ADOPTION OF COMPUTERIZED CLINICAL DECISION SUPPORT FUNCTIONALITIES AND THE QUALITY OF HOSPITAL CARE

A DISSERTATION

SUBMITTED ON THE TENTH DAY OF MAY 2023

TO THE DEPARTMENT OF HEALTH POLICY AND MANAGEMENT

OF THE SCHOOL OF PUBLIC HEALTH AND TROPICAL MEDICINE

OF TULANE UNIVERSITY

FOR THE DEGREE

OF

DOCTOR OF PHILOSOPHY

BY

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Abstract

The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 has triggered the wide adoption of electronic health records (EHRs) among eligible hospitals nationally. With the increased adoption of EHRs, hospitals' efficiency improved. However, the evidence of improvements in healthcare quality after the adoption of EHRs was mixed. This work assesses whether computerized clinical decision support (CCDS) functionalities, which are a part of EHRs, affected inpatient health care outcomes among acute stroke patients to illustrate whether CCDS may improve the quality of hospital care for acute health conditions. Previous works, limited to randomized clinical trials, did not evaluate how CCDS adoption in hospitals impacted the quality of acute stroke care at the national level. In answering this research question, it is assumed that improvements in hospital care quality were warranted by the adoption and use of CCDS functionalities, which contributed to resolving the complexity of clinical decisions for care providers.

The association between the adoption of CCDS and acute stroke quality measures in the 2013 and 2017 sample of the U.S. non-federal acute care hospitals was performed using rich administrative data on the key characteristics, including the adoption of CCDS adoption (American Hospital Association surveys), inpatient quality outcome measures (Hospital Compare) employing multivariable ordinary least-squares regression analyses with an instrumental variable controlling for time-invariant hospital characteristics (fixed effects). It has been shown that the adoption of CCDS had a clinically significant positive effect on the 30-day all-cause
acute stroke mortality rate (-0.015, p=0.69), and a statistically significant negative
effect on the 30-day acute stroke readmission rate (0.068, p=0.01).

Even though the results were inconclusive, this work informs further research on
the adoption and implementation of CCDS, including those that employ machine
learning and artificial intelligence, by expanding the framework for assessing
health IT adoption using administrative data and opening avenues for enhancing
measures of care quality.
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Chapter 1. Background and Significance

Section 1.1. Introduction

Problem Statement

The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 promised to improve health care quality by supporting the wide adoption of health information technology (IT) among eligible healthcare providers nationally (Goldstein & Thorpe Jane, 2010). Indeed, the legislation triggered the wide adoption of electronic health records (EHRs) among eligible hospitals. For instance, just in six years, the U.S. hospitals’ ownership of basic EHRs\(^1\) went from 12% in 2009 to 84% in 2015. With the increased adoption of EHRs, hospitals’ efficiency improved (Silow-Carroll, Edwards, & Rodin, 2012). However, the evidence of improvements in healthcare quality and patient safety after the adoption of EHRs was mixed (Asagbra, Burke, & Liang, 2019; Joynt et al., 2015).

Nevertheless, our nation pushed forward toward the adoption of more advanced digital tools in healthcare settings. As it was 20 years ago with EHRs, modern early adopters report on advances in healthcare using artificial intelligence (AI) and machine learning (ML) tools (Yu, Beam, & Kohane, 2018). These advancements have already found support among policymakers, and a few of them were granted federal funding.

\(^1\) Hospitals have adopted a basic EHRs with clinician notes when hospital includes a computerized system with capabilities in the following areas: patient demographics, physician notes, nursing assessments, patient problem lists, electronic lists of patient’s medications, discharge summaries, advanced directives, orders for medications, viewing laboratory and radiology results.
However, the implications of wide AI and ML adoption require meticulous study and understanding of adoption enablers and barriers. Data on wider AI and ML adoption and its potential clinical and operational benefits for healthcare providers are still accumulating. But given that AI and ML in hospitals are used to inform clinical decisions under the pressure of abundance and complexity of available clinical and non-clinical information (Sloane & Silva, 2020), it is possible to illustrate AI and ML adoption through the study of computerized clinical decision support tools (CCDS).

This dissertation attempts to explore the link between the adoption of EHRs and hospital care quality. In doing so it is assumed that improvements in healthcare quality in hospitals were specifically warranted by the adoption and use of CCDS capabilities (functions), which are a part of EHRs. The key mechanism by which CCDS may affect healthcare quality is through resolving the complexity of clinical decisions for care providers. This complexity stems from the abundance of clinical information which care providers should collect, operate, and decide upon concerning a specific patient, as well as the complexity of care processes in the care setting itself. Simply put CCDS is an electronic extension of clinical guidelines that have long been used to improve clinical care and patient outcomes.

It is known that the use of evidence-based care guidelines is associated with improvements in care quality. For example, adherence to the American Heart Association guideline recommendations in the acute phase of stroke is linked to a lower number of early deaths, while good adherence during both acute and early
clinical phases of stroke improved survival at 6 months (Donnellan, Sweetman, & Shelley, 2013).

In their turn, CCDS use is associated with increased adherence to clinical guidelines, which is however contingent on how well the CCDS is used by care providers. A Dutch randomized clinical trial (RCT) (Karlsson et al., 2018) showed that a CDSS, that alerted a physician of atrial fibrillation (AF) patient with an increased risk for thromboembolism without anticoagulant therapy, can increase guideline adherence for anticoagulant therapy among outpatients with AF. More specifically the CCDS produced. The primary endpoint was adherence to guidelines after 1 year. The analysis revealed a significant increase in guideline adherence in the CDS (73.0%, 95% CI 64.6%–81.4%) versus the control group. Another similar RCT study (Arts, Abu-Hanna, Medlock, & van Weert, 2017) failed to identify the effect of CCDS (alerting physicians about high stroke risk in AF patients) on the rate of adherence to AF guidelines (55% in CCDS intervention group, 50% in control group,  \( p = 0.23 \)), which authors attributed to the lack of CCDS use. Similarly, Richardson, K. J. et al. (2016) found no effect from implementing three stroke nursing care CCDS alerts (i.e., the National Institutes of Health’s Stroke Scale, neurological checks, and dysphagia screening) on the completeness of nursing documentation (adherence), which was linked to lack of order entry (under 10% for all cases).
The objective of the dissertation is to assess whether CCDS functionalities affected inpatient care outcomes for acute stroke patients. This study illustrates how CCDS may improve care quality in hospital settings for acute conditions. Furthermore, this study focuses solely on CCDS adoption under the Medicare EHR Incentive Program.

This study is strengthened by the use of rich administrative data, including a multiyear panel of data on hospital characteristics (including CCDS adoption), as well as data on acute stroke inpatient mortality and readmissions. The study also employs quantitative analytic methods, such as multivariable linear regression models using instrumental variables and fixed effects, to address an important and timely health care policy question. Previous studies on CCDS adoption in hospitals were limited to randomized clinical trials (RCTs) conducted within a single hospital or health system. This study, however, examines CCDS adoption across a national sample of hospitals.

Section 1.2. Meaningful Use Policy and Adoption of EHRs

This section describes provisions of the Meaningful Use policy, defines the EHRs, and outlines the adoption of EHRs among U.S. hospitals.

1.2.1. Meaningful Use Policy

The HITECH Act was implemented as a complex policy that is now known as Promoting Interoperability (formerly known as Meaningful Use). The Meaningful Use (MU) or Promoting Interoperability (PI) is a set of requirements that eligible (non-federal acute care adult hospitals) hospitals and Critical Access Hospitals
(CAHs) had to comply with to receive incentive payments, and, in the later years of the program, to avoid penalties while being reimbursed for services under Medicare and Medicaid programs. These requirements were defined under MU/PI goals and objectives, which were updated under each new iteration (stage) of the MU/PI policy.

The MU objectives concerning the adoption of specific EHR functionalities related to patient health information protection, recording, and retrieving patient demographic and clinical information, patient engagement and education, use of CCDS and Computerized Provider Order Entry (CPOE) tools, patient information interoperability, care quality improvement, and public health reporting. Each objective was assigned measures based on eligible hospitals’ and CAH’s attestation or reporting to the Centers for Medicare and Medicaid Services (CMS).

Historically, the MU policy was rolled out in three stages (see Figure 1.1). In Stage 1 (2011-2012) the policy required eligible hospitals and CAHs to attest to implementing all 14 core and menu MU objectives. Stage 2 (2014) expanded upon Stage 1 requirements with a focus on advancing clinical processes and ensuring that the EHRs were used to support the aims and priorities of the National Quality Forum (CMS, 2012). Stage 3 started in 2017, and focused on using CEHRT to improve health outcomes. The CCDS adoption started in 2011 as per the Stage 1 requirement for eligible hospitals to attest to implementing (1) one clinical decision support rule, and (2) a drug-drug and drug-allergy interaction rule.
Under the MU policy, eligible hospitals had two sources of possible EHRs incentive payments in case of successful attestation on the MU of health IT. The first is the Medicare EHRs Incentive Program operated federally by CMS, and the second one is the Medicaid EHRs Incentive Program operated by individual states. This study is focused on the Medicare EHRs Incentive Program only.

Excluding the Medicaid EHRs Incentive Program from the study has implications and limitations. On one hand, focusing solely on the Medicare EHRs Incentive Program may limit the generalizability of the findings, as the adoption of CCDS in hospitals could be influenced by different factors under the Medicaid program. This means that the findings may not fully represent the broader landscape of CCDS adoption in healthcare settings.

On the other hand, including both the Medicare and Medicaid programs in the study would likely increase the complexity of the analysis and potentially introduce confounding factors, as the two programs may have different eligibility criteria, payment structures, and implementation timelines. Additionally, data availability and quality may vary between Medicare and Medicaid programs, which could affect the robustness of the findings.

Furthermore, the Medicaid EHRs Incentive Program may have its unique characteristics and requirements, which could impact the adoption of CCDS differently compared to the Medicare program. Therefore, not including the Medicaid program in the study may result in an incomplete understanding of the overall impact of EHRs incentives on CCDS adoption in hospitals.
In summary, not including the Medicaid EHRs Incentive Program in the study may limit the generalizability of the findings and could result in an incomplete understanding of the overall impact of EHRs incentives on CCDS adoption in hospitals. However, including both programs in the study could introduce complexities and potential confounding factors.

Figure 1.1. Timeline of Meaningful Use Policy Stages (CMS, 2021).

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<tr>
<td>Registration for the EHRs Incentive Programs begins</td>
<td>Attestation for the Medicare EHRs Incentive Program begins</td>
<td>Medicare EHRs incentive payments start</td>
<td>Last year to initiate participation in the Medicare EHRs Incentive Program</td>
<td>Medicare payment adjustments begin for eligible hospitals that are not meaningful users of EHRs</td>
<td>Last year to receive Medicare EHRs incentive payment</td>
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1.2.2. Definition of EHRs

Electronic health record (EHRs) is defined as “an electronic version of a patient’s medical history, that… may include all the key administrative clinical data relevant to that person’s care. The EHRs may support care by the means of “evidence-based decision support, quality management, and outcomes reporting” (CMS, 2021).

In earlier studies of the adoption of EHRs in hospitals (Adler-Milstein, J. et al., 2014), the EHRs were divided into basic EHRs and advanced EHRs. Basic EHRs have full implementation of ten computerized functions (for example, electronically viewing patient information, laboratory, and radiology reports, and electronically ordering medications) in at least one clinical unit of a hospital. Advanced EHRs
had all ten basic functions and fourteen additional functions (for example, electronically requesting consultations and nursing orders, viewing clinical guidelines, and receiving clinical reminders) fully implemented in all major clinical units. The complete list of EHRs functions is shown in Table 1.1, where the advanced EHRs functionalities pertaining to CCDS are highlighted in grey.

Table 1.1. Comparison of Basic and Comprehensive EHRs (Adler-Milstein et al., 2014).

<table>
<thead>
<tr>
<th>EHRs Functionalities</th>
<th>Basic</th>
<th>Advanced</th>
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<tbody>
<tr>
<td>1. Electronically maintaining patient demographic information</td>
<td>+</td>
<td>+</td>
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<td>2. Electronically maintaining physician notes</td>
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<td>+</td>
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<tr>
<td>3. Electronically maintaining nursing assessments</td>
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<td>+</td>
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<td>4. Electronically maintaining patient problem lists</td>
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<td>+</td>
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<tr>
<td>5. Electronically maintaining patient medication lists</td>
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<td>+</td>
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<tr>
<td>6. Electronically maintaining discharge summaries</td>
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<td>+</td>
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<tr>
<td>7. Electronically viewing laboratory reports</td>
<td>+</td>
<td>+</td>
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<tr>
<td>8. Electronically viewing radiologic reports</td>
<td>+</td>
<td>+</td>
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<tr>
<td>9. Electronically viewing diagnostic test results</td>
<td>+</td>
<td>+</td>
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<tr>
<td>10. Electronically ordering medications</td>
<td>+</td>
<td>+</td>
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<tr>
<td>11. Electronically viewing advanced directives in clinical documentation</td>
<td></td>
<td>+</td>
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<tr>
<td>12. Electronically viewing radiological images</td>
<td></td>
<td>+</td>
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<tr>
<td>13. Electronically viewing diagnostic test images</td>
<td></td>
<td>+</td>
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<tr>
<td>14. Electronically viewing consultant reports</td>
<td></td>
<td>+</td>
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<tr>
<td>15. Electronically ordering laboratory tests</td>
<td></td>
<td>+</td>
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<tr>
<td>16. Electronically ordering radiology tests</td>
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<td>+</td>
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<td>17. Electronically requesting consultations</td>
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<td>+</td>
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<tr>
<td>18. Electronically requesting nursing orders</td>
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<td>+</td>
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<td>19. Electronically viewing clinical guidelines</td>
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<td>+</td>
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<tr>
<td>20. Electronically receiving clinical reminders</td>
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<td>+</td>
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<td>21. Electronically receiving drug-allergy alerts</td>
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<td>+</td>
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<tr>
<td>22. Electronically receiving drug-drug interaction alerts</td>
<td></td>
<td>+</td>
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<tr>
<td>23. Electronically receiving drug-laboratory interaction alerts</td>
<td></td>
<td>+</td>
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<tr>
<td>24. Electronically receiving drug-dose support alerts</td>
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1.2.3. Adoption of EHRs

The HITECH Act triggered the wide adoption of EHRs among eligible hospitals. In 2009 12% of hospitals reported having basic EHRs, whereas in 2015 it rose to 84%. Small, rural, and CAHs showed a similar trend averaging 80% for the adoption of basic EHRs by 2015. The Certified EHR Technology (CEHRT) adoption grew from 72% in 2011 to 96% in 2017 (Henry, 2016).

However, the adoption of EHRs was not universal among hospitals. It has been shown that the hospitals that were not eligible for the MU incentive payments (i.e., psychiatric, long-term care, and rehabilitation) lagged in terms of basic and advanced EHRs adoption rates in post-policy years compared to eligible hospitals (Adler-Milstein, J. & Jha, 2017; Walker, Mora, Demosthenidy, Menachemi, & Diana, 2016). This disproportionate effect of the policy was linked to the intentional selection of acute care hospitals into the eligible group. In the pre-MU policy period, non-eligible hospitals had lower basic EHRs adoption rates as well as lower ability to meet MU Stage 1 criteria compared to eligible hospitals, which was mostly impeded by the high up-front capital costs of purchasing EHRs and lack of adequate IT staff (Walker et al., 2016). Therefore, it is more likely that the MU policy intended to tackle the group of hospitals that already have a higher rate of EHRs adoption, with a better ability to invest in purchasing health IT.

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2 Hospitals have possession of a CEHRT if the EHR technology meets the technological capability, functionality, and security requirements adopted by the Department of Health and Human Services. Possession means that the hospital has a legal agreement with the EHR vendor, but it is not equivalent to adoption.
In their influential study, Jha et al. (2009) assessed the adoption of EHRs, where a hospital was deemed to have comprehensive EHRs if it had reported having the EHRs functionalities in all clinical units. If the hospital reported to have the EHRs functionalities in at least one clinical unit, then it was deemed to have basic EHRs. In the study, a hospital was deemed as an EHRs adopter if it had all 24 key functions (see Table 1.1). A similar approach was used in the assessment of the adoption of specific EHRs functionalities (Blavin, Buntin, & Friedman, 2010) and the adoption of specific CCDS functions (Mitchell, Jordan, Revere, & Ayadi, 2014).

Section 1.3. Adoption of CCDS

This section defines CCDS, outlines its adoption timeline, and explains the main assumptions about measuring CCDS adoption.

1.3.1. Definition of CCDS

The EHRs is a complex set of software modules that can be loaded and run on computers and perform predefined (programmed) automated procedures using clinical and non-clinical information. In essence, CCDS is a software module embedded in EHRs that receives patient information and compares this information against clinical and non-clinical indicators using clinical decision-making algorithms run on the databases of existing clinical knowledge. This module is designed to automate the process of clinical reasoning, which is routinely performed by clinicians while diagnosing and treating patients in clinical settings. The results of such automated process of clinical inquiry are reported to the user (care provider) in the form of text (clinical guidelines) and/or visual output,
reminders, or alerts (clinical reminders, drug allergy alerts, drug-drug interaction alerts, drug lab interaction alerts), recommendations (drug dosing support), or any other signal. Further, these instrument types are referred to as main CCDS functionalities.

There may be other CCDS functionalities that were excluded from this list of six main CCDS functionalities. However, these six CCDS functionalities cover the majority of reported CCDS implementations in healthcare to date (Sutton et al., 2020; White et al., 2023) and were used in mainstream research on the topic (Adler-Milstein, J. et al., 2014; Adler-Milstein, J. et al., 2015; Adler-Milstein, J. & Jha, 2017; Mitchell, J., Probst J Fau - Brock-Martin, et al., 2014; Shin, Menachemi, Diana, Kazley, & Ford, 2012; Walker et al., 2016).

1.3.2. Adoption of CCDS

The MU policy set forth January 1, 2011, as the start date for the adoption of CCDS functionalities by eligible hospitals and providers (CMS, 2016). Figure 1.2 shows that the share of non-federal acute hospitals that had EHRs adopted increased from 34.8% to 88.3% between 2011 (the MU policy start) and 2015 (the most recent reported year). For the same period, the share of comprehensive EHRs, that represent the CCDS functionalities (see Table A1 in Appendix) increased as well (from 8.8% to 40%).
Figure 1.2. Adoption of EHRs by the level of functionality, 2008-2015 (ONC, 2016).

**Notes:** The sample includes the U.S. non-federal acute care hospitals only. Basic EHRs and Comprehensive EHRs criteria are reported in Table A1 (Appendix). *Significantly different from the previous year (p < 0.05).

Source: ONC/AHA, AHA Annual Survey Information Technology Supplement.

As CCDS were usually a component of EHRs adopted by hospitals, the adoption of CCDS was linked to the MU policy and introduction of the Medicare EHRs Incentive Program. While this study does not assess the impact of the MU policy on CCDS adoption, it does use the MU policy to instrument endogenous CCDS adoption.

**1.3.3. Distinctions Between Adoption and Use of Health IT**

To correctly assess the impact of CCDS adoption on the quality of care, it is important to assure that not only hospitals have adopted the CCDS, but also that
care providers in these hospitals have used the CCDS to make better clinical decisions, that had positive effects on patients.

In health services research health IT (e.g., EMRs, EHRs, CPOE) adoption was assessed using two main approaches using (1) healthcare provider surveys and (2) data on provider attestation to CMS (MU attestation) about the meaningful use of health IT (MU attestation), including CCDS (Holmgren, A. J., Adler-Milstein, & McCullough, 2018a).

The MU attestation data is generated when providers report to CMS using a standardized online form on certain health IT functionalities defined by the Medicare EHRs Incentive Program requirements (CMS, 2014). The providers who meet pre-specified thresholds for all MU objectives are deemed to have attested for MU of health IT. Although it is impossible to confirm the truthfulness of hospitals’ responses to the attestation form, it is unlikely that hospitals would risk their participation in the Medicare program by falsely attesting to the existence of health IT.

The survey data on EHRs adoption originates either from the HIMSS Analytics database (a proprietary database of information systems for integrated health delivery systems provided by the Health Information Management Systems Society) (Diana, 2009), or AHA IT Survey (Adler-Milstein, J. et al., 2014; Adler-Milstein, J. et al., 2015; Adler-Milstein, J. & Jha, 2017; Mitchell, J., Probst J Fau - Brock-Martin, et al., 2014; Shin et al., 2012; Walker et al., 2016) data. The HIMSS Analytics database cannot be used for this study because it does not cover the period of this study (2013-2016). The AHA IT Survey is a voluntary
survey that provides a better choice of tools (questions) to capture the adoption of CCDS compared to the MU attestation data. The former report on whether a hospital had each of the six main CCDS functionalities shown to be part of comprehensive EHRs (see Table A1 in Appendix) as well as on the level of their adoption (e.g., in all units, in on unit, or not intention to implement), while the latter reports on implementing two the six main CCDS functions (i.e., drug-allergy and drug-drug interaction) without addressing the level of adoption (i.e., hospital may answer “YES” or “NO” to this question on the attestation form).

More recent studies, though limited to single health systems and specific EHRs vendors, reported the use of EHRs audit logs to assess users’ (clinicians’) interactions with EHRs (Adler-Milstein, Julia, Adelman, Tai-Seale, Patel, & Dymek, 2020; Sinha, Stevens, Su, Pageler, & Tawfik, 2021). While the EHRs audit logs are more reliable in measuring EHRs and CCDS use by care providers compared to survey or attestation data, the measures using audit logs are only tested now, and they are not available for most hospitals in the U.S.

This study uses the AHA IT Survey data to measure the adoption of six main CCDS functions assuming that the hospitals that responded to the AHA IT Survey questions regarding the six CCDS functions did adopt and used the CCDS functions in their work. Due to the way, the responses were constructed, the AHA IT Survey measure of CCDS adoption is superior to the MU attestation measure of CCDS adoption in terms of ensuring that the CCDS functions were adopted across all clinical units. Secondly, the AHA IT Survey was extensively used to assess the adoption of EHRs, including CCDS, in health services
research, that indicates the plausibility of the measure for assessing the true adoption and use of CCDS.

Section 1.4. CCDS Adoption and Quality of Care

One of the crucial elements of the EHRs is the CCDS, a capability that uses patient medical and non-medical information in a meaningful way to inform decisions by clinicians and improve health care quality and outcomes. While being widely known and discussed among healthcare professionals and policymakers, CCDS does not have a clearly outlined common definition. For instance, the CCDS can be classified as simple (alerts and reminders), mid-level (prognostic calculators and automated clinical practice guideline systems), and complex (artificial intelligence, data mining, or statistical methods) CCDSs (O'Sullivan, Fraccaro, Carson, & Weller, 2014). Alternatively, more comprehensive classifications of CCDS subdivide them into several taxonomies, including categories like the context of CCDSs use (inpatient vs. outpatient, prevention vs. diagnosis), knowledge and data source (external guidelines, internal historical operational data, manual vs. automatic), decision support mode (rule-based vs. neural network, requiring complex vs. simple resolution), information delivery mode (printed out vs. online session, push vs. pull), and workflow (system user – patient, clinician, or non-clinician staff) (Berlin, Sorani, & Sim, 2006; Sim & Berlin, 2003).

This indicates the complex and evolving nature of the CCDS, which is driven by practical implications (quality improvement, financing), policy changes (EHRs certification requirements), and technological innovation in healthcare (implementation of machine learning and artificial intelligence in healthcare
settings). It may be the case that because of the diversity in CCDS types and applications it is hard to perform reliable comparison of CCDS across platforms and care settings.

The CCDS was shown to have varying effects on the healthcare process and care outcomes. The next subsections review a few examples of CCDS effects on care.

1.4.1. CCDS Adoption and Care Process

Complex CCDSs have been shown to have several positive impacts on the care process and outcome measures. These include reductions in unnecessary treatment, improvements in physicians’ prescribing behavior, pain assessment, reductions in healthcare costs, and reductions in clinical workload in cancer care settings (Klarenbeek et al., 2020). The CCDSs use increased the rate of thromboprophylaxis (prevention of deep vein thrombosis) in surgical patients, and subsequently, decreased the risk of venous thromboembolism (VTE) events (Borab, Lanni, Tecce, Pannucci, & Fischer, 2017).

Complex CCDSs showed improvements in adherence to clinical guidelines for breast cancer management, while no effect was found in adherence to prostate cancer guidelines (Klarenbeek et al., 2020). In an implementation of diagnostic results, alert based CCDSs were able to increase specialist referral rates for severe aortic stenosis patients by 24.6% (Kirby, Kruger, Jain, O’Hair, & Granger, 2018). Overall, CCDS use was associated with better physician performance according to clinical guidelines in terms of prescribing and dosing appropriate
medications and administering appropriate laboratory tests and transfusions (Sahota et al., 2011).

1.4.2. CCDS Adoption and Care Outcomes

Adoption of complex CCDSs was associated with decreases in the utilization of clinical care without poor clinical outcomes for lung and breast cancer patients (Klarenbeek et al., 2020). While many studies concentrated on care process measures, not much evidence is available on the CCDS effects in acute care settings (Sahota et al., 2011). This study aims to address this gap in knowledge in terms of the effect of CCDS adoption on the quality of acute stroke care in hospitals.

Section 1.5. Adoption of CCDS and Quality of Acute Stroke Hospital Care

Today clinicians have access to the ever-increasing amount of evidence on providing better care. This abundance and complexity of such important information put a burden on navigating among several complex clinical guidelines. This is especially strenuous for clinicians while providing care to cardiovascular patients, who experience life-threatening urgent conditions like acute myocardial infarction or stroke. For example, the most recent guidance (clinical guideline) for early management of patients with acute ischemic stroke authored by 19 representatives of the American Heart Association Stroke Council (the American Heart Association/American Stroke Association) comprises 75 one-sided pages of tables packed with evidence-based information on managing acute ischemic stroke patients from pre-hospital (ambulance) setting to post-discharge accounting for patient’s age, sex, comorbidities, stroke complications, as well as treatments
received at previous stages (Powers et al., 2019). Such complexity causes information overload for caregivers, that in its turn, may influence clinicians' decisions and be associated with great variation in care quality (Sbaffi, Walton, Blenkinsopp, & Walton, 2020). Using CCDS in health care is known to be one of the ways to relieve clinicians from the burden of practicing evidence-based care (clinical guidelines). For example, an electronic clinical decision support tool (PedsGuide) was shown to increase adherence to guidelines and decrease cognitive load in febrile infant management when compared with the use of a standard reference tool (Richardson, K. M., Fouquet, Kerns, & McCulloh, 2019). Adherence scores on febrile infant cases using PedsGuide were greater compared with standard reference text (89% vs 72%, p=0.001). NASA-TLX (cognitive load assessment tool) scores were lower (better) with use of PedsGuide versus control (mental 6.34 vs 11.8, p<0.001; physical 2.6 vs 6.1, p=0.001; temporal demand 4.6 vs 8.0, p=0.003; performance 4.5 vs 8.3, p<0.001; effort 5.8 vs 10.7, p<0.001; frustration 3.9 vs 10, p<0.001).

The adoption of CCDS in hospitals may have a positive effect on the quality of inpatient care, particularly for patients admitted for acute health conditions, like acute myocardial infarction, acute stroke, or pneumonia. The following section reviews the evidence of how the adoption of CCDS is linked to acute stroke care quality and outcomes.

1.5.1. Acute Stroke

Stroke is one of the major acute health conditions that causes an enormous social and financial burden on the United States. Acute stroke is a leading cause of
mortality and disability nationally with approximately 795,000 Americans suffering from stroke annually. According to national Medicare data from July 2011 through June 2014 for acute ischemic stroke (AIS) the median (10\textsuperscript{th}, 90\textsuperscript{th} percentile) hospital risk-standardized 30-day mortality rate was 14.7\% (12.8\%, 17.0\%) and the median risk-standardized 30-day readmission rate was 12.6\% (11.5\%, 14.9\%) (Benjamin et al., 2017).

In 2017 stroke ranked as the 10th cause of high inpatient care costs, totaling approximately $7.4 billion (1.7\% of all national aggregate hospital costs) nationally. It represents 1.5\% of all inpatient stays, or 525,000 hospital stays (Liang L, 2017).

1.5.2. Impact of CCDS Adoption on the Quality of Acute Stroke Hospital Care

Several systematic reviews were performed to assess the effects of the CCDS on physician performance and patient outcomes (Garg et al., 2005; Hemens et al., 2011; Hunt, Haynes, Hanna, & Smith, 1998; Kruse & Ehrbar, 2020; Nieuwlaat et al., 2011; Roshanov, Misra, et al., 2011; Roshanov, You, et al., 2011; Sahota et al., 2011). These reviews identified that the majority (56-67\%) of CCDS evaluation studies were performed in outpatient care settings. Among the reviewed studies only one assessed the CCDSs effects on care outcomes among stroke patients, which identified no effect of CCDS on prescribing anti-thrombotic medications for stroke patients (clinical guidelines adherence) (Weir et al., 2003).

A Veteran Affairs Health System (VA) quality improvement study showed that using computerized stroke order sets at admission increased compliance with the Joint Commission (TJC) National Quality Measures for stroke. The intervention
group had higher compliance with the measures compared to the control group, namely “timely deep vein thrombosis prevention administered” (91% vs. 73%, p<.002), “veteran received antithrombotic therapy by the end of the second hospital day” (80% vs. 63%, p<.035), and “veteran assessed for rehabilitation services during admission” (97% vs. 70%, p<.001) (Akwe & Wallace, 2018). Another study reported a 27-minute (p=0.03) improvement in median Door-to-Needle time (a measure of timeliness for antithrombotic therapy) in acute ischemic stroke patients in a tertiary hospital in Brazil (Martins et al., 2020).

Section 1.6. Gaps in Knowledge and Research Questions

1.6.1. Limitations of previous studies

There is a limited number of studies that evaluated the impact of the CCDS on the quality of care. Usually, these were randomized clinical trials with limited external validity (performed in a health system, or a small population), the CCDSs evaluated included different types used at different levels and impacting different elements of the care process. It is hard to draw reliable conclusions from these disparate studies that can apply to all the CCDS implemented and used nationally. There is a handful of studies that evaluated the benefit of using the CCDS in inpatients with stroke (Sahota et al., 2011), however they were less likely to evaluate patient outcomes (mortality and readmissions) and they were less likely to show positive results.

1.6.2. Statement of Research Questions

Based on the previous discussion, this study aims to assess the effect of the adoption of CCDS on hospital care outcomes for acute stroke patients by
answering the following research question: what was the impact of the adoption of CCDS functionalities on the quality of hospital care among acute stroke patients?

1.6.3. Value of the Study

The proposed study contributes to the understanding of whether health IT may improve acute inpatient care outcomes through resolving complexity and increasing adherence to clinical guidelines, and open avenues to future evaluation of CCDS use in improving inpatient care quality. Specifically, this study assesses the link between CCDS adoption and acute stroke inpatient care outcomes using a national sample of non-federal acute care hospitals using a specification for CCDS adoption that does not discriminate between specific CCDS functions.

The following chapter outlines the theoretical underpinnings of the dissertation.
Chapter 2. Theoretical Framework and Hypotheses

In the previous chapter the following research question has been identified: what was the impact of the adoption of CCDS functionalities on the quality of hospital care among acute stroke patients? Because this study aims to assess the impact of adopting CCDS on the quality of hospital care, the Donabedian’s Quality framework is chosen as the theoretical model. This chapter explores the theoretical underpinnings of answering the research question.

Section 2.1. Theories for Assessing the Link Between the CCDS Adoption and Acute Stroke Inpatient Care Quality

2.1.1. Donabedian’s Quality Framework

Avedis Donabedian defines quality of health care in terms its structure, process, and outcomes (Donabedian, 1988). Structure refers to the attributes of the setting where health services are provided, such as facilities, equipment, human resources, and financial resources. Process is about “what is actually done in giving and receiving care”. It includes the care provider’s “activities in making a diagnosis and recommending treatment”. Outcome “denotes the effects of care on the health status of patients”. In the next sections acute stroke hospital care quality is mapped onto the Donabedian’s “quality triad” (Structure-Process-Outcome, SPO) framework to construct the conceptual model. With more than two decades since its conception, the SPO framework is still widely used to prioritize quality of hospital care metrics for quality improvement initiatives worldwide (Guta, 2022; Martinez et al., 2018).
Section 2.2. Theoretical Framework

This section outlines the SPO framework elements that are relevant to evaluation of acute stroke inpatient care quality.

2.2.1. Structure

The structural elements of health care are the backbone of the quality of care. The quality-of-care structures are comprised of clinical and non-clinical elements that are discussed below.

Clinical Structure

Clinical structures are the elements of care structure that directly affect acute stroke care processes and outcomes. For instance, having an emergency department, number of nursing staff, hospital’s teaching status and hospital accreditation are structural elements that are linked to improvements in clinical care outcomes. Hospitals that were accredited by The Joint Commission (TJC) have outperformed their nonaccredited counterparts in terms of the CMS Hospital Compare measures (Schmaltz, Williams, Chassin, Loeb, & Wachter, 2011).

Non-Clinical Structure

Non-clinical structures include the attributes of the hospital that are not related to clinical aspect of care directly, which, however, are necessary for effective operation of a healthcare organization. These are hospital size, ownership, participation in health system or in professional networks, as well as its rural location. For example, health system membership and management
centralization can positively affect a composite quality score, that is built from the CMS quality indicators of pneumonia, AMI, surgical infection prevention, and congestive heart failure (Hines & Joshi, 2008).

In recent years health IT has become another important structural element of care quality. EHRs provide a more secure and reliable flow of relevant clinical information between caregivers, which helps to enhance quality of care. The CCDS’ importance for the quality of care lies within its use of evidence-based clinical knowledge, usually codified in the form of clinical guidelines. According to the SPO framework, CCDS is deemed to be a structural element of the quality-of-care continuum.

2.2.2. Process

Acute stroke care process quality depends not only on stroke-specific and non-specific care structures discussed before, but also on non-specific care process.

Stroke care process dimensions include: patient assessment and diagnosis, stroke-specific medical and/or surgical treatment, patient referral, stroke-specific non-specific and primary prevention, secondary prevention, and inpatient rehabilitation (Chimatiro & Rhoda, 2019).

2.2.3. Outcome

Acute stroke care outcomes depend on the level of hospital care quality (process) in the short run, and access to outpatient care and its quality, as well as the patient’s individual characteristics and needs, in the long-term perspective. Stroke care outcomes were shown to be linked to functional independence,
length of stay, mortality, living at home, institutionalization (Chimatiro & Rhoda, 2019). Care outcomes are assessed using condition-specific hospital mortality, readmission, and patient adverse events.

**Section 2.3. Hypotheses**

Based on discussion in previous sections, this study aims to assess the effect of CCDS adoption on the quality of acute stroke care in hospitals. CCDS adoption in this study is deemed to be a structural element of hospital’s clinical infrastructure that links clinical guidelines (“right information for right patients in right time”) with clinicians at the point of care, where CCDS users provide the necessary level of care via adherence to clinical guidelines. It shall be noted that the conceptual model assumes that CCDS adoption does affect care the process for acute stroke patients (adherence to guidelines), which then affects care outcomes (shown with dashed lines in Figure 2.1). Based on previous studies (Bjerkreim et al., 2018; Lichtman, Leifheit-Limson, Jones, Wang, & Goldstein, 2013; Vahidy et al., 2017; Xian, Holloway, Pan, & Peterson, 2012), the quality of acute stroke care is assessed in terms of acute stroke mortality and readmissions. Hence, the study hypotheses (H) constructed as follows:

**H1. Adoption of CCDS in hospitals is associated with the improvement in acute stroke inpatient mortality, all other factors being equal.**

**H2. Adoption of CCDS in hospitals is associated with the improvement in acute stroke inpatient readmissions, all other factors being equal.**
Section 2.4. The Conceptual Model

The conceptual model applying the SPO framework to the assessment of the link between the CCDS adoption and the acute stroke care quality in the U.S. hospitals can be found in Figure 2.1.
Chapter 3. Methods and Materials

This chapter outlines the methodological approach for assessing the impact of the adoption of CCDS functionalities on the quality of hospital care among acute stroke patients.

Based on the research question and the hypotheses in the previous chapter, multivariable regression analyses are used to assess the impact of CCDS adoption on acute stroke hospital mortality and readmissions rates.

The study design and the data sources described in Sections 3.1 and 3.2. Sections 3.3 and 3.4 discuss the measurement and analytic strategy. Finally, Section 3.5 addresses ethical considerations of the study.

Section 3.1. Study Design

This is a retrospective study of the U.S. acute care hospitals to estimate the association between CCDS adoption and the level of acute stroke care quality in the U.S. hospitals. All analyses were performed at hospital level.

When estimating the impact of adopting CCDS on the quality of acute stroke care, there is no way to randomize hospitals into CCDS adoption. Some hospitals chose voluntarily to adopt CCDS, while others did not. The CCDS adopters may differ systematically from those that do not adopt CCDS in terms of better access to resources such as funding or technical support, leading to selection bias. Hospitals with greater access to resources may be more likely to adopt CCDS and could differ systematically from those with fewer resources. The
hospitals with more resources may also be able to spend these resources on improving acute stroke care by hiring more clinical staff or equipping their emergency departments with more and better imaging technology that increases probability of better outcomes for acute stroke patients. This means that CCDS adoption may be endogenous and can be linked to outcomes through unobserved factors, like access to resources. Therefore, to remedy potential endogeneity in treatment, this study applies multivariable regression analysis with an instrumental variable. The detailed approach is reported in subsection 3.4.1.

Section 3.2. Data Sources and Study Sample

3.2.1. Data Sources and Data Issues

(1) American Hospital Association Annual Hospital Survey (AHA Survey)

The AHA Survey is a voluntary survey completed annually by nearly 6,300 U.S. hospitals, that represent more than 400 health care systems. The hospitals report information on their organizational structure, service lines, utilization, finances, insurance, and payment models, and staffing for a specific fiscal year.

(2) American Hospital Association Hospital Survey IT Supplement (AHA IT Survey)

Since 2008 the American Hospital Association supplements its annual AHA Survey with an additional set of survey question (AHA IT Survey) about electronic medical records, interoperability, health information exchange barriers, reporting, and degree of electronic transition. The AHA IT Survey is annual
hospital-level survey that provides data on more than 3,000 hospitals, which represents about the half of all hospitals nationally. The AHA IT Survey dataset is structured as a single table by year and can be linked to the AHA Survey by unique hospital identifiers. The AHA IT Survey has been extensively used for health IT studies in health services research (Adler-Milstein, J. et al., 2015; Adler-Milstein, J. & Jha, 2017; Walker et al., 2016).

(3) CMS’ Hospital Compare Database

The Hospital Compare is a publicly available data on measurements of operational performance in the U.S. healthcare organizations, including hospitals (Werner & Bradlow, 2006). The Hospital Compare aggregates data under several federal programs and includes measures of hospital-level care outcomes as condition-specific mortality and readmission rates. The rates are publicly available and provided in the downloadable databases on the Hospital Care Compare website.

(4) Medicare CMS Cost Reports (CMS Cost Reports)

Medicare-certified hospitals are required to submit an annual cost report to a Medicare Administrative Contractor (MAC). The cost report contains information such as facility characteristics, utilization data, cost and charges by cost center (in total and for Medicare), Medicare settlement data, and financial statement data. CMS maintains the cost report data in the Healthcare Cost Report Information System (HCRIS), which includes data for the Hospital Cost Reports

3.2.2. Study Population

The study target population consists of the U.S. non-federal acute care hospitals, that provided inpatient care from 2013 to 2017. The sample is limited to non-federal hospitals, because they are inherently different from federal hospitals in terms of patient population and service lines, sources and mechanisms of financing, and the higher rates of EHRs adoption. Due to the intent of the MU policy and because of differences in public healthcare financing approaches the hospitals located in the U.S. territories (Puerto Rico, Virgin Islands, Guam, American Samoa) were excluded (Adler-Milstein, J. & Jha, 2017).

All analyses were limited to hospitals that primarily provided general and medical acute care, because they were eligible to receive the MU incentive payments, and because this type of hospitals was more likely to provide care for acute stroke patients.

Section 3.3. Measurement

The correct assessment of the impact of CCDS adoption on acute stroke mortality and readmissions requires a reliable measurement strategy. This section details how the treatment (CCDS adoption), the outcomes (acute stroke mortality and readmissions), as well as the covariates were measured.
3.3.1. Dependent Variables

The outcomes of interest of the dissertation are acute stroke mortality rate and acute stroke readmission rate. These measures have been traditionally used in assessing the outcomes of acute stroke inpatient care (Bjerkreim et al., 2018; Lichtman et al., 2013; Vahidy et al., 2017; Xian et al., 2012).

Mortality Measures

Acute Stroke Inpatient Mortality

The first outcome of interest is acute stroke inpatient mortality rate (ASMR), which is measured using the CMS’s Care Compare (former Hospital Compare) database as the part of the Hospital Inpatient Quality Reporting (IQR) Program. The acute stroke mortality rate is a risk-adjusted estimate of deaths within 30 days from the start of a hospital admission related to acute stroke. The reason behind measuring death within 30 days instead of inpatient deaths lies in using a more consistent measurement time window across different hospitals. The data for ASMR is available from the Hospital Compare’s Complications and Deaths – Hospitals dataset. The ASMR is reported annually as a percentage, where lower mortality rate indicates better outcomes for acute stroke inpatients.

Readmission Measure

Acute Stroke Readmission Rate

Acute stroke readmission rate (ASRR) is derived from Hospital Compare database and assessed as the number of expected unplanned readmissions to any acute care hospital within 30 days of discharge from an index acute stroke
hospitalization. The ASRR is reported annually as a percentage, where lower readmission rate indicates better outcomes for acute stroke inpatients.

Important Considerations for Measuring Outcomes

For both ASMR and ASRR the qualifying cases (deaths and readmissions respectively) are aggregated across three years (36 months) starting on July 1 of the first collection year and ending on June 30 of the third (last) collection year. To reconcile differences in measurement, the end year of measure collection is assigned as the measurement year. For example, if the record indicates that the ASMR values were collected for the period starting on July 1, 2012, and ending on June 30, 2015, this ASMR value is attributed to year 2015. This approach assumes that any hospital-level quality improvement activities, including CCDS adoption, will produce their potential beneficial effects over time, which is not to be realized in the outcome measures right in the first year of the CCDS adoption.

3.3.2. Independent Variable

Approaches to Measuring the Adoption of CCDS

To correctly identify the potential care quality improvement effects of the adoption of CCDS functionalities, it is important to make sure that the adopted technology was available in the care settings where such care is provided. This means that a CCDS functionality may provide potential benefits from its adoption if it was adopted across all units of a facility. Even if a hospital has adopted a CCDS functionality only in one of its units, there is no way to confirm if the CCDS capability was available in the exact clinical unit where acute stroke patients were
provided care. Hence, the hospital was deemed to adopt a CCDS functionality if it chose the “fully implemented across all units” response for the question “Does your hospital currently have a computerized system which allows for [one of the six CCDS functionalities]” (see Table 3.1).

Table 3.1. AHA IT Survey Questions Used to Measure the Adoption of CCDS Functionalities

<table>
<thead>
<tr>
<th>“Does your hospital currently have a computerized system which allows for* :”</th>
<th>Survey Response Choices</th>
<th>CCDS Adoption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clinical guidelines</td>
<td>1 - Fully implemented across all units</td>
<td>Yes</td>
</tr>
<tr>
<td>Clinical reminders</td>
<td>2 - Fully implemented in at least one unit</td>
<td>No</td>
</tr>
<tr>
<td>Drug allergy alerts</td>
<td>3 - Beginning to implement in at least one unit</td>
<td></td>
</tr>
<tr>
<td>Drug-drug interaction alerts</td>
<td>4 - Have resources to implement in the next year</td>
<td></td>
</tr>
<tr>
<td>Drug-lab interaction alerts</td>
<td>5 - Do not have resources but considering implementing</td>
<td></td>
</tr>
<tr>
<td>Drug dosing support</td>
<td>6 - Not in place and not considering implementing</td>
<td></td>
</tr>
</tbody>
</table>

Notes: * For each of the six main CCDS functionalities respondents were asked to check one of the response choices. AHA IT Survey - American Hospital Association Hospital Survey IT Supplement.

CCDS Adoption Measure

The adoption of CCDS is assessed as a binary **CCDS adoption** measure that captures the adoption of the main six CCDS functions fully across all clinical units according to the definition of a comprehensive EHRs system. This measure is categorized into two levels: “full CCDS adoption” for hospitals implementing all six main CCDS functions across all clinical units, and “not full CCDS adoption”
for hospitals that has adopted zero to five main CCDS functions across all clinical units (see Table 3.2).

### 3.3.3. Incentive to Adopt CCDS (Instrument)

**Rationale for using instrument.**

The adoption of CCDS in hospitals may be endogenous, i.e. may have unobserved factors that may cause variation in the quality of care. For instance, large size hospitals and academic teaching hospitals may adopt CCDS earlier and at higher rates compared to smaller, non-teaching hospitals. The former groups of hospitals also may also realize better acute stroke care outcomes, which may be due to more active push towards quality improvement from the hospital's leadership. This motivation may also cause hospitals to acquire CCDS to improve adherence to clinical guidelines and better quality of care, which translated into better acute stroke care outcomes. To rule out this potential confounding effect of the CCDS adoption, I used the incentive to adopt CCDS as an instrumental variable (IV). The incentive to adopt CCDS reflects the incentive for hospitals to drive the adoption of CCDS as part of EHRs during the MU policy rollout period, therefore their direct effect was realized in the higher rate of CCDS adoption. On the other hand, the incentive to adopt CCDS is not related to acute stroke care outcomes, because the CMS’ decision to pay EHRs incentives was not tied to the reporting of the acute stroke outcomes and was based solely on the hospitals’ attestation on the EHRs adoption. IVs use only the variation in the MU policy that is predicted by the incentive to adopt CCDS (instrument) that does not otherwise affect the measure of quality of care (outcome).
Identification of the instrument

The incentive to adopt CCDS measure was calculated based the predicted Medicare EHRs incentive payments by applying the formula for calculating actual Medicare EHRs incentive payments under the MU policy. The actual Medicare EHRs incentive payments are calculated as the product of:

- *initial amount* varying between $2,000,000 and $6,370,400, which was based on the annual number of acute care hospital discharges,
- *Medicare share*, which is the ratio of total charges less charity care charges paid by Medicare Parts A and C out of total charges calculated on the basis of annual inpatient days, and
- *transition factor*, which is a coefficient equal to 1.0 for the 1st year of hospital’s participation in the Medicare EHRs Incentive Program, to 0.75 for the 2nd year of participation, to 0.5 – for the 3rd year, and to 0.25 - for the 4th year in the program.

For each hospital the predicted Medicare EHRs incentive payments were then scaled to their total operating expenses. All data used for calculation of the incentive to adopt CCDS come from the fiscal year before 2010, which was the most recent pre-MU policy year. This is done because the values from 2009 were to be used to calculate the 2010 EHRs incentive payments if the MU-policy was then in place. Distribution of the incentive to adopt CCDS measure (percentage) is shown in Figure 3.1.
3.3.4. Covariates

This subsection outlines hospital characteristics used to assess contextual factors that have been shown to be linked to CCDS adoption and hospital effectiveness, including quality of care. Prior literature suggests that hospital size (by the number of beds), ownership (public non-federal, private non-profit and private for-profit), health system affiliation, teaching status, and payer mix were important hospital-level factors for adoption of EHRs functionalities, including CCDS. (Adler-Milstein, J. et al., 2017; Lin, Lyles, Sarkar, & Adler-Milstein, 2019).

Following hospital characteristics are included in the study:

- **Hospital size** is assessed as hospital's bed size category (three categories by number of beds: small (0-99 beds), medium (100-399 beds) and large (400 and more beds)).
• **Hospital accreditation status** was assessed as any major hospital accreditation, specifically by either of the four major hospital accreditation programs – the Joint Commission (TJC), ACHC-HFAP, CIHQ, DNV. This information was derived from the AHA Annual Survey.

• **Hospital ownership** is defined as a “type of authority responsible for establishing policy concerning overall operation of the hospital” (the AHA Survey definition). Based on previously used approaches (Mitchell, Jordan, Revere, et al., 2014) the hospital ownership was categorized into the following three categories: non-federal government, not-for-profit, and for-profit.

• **Hospital teaching status** is categorized and defined using the AHA Survey data definitions as follows (Holmgren, A. J., Phelan, Jha, & Adler-Milstein, 2021):
  - *Major teaching hospital* – the hospitals that are members of the Council of Teaching Hospitals (COTH) of the Association of American Medical Colleges.
  - *Minor teaching hospital* – the hospitals that have any one or more of the following: participating site recognized for one or more Accreditation Council for Graduate Medical Education accredited programs; medical school affiliation reported to the American Medical Association (AMA); internship or residency approved by American Osteopathic Association.
  - *Non-teaching hospital* – neither of above categories.
• **Hospital's rurality** is a categorical variable for a hospital deemed as metropolitan, micropolitan, or rural.

• **Hospitals’ participation in professional networks** is measured using an indicator of whether a hospital participated in specialty group or professional association (Sherer, Meyerhoefer, & Peng, 2016). For this study, I used hospitals’ membership in the American Hospital Association as the measure for participation in professional association.

• **Hospitals’ affiliation with health systems** is measured using an indicator of whether a hospital was a part of a health system. Health system participation was derived from the AHA IT Survey and/or the AHA IT Survey.

• **Hospital has emergency department (ED)** is measured as an indicator for having an ED in a study year. The reason behind controlling for hospital having ED is that the ED is the setting where acute stroke patients can get urgent care.

• **Medicaid Expansion** state is an indicator of the hospital operating in a state that expanded its Medicaid coverage under the provisions of the Affordable Care Act (ACA). Medicaid Expansion may have provided access to preventive care for people with acute stroke risk factors (for example, blood pressure control, smoking cessation, and body weight control counseling) in expanded states. This may have effectively decreased the population at risk of acute stroke hospitalizations in the expanded states, which may have decreased acute stroke mortality and readmissions.
Table 3.2. Variables and Data Sources.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Measure Type</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Acute stroke mortality rate (ASMR)</td>
<td>Risk-adjusted 30-day all-cause mortality rate reported as percentages from the data source.</td>
<td>Continuous</td>
<td>Hospital Compare</td>
</tr>
<tr>
<td>2. Acute stroke readmission rate (ASRR)</td>
<td>Risk-adjusted 30-day all-cause readmission rate reported as percentages from the data source.</td>
<td>Continuous</td>
<td>Hospital Compare</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. CCDS adoption</td>
<td>Whether a hospital reported to have all six of the key CCDS functions (i.e. clinical guidelines, clinical reminders, drug-allergy, drug-drug, drug-lab interaction alerts, and dose support) implemented across all clinical units during the reporting period.</td>
<td>Indicator</td>
<td>AHA IT Survey</td>
</tr>
<tr>
<td><strong>Covariates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Hospital size</td>
<td>Number of staffed inpatient beds 1 - Small (&lt; = 99) 2 - Medium (100-399) 3 - Large (&gt; = 400)</td>
<td>Categorical</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>5. Hospital ownership</td>
<td>Categories by the hospital control type 1 - Government-owned 2 - Not-for-profit 3 - For-profit</td>
<td>Categorical</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>6. Hospital teaching status</td>
<td>Hospital teaching status is defined by affiliation with formal medical education organizations and programs. 1 – Major teaching hospital 2 – Minor teaching hospital 3 – Non-teaching hospital</td>
<td>Categorical</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>7. Hospital accreditation</td>
<td>Whether the hospital is accredited by any major hospital accreditation program</td>
<td>Indicator</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>8. Participation in health system</td>
<td>Indicator for a hospital’s participation in health systems</td>
<td>Indicator</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>9. Participation in professional networks</td>
<td>Indicator for a hospital’s participation in professional networks</td>
<td>Indicator</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>10. Rurality</td>
<td>Hospital’s rural status 1 – Metropolitan 2 – Micropolitan 3 – Rural</td>
<td>Categorical</td>
<td>AHA Survey</td>
</tr>
<tr>
<td>11. Has ED</td>
<td>Whether hospital has emergency department</td>
<td>Indicator</td>
<td>Hospital Compare</td>
</tr>
<tr>
<td>12. Medicaid Expansion</td>
<td>Whether a hospital is in the state that ever expanded its Medicaid program under the Affordable Care Act.</td>
<td>Indicator</td>
<td>Kaiser Family Foundation website</td>
</tr>
<tr>
<td>------------------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
<td>---------</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>13. Incentive to adopt CCDS</td>
<td>Proportion of predicted Medicare EHRs incentive payments from the hospital’s inpatient operating expenses</td>
<td>Continuous</td>
<td>Medicare Incentive Program Public Use File</td>
</tr>
</tbody>
</table>

**Section 3.4. Analytic Plan**

The analytic sample is comprised of a 2013-2017 panel of the U.S. non-federal acute general and medical care hospitals. Hypotheses testing was performed using multivariable linear regression with instrument (IV) models. The models included year to control for any time-invariant organizational characteristics, and robust standard errors clustered at the hospital level to account for serial autocorrelation over time. All statistical analyses were performed using statistical software Stata ver.15.0 (StataCorp LLP, College Station, Texas).

**3.4.1. Analytic Approach**

Assessing the relationship between the acute stroke care quality and the adoption of CCDS using ordinary least squares (OLS) may cause biased estimates due to omitted variable bias. The adoption of CCDS is not exogenous, because when adopting CCDS hospitals make a decision to invest in purchasing and implementing health IT (which the CCDS is part of) in the hospital’s workflow in order to potentially gain not only improvements in quality of patient care, but also, and may be more of so, to profit financially though the improvements in non-clinical operations (e.g., more accurate and faster billing, savings from
Reduced costs on due to duplicate lab tests, procedures, savings from payroll
cuts due to automated processes).

Instrumental variables (IVs) were shown to be effective in cases when there is a
possibility of endogenous treatment. The IVs were initially suggested for the
estimation of local average treatments effects (Imbens & Angrist, 1994), and
have been extensively applied in healthcare (Evans & Lien, 2005; Kosec, 2014).
In applying the IVs two main requirements shall be satisfied: choosing a “strong”
joint and the excludability of the instrument.

**Excludability of the Instrument**

For the instrument to be excludable, it is required that the incentive to adopt
CCDS only affected acute stroke mortality and readmission rates through the
adoption of CCDS. The incentive to adopt CCDS should not affect the
ASMR\ASRR directly, or through any other unobserved variable.

The instrumental variable must be correlated with the endogenous variable of
interest (in this case, the adoption of computerized clinical decision support,
CCDS), meaning that it has a significant effect on the endogenous variable. The
instrument should be chosen such that it is related to the likelihood of the
treatment or exposure occurring, but it is not directly related to the outcome of
interest (in this case, acute stroke mortality and readmissions) except through its
effect on the treatment variable. In other words, the instrument should affect the
probability of CCDS adoption, but not directly affect the outcome of interest, to
ensure that it satisfies the excludability criterion.
Such incentive to adopt CCDS measure is excludable because it has direct impact on the CCDS adoption by incentivizing hospitals to adopt CCDS. The EHRs incentive payments also are not linked to the variation in the ASMR (quality of care). The weak instrument issue stems from the fact that the variation in the instrument cannot "pick up" variation in the treatment variable.

Expected Medicare EHRs incentive payments were calculated for each hospital in each year using hospital’s characteristics employed by CMS to calculate actual Medicare EHRs incentive payment: total number of inpatient discharges, total number of inpatient bed-days, number of inpatient bed-days paid by Medicare, total charges, and total charges for charity care.

While assessing the impact of the MU policies (i.e. Medicare EHRs Incentive Program) on the adoption of CCDS, the assessment of the effect of the state Medicaid EHRs Incentive Programs on the CCDS adoption was outside of the scope of this study. Excluding the Medicaid EHRs Incentive Program effects may affect the study results, which is discussed in Section 5.2 in detail.

**Treatment of Missing Data**

The AHA IT Survey data have missing values (gaps) in hospitals’ responses to the question on the adoption of CCDS functionalities, which stems from either not completing the survey (survey non-response), or not answering specific survey questions (item non-response). It is unclear why hospitals chose not to respond to the survey questions, which were used to construct the treatment (CCDS
adoption) variable in this analysis. Therefore, it is decided not to impute missing values for the CCDS adoption variable.

3.4.2. Statistical Model

Each hypothesis is tested using separate multivariate linear (OLS) probability models with year fixed effects. Standard errors will be clustered at hospital level. The statistical model (structural equation) for assessing the outcome in its general form will look like the following:

\[
\text{STROKE}_{it} = \beta_0 + \beta_1 \text{CCDS}_{it} + \beta_2 X_{it} + \lambda_t + \epsilon_{it} \quad (1)
\]

Where:
- \( \text{STROKE}_{it} \) – hospital level acute stroke mortality/readmission rate;
- \( \beta_0 \) – intercept term;
- \( \text{CCDS}_{it} \) – indicator for hospital’s CCDS functionality adoption;
- \( T_i \) – year dummy;
- \( X_{it} \) – hospital-level covariates;
- \( \lambda \) - fiscal year fixed effects and captures changes in all hospitals over the sample period;
- \( \epsilon_{it} \) – error term;
- \( i \) – index for individual hospital (observation unit);
- \( t \) – index for year (observation period).

The first-stage regression equation will be:

\[
\text{CCDS}_{it} = \gamma_0 + \gamma_1 \text{INCENT}_i + \gamma_2 X_{it} + \lambda_t + \mu_{it} \quad (2)
\]

Where:
- \( \text{INCENT}_i \) is the incentive to adopt CCDS as predicted Medicare EHRs incentive payments scaled on the predicted total operating costs as percentage;
- \( \gamma_0 \) – intercept term;
- \( \text{CCDS}_{it} \) – indicator for hospital’s CCDS functionality adoption;
- \( T_i \) – year dummy;
- \( X_{it} \) – hospital-level covariates;
- \( \lambda \) - fiscal year fixed effects and captures changes in all hospitals over the sample period;
- \( \mu_{it} \) – error term;
- \( i \) –
index for individual hospital (observation unit); \( t \) – index for year (observation period). In these models, the \( \text{CCDS}_t \) stands for CCDS adoption.

**Section 3.5. Ethics and Permissions**

Institutional Board Review permission was not sought because the data used for the study did not include information that allowed patient identification. Hospital data was accessed from publicly available databases and merged using NPI and AHA identifiers available from publicly available sources.
Chapter 4. Results

This chapter reports the results of the descriptive and regression analyses, with .

The analytic sample was constructed using 2013-2017 data on hospitals’ demographic characteristics (from the AHA Survey), CCDS adoption (from the AHA IT Survey), acute stroke mortality and readmissions (from the Hospital Compare database), and financial performance (from the CMS Cost Reports). The AHA IT Survey provides data on whether a hospital has adopted the CCDS functionalities of interest (independent variable), therefore it is impossible to know or predict the treatment value if a hospital has not responded to the survey. For this reason, the descriptive and regression analyses were performed using only those hospitals that responded to the AHA IT Survey. Due to considerable differences between the respondents and non-respondents (see Table A-4 in Appendix), the results of the analyses cannot be applied to the whole population target population of non-federal acute U.S. hospitals.

Several problems arose during the progression of this analysis. The instrumental variable, that was constructed using the approach described in detail in Chapter 3, has been shown negatively associated with the CCDS adoption first stage regression as well as being proven to be a ‘weak’ instrument. This showed that the original instrument cannot not be used for estimation of the CCDS adoption effect on acute stroke outcomes. In fact, this negative association between the incentive to adopt CCDS and the CCDS adoption was surprising, and it is discussed in this chapter with further.
For these reasons, after presenting the analysis as proposed in Chapter 3, an alternative analysis is presented to address these problems.

**Section 4.1. Descriptive Analysis**

The analytic sample includes 7,933 observations (hospital-years) representing 2,331 unique non-federal acute care general and medical hospitals in U.S. states in years between 2013 and 2017.

**4.1.1. Sample Characteristics by CCDS Adoption**

The analytic sample includes 7,933 observations (hospital-years) representing 2,331 unique non-federal acute care general and medical hospitals in U.S. states in years between 2013 and 2017.

<table>
<thead>
<tr>
<th>Table 4.1. Analytic Sample Characteristics (N=7,933).</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Characteristics</strong></td>
</tr>
<tr>
<td>Overall, count (%)</td>
</tr>
<tr>
<td>Hospital size, %</td>
</tr>
<tr>
<td>1 - Small (&lt;=99)</td>
</tr>
<tr>
<td>2 - Medium (100-399)</td>
</tr>
<tr>
<td>3 - Large (&gt;=400)</td>
</tr>
<tr>
<td>Hospital ownership, %</td>
</tr>
<tr>
<td>1 - Government owned</td>
</tr>
<tr>
<td>2 - Not-for-profit</td>
</tr>
<tr>
<td>3 - For-profit</td>
</tr>
<tr>
<td>Hospital teaching status, %</td>
</tr>
<tr>
<td>1 - Major teaching</td>
</tr>
<tr>
<td>2 - Minor teaching</td>
</tr>
<tr>
<td>3 - Non-teaching</td>
</tr>
<tr>
<td>Rurality, %</td>
</tr>
<tr>
<td>Metropolitan</td>
</tr>
<tr>
<td>Micropolitan</td>
</tr>
<tr>
<td>Rural</td>
</tr>
<tr>
<td>Health system affiliation, %</td>
</tr>
<tr>
<td>Any accreditation, %</td>
</tr>
<tr>
<td>Professional network participation, %</td>
</tr>
</tbody>
</table>
Both of the full CCDS adopters and non-full CCDS adopters were more likely to be medium size (60.6% and 58.6% respectively), not-for-profit (74.9% and 70.2% respectively), metropolitan (82.9% and 69.9% respectively), with the majority of hospitals located in Southern states (38.3% and 33.6% respectively). Both groups were comparable in terms of having emergency departments. The full CCDS adopters were more likely to be part of a health system (78.8%), be accredited by a major hospital accrediting body (97%), be a member of the American Hospital Association (90.7%), located in a state that has expanded its Medicaid program eligibility under the Affordable Care Act (35.9%). By teaching status, the full CCDS adopters’ group was dominated by minor teaching hospitals (47.5%), while non-teaching hospitals (50.0%) comprised half of all non-full CCDS adopters. The non-full CCDS adopters performed worse compared to full CCDS adopters on both acute stroke mortality (14.9% v. 14.7% respectively) and readmission (12.7% v. 12.5% respectively) rates. This difference is statistically significant at 99% level of confidence (p<0.001). Other analytic sample hospitals’
characteristics are in line with the previously reported data on the EHRs adoption. The mean incentive to adopt CCDS was lower for full CCDS adopters (1.3%) compared to non-full CCDS adopters (1.6%). As per Section 3.3., the incentive to adopt CCDS represents the share (percentage) of predicted Medicare EHRs incentive payments scaled to hospital’s predicted total operating costs. The main assumption of this study that with higher incentive to adopt CCDS hospitals are more likely to adopt CCDS is not supported by data. The implications of this finding are discussed in detail in Section 4.4.

4.1.2. Description of CCDS Adoption

The annual change in the rate of CCDS adoption is reported in Figure 4.1. There is a clear annual increase in percentage of hospitals that were full CCDS adopters among the 2013-2017 AHA IT Survey respondents.

![Figure 4.1. CCDS Adoption by Year among U.S. non-federal acute hospitals](source: 2013-2017 AHA IT Survey)
4.1.3. Description of Acute Stroke Mortality and Readmissions

Acute Stroke Mortality

The annual change in mean acute stroke mortality rate among full CCDS adopters and non-full CCDS adopters is reported in Figure 4.2. There is a clear decreasing trend in annual acute stroke mortality rates from 15.4% in 2013 to 14.2% in 2017 among full CCDS adopters, and from 15.3% in 2013 to 14.4% among non-full CCDS adopters. This decreasing trend corresponds to the national long-term trend in acute stroke mortality rate, which was linked to improvements in care management, increased access to effective drugs, as well as to increase in timely brain imaging (Benjamin et al., 2017).

From Figure 4.2 it is evident that for the full CCDS adopters the decrease was more pronounced (steeper line) than for non-full CCDS adopters.
The pre-2013 data on acute stroke mortality and readmission rates are not available from Hospital Compare database, which prohibits exploration of the differences in these measures between full CCDS adopters and non-full CCDS adopters.

**Acute Stroke Readmissions**

The annual change in mean acute stroke readmission rate among full CCDS adopters and non-full CCDS adopters is reported in Figure 4.3. There is a clear decreasing trend in annual acute stroke readmission rates from 13.4% in 2013 to 11.9% in 2017 among full CCDS adopters, and from 13.2% in 2013 to 11.9% among non-full CCDS adopters. This decreasing trend corresponds to the national long-term trend in acute stroke readmission rate.
Section 4.2. IV Regression Analysis

This section reports the first stage regression results.

4.2.1. First Stage Regression

The first stage regression predicts the adoption of CCDS using the incentive to adopt CCDS as an independent variable. The results of the first stage regression are reported in Table 4.2. The number of observations and clusters is different and less than the total sample size (N=7,933) because the sample is not balanced (not all years are present for each hospital).

Table 4.2. First Stage Regression Results.

<table>
<thead>
<tr>
<th>CCDS adoption</th>
<th>Mortality</th>
<th>Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>7,933</td>
<td>7,933</td>
</tr>
<tr>
<td>Number of clusters</td>
<td>2,331</td>
<td>2,331</td>
</tr>
<tr>
<td>The incentive to adopt CCDS, beta (SE)</td>
<td>-0.003 (0.008)</td>
<td>-0.003 (0.008)</td>
</tr>
<tr>
<td>Under-identification test, chi-squared (p-value)</td>
<td>0.18 (0.67)</td>
<td>0.18 (0.67)</td>
</tr>
<tr>
<td>Weak identification test, F statistic</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Note: Kleibergen-Paap rk LM statistic (chi-squared) is used for the under-identification test, and the Craig-Donald Wald F statistic is used for the weak identification test. SE – standard error.

From the results of the first stage regression, it is evident that the incentive to adopt CCDS is not fit to be used as an instrument for endogenous variable of CCDS adoption. First, the direction of the incentive to adopt CCDS (instrument) effect on the CCDS adoption (treatment) is negative for both acute stroke mortality (-0.003) and acute stroke readmissions (-0.003). This result indicates that with the increase in the incentive to adopt CCDS less hospitals adopted full CCDS. This effectively defies the assumption that the incentive to adopt CCDS
‘caused’ hospitals to adopt CCDS. Second, the instrument fails to provide ‘strong’ predicting power. Conservatively, for an instrument to pass ‘weak’ instrument test, where null hypothesis (H0) is that the equation weakly identified, it should report the F-statistic of 10 and over (Staiger & Stock, 1997). The size of the weak identification test statistic for both outcomes (F=0.3) is less than the conservative threshold that proves the incentive to adopt CCDS to be a ‘weak’ instrument.

At this step there is no practical reason to proceed with the full two-stage least squares regression to explore the effect of full CCDS adoption on acute stroke inpatient care outcomes, because the specified instrument turned out to be not valid for estimating the effects under question. Due to having an inadequate 2SLS regression model, an alternative analysis using ordinary least-squares (OLS) regression was conducted. In the following section the provisions of alternative analysis are described along with its results.

**Section 4.3. Alternative Analysis**

Several concerns about the limited findings of the planned analysis led to few adjustments in the analytical strategy. In this section the rationale for using fixed effects (FE) OLS regression to perform alternative analysis are described as well as the results of the OLS regression analysis.

**4.3.1. Rationale for Using FE OLS Regression**

As per subsection 3.4.1, assessing the relationship between the adoption of CCDS and acute stroke outcomes using OLS regression may cause biased estimates due to possible omitted variable bias. Such bias may be caused by endogenous CCDS adoption variable, because when adopting CCDS hospitals
may decide to invest in purchasing and implementing health IT in the hospital’s workflow in order to potentially gain not only improvements in quality of patient care, but also, and may be more of so, to profit financially though the improvements in non-clinical operations.

The FE OLS regression model is specified as follows:

\[ STROKE_{it} = \beta_0 + \beta_1 \text{CCDS}_{it} + \beta_2 X_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \]  

\( STROKE_{it} \) – hospital level acute stroke mortality or readmission rate; \( \beta_0 \) – intercept term; \( \text{CCDS}_{it} \) – indicator for hospital’s CCDS adoption; \( X_{it} \) – hospital-level covariates; \( \gamma \) - hospital fixed effects that capture time-invariant hospital characteristics; \( \lambda \) - year fixed effects that capture time-dependent changes common to all hospitals over the studied period; \( \varepsilon_{it} \) – error term; \( i \) – index for an individual hospital; \( t \) – index for the year. Standard errors are clustered at the hospital level. The results of the OLS regression are reported in the next subsection.

### 4.3.2. FE OLS Regression

Table 4.3 reports the estimates from the FE OLS regression results. The FE OLS regression model results indicate that the adoption of full CCDS is negatively associated with acute stroke mortality rate (-0.015), but this relationship is not statistically significant at a 90% confidence level. The direction of this effect is as per the hypothesized one (H2), however, the effect size is not statistically significant as well it is very small (0.015 percentage point decrease in ASMR).
Table 4.3. FE OLS Regression Results.

<table>
<thead>
<tr>
<th>CCDS adoption</th>
<th>Mortality</th>
<th>Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCDS adoption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital size, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 - Small (&lt;=99)</td>
<td>-0.015 (0.04)</td>
<td>0.068 (0.03)***</td>
</tr>
<tr>
<td>2 - Medium (100-399)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 - Large (&gt;=400)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital ownership, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 - Government-owned</td>
<td>Ref.</td>
<td>Ref.</td>
</tr>
<tr>
<td>2 - Not-for-profit</td>
<td>-0.120 (0.18)</td>
<td>0.036 (0.11)</td>
</tr>
<tr>
<td>3 - For-profit</td>
<td>-0.124 (0.22)</td>
<td>-0.015 (0.16)</td>
</tr>
<tr>
<td>Hospital teaching status, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 - Major teaching</td>
<td>Ref.</td>
<td>Ref.</td>
</tr>
<tr>
<td>2 - Minor teaching</td>
<td>0.249 (0.20)</td>
<td>-0.193 (0.18)</td>
</tr>
<tr>
<td>3 - Non-teaching</td>
<td>0.341 (0.21)</td>
<td>-0.147 (0.19)</td>
</tr>
<tr>
<td>Rurality, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metropolitan</td>
<td>0.124 (0.23)</td>
<td>-0.113 (0.16)</td>
</tr>
<tr>
<td>Rural</td>
<td>0.101 (0.32)</td>
<td>-0.160 (0.18)</td>
</tr>
<tr>
<td>Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td>Ref.</td>
<td>Ref.</td>
</tr>
<tr>
<td>2014</td>
<td>-0.457 (0.03)***</td>
<td>-0.538 (0.02)***</td>
</tr>
<tr>
<td>2015</td>
<td>-0.368 (0.05)***</td>
<td>-0.683 (0.04)***</td>
</tr>
<tr>
<td>2016</td>
<td>-0.749 (0.06)***</td>
<td>-1.023 (0.04)***</td>
</tr>
<tr>
<td>2017</td>
<td>-1.015 (0.07)***</td>
<td>-1.324 (0.04)***</td>
</tr>
<tr>
<td>Health system affiliation</td>
<td>0.103 (0.11)</td>
<td>0.096 (0.09)</td>
</tr>
<tr>
<td>Any accreditation</td>
<td>0.248 (0.19)</td>
<td>0.332 (0.18)*</td>
</tr>
<tr>
<td>Professional network participation</td>
<td>0.051 (0.15)</td>
<td>0.013 (0.13)</td>
</tr>
<tr>
<td>Has emergency department</td>
<td>-0.197 (0.14)</td>
<td>0.138 (0.11)</td>
</tr>
<tr>
<td>Medicaid Expansion State</td>
<td>-0.064 (0.06)</td>
<td>-0.093 (0.04)**</td>
</tr>
<tr>
<td>Intercept</td>
<td>15.165 (0.39)***</td>
<td>13.0 (0.36)***</td>
</tr>
</tbody>
</table>

Number of observations | 7,933 | 7,933 |
Number of groups       | 2,331 | 2,331 |
F-test                 | 37.11 | 101.09 |
R-squared              | 0.14  | 0.36  |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The model shows that full CCDS adoption increases the acute stroke readmission rate by 0.068 percentage points. The effect size is larger than for
ASMR and it is statistically significant. However, the direction of the full CCDS adoption on ASRR is negative, which contradicts the hypothesized effect. The observable hospital characteristics do not influence either of the outcomes. There is a consistent and statistically significant year effect on both outcomes, which may be explained by the historical negative trend in ASMR and ASRR observed in Figures 4.2 and 4.3.

The next chapter discusses the major findings of the study, its limitations, and its implications. It also puts forth future research and conclusions.

**Chapter 5. Discussion and Conclusion**

This dissertation has attempted to answer the research question of whether the adoption of CCDS functionalities affected the quality of hospital care among acute stroke patients by applying the SPO quality framework. This section discusses the major findings of the analyses, then outlines the theoretical, methodological, and practical implications of the study.

**Section 5.1. Major Findings**

**2SLS Model Failure**

The originally specified 2SLS regression model failed to answer the research question because the specified instrument proved to be an invalid (‘weak’) instrument. It was noted that finding a valid instrument is a very difficult task, which is shown in Section 4.2. The MU policy provided financial incentives to hospitals adopting health IT, which included CCDS, under the Medicare EHRs Incentive Program, which has been shown to increase the adoption of CCDS.
Alternative, FE OLS regression analysis was performed to answer the research question. Its results indicate that the full CCDS adoption increases acute stroke readmission rate by 0.068 percentage points. The effect size is larger than for ASMR and it is statistically significant. However, the direction of the full CCDS adoption on ASRR is negative, that contradicts the hypothesized effect.

Section 5.2. Limitations

This dissertation has several limitations to its theoretical approach, measurement strategy, model specification, and external validity.

5.2.1. Conceptual Model

The study rests on a couple of theoretical assumptions related to the use of CCDS by clinicians, to that of CCDS's improves adherence to clinical guidelines.

CCDS Use by Clinicians

In linking the CCDS adoption and improvements in quality of care, the theoretical framework that underlines this study assumes that physicians, nurses, and other care providers do use CDSS in the process of delivering care for acute stroke patients. While it is not possible to confirm whether clinicians have used CCDS while treating acute stroke inpatients, this study utilized the approach on measuring health IT adoption previously used (Mitchell, J., Probst J Fau - Brock-Martin, et al., 2014).

Adoption of CCDS Improves Adherence to Clinical Guidelines

While it has been shown that adoption of CCDS increased adherence to clinical guidelines contingent on high level of use of the CCDS solutions, this adherence
is not uniform in all cases. Evidence suggests that CCDS recommendations are used by clinicians selectively. The CCDS is more likely to be used in cases that pose more uncertainty for the provider in making the right clinical decision. Paramedics in the United Kingdom who used CCDS reported choosing to use it only with patients whom they had identified as 'suitable', rather than with all those who were 'eligible' (Porter et al., 2018). These paramedics developed their own approach to using CCDS, based on their own judgement and experience. For example, they used it only with patients with whom they were uncertain about the best course of action. Although they were confident in their own decision-making ability, which was based on past training, experience, and inherent judgement, not all paramedics were equally confident in performing at the same level. Another study reports similar results for nurses caring for older patients (Dowding et al., 2009). These unanticipated uses can increase variation in practice and the number of errors associated with clinical practice, contrary to the aim of introducing CDSS.

Although these examples are not related to acute stroke care, they illustrate how the provider’s judgement guides the use of CCDS in clinical settings. Specifically, the most effect of CCDS adoption and use on acute stroke care outcomes can be realized for hospitals that see more complex patients, as well as for care teams with less experienced clinicians. This analysis shows that indeed full CCDS adoption is associated with decrease in acute stroke mortality rate in major teaching hospitals (-0.221, p<0.05). Acute stroke readmission rate is also negatively associated with full CCDS adoption in major teaching hospitals.
(-0.049, p=0.59), although not statistically significant (Table 4.4). However, it is not clear from the model whether the decrease in ASMR associated with the adoption of full CCDS in major teaching hospitals was is because CCDS recommendations were more likely to be used in major teaching hospitals with their higher case mix index (more complex patients), or because in major teaching hospitals acute stroke patients are more likely to be seen by clinicians in training (e.g., interns and residents), who has less clinical experience compared to physicians who completed their training (Young et al., 2011).

Table 4.4. FE OLS Model Sensitivity Test Results.

<table>
<thead>
<tr>
<th>CCDS adoption</th>
<th>(1) Mortality</th>
<th>(1) Readmissions</th>
<th>(2) Mortality</th>
<th>(2) Readmissions</th>
<th>(3) Mortality</th>
<th>(3) Readmissions</th>
<th>(4) Mortality</th>
<th>(4) Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCDS adoption</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCDS adoption for major teaching hospitals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital teaching status, %</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 - Major teaching</td>
<td>0.294 (0.20)</td>
<td>-0.193 (0.18)</td>
<td>0.109 (0.21)</td>
<td>-0.224 (0.20)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 - Minor teaching</td>
<td>0.341 (0.21)</td>
<td>-0.147 (0.19)</td>
<td>0.205 (0.22)</td>
<td>-0.178 (0.20)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 - Non-teaching</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Any accreditation</td>
<td>0.248 (0.19)</td>
<td>0.332 (0.18)*</td>
<td>0.250 (0.19)</td>
<td>0.332 (0.18)*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional network participation</td>
<td>0.051 (0.15)</td>
<td>0.013 (0.13)</td>
<td>0.048 (0.15)</td>
<td>0.012 (0.13)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has emergency department</td>
<td>-0.197 (0.14)</td>
<td>0.138 (0.11)</td>
<td>-0.196 (0.14)</td>
<td>0.138 (0.11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>15.161 (0.39)**</td>
<td>13.0 (0.36)***</td>
<td>15.281 (0.40)**</td>
<td>13.0 (0.37)***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>7,933</td>
<td>7,933</td>
<td>7,933</td>
<td>7,933</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of groups</td>
<td>2,331</td>
<td>2,331</td>
<td>2,331</td>
<td>2,331</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-test</td>
<td>37.11</td>
<td>101.09</td>
<td>35.61</td>
<td>95.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.14</td>
<td>0.36</td>
<td>0.14</td>
<td>0.36</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
5.2.2. Design

This dissertation assessed CCDS adoption and acute stroke inpatient care outcomes between 2013 and 2017. This period corresponds with the later stages of the MU policy (Medicare and Medicaid EHRs Incentive Program), when most non-federal acute care hospitals had already adopted EHRs, including CCDS. Hence it is more likely that increase in CCDS adoption in 2013-2017 has smaller magnitude compared to that of pre-2013 period (early adopters). This may underestimate the observed effect of CCDS adoption on acute stroke care outcomes.

Health IT adoption is a complex organizational process that may last way after the purchase and initial deployment of the EHRs. This period of post-adoption adjustment varies and depends on hospital’s size (more beds require more staff, which translates into more training on health IT use), the level of maturity in hospital’s workflows (the higher level of process standardization, the faster and more successful is transition to computerized clinical and non-clinical workflows), access to IT staff (support and fine tuning of health IT), and resistance from clinical staff. Therefore, with each additional year since the initial CCDS adoption and continuous use (CCDS use tenure) hospitals are able to fine tune their CCDS-related processes, adjust CCDS for their individual workflows, with increased productivity of CCDS use, which translates in better clinical outcomes.

5.2.3. Measurement

Next the limitations in measuring the treatment, outcome and omitted variables are discussed.
**Treatment Specification**

This study solely relies on the AHA IT Survey in measuring CCDS adoption, the choice of which assumes that hospitals truthfully responded to the survey, that they indeed used CCDS after adoption to improve adherence to clinical guidelines in providing care to acute stroke inpatients.

The CCDS identification for this study was performed according to previously used methods and it has been shown to be valid and representative of real adoption of CCDS functionalities among hospitals. It is possible to improve the identification of CCDS adoption by using the MU attestation data, which is publicly available from the CMS website. However, the identification of CCDS adoption using the MU attestation data provides a limited view of real CCDS adoption because of the way it reports CCDS adoption (see Table 5.1). The MU attestation data on CCDS adoption is limited to the following two measures: (1) implementing either one (Stage 1) or five (Stage 2-3) clinical decisions support rules, and (2) implementing drug-drug and drug-allergy interaction rules. Both MU attestation measures only partially cover the types of the six main CCDS functionalities available in EHRs. Moreover, the MU attestation requires only Yes/No response from a hospital, while the AHA IT Survey provides answer choices to capture several levels of CCDS adoption – from “Fully implemented across all clinical unites” to “Not in place and not considering implementing” (see Table 3.2).

Table 5.1. Comparing CCDS Adoption Measures in the AHA IT Survey and the MU Stages 2-3 Attestation Dataset.

<table>
<thead>
<tr>
<th></th>
<th>MU Attestation Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

68
### AHA IT Survey

(6 response choices)

<table>
<thead>
<tr>
<th>Clinical guidelines</th>
<th>Implement five clinical decision support rules (Yes/No)</th>
<th>Drug-drug and drug-allergy interaction rules (Yes/No)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clinical reminders</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Drug-allergy alerts</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Drug-drug interaction alerts</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Drug-lab interaction alerts</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Drug dosing support</td>
<td>+</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** “+” denotes that the CCDS functions from AHA IT Survey correspond to the MU Attestation data.

---

**Survey non-response**

The use of administrative (secondary) data sources may cause limitations in data like missing data. However, all the data sources used in this study are commonly used in health services research.

**Outcome Specification**

It is possible that the model for assessing the care quality in terms of hospital mortality and readmission rates does not account for the effect of patient safety practices in the hospital, that may influence both the mortality and readmissions rates.

A second limitation was inability to control for patient characteristics. Without patient data, the study cannot determine the true appropriateness of individual acute stroke therapies. However, use of the nationally validated risk-adjusted measures of acute stroke readmissions and mortality from the Hospital Compare database warrants that these measures consider individual patient characteristics that are directly related to the quality outcomes.
Omitted Variables

It is not possible to completely rule out the effect of historical trends on both the treatment and outcomes. Between 2013 and 2017 the nation saw the rollout of major healthcare policies, including the states’ Medicaid Expansion (since 2011) and introduction of the Hospital Readmission Reduction Program (HRRP) in 2012. In 2012 the HRRP was rolled out nationally to incentivize hospitals to decrease readmissions for major health conditions, including acute myocardial infarction, heart failure, and pneumonia (Mcllvennan, Eapen, & Allen, 2015). Acute stroke was not in the list of the priority health conditions to be monitored under the HRRP. However, it is possible that hospital’s participation in the HRRP could have improved overall hospital’s care structures and processes that had a positive spillover effect on acute stroke readmissions as well. To account for secular trends, the analytic model included the indicator for hospital’s operating in a Medicaid Expansion state, as well as year fixed effects, that account for hospital-invariant characteristics.

CCDS Vendor Bias

Different CCDS systems from different EHRs vendors may have varying types and levels of capabilities, features, or effectiveness (performance). For instance, leading to potential bias in the estimated effect of CCDS adoption on stroke care quality. For example, there are significant associations between specific vendors and the level of hospital performance for the MU criteria, that are not CCDS relevant. Epic was associated with significantly higher performance on 5 of the 6 criteria; relationships for other vendors were mixed, with some associated with
significantly worse performance on multiple criteria. EHR vendor choice accounted for between 7% and 34% of performance variation across the 6 criteria (Holmgren, J., Adler-Milstein, & McCullough, 2018b). The dissertation analyses do not account for the CCDS vendor in hospital implementation, which may introduce this CCDS vendor bias. However, the CCDS adoption measure using in the dissertation accounts for potential CCDS vendor bias by identifying specific CCDS functions that are relevant to provision of effective care, that is expected to improve acute stroke care outcomes.

5.2.4. FE OLS Model Specification

While the use of 2SLS is ideal, finding a strong instrument can be difficult, and invalid analytic approaches should be avoided. If 2SLS is not feasible, one option is to estimate an association between CCDS adoption and the outcomes using OLS. The OLS model does not remedy endogeneity of the treatment, which can lead to biased estimates of the effect on acute stroke mortality and readmissions. However, using panel data fixed effects OLS model allows to control for unobserved heterogeneity and time-invariant confounding factors, which can improve the estimation of the causal effect of interest. Fixed effects (FE) models estimate the effects of changes within hospitals over time, by including hospital fixed effects in the regression model. This helps to control for time-invariant confounding factors that are specific to each hospital, including those that may be correlated with both the treatment (CCDS adoption) and the outcomes (acute stroke mortality and readmissions).
Random effects (RE) OLS and pooled OLS (cross sections) models were also considered for the alternative analyses. The RE OLS model was not pursued, because it assumes that hospital-specific effects are uncorrelated with the CCDS adoption, which is not the case due to endogeneity of the CCDS adoption (Clark & Linzer, 2015).

Next the model efficiency was assessed for pooled OLS and FE OLS models using Bayesian information criterion (BIC) and Akaike information criterion (AIC) (Neath & Cavanaugh, 2012). The pooled OLS model (AIC=30,748, BIC=30,881 on ASMR; AIC=23,406, BIC=23,538 on ASSR) was shown to be inferior compared to FE OLS model (AIC=19,594, BIC=19,720 on ASMR; AIC=13,792, BIC=13,917 on ASSR).

A major limitation of using the FE OLS regression model is inability to extrapolate the observed association of CCDS adoption and acute stroke outcomes to the general population of hospitals. This is because the FE OLS model estimates using variation within the sample. Despite its promise for controlling unobserved confounders, using FE OLS model does not guarantee correct identification of causal effect. Hence, the associations identified in this study are not to be interpreted as causal. Nevertheless, the study results provide additional evidence on the complex nature of the relationship between CCDS adoption and quality of acute stroke inpatient care.

5.2.5. External Validity

The findings of this study are limited to acute stroke outcomes among Medicare beneficiaries treated in hospitals that were late CCDS adopters and which chose
to respond to the AHA IT Survey. This limits the generalizability of the results to other non-federal acute care hospitals.

Section 5.3. Implications

The analysis was not performed according to the initial design and failed to answer the research question. However, the work performed under this dissertation revealed several implications both for the practice and future research in the field of CCDS adoption and its effects on acute stroke care outcomes.

5.2.1. Theoretical Implications

This dissertation employed the SPO framework, which is shown to be relevant in studying the quality of hospital care. The conceptual model for this study uses key hospital characteristics, i.e. accreditation status and teaching status, having emergency department, as the measures of care structure, while hospital mortality and readmissions are specified as the outcomes of care. Apparently, the conceptual model may benefit from adding the stroke care process measures. For example, Hospital Compare annually reports two measures of stroke process quality – time-to-brain imaging (TBI) and time-to-thrombolysis (TTL), that capture the level of timely hospital care for acute stroke patients. However, these measures are missing for most of the analytic sample (72% for TBI, 82% for TTL).

5.2.2. Methodological Implications

This dissertation attempted to assess the causal relationship between the adoption of CCDS in hospitals and acute stroke hospital care outcomes. The
2SLS model was used to study this relationship due to endogeneity of the CCDS adoption. Because of the failure of 2SLS model, an alternative analytic approach was chosen to assess the relationship using an OLS regression model. The failure of the 2SLS model and use of OLS model in this case has certain methodological implications.

**2SLS Model**

The instrument (incentive to adopt CCDS) failed to satisfy the excludability requirement by being proved as a ‘weak’ instrument. This confirms that the size of financial incentives from participating in the Medicare EHRs Incentive Program (the incentive to adopt CCDS) was not sufficient for hospitals to adopt CCDS functionalities. The instrument is calculated based on the predicted Medicare EHRs incentive payments, which does not account for the Medicaid EHRs incentive payments as well as the Medicare EHRs payment adjustments (penalties). Such specification may be the cause of underestimation of the instrument’s effect on the treatment, that may be evidenced by the observed ‘weak’ instrument and the negative effect of the incentive to adopt CCDS on the CCDS adoption.

Alternative instruments, that are strongly correlated with the endogenous variable, can be sought to correctly specify the 2SLS model. Such instruments may be found among other concurrent healthcare policies, factors that drove local hospital market competitions, or health IT infrastructures and resources.
Adoption of CCDS may have been influenced by the changes in regulations other than the MU policy. Between 2012 and 2014 the U.S. hospitals were subject to new three major Medicare value-based payment programs launched by the Affordable Care Act (2010): the Hospital Readmissions Reduction Program (HRRP), Hospital Value-Based Purchasing Program (HVBP) and Hospital-Acquired Condition Reduction Program (HAC) (CMS, 2022b). The ACA also launched accountable care organizations (ACOs) to become a major type of Medicare providers (Blumenthal & Abrams, 2020). All these programs provided financial incentives for hospitals to modify and optimize their workflows, which may increase the likelihood of CCDS adoption. Either of these policies as well as a compound measure of dependency on public funding (e.g., Medicare share) could be considered for instrumenting the CCDS adoption.

Local market conditions or competition among healthcare providers may influence the adoption of CCDS as well. Hospitals’ and health systems’ transition to ACOs could have contributed to increased competition in local markets, which in turn may be associated with a higher rate of CCDS adoption (Yeager, Zhang, & Diana, 2015). For instance, indicators such as the number of hospitals or healthcare providers in a local market, market concentration, or competition among providers, could potentially serve as instruments for CCDS adoption.

Technological advancements or changes in the availability of IT resources may also affect the adoption of CCDS. For instance, indicators such as the availability of IT staff or other technology infrastructure at the institutional or regional level could potentially serve as instruments for CCDS adoption.
Identifying suitable alternative instruments for the adoption of CCDS depends on the availability of relevant data.

**OLS Model**

The OLS model does not remedy endogeneity of the treatment, which can lead to biased estimates of the effect on acute stroke mortality. Moreover, such estimates are not robust for assumptions about the model, which may association. Nevertheless, the FE OLS model provides a reliable statistical approach in assessing the link between CCDS adoption and acute stroke outcomes that controls for endogeneity caused by time-invariant unobserved hospital characteristics. After finding strong instrument and running 2SLS model, it will be possible to test for endogeneity using Hausman specification test (Hausman, 1978). This information could be valuable for researchers and practitioners in the field of health services research and econometrics.

**5.2.3. CCDS Implications**

This study has shown that the adoption of full CCDS is associated with an increase in acute stroke readmission rates. Even though this result is in line with the results of similar study of the CCDS adoption effect on heart failure mortality (Mitchell, Jordan, Revere, et al., 2014), given the methodological limitations of this dissertation, this association must be taken with caution. It is possible that the increase in acute stroke readmissions is driven by more complex acute stroke cases treated in large hospitals, which were predominant among AHA IT respondents (21.2%) compared to non-responders (11.3%). The analyses with more robust methodology with representative hospital sample may provide better
estimates of true impact of CCDS adoption on acute stroke readmissions and mortality.

5.2.4. Management and Policy Implications

The results of this study again underline the importance of careful use of health IT to improve care quality. It is particularly important today, when the healthcare industry is adopting new health IT run on tools using machine learning (ML) and artificial intelligence (AI) models. Adoption of AI and ML tools in healthcare has been shown to suffer from issues similar to those with CCDS, including developing, testing and validating the AI and ML models using single institutional data, the lack of interpretability of AI models ('black box' design based neural network models), and low trust in AI modelling results with high false-positive rates (Luk, Ford, Phillips, & Kalet, 2022). This study results imply that health administrators and decision-makers may consider wider adoption (and use) of EHRs or CCDS with comprehensive set of multiple CCDS functionalities (full CCDS) in emergency departments and clinical settings with high turnover of complex patients that need urgent care, especially for wards with less experienced clinical staff. CMS should consider developing and introducing more comprehensive measures of acute stroke care (besides acute stroke mortality and readmissions) with their subsequent public reporting. Using stroke patient registry data for public reporting could be a viable alternative (Siegler et al., 2013; Tascione et al., 2022; Wildenschild et al., 2014).
Section 5.4. Future Research

Even though the results of this dissertation are inconclusive, this work informs further research of the adoption and implementation of CCDS, including those that employ machine learning and artificial intelligence, by expanding the framework for assessing health IT adoption using administrative data, and opening avenues for enhancing measures of acute stroke care quality.

Section 5.5. Conclusion

The adoption of IT in healthcare settings has occurred rapidly. This analysis contributes to the understanding of how hospital IT adoption and quality of care are related. Hospital administrators should exercise caution in putting their expectations from CCDS performance in terms of hospital care quality. This study adds to the evidence that CDSS may be associated with better acute stroke quality of care indicators within hospitals. Relevant to health care policy, this study supports the notion of using the Meaningful Use Criteria to improve the adoption of CCDS. CDSS can be an important structural tool to promote process quality by providing clinical guidelines and reminders to clinicians.
### Appendix

Table A1. Electronic Functions Required for Hospital Adoption of Basic or Comprehensive EHRs (ONC, 2016).

<table>
<thead>
<tr>
<th>EHR Functions Required</th>
<th>Basic EHR without Clinician Notes</th>
<th>Basic EHR with Clinician Notes</th>
<th>Comprehensive EHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronic Clinical Information</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Patient demographics</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Physician notes</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Nursing assessments</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Problem lists</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Medication lists</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Discharge summaries</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Advance directives</td>
<td>★</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computerized Provider Order Entry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lab reports</td>
<td>★</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiology tests</td>
<td>★</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medications</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>Consultation requests</td>
<td>★</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nursing orders</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Results Management</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>View lab reports</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>View radiology reports</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>View radiology images</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>View diagnostic test results</td>
<td>★</td>
<td>★</td>
<td>★</td>
</tr>
<tr>
<td>View diagnostic test images</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>View consultant report</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision Support</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clinical guidelines</td>
<td></td>
<td></td>
<td>★</td>
</tr>
<tr>
<td>Clinical reminders</td>
<td></td>
<td></td>
<td>★</td>
</tr>
<tr>
<td>Drug allergy results</td>
<td></td>
<td></td>
<td>★</td>
</tr>
<tr>
<td>Drug-drug interactions</td>
<td></td>
<td></td>
<td>★</td>
</tr>
<tr>
<td>Drug-lab interactions</td>
<td></td>
<td></td>
<td>★</td>
</tr>
<tr>
<td>Drug dosing support</td>
<td></td>
<td></td>
<td>★</td>
</tr>
</tbody>
</table>

NOTES: Basic EHR adoption requires each function to be implemented in at least one clinical unit, and Comprehensive EHR adoption requires each function to be implemented in all clinical units.
Table A2. Comparison of 2013-2017 AHA IT Survey Responders to Non-responders (N=12,178).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Respondents</th>
<th>Non respondents</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall, count (%)</td>
<td>7,933 (65.1)</td>
<td>4,245 (34.9)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Hospital size, %</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 - Small (&lt;=99)</td>
<td>19.0</td>
<td>27.7</td>
<td></td>
</tr>
<tr>
<td>2 - Medium (100-399)</td>
<td>59.8</td>
<td>61.0</td>
<td></td>
</tr>
<tr>
<td>3 - Large (&gt;=400)</td>
<td>21.2</td>
<td>11.3</td>
<td></td>
</tr>
<tr>
<td>Hospital ownership, %</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>1 - Government owned</td>
<td>13.1</td>
<td>12.1</td>
<td></td>
</tr>
<tr>
<td>2 - Not-for-profit</td>
<td>73.1</td>
<td>59.8</td>
<td></td>
</tr>
<tr>
<td>3 - For-profit</td>
<td>13.8</td>
<td>28.1</td>
<td></td>
</tr>
<tr>
<td>Hospital teaching status, %</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>1 - Major teaching</td>
<td>11.5</td>
<td>5.0</td>
<td></td>
</tr>
<tr>
<td>2 - Minor teaching</td>
<td>45.4</td>
<td>40.3</td>
<td></td>
</tr>
<tr>
<td>3 - Non-teaching</td>
<td>43.1</td>
<td>54.7</td>
<td></td>
</tr>
<tr>
<td>Rurality, %</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Metropolitan</td>
<td>78.0</td>
<td>71.0</td>
<td></td>
</tr>
<tr>
<td>Micropolitan</td>
<td>17.5</td>
<td>19.6</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>4.5</td>
<td>9.5</td>
<td></td>
</tr>
<tr>
<td>Health system affiliation, %</td>
<td>72.7</td>
<td>76.6</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Any accreditation, %</td>
<td>95.7</td>
<td>91.8</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Professional network participation, %</td>
<td>89.7</td>
<td>81.0</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Has emergency department, %</td>
<td>98.1</td>
<td>98.5</td>
<td>0.14</td>
</tr>
<tr>
<td>Medicaid Expansion state, %</td>
<td>31.6</td>
<td>28.3</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>U.S. Census Region, %</td>
<td></td>
<td></td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Northeast</td>
<td>18.3</td>
<td>15.7</td>
<td></td>
</tr>
<tr>
<td>Midwest</td>
<td>29.0</td>
<td>16.7</td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>36.5</td>
<td>44.1</td>
<td></td>
</tr>
<tr>
<td>West</td>
<td>16.2</td>
<td>23.5</td>
<td></td>
</tr>
<tr>
<td>Acute stroke mortality rate, mean % (SD)</td>
<td>14.8 (1.8)</td>
<td>14.8 (1.6)</td>
<td>0.029</td>
</tr>
<tr>
<td>Acute stroke readmissions, mean % (SD)</td>
<td>12.6 (1.2)</td>
<td>12.6 (1.1)</td>
<td>0.48</td>
</tr>
<tr>
<td>Incentive to adopt CCDS, mean % (SD)</td>
<td>1.4 (1.1)</td>
<td>1.8 (1.7)</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Note: * includes Joint Commission, CMS Medicare, DNV, CIHQ, ACHC-HFAP, CARF-Rehab accreditation and/or certification. Groups compared using Pearson’s chi-squared (categorical and binary) and ANOVA (continuous) tests.


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