on panel data and typically find very similar results.[24]

Second Stage The second stage equations are then given by:

$$\Delta Y_h = \lambda + \beta \widehat{\Delta\text{RHIO}_h} + \eta \Delta X_{h,c(h)} + \epsilon_h, \tag{3.3}$$

and

$$\Delta Y_c = \lambda + \beta \widehat{\Delta\text{RHIO}_c} + \eta \Delta X_c + \epsilon_c, \tag{3.4}$$

for the hospital and county levels, respectively. We examine four health outcomes: (1) county-level deaths from influenza (flu) and pneumonia per 100,000 people, (2) hospital-level 30-day readmission rates for patients with acute myocardial infarction (AMI), (3) hospital-level 30-day readmission rates for patients with heart failure, and (4) hospital-level 30-day readmission rates for patients with pneumonia.[25] The terms $\widehat{\Delta\text{RHIO}_h}$ and $\widehat{\Delta\text{RHIO}_c}$ represent the predicted changes in RHIO participation at the hospital and county levels from first stage Equations 3.1 and 3.2, respectively. We maintain the same baseline controls as in the first stage, continue to cluster standard errors at the state level, and weight observations by baseline hospital bed size or county population. The coefficient β represents our main parameter of interest. We also check for robustness using two-way fixed effects versions of these second stage equations and find similar results.[26]

[24]Two-way first effect versions of Equations 3.1 and 3.2 are given by Appendix Equations B.1 and B.2, respectively. These panel specifications incorporate all annual data from 2009 to 2019 with hospital/county fixed effects and year fixed effects. They yield qualitatively similar but often quantitatively slightly smaller point estimates.

[25]Our measure of flu and pneumonia deaths per capita always uses county-level population in 2000 as the denominator to ensure that changes in population do not drive our results. Our measures of readmission rates by condition come directly from the CMS Hospital Compare data.

[26]Two-way first effect versions of Equations 3.3 and 3.4 are given by Appendix Equations B.3 and B.4, respectively. These panel specifications incorporate all annual data from 2009 to 2019 with hospital/county fixed effects and year fixed effects. They yield qualitatively similar but often quantitatively smaller point estimates.

3.3 Summary Statistics

Tables 2 and 3 present summary statistics of our outcomes, HIE measures, and key legal dimensions at the hospital and county levels, respectively. On average, 60% of hospitals (weighted by bed size) participated in a RHIO during our sample period. As illustrated in Figure 1, RHIO participation grew substantially, with average hospital participation increasing by 56 percentage points from 2009 to 2019. For health outcomes, the average hospital in our sample had 30-day hospitals readmission rates of 16.5%, 21.9%, and 17.2% for patients with AMI, heart failure, and pneumonia, respectively.[27] Counties where these hospitals are located experienced an average of 66.7 flu and pneumonia deaths per 100,000 people annually. All health measures improved over time, as evidenced by negative long-difference changes. Regarding the legal environment, 19.6% of hospitals are in states with opt-out patient consent laws from 2009 to 2019, a proportion that increased substantially over time (with an average long-difference change of 21.8 percentage points). The average hospital had an HIE legal index of 2.8, which similarly rose during the study period, as also depicted in Panel B of Figure 3. County-level statistics largely mirror these hospital-level averages, with minor variations due to differences in weights.[28]

3.4 First Stage Results

Table 4 presents the results of estimating first stage Equations 3.1 and 3.2 at the hospital and county levels, respectively. Overall, we find that state HIE legal environments—as measured by the single opt-out patient consent model or by the LASSO-chosen legal dimensions—significantly influence hospital participation in health information exchange organizations.

Column 1 of Panel A shows that hospitals in states that adopt opt-out patient consent laws between 2009 and 2019 experience a 21 percentage point increase in their probability of RHIO participation compared to those in states without such changes. County-level estimates in Column 2 are slightly larger due to differences in weighting. These estimates are robust to

[27] Recall that our readmission rate data only extend through 2018 for AMI and heart failure and 2017 for pneumonia. These measures also require at least 10 patients in the denominator in order to be reported, resulting in some hospitals having missing values in certain years. AMI readmission rates have the most missing values as it is the least common of the three conditions.

[28] Our measures of HIE and three of our outcomes are at the hospital level, one outcome is at the county level, and our legal dimensions are at the state level. For hospital statistics, we assign each hospital the county and state characteristics of its location. We then weight hospitals by their baseline bed sizes. For county-level statistics, we assign each county its state characteristics and aggregate hospital-level measures to the county level using bed-size-weighted averages of hospitals within the county. We then weight counties by baseline populations. This approach creates slight differences in measures between the two summary statistics tables.

excluding controls or winsorizing the top and bottom 2.5% of observations of the change in RHIO.[29] A two-way fixed effects version yields smaller, less precise estimates, likely reflecting the time needed for legal changes to affect hospital behavior (Appendix Table B2). However, the F-statistic of only 7.1 (7.8 at the county level) raises weak instrument concerns. Moreover, as discussed earlier, selecting this single legal dimension involves some discretion. Appendix Table B3 demonstrates that other individual legal dimensions also predict hospital RHIO participation but similarly lack sufficient predictive power for use as individual instruments. Naively using all 12 dimensions simultaneously as instruments results in an F-statistic of only 11.8.[30]

Our LASSO-based approach for selecting relevant legal dimensions produces a substantially stronger first stage. Panel B of Table 4 presents the first-stage results using the three legal dimensions chosen by LASSO at both geographic levels. At the hospital level, LASSO selects three distinct laws: authorization for public health authorities to access HIEs, allowance of participant fees for HIE, and permission for patients to request HIE restrictions. At the county level, LASSO selects this last dimension along with measures of opt-out patient consent laws from both early and late in our sample period. Despite differences in instrument sets across the two geographic levels, our second-stage results will remain largely consistent. Importantly, the first-stage F-statistics reach approximately 27 at both levels—significantly higher than those with the opt-out law alone. To summarize the first stage in a single dimension, we calculate the predicted change in RHIO participation based on an OLS regression using the three LASSO-selected legal dimensions, labeled the "post-LASSO prediction." Regressing this prediction on the actual change in RHIO participation highlights the predictive power of the LASSO-selected instruments. Appendix Figure B2 maps the geographic distribution of these post-LASSO predictions, illustrating the state-level variation and again revealing substantial heterogeneity in our instruments even within geographic regions.

As with our opt-out instrument, these LASSO-based first stage estimates are robust to excluding controls or winsorizing observations.[31] The two-way fixed effects version of the first stage selects similar legal dimensions and produces comparable estimates (Appendix Table B2). Our results are also robust to modifying our LASSO procedure in multiple ways: (1) selecting on changes rather than levels of legal dimensions (Appendix Table B1), (2) relaxing the maximum constraint on selected instruments (Appendix Tables B5 and B6), and (3) expanding the potential instrument set to include interactions between legal dimensions (Appendix Table B5) and—for the panel version—lags of legal dimensions (Appendix Table B6). Across these specifications, LASSO frequently selects patient consent models (opt-in or opt-out), authoriza-

[29] Tables with these robustness checks are available upon request.
[30] Appendix Table B4 shows similar results with the two-way fixed effects version of the first stage regression.
[31] Tables with these robustness checks are again available upon request.

tion of patient restriction requests, and public health authority access as the most predictive instruments for hospital RHIO participation.

3.5 Identifying Assumptions and Validity Checks

The validity of our instrumental variables strategy relies on four key assumptions: (1) relevance of our instrument, (2) independence of our instrument, (3) monotonicity, and (4) an exclusion restriction. We now discuss the plausibility of each of these assumptions to support the credibility of our approach towards identification.

Our first assumption, relevance, requires that our instruments significantly predict hospital participation in health information exchange organizations. The first stage estimates in Table 4 clearly demonstrate that both the opt-out patient consent law and our LASSO-selected legal dimensions strongly predict hospital RHIO participation. The F-statistics of approximately 27 for our LASSO approach exceed conventional thresholds for instrument strength, providing further evidence that this assumption holds.

The independence assumption requires that our instruments be as good as randomly assigned. To evaluate this assumption, Figure 5 presents comprehensive balance checks for our LASSO-chosen instruments. The three panels plot estimated coefficients and 95% confidence intervals from regressions of our post-LASSO prediction (i.e., the one-dimensional representation of our LASSO-chosen instruments) on various county-level characteristics. Overall, we find that our LASSO-chosen legal dimensions show no systematic differences across economic, demographic, and political dimensions. Panel A shows that our instrument is not statistically associated with baseline (2009) county unemployment rates, poverty rates, median household incomes, or population age distributions; neither is it related to baseline measures of our second stage health outcomes (i.e., flu and pneumonia deaths per capita and hospital readmission rates for pneumonia, heart failure, and AMI). Panel B further shows that our instrument is unrelated to additional county demographic and political characteristics as well as healthcare market measures including hospital system concentration, hospital EHR vendor concentration, care fragmentation, and participation in various CDC infectious disease surveillance programs.[32] Panel C extends this analysis to show that our instrument is also unrelated to long-

[32]In more detail, Panel B of Figure 5 shows that our instrument is unrelated to county population in 2000, number of hospitals in 2007, number of hospital beds in 2007, median population age in 2000, female share of the population in 2000, white share of the population in 2000, hospital system concentration in 2007, hospital EHR vendor concentration in 2015, medical care fragmentation averaged across 2000-2010 (Agha et al., 2019), and democratic vote shares in 2008, 2012, 2016, and 2020. This panel also shows our instrument is unrelated to whether the county is located in a metropolitan area, whether the state is covered by the CDC Emerging Infections Program (EIP), whether the state is covered by the CDC Influenza Hospitalization Surveillance Program, and the

difference changes in county unemployment rates, poverty rates, median household incomes, and age distributions. Out of all three of these panels, we observe only isolated significant relationships with county uninsured rates in 2009, county median house prices in 2000, and the long-difference change in county uninsured rates—such significance is not unexpected given the multiple hypothesis testing. Similar balance checks for our opt-out instrument are shown in Appendix Figure B3. In sum, state-level adoption of HIE legal dimensions does not appear to be predicted by political, economic, or demographic variables. It appears that the rapid proliferation of state legislation during this period of accelerated HIT adoption generated plausibly exogenous variation in the types of legal changes implemented across states.[33]

Monotonicity and the exclusion restriction are more difficult to test. Our monotonicity assumption is that HIE-permissive laws affect hospital HIE choices in weakly the same direction for all hospitals—that is, these laws either increase hospital RHIO participation or have no effect, but do not decrease participation for any hospitals. While this assumption is difficult to test, it is conceptually reasonable given the nature of the legal dimensions we examine, which generally reduce barriers to HIE participation. Finally, the exclusion restriction requires that our instruments affect health outcomes only through their influence on hospital participation in RHIOs and HIE more broadly. While this assumption cannot be tested directly, several factors support its plausibility. First, the legal dimensions that comprise our instruments apply only to HIE, not to other aspects of healthcare such as HIT more broadly. Second, the lack of significant relationships between state-level changes in HIE legal dimensions and county-level changes in demographics, economic status, and political dimensions (shown in Panel C of Figure 5) shows that these laws are not changing other observable county characteristics that might independently affect health outcomes. Collectively, these validity checks strengthen our confidence that our instrumental variables approach isolates the causal effect of HIE on health outcomes, allowing us to draw meaningful conclusions about the impact of information sharing in healthcare settings.

4 Results: Effects of HIE on Health Outcomes

4.1 Second Stage Results

Table 5 presents our 2SLS estimates of how hospital participation in health information exchange organizations affects health outcomes across both county and hospital levels. These

share of the state covered by the CDC IHSP.

[33] See Bronsoler, Doyle, Schmit, and Van Reenen (2022) for further discussion of the quasi-random nature of these state-level HIE laws.

results reveal a consistent pattern: increased RHIO participation significantly reduces both mortality and hospital readmissions across multiple conditions. Using state opt-out patient consent laws as an instrument (Panel A), we find that a 10 percentage point increase in RHIO participation leads to substantial health improvements: flu and pneumonia deaths decrease by 2.9 per 100,000 people (4.9% of the mean), pneumonia readmission rates drop by 0.4 percentage points (2.3% of the mean), and heart failure readmission rates decline by 0.3 percentage points (1.4% of the mean). While AMI readmission rates also decrease, this effect is small in magnitude and not statistically significant. However, the relatively low first-stage F-statistics raise concerns about instrument weakness in these specifications. Our preferred estimates, using LASSO-selected legal dimensions as instruments (Panel B), demonstrate more robust but slightly smaller effects. With this approach, we find that a 10 percentage point increase in RHIO participation reduces flu and pneumonia mortality by 2.1 deaths per 100,000 people (3.6% of the mean), lowers pneumonia readmission rates by 0.2 percentage points (1% of the mean), and decreases heart failure readmission rates by 0.2 percentage points (0.8% of the mean). AMI readmission rates also decrease but again not statistically significantly.[34]

Comparing our 2SLS estimates to equivalent OLS estimates (Panel C of Table 5) reveals striking differences in magnitudes. The OLS results are substantially smaller, with only the relationship between RHIO participation and flu and pneumonia mortality reaching statistical significance—and even then, merely at the 10% level. This pattern suggests that conventional OLS approaches would substantially underestimate the health benefits of hospital participation in information exchange networks. The upward bias in these negative OLS estimates is likely due to selection in hospital RHIO participation decisions. It is possible that hospitals facing greater challenges—perhaps from higher-risk patient populations or additional resource constraints—may simultaneously trend towards worse health outcomes while also being more motivated to join RHIOs as a potential solution to improve their declining performances. Such selection bias would attenuate the estimated negative treatment effects. Appendix Figure B4 provides evidence supporting this explanation, showing that counties with greater growth in RHIO participation have significantly older populations at baseline and larger increases in their oldest elderly (those over age 85) over time. These differences in observable characteristics suggest there may be different in observable characteristics as well. Our instrumental variables strategy overcomes this limitation by leveraging quasi-exogenous variation in RHIO participation driven by legal changes that plausibly affect only HIE decisions.[35]

[34]Fewer hospitals report AMI readmission rates because the condition is relatively less common than pneumonia and heart failure. As a result, regressions looking at the effect on AMI readmissions have more limited numbers of observations and weaker first-stage F-statistics.

[35]It is also worth noting that 2SLS and OLS estimate treatment effects for different populations. The local average treatment effect estimated by 2SLS represents the impact of RHIO participation on health outcomes for

Our 2SLS findings are stable across multiple alternative specifications. The results remain virtually unchanged when county-level controls are omitted, though these controls enhance precision (Appendix Table B7).[36] Similarly, outlier values in outcome variables do not drive our findings, as winsorizing the top and bottom 2.5% of observations yields consistent estimates. The results also persist across variations in our first-stage LASSO selection approach—whether selecting on changes rather than levels of legal dimensions, relaxing the maximum constraint on selected instruments, or expanding the potential instrument set to include interactions between legal dimensions as well as their lagged values.[37] Additionally, employing a two-way fixed effects panel specification instead of our long-differences approach produces comparable estimates both with (Appendix Table B8) and without (Appendix Table B9) controls, though we do observe some loss of precision for the estimates of the effect on flu and pneumonia mortality.[38] These robustness checks strengthen our interpretation of our 2SLS estimates as identifying a causal relationship between RHIO participation and improved health outcomes, as our findings do not appear to be driven by specific modeling choices.

Restricting our sample to a shorter duration yields smaller estimates of the effect of participation in health information exchange organizations on health outcomes. This difference suggests that the full potential of information exchange may take time to materialize. When restricting our sample to 2009-2015 rather than the full 2009-2019 period (Appendix Table B10), we observe notably smaller coefficients: the effect on flu and pneumonia mortality decreases from -21.2 to -13.8, that on pneumonia readmissions decreases from -1.7 to -1.2, and that on heart failure readmissions decreases from -1.7 to -1.4. While confidence intervals generally overlap between these specifications, this temporal pattern supports our hypothesis that HIE benefits require time to fully materialize. Providers likely need an adjustment period to effectively integrate new information systems into their clinical workflows and leverage shared patient data to improve care delivery. This time-dependent effect may also explain why our findings demonstrate larger and more significant impacts than many previous studies—our extended sample period and long-differences approach better capture the full benefits of HIE that emerge after initial implementation and learning.

complier hospitals whose participation decisions respond to changes in the state-level legal environment. This may differ from the average treatment effect across all hospitals that OLS estimates.

[36] For example, estimates for heart failure readmission rates maintain similar magnitudes without controls but lose statistical significance.

[37] Tables with these robustness checks are available upon request.

[38] One notable exception appears in the two-way fixed effects specification without controls, where we find a significant negative relationship between RHIO participation and AMI patient readmission rates. This is the only instance where this relationship reaches statistical and economic significance.

4.2 Magnitudes

Our estimates of the effects of hospital RHIO participation on health outcomes are large. From 2009 to 2019, hospital participation in RHIOs increased by more than 50 percentage points (Tables 2 and 3, Figure 1). Multiplying our estimates by this increase implies that observed changes in hospital participation in RHIOs over the last decade led to 10.6 fewer flu and pneumonia deaths per 100,000 people (18.0% of the mean) and 0.8 percentage point decreases in hospital readmission rates for both pneumonia and heart failure patients (4-5% of the means).[39] Given an adult population of 260 million in the US, the decrease in flu and pneumonia mortality alone translates to approximately 27,560 lives saved annually. Assigning a value of $7.5 million per statistical life (Federal Emergency Management Agency, 2020), this equates to $206.7 billion in annual benefits. The mortality reduction represents just one benefit of hospital participation in RHIOs, with lower readmission rates and potentially other unmeasured benefits adding further value. While a formal cost-benefit analysis is beyond the scope of this paper, these estimates suggest that the benefits of HIE may well outweigh the costs.[40]

4.3 Mechanisms

Two potential mechanisms underlie the effects of hospital participation in health information exchange organizations on health outcomes: (1) improved care coordination between providers, and (2) enhanced communication between providers and public health agencies. We now discuss each of these mechanisms in detail.

Care Coordination Between Providers Hospital participation in HIE organizations may benefit patients by facilitating increased information sharing across providers in different health systems, thereby enhancing care coordination. Despite progress, significant gaps in HIE persist even at the end of our sample period. Figure 6 demonstrates a strong positive correlation between hospital RHIO participation and hospital HIE with external healthcare providers: counties with greater increases in hospital RHIO participation also experienced larger increases in

[39] Using the second stage estimates from our preferred specification given in Panel B of Table 5.

[40] Such costs could include the $30 billion federal investment in the HITECH Act as well as direct costs to hospitals including expenses for HIT software and hardware acquisition, implementation and installation costs, opportunity costs associated with training healthcare providers and staff on new systems, workflow disruption during transition periods, ongoing maintenance and technical support, potential interoperability challenges between different systems, administrative costs for patient consent management, and compliance costs related to privacy and security regulations.

their hospitals engaging in HIE with other hospitals outside of their own systems.[41,42] Over 80% of physicians believe that such increases in HIE improve care quality and enhance care coordination (ONC, 2022). Our findings of decreased hospital readmission rates for pneumonia and heart failure patients align with these perceptions, as these typically complex patients often require care across multiple settings. This interpretation is also consistent with the results of prior studies including Dix et al. (2025), which finds that better compatibility between the EHR systems used by different hospitals—which facilitates more efficient HIE between those organizations—yields health and cost benefits for the patients who are shared across these facilities. By facilitating more comprehensive HIE with other healthcare providers, RHIO participation may thus benefit patients through improved provider care coordination.

Communication with Public Health Agencies Hospital participation in HIE organizations may also benefit patients by enabling communication between providers and public health agencies. A 2023 survey found that 86% of RHIOs provided data to public health agencies, primarily state (89%) and local (55%) entities (Rosenthal et al., 2024). This connection facilitates better tracking of infectious disease spread, with 64% of connected RHIOs sharing immunization records, 63% sharing electronic lab results, and 61% sharing syndromic surveillance data (Rosenthal et al., 2024). Importantly, 46% of these connections allow for bi-directional exchange, meaning that both healthcare providers and public health agencies send *and* receive patient health data. With improved information flows to public health agencies, these agencies can in turn quickly alert healthcare providers and vulnerable populations about emerging disease threats. Agencies can also take actions such as advising pharmacies to stock testing and treatment supplies, recommending hospitals reserve inpatient beds, or instructing skilled nursing facilities to limit visitor access to protect vulnerable patients.[43]

To test this potential mechanism, we employ the survey data on RHIO capabilities, which measures whether a given RHIO respondent shares data with public health authorities. Our main long-difference specification covers 1,120 counties from 2009 to 2019. Of these, 776 report data sharing with public health authorities, 141 report no data sharing, and 203 lack RHIO Survey coverage (meaning that either no RHIOs existed in those counties in 2015, or existing RHIOs did not respond to the survey). We classify these 203 uncovered counties as

[41] Appendix Figure B5 shows this correlation is robust to adding county-level controls and restricting the analysis to 2009-2015.

[42] This figure is at the county level because a hospital-level version would have only three dots: hospitals that do not change their RHIO participation over time ($N = 694$), those that gain RHIO participation ($N = 1048$), and those that lose RHIO participation ($N = 57$).

[43] The COVID-19 pandemic highlighted numerous examples of such coordinated public health responses (e.g., Brown, 2020; Office of Governor Mike Dunleavy, 2020; Colorado Department of Regulatory Agencies, 2020).

not sharing data with public health authorities, as the areas are unlikely to contain a RHIO. We then interacted this county-level measure with the instrument to consider heterogeneity in the reduced-form effects of RHIO membership on flu and pneumonia deaths. Table 6 shows that the negative relationship between the LASSO index of laws that made it easier to join a RHIO and share health information stems from areas where RHIOs share data with public health authorities. This provides suggestive support for the mechanism that RHIO membership lowers mortality because it improves the infectious-disease surveillance and performance of public health interventions.

5 Conclusion

In an increasingly digital healthcare landscape, the electronic sharing of patient information across organizations has become a critical dimension of care delivery. Despite substantial public and private investments, early studies on the adoption of the health information technology found modest or disappointing results on patient outcomes. This paper demonstrates, however, that using this technology to facilitate information exchange significantly improves health outcomes, particularly when examined over longer time horizons to allow for necessary adjustment periods.

Using changes in state legal environments as instruments for hospital participation in health information exchange organizations, we find a significant positive relationship between information sharing and health outcomes. We estimate that the national 50 percentage point increase in hospital participation in health information exchange organizations from 2009 to 2019 reduced flu and pneumonia deaths by 10.6 per 100,000 people (18% of the mean) and decreased readmission rates for pneumonia and heart failure patients by 0.8 percentage points each (4-5% of the means). These effects are likely due to both enhanced care coordination between providers as well as improved communication between healthcare facilities and public health agencies.

Our findings have important implications for ongoing policy debates surrounding healthcare data sharing. While privacy concerns remain central to discussions of health information exchange, our findings quantify the substantial health benefits that may be foregone when barriers to information sharing persist. Future research should further investigate the specific mechanisms through which information exchange improves outcomes; this will better inform the design of policies that maximize the benefits of health information exchange while minimizing its costs. As healthcare systems continue to digitize, understanding these trade-offs becomes increasingly vital for ensuring that technological advances translate into meaningful

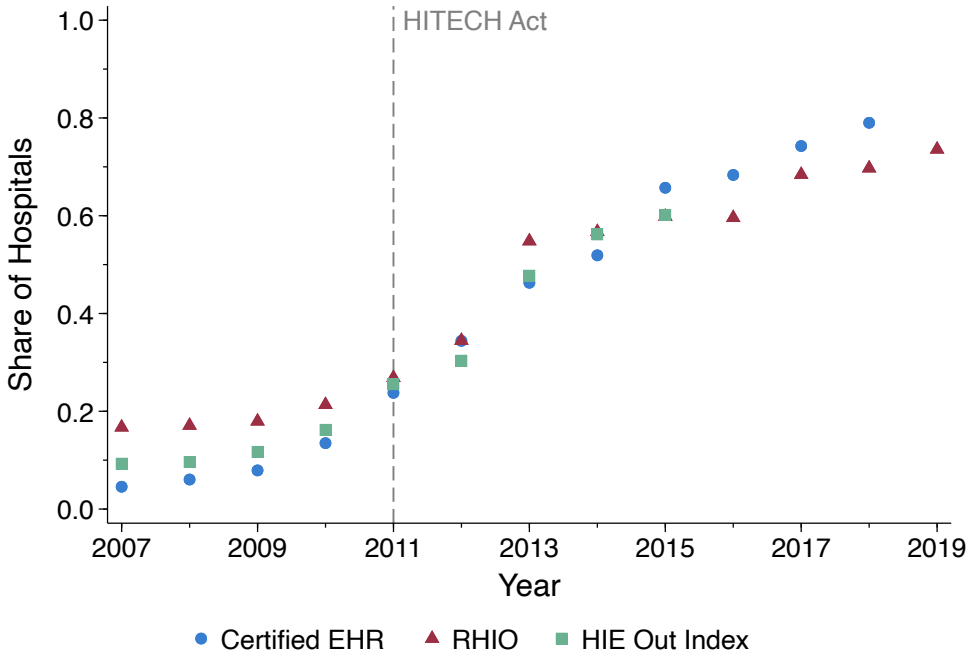
improvements for patient outcomes and public health.

Table 1: HIE Legal Database Questions

Category	Legal Question	Prediction
Governance		
	Does the state have a law relating to an HIE pilot project?	+
	Does a law authorize the state or a state-designated entity to retain control over the statewide HIE's operations?	+
Sustainability and Financial Incentives		
	Does the law incentivize HIE participation (excluding funds to be spent solely on HIE creation or implementation)?	+
	Does the law specify state resources?	+
	Does the law specify participant fees?	+
	Does a law provide authority to request or accept funds from federal or private sources?	+
	Does the law provide immunity from liability for the HIE/HIO or its participants?	+
Uses and Users		
	Does the law mandate any providers to access or contribute to HIE data?	+
	Does the state authorize a public health authority to access HIE data or otherwise authorize the HIE to be used for public health purposes?	+
Data Protections		
	Is the patient consent model for HIE specified to be opt in?	-
	Is the patient consent model for HIE specified to be opt out?	+
	Does the state have a law permitting patients to request specific restrictions, changes, or amendments, or otherwise exercise granular control over their data?	-

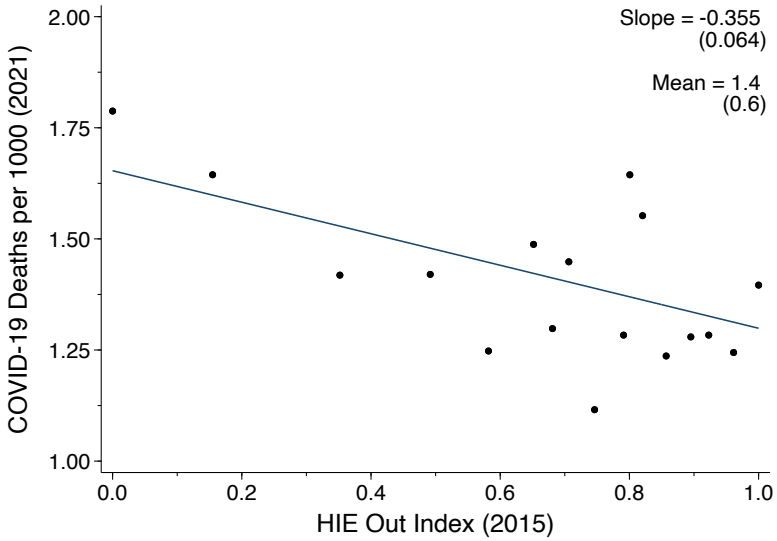
Notes: Table presents the 12 legal questions in our Health Information Exchange (HIE) Legal Database. Column 1 shows the category of each question, Column 2 provides the question text (all questions have yes/no answers), and Column 3 indicates our ex ante prediction of how an affirmative answer relates to HIE usage ("+" for expected to increase usage, "-" for expected to decrease usage). For data protections, opt-in and opt-out are separate dimensions because states may leave patient consent procedures unspecified. "HIO" stands for Health Information Organization.

Figure 1: EHR Adoption and HIE Participation

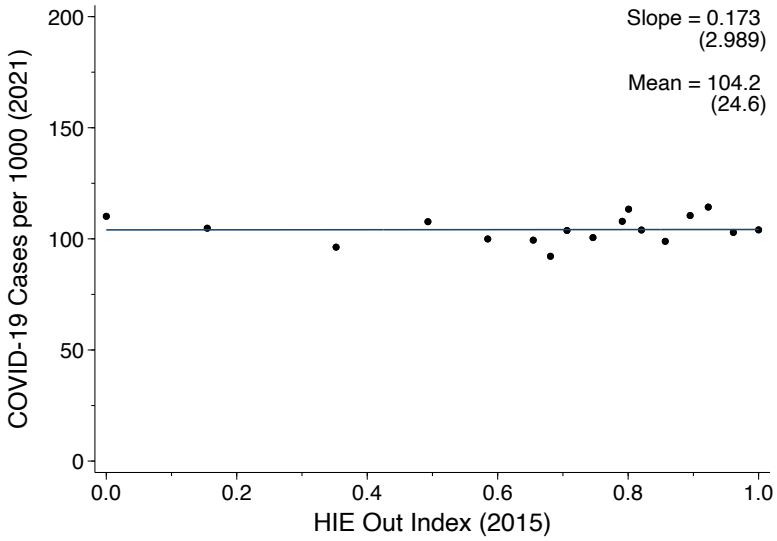


Notes: Figure shows the share of hospitals that report having certified EHR systems (blue dots) and participating in Regional Health Information Organizations (RHIOs; red triangles) from 2007 to 2019. Figure also shows the average hospital's ability to exchange health information with organizations outside its own hospital network (HIE Out Index; green squares) from 2007 to 2015. Certified EHR systems are defined as those capable of electronic clinician documentation and computerized physician order entry. The vertical dotted gray line at 2011 designates the start of federal funding for certified EHR systems under the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009.

Figure 2: Correlation Between HIE and COVID-19 Outcomes



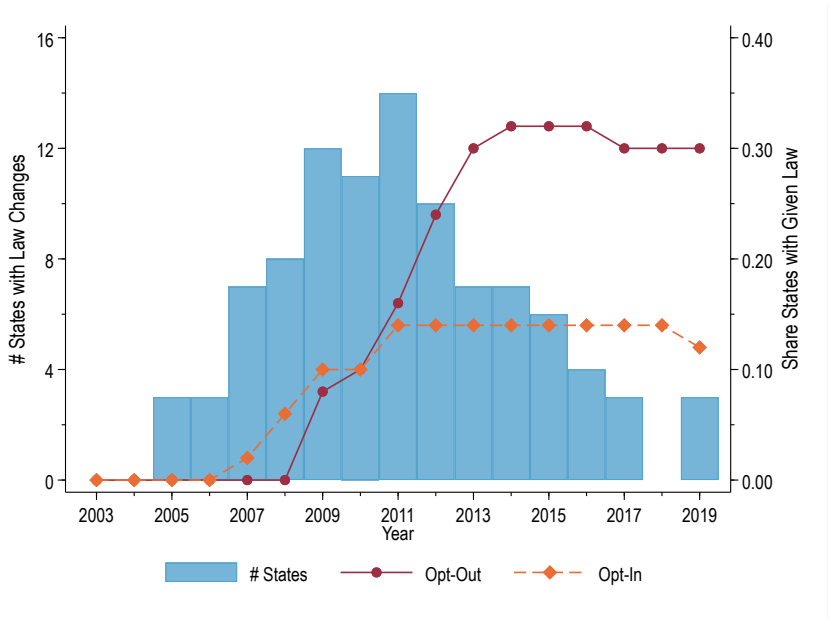
(a) COVID-19 Deaths



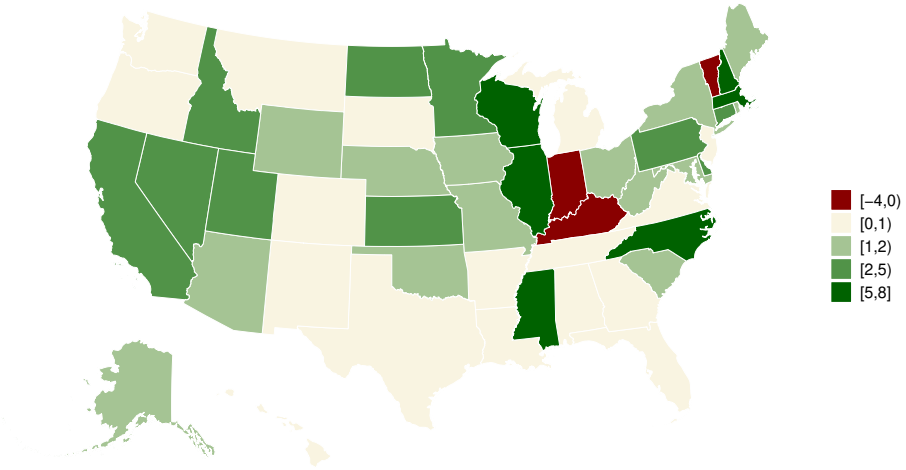
(b) COVID-19 Cases

Notes: Figure shows the correlation between Health Information Exchange (HIE) and COVID-19 outcomes across counties (N = 1,785). Both panels present binscatter plots where the x-axis is the county-level average hospital HIE Out Index in 2015, with hospitals weighted by bed size and the index calculated as each hospital's ability to exchange health information with organizations outside its own hospital network as described in the text. The y-axis in Panel A is COVID-19 deaths per 1,000 people, while that in Panel B is COVID-19 cases per 1,000 people. Population for each county is measured in 2019. Each panel includes the mean and standard deviation (SD) of its dependent variable, along with estimated coefficients and standard errors (SEs) from population-weighted county-level regressions of each outcome on HIE. Data sources: AHA IT Survey for HIE Out Index; 2019 Census Bureau estimates for population; Covid Act Now API for COVID-19 data.

Figure 3: Evolution of HIE Laws



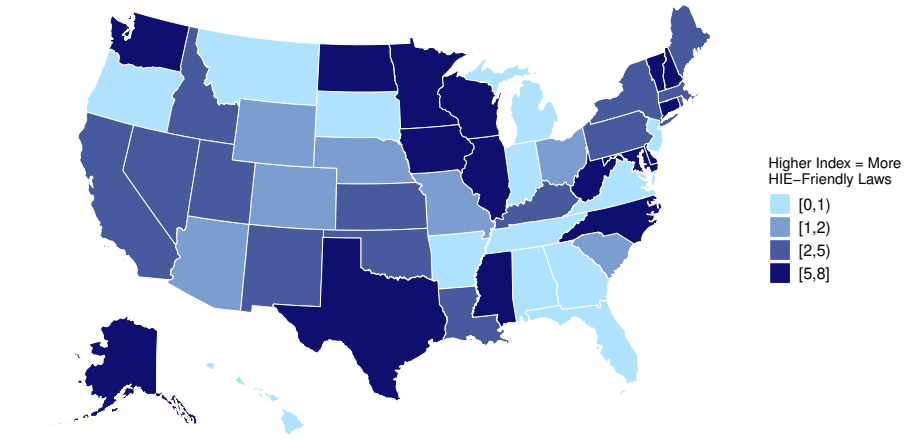
(a) Annual Changes in HIE laws (2003-2019)



(b) Change in HIE Legal Index by State (2009-2019)

Notes: Figure shows changes over time in the legal environment for Health Information Exchange (HIE) across states. Panel A plots the annual number of states with any changes in HIE laws (bars), alongside the share of states with opt-out patient consent laws (red dots) and opt-in patient consent laws (orange triangles) from 2003 to 2019. Panel B maps the change in the HIE Legal Index by state from 2009 to 2019, with red indicating a negative change and thus decreased permissibility towards HIE, beige showing no change, and green shades representing a positive change and thus increased permissibility (darker for larger increases). The HIE Legal Index summarizes each state's legal environment for HIE by summing indicators for 12 HIE laws, with measures normalized so that HIE-favorable laws are coded as +1 and unfavorable laws as -1. Further details on the construction of this index are provided in the text.

Figure 4: State of HIE Legal Index in 2019



Notes: Figure displays the level of the HIE Legal Index by state in 2019, with darker blue indicating more HIE-friendly legal environments. The HIE Legal Index summarizes each state's legal environment for HIE by summing indicators for 12 HIE laws, with measures normalized so that HIE-favorable laws are coded as +1 and unfavorable laws as -1. Further details on the construction of this index are provided in the text.

Table 2: Hospital-Level Summary Statistics

	(1) Mean	(2) SD	(3) N
Panel A: Levels			
RHIO	0.604		16360
HIE Out Index	0.581		16360
Flu & Pneumonia Death Rate per 100K	66.71	31.91	16290
AMI 30-Day Hospital Readmission Rate*	16.54	1.511	7285
Heart Failure 30-Day Hospital Readmission Rate*	21.90	1.840	11002
Pneumonia 30-Day Hospital Readmission Rate+	17.23	1.453	10720
Data: Opt-Out patient consent model	0.196		16360
Fin: Liability immunity for HIE/participants	0.347		16360
Use: Authorize public health authority access	0.488		16360
Gov: State control of statewide HIE	0.436		16360
HIE Legal Index	2.792	2.807	16360
Panel B: Long-Differences			
RHIO	0.557	0.550	1799
HIE Out Index	0.653	0.361	1799
Flu & Pneumonia Deaths per 100K	-5.558	25.12	1792
AMI 30-Day Hospital Readmission Rate*	-3.378	1.494	829
Heart Failure 30-Day Hospital Readmission Rate*	-1.823	2.112	1349
Pneumonia 30-Day Hospital Readmission Rate+	-0.952	1.609	1705
Data: Opt-Out patient consent model	0.218	0.413	1799
Fin: Liability immunity for HIE/participants	0.196	0.430	1799
Use: Authorize public health authority access	0.450	0.544	1799
Gov: State control of statewide HIE	0.187	0.474	1799
HIE Legal Index	1.590	2.431	1799

Notes: Table presents hospital-level summary statistics. Panel A shows levels from a 2009-2019 hospital panel, restricted to hospitals with HIE measures in both 2009 and 2019. Panel B shows long-differences (2009-2019 changes). RHIO indicates hospital participation in Regional Health Information Organizations. HIE Out Index (0-1 scale) measures hospital ability to exchange information with external organizations; values after 2015 are predicted using related AHA IT Survey questions. HIE Legal Index (-2 to 10 scale) measures state-level legal permissibility for HIE. "Data," "Fin," "Use," and "Gov" represent the four HIE legal dimensions, with one representative law shown for each category. "AMI" stands for acute myocardial infarction. Flu and pneumonia rates are measured at the county level; legal dimensions are measured at the state level; all other variables are measured at the hospital level. Hospitals are weighted by baseline bed size. Column (1) shows means; Column (2) shows standard deviations; Column (3) shows observations. * Variable last measured in 2018; + Variable last measured in 2017.

Table 3: County-Level Summary Statistics

	(1) Mean	(2) SD	(3) N
Panel A: Levels			
RHIO	0.611		10595
HIE Out Index	0.571		10595
Flu & Pneumonia Deaths per 100K	58.79	23.07	10595
AMI 30-Day Hospital Readmission Rate*	16.57	1.316	4641
Heart Failure 30-Day Hospital Readmission Rate*	21.99	1.603	7701
Pneumonia 30-Day Hospital Readmission Rate+	17.25	1.254	7612
Data: Opt-Out patient consent model	0.179		10595
Fin: Liability immunity for HIE/participants	0.309		10595
Use: Authorize public health authority access	0.457		10595
Gov: State control of statewide HIE	0.413		10595
HIE Legal Index	2.940	2.743	10595
Panel B: Long-Differences			
RHIO	0.541	0.440	1120
HIE Out Index	0.662	0.262	1120
Flu & Pneumonia Deaths per 100K	-4.568	17.91	1120
AMI 30-Day Hospital Readmission Rate*	-3.343	1.074	512
Heart Failure 30-Day Hospital Readmission Rate*	-1.827	1.695	900
Pneumonia 30-Day Hospital Readmission Rate+	-0.930	1.301	1131
Data: Opt-Out patient consent model	0.200	0.400	1120
Fin: Liability immunity for HIE/participants	0.186	0.413	1120
Use: Authorize public health authority access	0.389	0.526	1120
Gov: State control of statewide HIE	0.200	0.465	1120
HIE Legal Index	1.738	2.384	1120

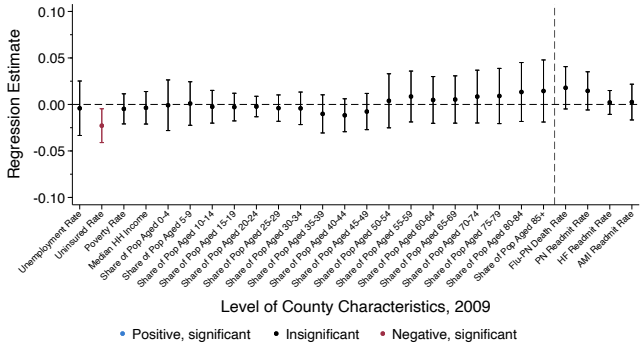
Notes: Table presents county-level summary statistics. Panel A shows levels from a 2009-2019 county panel, restricted to counties that contain at least one hospital with HIE measures in both 2009 and 2019. Panel B shows long-differences (2009-2019 changes). RHIO indicates average hospital participation in Regional Health Information Organizations within the county. HIE Out Index (0-1 scale) measures average hospital ability to exchange information with external organizations; values after 2015 are predicted using related AHA IT Survey questions. HIE Legal Index (-2 to 10 scale) measures state-level legal permissibility for HIE. 'Data," "Fin," "Use," and "Gov" represent the four HIE legal dimensions, with one representative law shown for each category. "AMI" stands for acute myocardial infarction. Flu and pneumonia rates are measured at the county level; legal dimensions are measured at the state level; all other variables are measured at the hospital level. Hospital-level measures are aggregated to the county level using bed-size-weighted averages of hospitals within the county. Counties are weighted by baseline population. Column (1) shows means; Column (2) shows standard deviations; Column (3) shows observations. * Variable last measured in 2018; + Variable last measured in 2017.

Table 4: First Stage Results: Effects of the Legal Environment on RHIO

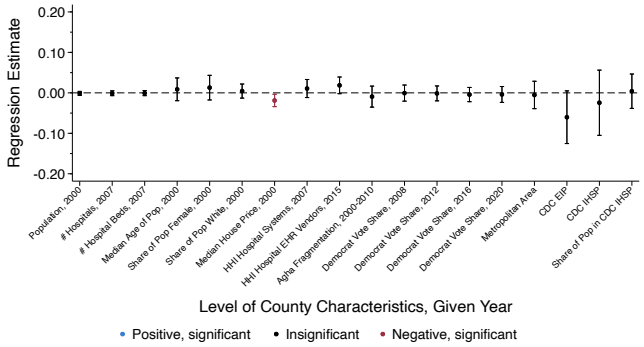
	ΔRHIO	
	(1) Hospital-Level	(2) County-Level
A. Opt-Out Law		
ΔOpt-Out	0.2060**	0.2139***
	(0.0771)	(0.0766)
F-Statistic	7.1	7.8
Observations	1799	1120
B. LASSO-Selected Laws		
Use: Authorize public health authority access (2011)	-0.1423***	
	(0.0461)	
Fin: Participant fees (2010)	-0.1259*	
	(0.0671)	
Data: Patients may request restrictions (-) (2014)	0.2071***	0.1214
	(0.0746)	(0.0983)
Data: Opt-Out patient consent model (2016)		0.1883**
		(0.0780)
Data: Opt-Out patient consent model (2010)		-0.4726***
		(0.1211)
Memo: Post-Lasso Prediction	*1.0000****	*1.0000****
	(0.1258)	*(0.1515)*
F-Statistic	27.5	27.3
Observations	1799	1120

Notes: Each column in each panel presents a separate first stage long-differences regression estimating the effect of changes in HIE legal environments on changes in hospital participation in Regional Health Information Organizations (RHIO). Column 1 reports hospital-level regressions with hospitals weighted by baseline bed sizes (following Equation 3.1); Column 2 reports county-level regressions with counties weighted by baseline population (following Equation 3.2). In Panel A, the independent variable is the change in state opt-out patient consent laws. In Panel B, we employ LASSO to select three legal dimensions from the set of all state legal dimensions across all sample years as independent variables. The italicized memo line summarizes the first stage strength by reporting the coefficient from regressing the "post-LASSO prediction" (i.e., the predicted change in RHIO from an OLS regression using the three LASSO-selected dimensions) on the actual change in RHIO. "(-)" indicates that we predict the legal dimension will decrease HIE and thus multiply the indicator for that dimension by negative one before including it in the regression. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

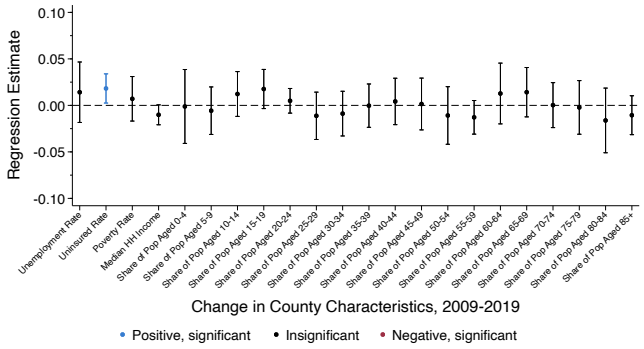
Figure 5: Balance Checks for LASSO Instrument



(a) $\Delta Z_{s(c)}$ and Baseline County Characteristics



(b) $\Delta Z_{s(c)}$ and Additional County Characteristics



(c) $\Delta Z_{s(c)}$ and ΔCounty Characteristics

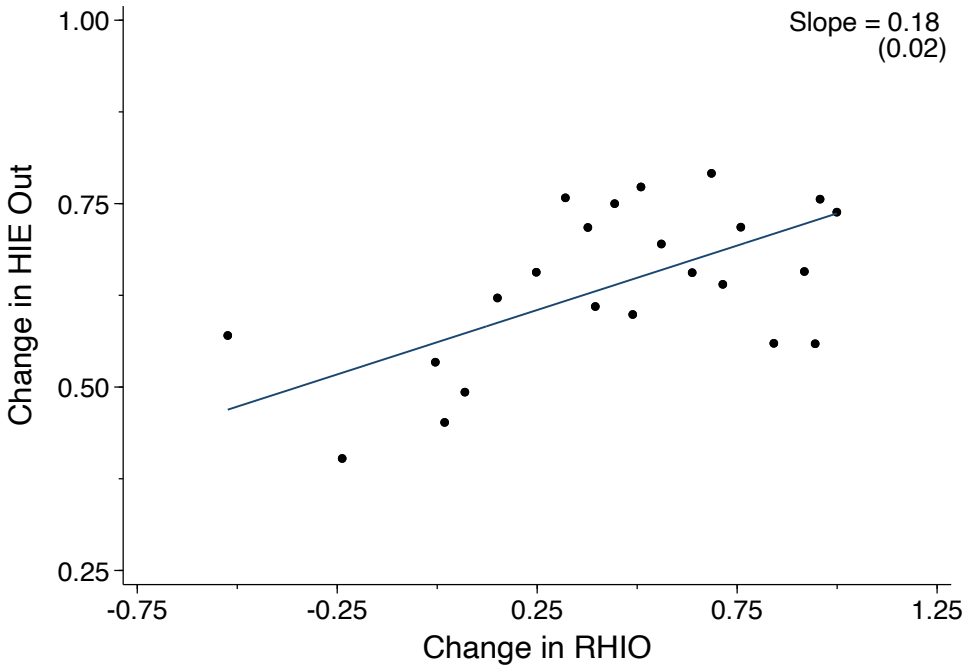
Notes: Figure presents estimated coefficients (dots) and 95% confidence intervals (bars) from county-level regressions of the change in the instrument ($\Delta Z_{s(c)}$) on various county characteristics. Instrument is the post-LASSO prediction (i.e., the predicted change in RHIO from 2009 to 2019 from an OLS regression using the three LASSO-selected legal dimensions). Panel A shows regressions on 2009 baseline levels of our control variables (county-level population shares in 5-year age bins, uninsurance rate, unemployment rate, poverty rate, and median household income) and outcome variables (deaths from flu and pneumonia per capita as well as hospital readmission rates for pneumonia, heart failure, and AMI). Panel B displays regressions on levels of additional characteristics (e.g., population, number of hospitals) in the given year. If no year is given, characteristic is time-invariant. Panel C shows regressions on long-difference changes in the baseline controls from Panel A. All continuous characteristics are standardized to have mean zero and standard deviation one before the regression. Standard errors are clustered at the state level. Counties are weighted by baseline population. Blue indicates a statistically significant positive relationship; red indicates a significant negative one; black indicates an insignificant one.

Table 5: Second Stage Results: Effects of RHIO on Health Outcomes

	County-Level ΔDeaths per 100K	Hospital-Level Δ30-Day Hospital Readmission Rates		
	(1) Flu/Pneumonia	(2) Pneumonia	(3) Heart Failure	(4) AMI
A. 2SLS, Opt-Out Instrument				
ΔRHIO	-28.8119*	-3.9512**	-3.0375**	-0.4753
	(15.8562)	(1.8306)	(1.5143)	(0.7842)
First Stage F-Statistic	7.8	4.4	4.7	5.6
B. 2SLS, LASSO-Selected Instruments				
ΔRHIO	-21.1741**	-1.6701**	-1.6945**	-0.2018
	(9.7621)	(0.7039)	(0.7367)	(0.9246)
First Stage F-Statistic	27.3	16.2	22.9	9.0
C. OLS				
ΔRHIO	-2.6444*	0.1192	-0.2094	0.0565
	(1.3321)	(0.1061)	(0.1464)	(0.0901)
Mean of Outcome (Levels)	58.79	17.25	21.99	16.57
(SD)	(23.07)	(1.25)	(1.60)	(1.32)
Years	2009-2019	2009-2017	2009-2018	2009-2018
Observations	1120	1704	1349	829

Notes: Each column in each panel presents a separate long-differences regression estimating the effect of changes in hospital participation in Regional Health Information Organizations (RHIO) on changes in health outcomes. Column 1 reports county-level regressions weighted by baseline population (Equation 3.4), while Columns 2-4 report hospital-level regressions weighted by baseline bed sizes (Equation 3.3). Panel A presents 2SLS estimates using the change in state opt-out patient consent laws as the instrument. Panel B presents 2SLS estimates using LASSO-selected legal dimensions as the instruments. Panel C presents OLS estimates for comparison. For each outcome, the mean (SD) level, measurement years, and observation count are provided. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 6: Correlation between RHIO Participation and HIE Out Index



Notes: Figure shows the correlation between county-level changes in hospital participation in health information exchange organizations and county-level changes in hospital health information exchange (N = 1,120). Figure is a binscatter plot with the x-axis showing county-level changes in the average hospital participation in Regional Health Information Organizations (RHIO) and the y-axis showing county-level changes in the average hospital HIE Out Index, from 2009 to 2019. Counties are weighted by baseline population. HIE Out Index is defined as described in the text, with levels in 2016-2019 proxied with other survey questions due to the original survey questions ending in 2015. The estimated regression coefficient and standard error (SE) are given.

Table 6: Reduced Form Heterogeneity

	County-Level ΔDeaths per 100K	
	(1) Flu/Pneumonia	(2) Flu/Pneumonia
Post-Lasso $\widehat{\Delta RHIO}$	-21.2560**	2.5700
	(8.7635)	(16.3547)
Post-Lasso $\widehat{\Delta RHIO}$ × RHIO Shares with PHA		-30.9652***
		(16.8527)
RHIO Shares with PHA		-0.3909
		(1.9618)
Observations	1096	1096

Notes: Each column presents a separate reduced form county-level long-differences regression estimating the effect of post-lasso predicted changes in hospital participation in Regional Health Information Organizations (RHIO) on changes in health outcomes, from 2009 to 2019. Regressions are weighted by baseline population and include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Counties with changes in health outcomes in the the top and bottom 1% of the distribution are excluded from the regressions. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

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A Details of HIE Legal Database

To study how state policies influence health information exchange (HIE), we constructed a comprehensive panel database of state-level HIE laws from 2000 to 2019, expanding and extending the methodology developed by Schmit et al. (2018). This appendix provides additional details on our data collection and coding methodology. Further details are also available in Bronsoler, Doyle, Schmit, and Van Reenen (2022).

A.1 Data Collection

On February 14, 2020, we searched Westlaw historical databases for HIE-related state statues and regulations from 2000 to 2019. These databases include laws in effect at the end of each calendar year, with minor variations by state.[44] We identified relevant laws using two complementary approaches:

(i) We searched the databases for each law previously included in the Schmit et al. (2018) database, which contains only laws in effect in 2016.

(ii) We conducted new searches using the same search terms described in Schmit et al. (2018) to capture both repealed and newly enacted legislation over our entire sample period.

Following Schmit et al. (2018), we retained only laws pertaining to health information organizations "that facilitate access to identifiable health information among different entities for the purpose of patient treatment." All identified laws were then downloaded, de-duplicated, and scoped, with detailed legal citation information preserved for each law.

A.2 Data Coding

We coded each relevant law using the criteria described in Schmit et al. (2018), with minor variations to simplify coding of some dimensions, eliminate dimensions outside our focus, and add dimensions of interest (details in Appendix Table A1). In particular, we coded the laws using the Public Health Law Information Portal, a policy surveillance platform developed by the Centers for Disease Control and Prevention's Public Health Law Program. Our coding team consisted of a licensed attorney with expertise in policy surveillance research (the "coding lead") as well as four research assistants (the "primary coders"). The coding lead implemented the following protocol:

[44] For example, the 2019 historical database would include laws in effect approximately December 2019, though some states' laws are not archived until early January of the subsequent year.

(i) All four primary coders began by coding the same five jurisdictions for every year between 2000-2019 to assess accuracy and consistency.

(ii) The remaining jurisdictions were divided among the coding team with systematic redundancy: 50% of jurisdictions had complete overlap between at least two primary coders, while the other 50% were coded by a single primary coder with another providing redundancy for one sample year (e.g., one person coding years 2000-2019 and another coding year 2012).

(iii) For jurisdictions coded by two primary coders, the coding lead conducted regular meetings to review and resolve any differences between coders, serving as the tie-breaker when necessary while deferring to interpretations consistent with Schmit et al. (2018).

(iv) For jurisdictions coded by only one primary coder, the coding lead verified that the legal citations supported the coding. If the coding lead decided that a code was incorrect, they also verified the codes for adjacent years to ensure accuracy and consistency.

We also implemented two additional validation steps to ensure the accuracy of our database:

(i) The coding lead independently verified every instance where a law was updated or repealed.

(ii) The coding lead reviewed graphical depictions of each state's coding values across all dimensions and years to identify potential coding errors, such as unusual patterns or oscillating values.

These rigorous procedures resulted in an accurate and comprehensive panel database that tracks the evolution of state-level HIE legal environments over the past two decades.

Table A1: Coding HIE Legal Database

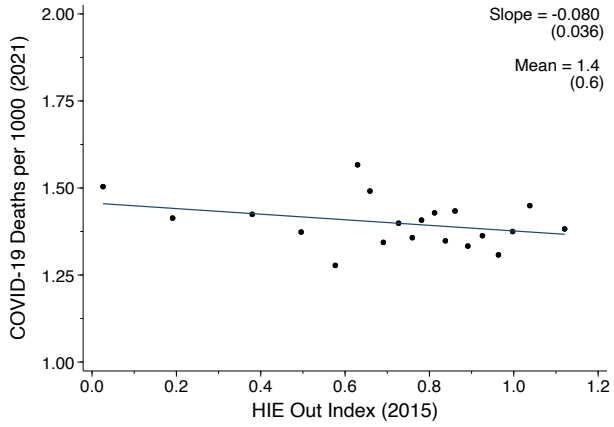
#	*Coding Question*	*Comparison to Schmit et al. (2018)*
1	Does the state have a law relating to an HIE pilot project?	Adapted for longitudinal analysis
2	Does the law authorize implementation of a statewide HIE?	Identical
2.1	Who retains control over the statewide HIE's operations?	Identical
3	Does the law incentivize HIE participation (excluding funds to be spent solely on HIE creation or implementation)?	Identical
4	Does the law specify the users and uses of the HIE?	Identical
4.1	Does the law mandate any providers to access or contribute to HIE data?	Identical
4.2	Does the state authorize non-healthcare providers (e.g., payers, researchers, public health) to access or use the HIE?	Composite of different dimensions
4.2.1	Does the state authorize a public health authority to access HIE data or otherwise authorize the HIE to be used for public health purposes?	Identical
5	Are there provisions in the law designed to promote privacy, security, or confidentiality related to HIE data?	Identical
5.1	Does the law require privacy protections for the HIE (excluding direct reference to state or federal privacy laws)?	Identical
5.1.1	Is patient consent required for disclosure of patient data in the HIE?	Identical
5.1.2	Does the state have a law permitting patients to request specific restrictions, changes, amendments, or otherwise exercising granular control over their data?	New dimension, but related to prior dimensions
5.2	Does the law address administrative, technical, or physical safeguards to secure HIE data (excluding direct references to state or federal laws)?	Identical
5.3	Are there express duties for providers or other HIE users to protect patient data from unauthorized accesses/disclosures?	Identical
6	Does the law specify sources of HIE funding, including acceptable or permissible funding sources?	Identical
6.1	State Resources	Identical
6.2	Participant Fees	Identical
6.3	Authority to request or accept funds from federal or private sources	Composite of different dimensions
7	Does the law provide immunity from liability for the HIE/HIO or its participants?	Identical

Notes: Table presents the coding questions used to categorize state-level HIE laws from 2000 to 2019, with comparisons to the original Schmit et al. (2018) protocol.

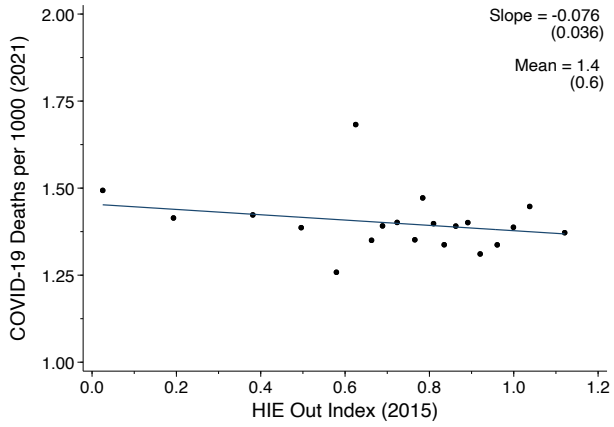
B Additional Figures & Tables

B.1 Data & Setting

Figure B1: Correlation Between HIE and COVID-19 Deaths - Robustness to Adding Controls



(a) Control for County Characteristics



(b) Add Control for 2019 COVID-19 Deaths

Notes: Figure shows the correlation between Health Information Exchange (HIE) and COVID-19 outcomes across counties (N = 1,785). Both panels present binscatter plots where the x-axis is the county-level average hospital HIE Out Index in 2015, with hospitals weighted by bed size and the index calculated as each hospital's ability to exchange health information with organizations outside its own hospital network as described in the text. The y-axis for both panels is county-level COVID-19 deaths per 1,000 people, where population is measured in 2019. Panel A controls for county-level socioeconomic factors measured in 2019 including the uninsurance rate, unemployment rate, poverty rate, shares of the population in age buckets (e.g., less than 1 year old, 1-4 years old, ..., greater than 85 years olds) and median household income. Panel B additionally controls for county-level COVID-19 death rates from 2020. Each panel includes the mean and standard deviation (SD) of the dependent variable, along with estimated coefficients and standard errors (SEs) from population-weighted county-level regressions with the given controls. Data sources: AHA IT Survey for HIE Out Index; 2019 Census Bureau estimates for population and county characteristics; Covid Act Now API for COVID-19 data.

B.2 Empirical Strategy

B.2.1 Equations for two-way fixed effects regressions

We check the robustness of our estimates to an alternative two-way fixed effects specification run on a panel version of our data. For this specification, the first stage equations are given as:

$$\text{RHIO}_{ht} = \alpha + \mu_h + \mu_t + \delta Z_{s(h),t} + \gamma X_{h,,c(h)t} + \varepsilon_{ht} \tag{B.1}$$

and

$$\text{RHIO}_{ct} = \alpha + \mu_c + \mu_t + \delta Z_{s(c)t} + \gamma X_{ct} + \varepsilon_{ct}, \tag{B.2}$$

for the hospital and county levels, respectively. All variables are the same as those in Equations 3.1 and 3.2 with the exception that they are now levels in year t. All other estimation details also remain the same.

The second stage equations are then specified as:

$$Y_{ht} = \lambda + \beta \widehat{\text{RHIO}_{ht}} + \eta X_{ht,c(h)t} + \epsilon_{ht}, \tag{B.3}$$

and

$$Y_{ct} = \lambda + \beta \widehat{\text{RHIO}_{ct}} + \eta X_{ct} + \epsilon_{ct}, \tag{B.4}$$

for the hospital and county levels, respectively. All variables are the same as those in Equations 3.3 and 3.4 with the exception that they are now levels in year t. All other estimation details also remain the same.

B.2.2 Additional Tables and Figures

Table B1: Long-Differences First Stage - Robustness to LASSO Over Change in Laws

	ΔRHIO	
	(1) Hospital-Level	(2) County-Level
A. LASSO-Selected Laws		
ΔOpt-In patient consent model (-)	0.2471**	0.3559***
	(0.0999)	(0.0546)
ΔPatients may request restrictions (-)	-0.2015*	-0.3074***
	(0.1015)	(0.0595)
ΔOpt-Out patient consent model	0.0836	
	(0.1021)	
ΔCan accept federal/private funds		-0.0997**
		(0.0447)
Memo: Post-Lasso Prediction	*1.0000****	*1.0000****
	(0.1765)	*(0.1574)*
F-Statistic	20.4	25.9
Observations	1799	1120

Notes: Each column in each panel presents a separate first stage long-differences regression estimating the effect of changes in HIE legal environments on changes in hospital participation in Regional Health Information Organizations (RHIO). Column 1 reports hospital-level regressions with hospitals weighted by baseline bed sizes (following Equation 3.1); Column 2 reports county-level regressions with counties weighted by baseline population (following Equation 3.2). We employ LASSO to select three legal dimensions from the set of all long-differences changes in state legal dimensions as independent variables. The italicized memo line summarizes the first stage strength by reporting the coefficient from regressing the "post-LASSO prediction" (i.e., the predicted change in RHIO from an OLS regression using the three LASSO-selected dimensions) on the actual change in RHIO. "(-)" indicates that we predict the legal dimension will decrease HIE and thus multiply the indicator for that dimension by negative one before calculating the change and including it in the regression. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B2: TWFE Panel First Stage

	RHIO	
	(1) Hospital-Level	(2) County-Level
A. Opt-Out Law		
Opt-Out	0.0881*	0.0777
	(0.0483)	(0.0494)
F-Statistic	3.3	2.5
Observations	16360	10593
B. LASSO-Selected Laws		
Use: Authorize public health authority access	0.0718**	0.1032***
	(0.0307)	(0.0332)
Fin: Liability immunity for HIE/participants	0.1022**	
	(0.0408)	
Data: Opt-In patient consent model (-)	0.0767**	0.1569***
	(0.0317)	(0.0518)
Data: Patients may request restrictions (-)		-0.1289**
		(0.0549)
Memo: Post-Lasso Prediction	*1.0000****	*1.0000****
	(0.2566)	*(0.2193)*
F-Statistic	31.5	45.7
Observations	16360	10593

Notes: Each column in each panel presents a separate first stage two-way fixed effects regression estimating the effect of HIE legal environments on hospital participation in Regional Health Information Organizations (RHIO). Column 1 reports hospital-level regressions with hospitals weighted by baseline bed sizes (following Appendix Equation B.1); Column 2 reports county-level regressions with counties weighted by baseline population (following Appendix Equation B.2). In Panel A, the independent variable is whether the state has an opt-out patient consent law. In Panel B, we employ LASSO to select three legal dimensions from the set of all 12 state legal dimensions as independent variables. The italicized memo line summarizes the first stage strength by reporting the coefficient from regressing the "post-LASSO prediction" (i.e., the predicted RHIO from an OLS regression using the three LASSO-selected dimensions) on the actual RHIO. "(-)" indicates that we predict the legal dimension will decrease HIE and thus multiply the indicator for that dimension by negative one before including it in the regression. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B3: Long-Differences First Stage at Hospital-Level: All Legal Dimensions

	ΔRHIO					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Governance						
ΔHIE pilot project	0.00637					0.183***
	(0.0735)					(0.0615)
ΔState control of statewide HIE		-0.0162				0.0219
		(0.0699)				(0.0909)
B. Sustainability and Financial Incentives						
ΔFinancial incentive for participation	-0.0760					0.0150
	(0.0648)					(0.0895)
ΔState resources		-0.00927				0.0321
		(0.0793)				(0.121)
ΔParticipant fees			-0.0758			-0.0939
			(0.0858)			(0.0835)
ΔCan accept federal/private funds				-0.106*		-0.136
				(0.0615)		(0.0895)
ΔLiability immunity for HIE/participants					0.0845	-0.115
					(0.0726)	(0.0825)
C. Use and Users						
ΔRequire providers access/contribute	-0.000964					-0.0746
	(0.0846)					(0.0811)
ΔAuthorize public health authority access		0.0753				0.0990*
		(0.0509)				(0.0527)
D. Data Protections						
ΔOpt-In patient consent model (-)	0.108**					0.340***
	(0.0505)					(0.113)
ΔOpt-Out patient consent model		0.206**				0.158
		(0.0771)				(0.0999)
ΔPatients may request restrictions (-)			-0.193***			-0.283***
			(0.0666)			(0.0842)
F-Statistic						11.8
Observations						1799

Notes: Each column in each panel presents a separate first stage, hospital-level, long-differences regression estimating the effect of changes in one dimension of the HIE legal environment on changes in hospital participation in Regional Health Information Organizations (RHIO) following Equation 3.1. Column 6 is a slight exception, as this column presents the results of a single regression estimating the effect of changes in *all 12* dimensions of the HIE legal environment on changes in hospital participation in RHIO. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. "(-)" indicates that we predict the legal dimension will decrease HIE and thus multiply the indicator for that dimension by negative one before calculating the change and including it in the regression. Hospitals are always weighted by baseline bed size. F-Statistics and observations are omitted in Columns 1-5 for readability. All regressions have 1799 observations. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B4: TWFE Panel First Stage at Hospital-Level: All Legal Dimensions

	RHIO					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Governance						
HIE pilot project	-0.0111					-0.0226
	(0.0738)					(0.0976)
State control of statewide HIE		0.0411				-0.0150
		(0.0331)				(0.0561)
B. Sustainability and Financial Incentives						
Financial incentive for participation	0.0148					0.0134
	(0.0617)					(0.0787)
State resources		0.00646				-0.0953
		(0.0395)				(0.0880)
Participant fees			0.0339			0.0113
			(0.0337)			(0.0605)
Can accept federal/private funds				-0.000627		0.0145
				(0.0371)		(0.0804)
Liability immunity for HIE/participants					0.114***	0.0696*
					(0.0373)	(0.0400)
C. Use and Users						
Require providers access/contribute	-0.00207					-0.0266
	(0.0435)					(0.0535)
Authorize public health authority access		0.0805**				0.0953**
		(0.0304)				(0.0401)
D. Data Protections						
Opt-In patient consent model (-)	0.0433*					0.0896*
	(0.0233)					(0.0523)
Opt-Out patient consent model		0.0881*				0.0448
		(0.0483)				(0.0541)
Patients may request restrictions (-)			-0.0599			-0.0693
			(0.0432)			(0.0624)
F-Statistic						4.4
Observations						16360

Notes: Each column in each panel presents a separate first stage, hospital-level, two-way fixed effects regression estimating the effect of one dimension of the HIE legal environment on hospital participation in Regional Health Information Organizations (RHIO; following Appendix Equation B.1). Column 6 is a slight exception, as this column presents the results of a single regression estimating the effect of *all 12* dimensions of the HIE legal environment on hospital participation in RHIO. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. "(-)" indicates that we predict the legal dimension will decrease HIE and thus multiply the indicator for that dimension by negative one before including it in the regression. Hospitals are always weighted by baseline bed size. F-Statistics and observations are omitted in Columns 1-5 for readability. All regressions have 16360 observations. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B5: Long-Differences First Stage - Robustness to Alternative LASSO Procedures

	ΔRHIO	
	(1) Hospital-Level	(2) County-Level
A. Baseline: No interactions, maximum of 3		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.1258)	(0.1515)
F-Statistic	27.5	27.3
Number of Instruments	3	3
B. No interactions, no maximum		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.0365)	(0.0841)
F-Statistic	8.7	14.9
Number of Instruments	27	11
C. With interactions, maximum of 3		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.1334)	(0.0867)
F-Statistic	34.1	41.2
Number of Instruments	3	3
D. With interactions, no maximum		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.0399)	(0.0657)
F-Statistic	6.9	8.9
Number of Instruments	49	34
Observations	1799	1120

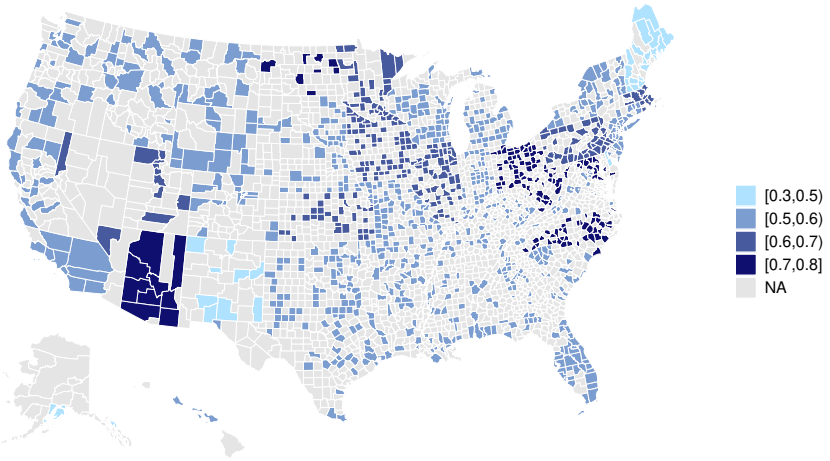
Notes: Each column in each panel presents a separate first stage long-differences regression estimating the effect of changes in HIE legal environments on changes in hospital participation in Regional Health Information Organizations (RHIO). Column 1 reports hospital-level regressions with hospitals weighted by baseline bed sizes (following Equation 3.1); Column 2 reports county-level regressions with counties weighted by baseline population (following Equation 3.2). We employ LASSO to select legal dimensions from the set of all state legal dimensions across all sample years as independent variables. Panel A is our baseline specification, which limits LASSO to choosing a maximum of three legal dimensions. Panel B relaxes this constraint. Panel C is the same as Panel A but adds to the set of possible instruments all two-way interactions between all state legal dimensions across all sample years. Panel D is the same as Panel C but relaxes the constraint of choosing a maximum of three instruments. "Post-Lasso Prediction" is the predicted change in RHIO from an OLS regression using the LASSO-selected dimensions; regressing this on the actual change in RHIO summarizes the first stage strength. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B6: TWFE Panel First Stage - Robustness to Alternative LASSO Procedures

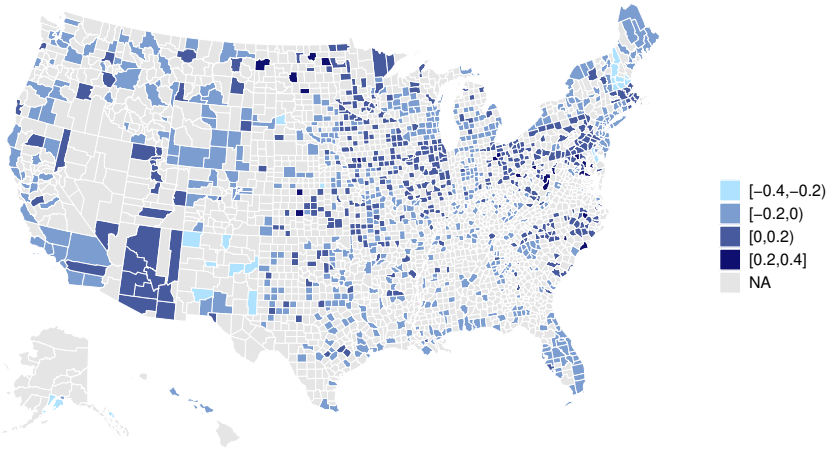
	RHIO	
	(1) Hospital-Level	(2) County-Level
A. Baseline: Without lags, maximum of 3		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.2566)	(0.2193)
F-Statistic	31.5	45.7
Number of Instruments	3	3
B. Without lags, no maximum		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.1907)	(0.1789)
F-Statistic	16.7	20.6
Number of Instruments	8	9
C. With lags, maximum of 3		
Post-Lasso Prediction	1.0000	1.0000*
	(0.8006)	(0.3787)
F-Statistic	7.5	26.9
Number of Instruments	3	3
D. With lags, no maximum		
Post-Lasso Prediction	1.0000***	1.0000***
	(0.1191)	(0.0862)
F-Statistic	9.5	14.5
Number of Instruments	42	47
Observations	16358	10593

Notes: Each column in each panel presents a separate first stage two-way fixed effects regression estimating the effect of HIE legal environments on hospital participation in Regional Health Information Organizations (RHIO). Column 1 reports hospital-level regressions with hospitals weighted by baseline bed sizes (following Appendix Equation B.1); Column 2 reports county-level regressions with counties weighted by baseline population (following Appendix Equation B.2). We employ LASSO to select legal dimensions from the set of all state legal dimensions as independent variables. Panel A is our baseline specification, which limits LASSO to choosing a maximum of three legal dimensions. Panel B relaxes this constraint. Panel C is the same as Panel A but adds to the set of possible instruments all lags of all state legal dimensions across all sample years. Panel D is the same as Panel C but relaxes the constraint of choosing a maximum of three instruments. "Post-Lasso Prediction" is the predicted RHIO from an OLS regression using the LASSO-selected dimensions; regressing this on the actual RHIO summarizes the first stage strength. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure B2: Maps of Post-LASSO Prediction of ΔRHIO ($\Delta Z_{s(c)}$)



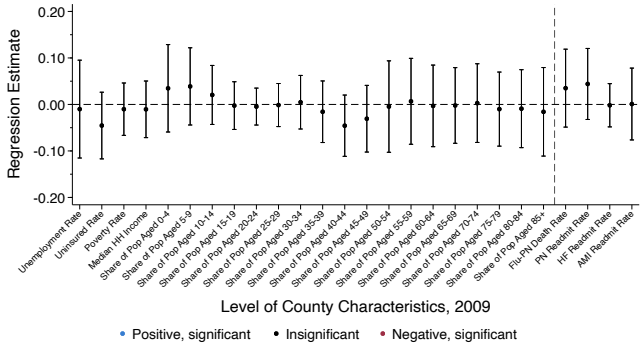
(a) Post-LASSO Prediction



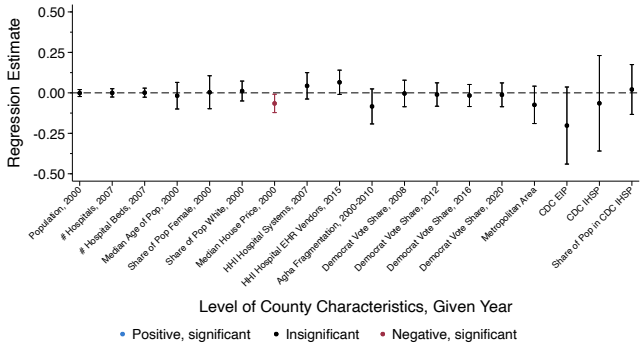
(b) Post-LASSO Prediction, Residualized for Controls

Notes: Maps show the county-level post-LASSO predictions of changes in RHIO participation from 2009 to 2019. Post-LASSO predictions are calculated by: (1) using LASSO to select three legal dimensions from the set of all state legal dimensions across all sample years as independent variables for the first stage, county-level, long-differences regression (Equation 3.2), (2) running an OLS regression of the change in RHIO participation on these LASSO-chosen dimensions, and (3) generating predicted values from this regression. These predictions provide a single-dimension representation of the instrument ($\Delta Z_{s(c)}$). Panel A presents the raw post-LASSO prediction levels, while Panel B shows these levels after residualizing for baseline control variables: county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Levels are defined only for counties in our analytical sample—those containing hospitals with RHIO participation data in both 2009 and 2019 ($N = 1120$).

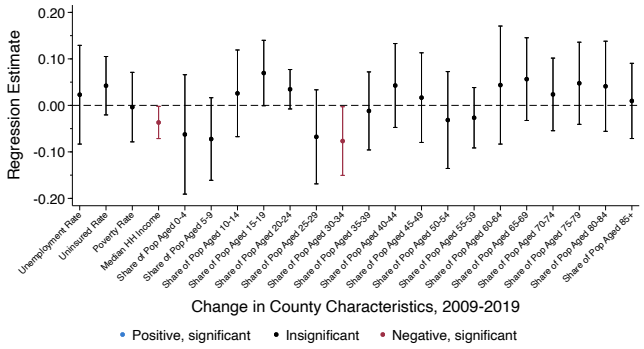
Figure B3: Balance Checks for ΔOpt-Out Instrument



(a) $\Delta Z_{s(c)}$ and Baseline County Characteristics



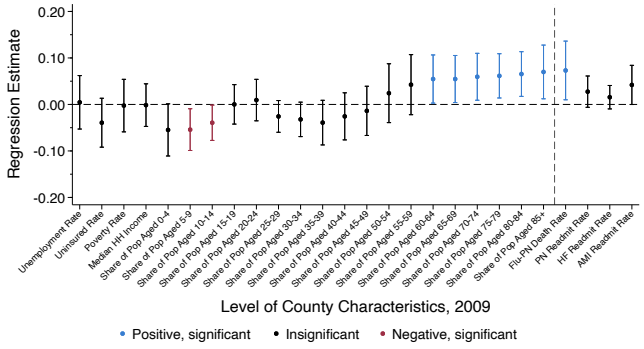
(b) $\Delta Z_{s(c)}$ and Additional County Characteristics



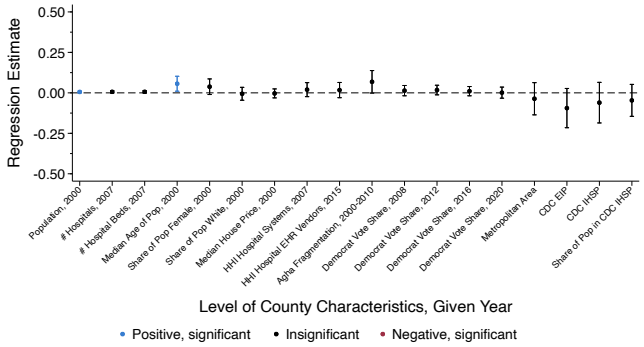
(c) $\Delta Z_{s(c)}$ and ΔCounty Characteristics

Notes: Figure presents estimated coefficients (dots) and 95% confidence intervals (bars) from county-level regressions of the change in the instrument ($\Delta Z_{s(c)}$) on various county characteristics. Instrument is the change in state-level opt-out patient consent laws from 2009 to 2019 (ΔOpt-Out). Panel A shows regressions on 2009 baseline levels of our control variables (county-level population shares in 5-year age bins, uninsurance rate, unemployment rate, poverty rate, and median household income) and outcome variables (deaths from flu and pneumonia per capita as well as hospital readmission rates for pneumonia, heart failure, and AMI). Panel B displays regressions on levels of additional characteristics (e.g., population, number of hospitals) in the given year. If no year is given, characteristic is time-invariant. Panel C shows regressions on long-difference changes in the baseline controls from Panel A. All continuous characteristics are standardized to have mean zero and standard deviation one before the regression. Standard errors are clustered at the state level. Counties are weighted by baseline population. Blue indicates a statistically significant positive relationship; red indicates a significant negative one; black indicates an insignificant one.

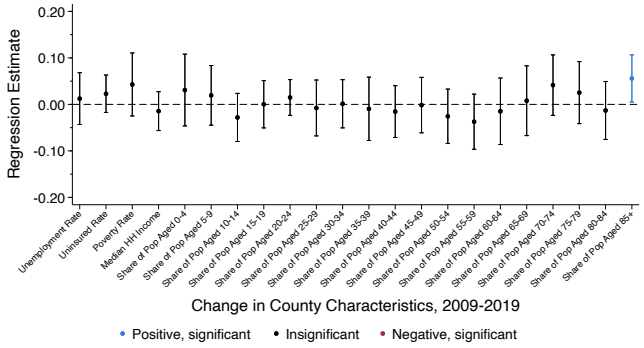
Figure B4: Balance Checks for Endogenous Variable (ΔRHIO)



(a) ΔRHIO and Baseline County Characteristics



(b) ΔRHIO and Additional County Characteristics



(c) ΔRHIO and ΔCounty Characteristics

Notes: Figure presents estimated coefficients (dots) and 95% confidence intervals (bars) from county-level regressions of the change in actual RHIO participation (ΔRHIO) on various county characteristics. Panel A shows regressions on 2009 baseline levels of our control variables (county-level population shares in 5-year age bins, uninsurance rate, unemployment rate, poverty rate, and median household income) and outcome variables (deaths from flu and pneumonia per capita as well as hospital readmission rates for pneumonia, heart failure, and AMI). Panel B displays regressions on levels of additional characteristics (e.g., population, number of hospitals) in the given year. If no year is given, characteristic is time-invariant. Panel C shows regressions on long-difference changes in the baseline controls from Panel A. All continuous characteristics are standardized to have mean zero and standard deviation one before the regression. Standard errors are clustered at the state level. Counties are weighted by baseline population. Blue indicates a statistically significant positive relationship; red indicates a significant negative one; black indicates an insignificant one.

B.3 Results: Effects of HIE on Health Outcomes

Table B7: Long-Differences Second Stage - Robustness to No Controls

	County-Level ΔDeaths per 100K	Hospital-Level Δ30-Day Hospital Readmission Rates		
	(1) Flu/Pneumonia	(2) Pneumonia	(3) Heart Failure	(4) AMI
A. 2SLS, Opt-Out Instrument				
ΔRHIO	-29.3748*	-3.5440*	-2.2706	-0.1017
	(15.8780)	(1.8165)	(1.8290)	(0.8697)
First Stage F-Statistic	6.5	4.1	3.4	4.1
B. 2SLS, LASSO-Selected Instruments				
ΔRHIO	-22.2670**	-1.6522**	-1.5569	-0.0073
	(10.8484)	(0.8100)	(1.0423)	(1.1529)
First Stage F-Statistic	20.5	15.9	14.1	6.6
C. OLS				
ΔRHIO	-2.3036	0.1176	-0.1616	0.1077
	(1.5142)	(0.1013)	(0.1547)	(0.0986)
Mean of Outcome (Levels)	58.79	17.25	21.99	16.57
(SD)	(23.07)	(1.25)	(1.60)	(1.32)
Years	2009-2019	2009-2017	2009-2018	2009-2018
Observations	1120	1704	1349	829

Notes: Each column in each panel presents a separate long-differences regression estimating the effect of changes in hospital participation in Regional Health Information Organizations (RHIO) on changes in health outcomes. Column 1 reports county-level regressions weighted by baseline population (Equation 3.4), while Columns 2-4 report hospital-level regressions weighted by baseline bed sizes (Equation 3.3). Panel A presents 2SLS estimates using the change in state opt-out patient consent laws as the instrument. Panel B presents 2SLS estimates using LASSO-selected legal dimensions as the instruments. Panel C presents OLS estimates for comparison. For each outcome, the mean (SD) level, measurement years, and observation count are provided. All regressions include no controls. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B8: TWFE Panel Second Stage

	County-Level Deaths per 100K	Hospital-Level 30-Day Hospital Readmission Rates		
	(1) Flu/Pneumonia	(2) Pneumonia	(3) Heart Failure	(4) AMI
A. 2SLS, Opt-Out Instrument				
RHIO	-29.4591	-4.0380***	-2.6243*	-0.3953
	(25.2698)	(1.3637)	(1.5713)	(0.7927)
First Stage F-Statistic	2.5	7.7	4.3	4.5
B. 2SLS, LASSO-Selected Instruments				
RHIO	-14.3329*	-3.1847***	-2.0663**	-1.0314
	(7.6837)	(0.9316)	(0.9793)	(0.7360)
First Stage F-Statistic	45.7	20.4	18.3	16.8
C. OLS				
RHIO	-0.4818	0.0524	-0.0656	0.0143
	(0.4174)	(0.0349)	(0.0509)	(0.0441)
Mean of Outcome (Levels)	58.79	17.25	21.99	16.57
(SD)	(23.07)	(1.25)	(1.60)	(1.32)
Years	2009-2019	2009-2017	2009-2018	2009-2018
Observations	10593	13533	12242	7956

Notes: Each column in each panel presents a separate two-way fixed effects regression estimating the effect of hospital participation in Regional Health Information Organizations (RHIO) on health outcomes. Column 1 reports county-level regressions weighted by baseline population (Appendix Equation B.4), while Columns 2-4 report hospital-level regressions weighted by baseline bed sizes (Appendix Equation B.3). Panel A presents 2SLS estimates using the change in state opt-out patient consent laws as the instrument. Panel B presents 2SLS estimates using LASSO-selected legal dimensions as the instruments. Panel C presents OLS estimates for comparison. For each outcome, the mean (SD) level, measurement years, and observation count are provided. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B9: TWFE Panel Second Stage - Robustness to No Controls

	County-Level Deaths per 100K	Hospital-Level 30-Day Hospital Readmission Rates		
	(1) Flu/Pneumonia	(2) Pneumonia	(3) Heart Failure	(4) AMI
A. 2SLS, Opt-Out Instrument				
RHIO	-27.4775	-3.0967**	-3.9561***	-4.2405***
	(34.0385)	(1.2485)	(1.3579)	(1.3815)
First Stage F-Statistic	1.72	10.8	10.9	11.2
B. 2SLS, LASSO-Selected Instruments				
RHIO	-18.5273	-1.9978**	-3.3516***	-3.6820***
	(14.2947)	(0.8031)	(0.9648)	(0.9795)
First Stage F-Statistic	28.2	35.7	33.9	31.8
C. OLS				
RHIO	-0.3784	0.0593*	-0.0571	0.0327
	(0.4009)	(0.0338)	(0.0545)	(0.0451)
Mean of Outcome (Levels)	58.79	17.25	21.99	16.57
(SD)	(23.07)	(1.25)	(1.60)	(1.32)
Years	2009-2019	2009-2017	2009-2018	2009-2018
Observations	10593	13533	12242	7956

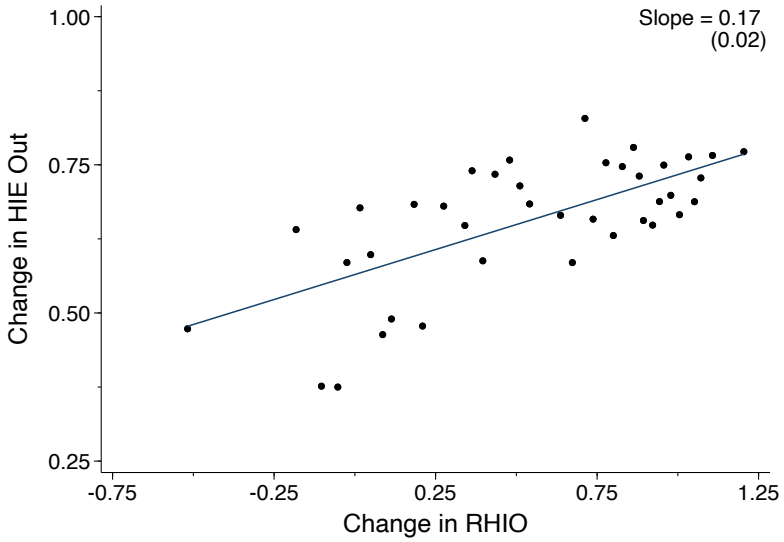
Notes: Each column in each panel presents a separate two-way fixed effects regression estimating the effect of hospital participation in Regional Health Information Organizations (RHIO) on health outcomes. Column 1 reports county-level regressions weighted by baseline population (Appendix Equation B.4), while Columns 2-4 report hospital-level regressions weighted by baseline bed sizes (Appendix Equation B.3). Panel A presents 2SLS estimates using the change in state opt-out patient consent laws as the instrument. Panel B presents 2SLS estimates using LASSO-selected legal dimensions as the instruments. Panel C presents OLS estimates for comparison. For each outcome, the mean (SD) level, measurement years, and observation count are provided. All regressions include no controls. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B10: Long-Differences Second Stage - Shorter Sample Period (2009-2015)

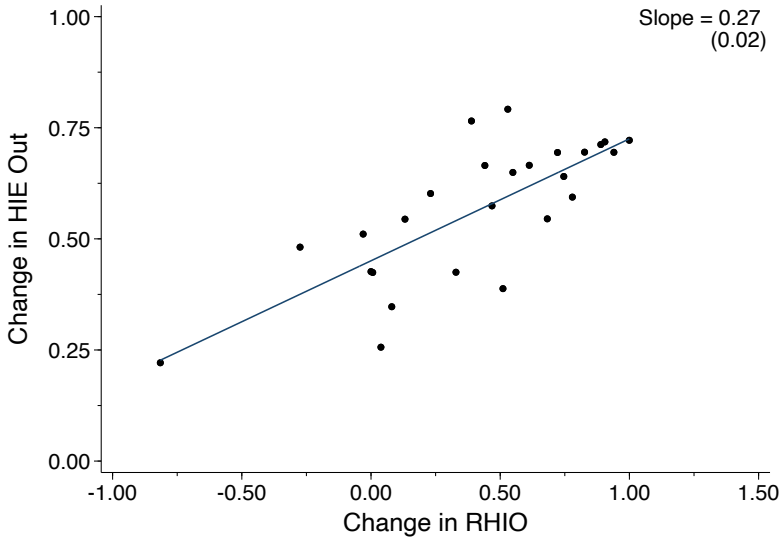
	County-Level ΔDeaths per 100K	Hospital-Level Δ30-Day Hospital Readmission Rates		
	(1) Flu/Pneumonia	(2) Pneumonia	(3) Heart Failure	(4) AMI
A. 2SLS, Opt-Out Instrument				
ΔRHIO	-13.3153	-2.7490**	-1.6602**	-0.3616
	(9.2202)	(1.0982)	(0.7446)	(0.7731)
First Stage F-Statistic	6.4	8.6	8.0	7.3
B. 2SLS, LASSO-Selected Instruments				
ΔRHIO	-13.8316***	-1.1924**	-1.4482***	-0.0954
	(3.7258)	(0.4941)	(0.5080)	(0.3517)
First Stage F-Statistic	24.2	33.9	31.7	24.3
C. OLS				
ΔRHIO	-0.7642	-0.0846	-0.1599	0.0745
	(1.0823)	(0.1185)	(0.1216)	(0.0797)
Mean of Outcome (Levels)	59.41	17.07	22.05	16.87
(SD)	(23.64)	(1.36)	(1.69)	(1.39)
Years	2009-2015	2009-2015	2009-2015	2009-2015
Observations	1384	1807	1642	1022

Notes: Each column in each panel presents a separate long-differences regression estimating the effect of changes in hospital participation in Regional Health Information Organizations (RHIO) on changes in health outcomes. The sample period is shortened to 2009 through 2015. Column 1 reports county-level regressions weighted by baseline population (Equation 3.4), while Columns 2-4 report hospital-level regressions weighted by baseline bed sizes (Equation 3.3). Panel A presents 2SLS estimates using the change in state opt-out patient consent laws as the instrument. Panel B presents 2SLS estimates using LASSO-selected legal dimensions as the instruments. Panel C presents OLS estimates for comparison. For each outcome, the mean (SD) level, measurement years, and observation count are provided. All regressions include controls for county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Standard errors, clustered at the state level, appear in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure B5: Correlation between RHIO Participation and HIE Out Index - Robustness



(a) Add Controls



(b) Restrict to 2009-2015 Period

Notes: Figure shows the correlation between county-level changes in hospital participation in health information exchange organizations and county-level changes in hospital health information exchange. Both panels present binscatter plots with the x-axis showing county-level changes in the average hospital participation in Regional Health Information Organizations (RHIO) and the y-axis showing county-level changes in the average hospital HIE Out Index. HIE Out Index is defined as described in the text. In Panel A, the change is from 2009 to 2019 (N = 1,120); levels of the HIE Out Index for 2016-2019 are thus proxied with other survey questions due to the original survey questions ending in 2015. In Panel B, the change is from 2009 to 2015 (N = 1,384); thus, no proxy for the HIE Out Index is necessary. Counties are weighted by baseline population. The estimated regression coefficients and standard errors (SEs) are given. Panel A controls for baseline county-level population shares in 5-year age bins (<1, 1-4, ..., 80-84, 85+), uninsurance rate, unemployment rate, poverty rate, and median household income. Panel B includes no controls.