PERFORMANCE OF ACCOUNTABLE CARE ORGANIZATIONS: HEALTH INFORMATION TECHNOLOGY AND QUALITY-EFFICIENCY TRADEOFFS

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ABSTRACT

Accountable Care Organizations (ACO) were established under the Affordable Care Act to address systemic problems afflicting the US healthcare system related to high costs and poor quality issues. ACOs represent groups of healthcare providers that are responsible for coordinating patient care with the goal of improving health outcomes for their patient population. To develop a better understanding of the role of health information technology (IT) in a value-based care environment, we study whether (a) there are potential tradeoffs between ACO efficiency and quality, and (b) effective use of health IT enables ACOs to balance competing efficiency and quality objectives. We test our models with a nationwide sample of ACO data using a two-stage approach based on data envelopment analysis and econometric estimation. We observe that efficient ACOs do not make tradeoffs with respect to healthcare quality, compared to inefficient ACOs. Further, we observe that hospitals that participated in ACOs, and used IT effectively for care coordination with other providers, exhibit a positive association between efficiency and quality. ACOs with higher levels of meaningful use achievement of health IT demonstrate better patient health outcomes because of greater information integration with other care providers. Our findings imply that value-based incentives alone are not sufficient to resolve tradeoffs between healthcare quality and efficiency, and healthcare policy needs to incorporate appropriate incentives to foster effective IT use for health information sharing and care coordination between healthcare providers.

Keywords: Accountable care organization, health information technology, data envelopment analysis, quality, efficiency, meaningful use.

1. Introduction

The U.S. healthcare system is characterized by a fragmented delivery model with misaligned financial incentives that lead to excess expenditures, low patient satisfaction, poor care quality, and inefficient care delivery (Nattinger et al. 2018). To address these concerns, Section 3022 of the Patient Protection and Affordable Care Act (also known as ACA) authorized the Centers for Medicare and Medicaid (CMS) to establish Medicare Accountable Care Organizations (ACO), with the goal of providing better patient care, improving population health, and lowering health expenditures (McClellan et al. 2010).

An ACO represents a group of physician practices, hospitals, health systems (or networks), and other healthcare providers, created to provide coordinated, patient-centric care to assigned beneficiaries under one umbrella. As part of the movement towards value-based healthcare, CMS requires ACOs to deliver cost-effective and high-quality healthcare through financial incentives based on the dual objectives of *efficiency* and *care quality*.[1] ACO participants share in a portion of the cost savings if the focal ACO reduces expenditures sufficiently below a cost benchmark and achieves a minimum quality threshold at the same time (McWilliams et al. 2016).

The healthcare literature has documented tradeoffs when healthcare providers aim to balance competing performance objectives with respect to the efficiency and quality of care delivery (Jha et al. 2009, Senot et al. 2016).[2] These tradeoffs occur when decision-makers try to allocate limited resources to achieve multiple, often conflicting, organizational objectives, that run counter to the goals of the ACO program (Newhouse 1970). While prior research on health IT primarily focus on its impact on individual measures of hospital performance in a FFS environment (Agha 2014, Adjerid et al. 2018, Bao et al. 2020, Bardhan et al. 2015), they ignored the inter-dependencies between different performance measures that can lead to a limited understanding of the overall impact of health IT on organizational performance. There exists a

[1] Value-based care is a type of healthcare model that pays providers based on patient health outcomes and cost savings, instead of fees solely based on the volume of services.
[2] The literature has defined *efficiency* based on how productively inputs are transformed into outputs, where health expenditures (costs associated with resources expended) are often treated as inputs and services provided are treated as outputs (Shreay et al. 2014).

significant void in the extant research on value-based care related to the impact of health IT on the ability of healthcare providers to balance quality-efficiency tradeoffs (Kumar et al. 2013). To the best of our knowledge, ours is one of the first studies to explore the tradeoffs involved in balancing competing organizational objectives in the context of value-based healthcare, and the impact of effective IT use on the strength of the association between ACO efficiency and quality.

Unlike other healthcare organizations, ACO participants practice and deliver healthcare under different incentive structures, which may affect the way in which they deploy and implement health IT systems. In a traditional fee for service (FFS) payment model, providers focus on practice efficiency because their payments are based mostly on the volume of services provided. On the other hand, ACOs have to strike the right balance between attaining quality and efficiency goals, because the magnitude of incentive payments are based on their ability to meet these dual objectives. For instance, providers are less likely to leverage health IT to advance care coordination in a FFS setting due to a lack of incentives to attain quality goals by reducing the volume of services, such as the number of tests provided (Brice et al. 2018, Kumar et al. 2013). However, ACO providers are more likely to use IT effectively to share patient health information and coordinate patient care across multiple providers, with a goal of informing care decisions to improve patient health outcomes and reduce the cost of patient care (Levinson 2019).

Second, ACO performance is evaluated based on overall patient outcomes across all entities that comprise an ACO. ACO participants share greater financial incentives and risk by being accountable for patient care across the entire episode of care (which may last up to one year for chronic diseases), which incentivizes participating entities to form a virtual healthcare organization to improve care coordination (Hagland 2018). Unlike traditional FFS payment models, the relationship between participating ACO providers changes from competition to collaboration, leading to greater inter-organizational information sharing and coordination of patient care. Further, to mitigate agency risks that may arise when participating entities act in their best interests (Adjerid et al. 2018), ACOs typically share a common IT infrastructure to integrate patient data across participants, share best practices, monitor care quality reporting across providers, and improve the overall transparency of care (Lowell 2018).

The unique characteristics of ACO incentives differentiates them from other care settings. While other payment models, such as the hospital value-based purchasing program (HVBP), were developed to reward Medicare providers based primarily on their care quality, the ACO program allows healthcare providers to share a percentage of risk-adjusted, cost savings based on the quality of care delivered.[3] Hence, it is important to develop a better understanding of the impact of health IT in the context of value-based care where incentives are structured to reward both quality and benchmark cost savings, and specifically, study whether health IT enables ACOs to balance competing quality and efficiency goals. We focus on two research questions: (a) Is ACO efficiency positively associated with quality? and (b) Does effective use of health IT enable ACOs to mitigate quality-efficiency tradeoffs? These questions have significant implications for design of value-based care programs that contribute to efficient, yet high-quality healthcare.

In this study, we focus on the Medicare Shared Savings Program (MSSP), one of the largest and earliest ACO programs in the United States. Our study is based on a nationwide sample of ACO data from 2013 to 2018. We supplement this dataset with data reported by the CMS meaningful use (MU) program, which requires eligible healthcare providers to *meaningfully* utilize certified electronic health records (EHR) to capture, document, and exchange patient clinical information across otherwise disparate providers (Wani and Malhotra 2018). We also utilize the American Hospital Association (AHA) IT supplement to collect longitudinal data on the effective use of health IT by participating hospitals (within ACOs) to develop measures of internal and external information integration.

We implement a two-stage approach to measure ACO efficiency using data envelopment analysis (DEA) in the first stage, followed by panel regression estimation on the ACO efficiency characterizations in the second stage. We observe that efficient ACOs do not exhibit any tradeoffs with respect to care quality. Further, we find that effective use of health IT across ACO providers has a positive effect on the association

[3] The HVBP program is part of the CMS Hospital Quality Initiatives that rewards acute-care hospitals for quality inpatient services to Medicare patients.

between *ACO efficiency* and *quality*. In other words, IT-enabled information integration mitigates trade-offs between ACO efficiency and quality, enabling ACOs to deliver high-quality care in an efficient manner.

To highlight the critical role of ACO incentives in shaping health IT use, we supplement our main findings with an analysis of hospitals based on their participation in ACOs. We observe that, hospitals that did not participate in ACOs, exhibited significant tradeoffs between efficiency and care quality. Specifically, efficient hospitals that did not participate in ACOs exhibited higher mortality and readmission rates, compared to efficient ACO hospitals. On the other hand, ACO hospitals that performed efficiently and used IT effectively also exhibited lower readmission rates and higher experiential quality. Consequently, hospitals that participated in ACOs were able to resolve these quality-efficiency tradeoffs, compared to non-ACO hospitals that may practice under alternate payment models, such as the FFS and HVBP programs.

We contribute to the extant literature on the role of effective IT use in value-based healthcare delivery, and provide important managerial insights. Our context-specific conceptualization of health IT use highlights the role of *IT-enabled information integration* as the primary mechanism in resolving tradeoffs between ACO quality and efficiency. Our findings suggest that balancing competing performance objectives requires healthcare policy makers to provide appropriate incentives that not only include performance-based payments but also promote effective IT use.

2. Background

The ACO program provides value-based care by incentivizing primary care practices, multi-specialty group practices, hospitals, and other healthcare providers to coordinate patient care with the goal of improving health outcomes for the patient population under their care. In the MSSP program, participating providers agree to be accountable for care provided to assigned Medicare FFS beneficiaries. CMS assigns beneficiaries to ACOs based on the primary care practitioners who provide the bulk of healthcare services.[4]

[4] Details about beneficiary assignment, cost and quality benchmarks, payment calculations, and other regulations can be found at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram.

Although patients are free to choose providers, participating ACO providers are likely to refer patients to providers within the same ACO, in order to manage patients across their entire episode of care (Gold 2015).[5]

The MSSP created incentives for providers to provide efficient and high-quality care by offering bonus payments when participating providers met defined cost and quality performance criteria. Specifically, ACOs must lower their health expenditures sufficiently below a pre-determined, risk-adjusted cost benchmark *and* meet minimum quality criteria to be eligible to receive shared savings. On the other hand, if their costs exceed the cost benchmark significantly, ACOs may incur shared losses (i.e., penalties). CMS defines and tracks more than thirty quality measures across four dimensions: *patient/caregiver experience*, *care coordination/patient safety*, *preventive health*, and *at-risk population*. They calculate a quality score for each measure by comparing the ACO's actual (realized) quality with its respective quality benchmark. We aggregate these quality scores across all measures to create a *composite* quality score, which is used to determine whether an ACO is eligible for shared incentives based on generated savings (or losses). In other words, the magnitude of incentive payments (or penalty) depends on the extent of cost savings (or losses) generated, contingent on the ACO achieving its quality benchmark.

Hence, ACOs need to pursue the dual objectives of cost savings and quality improvement, instead of making tradeoffs between these objectives in order to maximize incentive payments. In this respect, we highlight the differences between the ACO program and other value-based payment models such as HVBP, that predominantly use quality ratings to calculate incentive payments and impose a 2% penalty on hospitals that do not meet quality benchmarks. The ACO program consists of two models for participating healthcare providers, known as one-sided and two-sided risk models. The one-sided model (Track 1) includes shared savings only, and ACOs in Track 1 are not penalized even if their expenditures are significantly higher than the cost benchmark. However, ACOs in the two-sided risk model (i.e., Track 2) incur higher risks and greater rewards compared to the one-sided model. In other words, Track 2 ACOs are liable for shared losses

[5] As an illustrative example of a functional ACO in Appendix A, see the link to the Southwestern Health Resources ACO (https://www.southwesternhealth.com/aco-model), which describes ACO participants, as well as their governance and management structures, and the dollar value of shared savings, during a recent three-year period.

if their costs exceed their risk-adjusted cost benchmark. ACOs can enroll in Track 1 for a maximum period of six years, and are then required to transition to a two-sided risk model to continue their participation in the MSSP. Early research has shown that spending reductions by ACOs have yielded an overall $3.53 billion in Medicare savings in five years between 2013 and 2017 (Joszt 2019).

3. Related Literature

3.1. Quality-Efficiency Tradeoffs

While the ACO program incentivizes providers to deliver less expensive, yet high-quality healthcare, healthcare organizations often need to accommodate tradeoffs between improvements in care quality and efficient utilization of clinical resources (Jha et al. 2009, Senot et al. 2016). For instance, to improve efficiency, providers may need to reduce staffing levels and/or lower investments in capital assets, such as medical equipment and technologies, that may increase provider workload and clinical resource utilization (Hvenegaard et al. 2011). Excessive workload induces job-related burnout and stress, which in turn, increases the risk of medical errors, thereby adversely affecting patient health outcomes (Kane et al. 2007). Similarly, healthcare professionals may reduce the intensity of care delivery by shortening the length of hospital stay (Martini et al. 2014) that may, in turn, lead to early patient discharge with higher risk of complications (Joynt and Jha 2013). On the other hand, efforts to improve patient outcomes demand substantial investments in training and capital expenses, and may be associated with a short-term decline in practice efficiency (due to higher costs). For example, Kazley et al. (2012) reported that healthcare providers made significant investments in training clinicians that resulted in higher patient satisfaction and patient medication adherence. Further, hospitals can hire social workers to follow up with patients and coordinate care across providers, which can improve patient safety through greater monitoring but also increase operating expenses (Hvenegaard et al. 2011).

While quality-efficiency tradeoffs are inevitable in resource-constrained organizations (Newhouse 1970), financial incentives to healthcare providers play a critical role in shaping the relationship between quality and efficiency (Kumar et al. 2013). In a FFS environment, reimbursements are based typically on the volume of healthcare services (such as tests and procedures). Providers are more likely to focus on increasing the volume of services, even though some services may be redundant and unlikely to improve outcomes (Ayabakan et al. 2017b). Similarly, under the HVBP model, where incentives are predominantly based on quality of care, hospitals may realize higher quality at lower efficiency due to the increased costs associated with personnel training, new medical equipment, and providing a more extensive array of services (Izón and Pardini 2018, Norton et al. 2021). Hence, a misalignment between payment models and incentives can lead to agency problems that are characterized by tradeoffs between quality and efficiency (Chu et al. 2002).

Unlike payment models that focus mostly on a single performance dimension, incentive payments to ACO participants depend not only on the efficiency of resource expenditures, but also on patient health outcomes. This requires ACO participants to leverage IT-enabled capabilities to share best practices across providers, facilitate information exchange for care coordination, and allocate limited resources in a way that emphasizes *both* efficiency- and quality-oriented practices. Hence, greater alignment of incentive payments with performance goals can lead ACO participants to prioritize both quality and efficiency objectives instead of making tradeoffs against one another.

3.2. Health IT & Virtual Organizations

Another factor that leads to tradeoffs between quality and efficiency is the challenge of effectively coordinating patient care across providers. For instance, clinicians are likely to order unnecessary procedures or prescribe incorrect medications if they are not aware of patients' medical histories and allergies, leading to redundant tests and procedures with little impact on health outcomes (Ayabakan et al. 2017b, Jamalabadi et al. 2020). Care coordination challenges are especially relevant in the context of ACOs where performance is measured based on patient health outcomes across all ACO providers. This requires participants to work across organizational boundaries and coordinate patient care in a cost-effective manner. We observe that ACOs represent *virtual organizations*, defined as "organizations that are characterized by highly dynamic processes, contractual relationships among entities, edgeless, permeable boundaries, and reconfigurable structures" (Desanctis and Monge 1999). Unlike traditional organizations, knowledge communication, coordination, and development of trust can be challenging within virtual organizations, due to the temporal and spatial separation between team members (Kanawattanachai and Yoo 2007). These unique characteristics of virtual organizations may impede coordination efforts across participants and hinder their ability to resolve quality-efficiency tradeoffs adequately.

A viable approach to overcoming coordination challenges within virtual organizations is to utilize IT for effective communication. IT can enable better information processing capacity, integration of knowledge assets, and inter-organizational communication, thereby improving the speed and efficiency of virtual coordination (Ravichandran et al. 2017). IT integration also improves syntactic and semantic consistency during communication, which facilitates collaboration by fostering mutual understanding, inter-organizational relationships, and trust across partners (Desanctis and Monge 1999, Im and Rai 2014, Majchrzak et al. 2005). Further, IT provides a mechanism to monitor ACO participants' adherence to practice protocols and reduces transaction costs incurred due to information transfer across multiple partners (Kleis et al. 2012). Hence, effective use of IT enables virtual organizations to monitor the performance of individual entities, promote evidence-based best practices, and focus on patient outcomes data, including achievement of desired cost savings and quality benchmarks (Dennis et al. 2012).

While the literature has investigated the performance impacts of health IT on health outcomes and patient satisfaction, it remains unclear whether health IT use can improve organizational capabilities to mitigate tradeoffs between competing priorities in a value-based care environment. Our study draws on the theories of virtual organizations and information processing, to develop a theoretical foundation to study the core phenomenon of interest, i.e., the role of effective IT use on the relationship between efficiency and quality outcomes in ACOs. Specifically, we focus on the effective use of health IT to exchange and integrate patient health information in a setting where the incentives are designed to mitigate the risk of quality-efficiency tradeoffs (Wani and Malhotra 2018). Hence, our context-specific conceptualization of IT use in a value-based healthcare setting provides a better understanding of how IT-enabled capabilities can resolve tradeoffs between conflicting objectives in virtual healthcare organizations.

4. Research Hypotheses

4.1 Efficiency and Quality of Care

ACOs can achieve cost savings and quality improvements due to several unique characteristics of the MSSP incentive program. First, the dual objectives of the ACO program are likely to motivate participants to practice healthcare based on value provided to patients, and not on costs alone. In a FFS environment, reimbursements to providers are calculated based on the volume of services delivered, independent of the quality of health outcomes. Physicians often order more services than necessary, leading to over-utilization of resources that could otherwise be allocated to other areas (Chiedi 2019, Jamalabadi et al. 2020). In contrast, ACOs monitor the costs and outcomes of individual providers and identify those with subpar performance to evaluate how unnecessary services can be eliminated and health outcomes improved. Some ACOs analyze clinician performance to develop lists of preferred providers who are aligned with ACO objectives, to help participants make informed patient referrals that take into account both cost and quality.

Second, ACOs consist of centralized management boards that define and promote evidence-based best practice guidelines. Management teams advise physicians on re-engineering workflows and embedding these guidelines into clinical pathways (Toussaint et al. 2013). For example, many ACOs provide care providers with dashboards listing preventive services (such as breast cancer screenings) and treatments that are overdue (Levinson 2019). While preventive care is a major focus of ACOs, it raises awareness of gaps in care and allows providers to undertake proactive interventions. Further, they are able to use data to identify the clinical appropriateness of certain procedures and avoid duplicate tests (Ayabakan et al. 2017b). Hence, ACO participants can deliver high-quality care while taking into account patient-specific conditions, thereby delivering better health outcomes with greater efficiency (Lilienfeld et al. 2013).

Drawing on information processing theory, ACOs can be characterized as social systems that rely on information integration within and beyond organizational boundaries to mitigate uncertainty (Hult et al. 2004, Premkumar et al. 2005). Uncertainty may arise due to greater mobility and vulnerability of patients who suffer from chronic diseases and often seek care from multiple providers. These patients are especially vulnerable to poor outcomes associated with fragmented care that is exacerbated when providers are unable to share patient health data (Chiedi 2019). ACOs are able to draw on their superior information integration capabilities to mitigate uncertainty stemming from information sharing failures, which can facilitate better care coordination, monitor adherence to clinical protocols, and greater alignment with ACO goals.

ACOs also allow greater specialization of labor to accommodate the needs of diverse patient populations where participants often refer patients to other providers within the same ACO (Colla et al. 2016, Gold 2015). This is of particular importance for Medicare patients because ACOs are able to track their assigned beneficiaries and ensure smoother transitions of care across providers (Burns and Pauly 2012, Toussaint et al. 2013). For example, ACOs designate care coordinators to ensure that primary care doctors have access to relevant medical records and engage patients in managing their health (Chiedi 2019). As a result, patients are more likely to adhere to their treatment regimen and consult with ACO providers in ambulatory settings instead of incurring costly emergency room visits or hospitalizations (McWilliams et al. 2016). In other words, ACOs are able to deliver better care and reduce unnecessary emergency services, which in turn, improves resource utilization and cost savings, while improving patient health outcomes.

On the other hand, healthcare providers that do not participate in ACOs are unlikely to engage in care coordination initiatives, since they are not compensated for their efforts in a volume-based, FFS environment with no penalties for low-quality outcomes (Chiedi 2019, Kumar et al. 2013). Further, the incentive mechanisms of the ACO program may contribute to credible commitment, since it instills greater discipline among ACO participants to practice high quality, efficient care, and promotes awareness that inability to achieve defined cost and quality benchmarks may lead to a loss of incentive payments and significant penalties. Hence, efficient ACOs rely on shared discipline and trust among providers to ensure that clinical and administrative processes facilitate better integration across providers, and support greater visibility into quality and cost metrics. In other words, efficient ACOs are likely to optimize resource allocation to deliver high-quality care, and are less likely to trade-off improvements in efficiency at the expense of quality.

H1: *Efficient ACOs are more likely to exhibit greater quality based on their patients' health outcomes, compared to inefficient ACOs.*

4.2 Effective Use of Health IT

While care coordination is critical to balance quality-efficiency tradeoffs, these initiatives are difficult to implement without timely access to patient health information. This is particularly true for virtual organizations such as ACOs, where participants need to overcome information sharing challenges and communicate patient health information across organizational boundaries with all providers that are responsible for patient care (Chiedi 2019). We draw on inter-organizational systems and virtual organizations theory to develop our hypotheses on the role of effective IT use on ACO performance.

Virtual organizations theory suggests that participants need to share contextual knowledge and task information so that they can effectively coordinate with each other and contribute to shared organizational goals (Kanawattanachai and Yoo 2007). However, compared to intra-firm collaboration, the efficiency of inter-organizational communication may be significantly lower due to transaction costs and lack of trust in virtual organizations (Majchrzak et al. 2005). An inability to communicate and share knowledge has a negative impact on cognition-based trust, which further impedes coordination (Dennis et al. 2012). Therefore, inter-organizational systems provide collaborative tools to overcome organizational barriers toward information exchange and coordination, greater communication, integration of knowledge, management of knowledge assets, and information processing capability (Ravichandran et al. 2017).

In this study, we specifically focus on the role of MU achievement to understand the effective use of health IT by ACO providers to share patient health information across ACO participants. The MU program was designed to incentivize providers to use EHR systems to achieve specific clinical objectives, such as electronic documentation of patient health data, computerized provider order entry (CPOE) for medication orders, exchange of patient health information, and clinical decision support (Wani and Malhotra 2018). As described in Table A1 of Appendix A, ACO providers must demonstrate a variety of capabilities to capture patient health data electronically in a standardized format, use data to track critical clinical conditions, and communicate patient health information with other providers. Hence, MU achievement serves as a useful proxy for effective IT use within ACOs, as it represents the extent to which EHRs are used to document and share patient health data across virtually connected provider organizations.

The MU program requires eligible healthcare providers to document and maintain up-to-date patient health data. Structured documentation systems within EHRs ensure that patient data are stored in standard format, which reduces the latency of patient data retrieval, decreases manual errors, and enables greater health information sharing, allowing providers to access patients' longitudinal clinical history (Silow-Carroll et al. 2012). Access to relevant and timely patient data enables ACO providers to make accurate diagnoses and recommend appropriate treatments, and reduces the likelihood of medical errors and poor outcomes (Bao et al. 2020).

MU achievement is a multi-dimensional construct that captures different dimensions of effective EHR use. For instance, MU requires clinicians to utilize patient data to support implementation of drug-drug interaction checks and comply with evidence-based practices. EHRs support these decision support features by embedding clinical pathways in process workflows, which enables greater integration of provider knowledge with patient data (Shortell et al. 2010). A recent report indicates that ACO providers use EHRs to develop their own care management plans and send early warning alerts to patients based on tracking their health data (Chiedi 2019). ACO providers can request nurse practitioners to intervene and implement appropriate corrective action for at-risk patients. In other words, effective use of EHR systems can enable ACOs to optimize workflows with automatic triggers based on adherence to clinical protocols, which in turn, improves outcomes and reduces adverse events (Boulding et al. 2011, Senot et al. 2016). Hence, we posit that effective health IT use by ACOs is likely to be associated with greater quality.

H2: *Effective use of health IT is associated with greater ACO quality, measured in terms of patient health outcomes.*

Prior research in supply chain management has studied the fit between organizational information processing requirements and capabilities, specifically focusing on the role IT use in mitigating task uncertainty, resource allocation, fostering shared trust, and improvements in the quality of decision-making, resulting in improved organizational performance (Srinivasan and Swink 2015). Integration of patient data that resides in fragmented silos across virtually connected providers, is a complex process that requires coordination and the need for inter-organizational information sharing (Barrett and Konsynski 1982). ACOs can facilitate greater information integration through a variety of strategies, including standardization on a common EHR system, to share patient health data across providers affiliated with different organizations, thereby reducing information gaps and uncertainty associated with patient information.

Based on a field study of six ACOs, Levinson (2019) observed that effective use of EHR systems helped ACOs to not only improve care quality but also generate cost savings by improving the efficiency of care delivery. Standardization across a single EHR system enabled information sharing across ACO providers, supporting efforts to coordinate care, reducing costs associated with duplicate tests and redundant procedures, and maintenance of separate EHR systems (Chiedi 2019). Information integration also enables ACO providers to share clinical data and patient records, allowing them to access a common care checklist, updated with daily data on patient admissions, discharges, and transfers, and track patients' medications and tests (Levinson 2019). As a result, providers are able to make informed treatment decisions during transitions in patient care, that not only improves their health outcomes but also reduces inefficiencies due to redundant resource utilization, thereby lowering treatment costs (Atasoy et al. 2017).

Meaningful use of health IT also requires ACO providers to utilize information exchange capabilities to prospectively stratify patients based on the potential severity of their health conditions (Bates et al. 2014). This allows ACOs to prioritize high-risk patients for dedicated care and provide integrated care management resources across the ACO network (Hsu et al. 2017). These decision support capabilities allow providers to allocate clinical resources for preventive care of high-risk patients, thereby reducing the rate of unnecessary emergency room visits while maintaining practice efficiency (Levinson 2019). On the other hand, if ACO providers are unable to harness population health analytics due to a lack of information integration, they are less likely to implement care management strategies based on patient risk.

Inter-organizational systems theory suggests that a variety of factors, such as the relevance and accuracy of information, may affect the performance of information sharing initiatives (DeLone and

McLean 1992, Gil-Garcia and Sayogo 2016). EHR systems support ACOs' analytics capabilities and allow management to monitor practice efficiency and performance through integration of patients' medical records, and support data-driven operational decisions based on a common "source of truth" (Silow-Carroll et al. 2012). Specifically, ACOs can use health IT systems to generate financial and quality dashboards to track spending and clinical outcomes across providers, and evaluate adherence to standardized care protocols, thereby enabling greater transparency of patient care (Levinson 2019). In turn, care transparency allows organizations to shape individual providers' perceptions of integrity, commitment, and contribution to shared goals, thereby fostering higher levels of trust (Dennis et al. 2012). Hence, the inter-organizational setup of ACOs highlights the importance of MU achievement (and information integration) as the critical mechanism that allows ACO participants to share and coordinate patient care information across organizational boundaries, thereby improving overall care quality (Kellerman and Jones, 2013).

Standardization on a common EHR system allows greater visibility into practice management data, enabling ACOs to anticipate challenges and address gaps in care coordination that may impair performance. Further, monitoring of provider performance through effective use of IT can foster a learning environment where participants are less likely to engage in opportunistic behavior (Dennis et al. 2012). Due to reputational considerations, greater transparency can also motivate participants to improve their own performance by benchmarking against best-practice leaders, thereby supporting the dual organizational goals of cost savings and quality improvement (Adjerid et al. 2018).

Hence, we argue that when an ACO effectively utilizes its IT capability to exchange health information and coordinate care, it is more likely to resolve tradeoffs between efficiency and quality.

H3: *Effective IT use has a positive interaction effect on the association between ACO quality and efficiency.*

Figure 1 represents our conceptual model and describes the primary research hypotheses.

5. Data and Variable Construction

We draw on the MSSP public use file from CMS to obtain longitudinal data on ACO-specific operating characteristics and financial performance, including the number of assigned beneficiaries, contract start date, service area, and total expenditures. We matched this dataset with ACO quality metrics and the names of participating entities, using ACO name, identity number, assigned beneficiaries, and total expenditures. We eliminated ACOs with missing values in order to conduct meaningful analyses using DEA. Overall, our data set consists of 2,343 ACO-year observations across six years from 2013 to 2018.[6] We manually collected a longitudinal list of hospital participants for each ACO by mapping participating entities with Healthgrove.com, a publicly available data source. We matched our data with public reporting from each ACO's website to ensure accuracy. We also utilized data from the AHA IT Supplement and Health Information Management Systems Society (HIMSS) database to develop our measures of health IT integration and use.

5.1. ACO Quality

We deployed a composite measure of quality that CMS uses to evaluate ACO performance, since the magnitude of incentive payments is based partially on this composite score (McClellan et al. 2010). We calculated ACO quality based on a pre-determined set of individual quality measures that take into account the population risk of its assigned beneficiaries and historical performance. We followed the MSSP quality measure benchmark to consolidate the individual quality measures into a single composite quality score, *ACO_Quality*. Since all ACOs came under the purview of the "pay-for-reporting" plan during the first year (i.e., 2013), ACO quality measures are evaluated based on whether the ACO simply submitted a quality report to CMS. This lead to 97.5% (198 out of 203) of the ACOs having a 100% quality score in 2013, and the remaining ACOs had a quality score of zero because they failed to submit a quality report. Since a binary method does not accurately measure the true quality of ACOs, we excluded the first year and used the remaining five-year period from 2014 to 2018 for our main analyses.

5.2. ACO Efficiency

Our measure of *ACO Efficiency* is consistent with the literature using contextualized definitions based on the ACO program. We define efficiency as the input resources that an ACO expends to produce a given

[6] The number of ACOs varies across years since new participants joined the MSSP ACO program in recent years, while some ACOs dropped out of the program.

level of output services. The three outputs correspond to the major patient services provided by an ACO – *inpatient discharges*, *ED visits*, and *primary care services* (Highfill and Ozcan 2016, Huerta et al. 2013, Kazley and Ozcan 2009). We propose five inputs that represent resources deployed during care delivery: number of *primary care physicians*, *specialists*, *other clinicians* (nurse practitioners, physician assistants, and clinical nurse specialists), *operating expenses*, and *capital investment* (McCallion et al. 2000, Shreay et al. 2014). Operating expenses represent costs incurred during the process of healthcare delivery, excluding the cost of physicians and other suppliers. We utilize expenditures on durable medical equipment as a proxy for capital investment.

Consistent with prior studies that utilized DEA to evaluate hospital efficiency (Hollingsworth 2008), our operationalization of ACO efficiency measures the extent to which ACO providers minimize the utilization of limited input resources, to produce healthcare services (i.e., outputs). Since the literature has used "per-capita" measures to evaluate ACO performance (McClellan et al. 2010, McWilliams et al. 2016) and CMS evaluates ACO cost savings based on a per-beneficiary benchmark, we transformed all input and output variables into *per-beneficiary* measures. We observe that the inputs are positively correlated with outputs, which validates our DEA "production frontier" model (Tiemann and Schreyogg 2012).

5.3. Effective Health IT Use

Since interoperability continues to be a challenge, we observe that adoption of health IT alone does not guarantee effective information integration. We operationalized effective health IT use based on the extent of *MU Achievement*, defined as the percentage of eligible providers within an ACO who qualified for MU incentive payments in the focal performance year. Eligible providers received MU incentive payments only if they demonstrated use of certified EHR systems by achieving all core objectives and at least five menu objectives, which emphasize several capabilities including health record documentation, information exchange, and care coordination (see Table A1 in the Appendix for details). Hence, although *MU Achievement* is measured as a single variable, it represents multiple attributes of IT use that include CPOE, clinical decision support, electronic exchange of clinical data with other providers, and medication reconciliation across patient care transitions. We specifically focus on ACO eligible providers, since they are accountable for coordinating patient care, sharing treatment plans and patient health information, and monitoring patient outcomes across the care continuum (Burns and Pauly 2012, McClellan et al. 2010). MU achievement requires ACOs to demonstrate the "*use of EHRs in continued treatment processes*", as described in Figure A1. Hence, *MU Achievement* is a proxy for effective IT use since it represents the proportion of ACO providers who used EHRs to document and exchange health information with other providers for care coordination.

We also deployed an alternate measure of effective health IT use among hospital-managed ACOs that measures the extent of *information integration* across internal and external providers. We have described this analysis in the "Robustness Checks" section.

5.4. Control Variables

We control for several factors that may affect ACO quality. To account for ACO size, we constructed two variables, *ACO_Size* and *No_Entity*, as the number of assigned beneficiaries and distinct healthcare entities within an ACO, respectively. Both variables may influence the effectiveness of care coordination across the patient population, especially where ACOs consist of several disparate entities. We define *ACO Experience* as the number of years that an ACO has been enrolled in the MSSP, measured at the beginning of each year. *Track2* is a binary variable with a value equal to one if an ACO is enrolled in a two-sided risk model, and zero otherwise. *Advance Pay* indicates whether an ACO participates in the Advance Payment Program, where the ACO was provided upfront financial support to invest in relevant infrastructure for care coordination (Nattinger et al. 2018). *Weighted Risk* measures the risk of an ACO's assigned beneficiary population and calculated as the weighted average risk score of all beneficiaries. A higher value of weighted risk indicates greater severity of the patient population served.

Based on data obtained from ACOs, we constructed a binary variable, *ACO Type*, which is equal to one if an ACO is managed by hospitals (McWilliams et al. 2016), and zero if the ACO is solely led by physician groups. An ACO is classified as *hospital-managed* if its participants include hospitals, has a partnership or joint venture with hospitals, or distributes shared savings to hospitals, (Colla et al. 2016). Table 1 presents definitions and descriptive statistics of all variables.

6. Empirical Analyses

In this section, we first describe our research design and model specification, followed by the econometric results of our two-stage estimation framework.

6.1. Baseline Models

We adopt a two-stage empirical framework to estimate the model shown in Figure 1 (Ayabakan et al. 2017a). In the first stage, we deployed DEA to calculate a relative efficiency score for each ACO. DEA has been adopted widely to analyze hospital productivity and is particularly suited to measure the efficiency of complex service organizations for several reasons (Hollingsworth 2008, Huerta et al. 2013). Unlike simple ratio or regression approaches, DEA is a non-parametric approach to measure ACO efficiency, that allows us to consider multiple inputs and outputs simultaneously (McCallion et al. 2000). DEA does not require *a priori* specification of the underlying production function, unlike regression-based approaches (Tiemann and Schreyogg 2012). We used the Banker-Charnes-Cooper (BCC) model, which accounts for variable returns to scale in the production function (Banker et al. 1984). Since healthcare organizations typically exercise more control over their deployment of input resources, we adopted an input-oriented BCC model to measure ACO efficiency (Shreay et al. 2014). Further, since hospital-managed ACOs are different from physician-led ACOs in terms of their governance, we conducted separate DEA analyses for each *ACO Type*. The *ACO Efficiency* score ranges in value between zero and one, and represents the technical efficiency of a focal ACO, relative to other ACOs of the same type.

In the second stage, we used the *ACO_Quality* score as the dependent variable in our econometric models.[7] We estimated the association between our independent variables, *MU Achievement* and *ACO Efficiency*, and dependent variable of interest, *ACO_Quality*, through hierarchical regressions. For our main analyses, we include fixed effects to capture unobserved ACO heterogeneity and yearly ACO program changes. First, we test hypotheses H1 and H2 using equation (1) as follows:

[7] ACOs need to focus on efficiency (i.e., cost savings) initially to meet their benchmark saving rate. Only then, the actual amount of shared savings is determined based on their quality scores. Hence, we treat ACO quality as the dependent variable and efficiency as the independent variable of interest in our estimation models.

$$ACO\_Quality_{it} = \alpha_0 + \alpha_1 MUAchievement_{it} + \alpha_2 ACOEfficiency_{it} + \beta X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (1)$$

where *i* indicates an individual ACO and *t* denotes the year index from 2014 to 2018. γ and μ represent ACO-specific and time fixed effects, respectively. *X* describes the list of control variables. Since the ACO's location may change over time due to changes in participants, we include ACO-specific, regional dummies to control for geographic variations in ACO performance.[8]

To examine the impact of MU achievement on the association between ACO efficiency and quality (H3), we estimate the model specified in equation (2).

$$\begin{aligned} ACO\_Quality_{it} = {} & \alpha_0 + \alpha_1 MUAchievement_{it} + \alpha_2 ACOEfficiency_{it} \\ & + \alpha_3 MUAchievement * ACOEfficiency + \beta X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (2)$$

where we include an additional interaction term, *MU Achievement*ACO Efficiency*, while controlling for other variables. A positive and significant interaction indicates that *MU Achievement* has a positive impact on the association between ACO efficiency and quality, thereby enhancing the strength of the relationship. To mitigate multi-collinearity, we followed Bharadwaj et al. (2007) and used mean-centered values of *MU Achievement* and *ACO Efficiency*.

Table 2 illustrates the DEA results for hospital-managed and physician-led ACOs from 2014 to 2018. Although the average DEA-based efficiency score is 0.91, we observe that less than 25% of ACOs are rated as fully efficient each year (when considering non-zero slacks in the DEA model). Further, Mann-Whitney tests indicate that physician-led ACOs exhibit significantly higher efficiency than hospital-managed ACOs, confirming efficiency differences between the two types of ACOs. Our sample size is significantly larger than the threshold for DEA model validity, based on the number of inputs and outputs in the DEA model (Cooper et al. 2011).

[8] Based on geographic location, the U.S. Census Bureau assigns each state to one of the nine divisions: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. We use this geographic definition because a large number ACOs are located in multiple states.

Table 3 presents the correlation matrix of variables in the second-stage econometric model. The variance inflation factors of all variables are less than five, suggesting that multi-collinearity is not a serious concern. We clustered standard errors at the ACO level in all models.

6.2. Estimation Results

We now report estimation results for the fixed effects models, as specified in equations (1) and (2). Table 4 represents the OLS estimation results of the second-stage model. As shown in column (1), the coefficient of *MU Achievement* is positive and significant (coeff. = 0.048; p-value < 0.01), suggesting that a 1% increase in meaningful use among ACO providers is associated with 0.05% improvement in average ACO quality. Further, the coefficient of *ACO Efficiency* is insignificant, indicating that efficiency and quality of care are not significantly associated, even when ACO providers receive incentives to deliver quality care. Hence, our results do not support H1. However, we observe that meaningful use of IT is positively associated with ACO quality, supporting H2.

Column (2) presents the estimation results of equation (2), where our primary focus is on the interaction effect, *MU Achievement*ACO Efficiency*. The significant interaction term (coeff. = 0.309; p-value = 0.03) indicates that *MU Achievement* positively influences the relationship between ACO efficiency and quality. To further illustrate the interaction effect of meaningful use, we plot the association between ACO quality and efficiency in Figure 2 based on the level of *MU Achievement*. We separated ACOs into two groups, based on their median *MU Achievement*, while holding other control variables at their mean values. The dashed line represents ACOs with low levels of MU achievement, while the solid line represents ACOs that exhibit high levels of MU achievement. We observe that the relationship between ACO efficiency and quality is negative for ACOs with low MU achievement. In contrast, ACOs with higher levels of meaningful use exhibit a positive association between efficiency and quality that increases with greater ACO efficiency. Our results suggest that when ACOs meaningfully use EHRs for care coordination, they are likely to achieve efficiency and quality objectives simultaneously.

Hence, our main results support hypotheses H2 and H3 with respect to the critical role of effective health IT use in driving ACO performance, but do not support H1. We observe that the coefficients of

Track2 are positive and significant across all models, indicating that participating ACOs in the two-sided risk model are more likely to report higher quality. *No_Entity* is negative and significant, suggesting that ACOs with more participating entities, are likely to report lower quality, possibly because of challenges in care coordination across entities. Further, we observe that experienced ACOs are likely to exhibit lower quality, which can be attributed to a reduction in quality-focused improvements over time as ACOs pursue cost savings to reap performance incentives (Ayabakan et al. 2021).

6.3. Endogeneity Concerns

One may argue that MU achievement is endogenous with ACO quality, since high-quality ACOs may be more likely to invest in EHRs and encourage participating providers to use these systems. Although we control for geographic variations in ACO characteristics, it is possible that ACOs in metropolitan areas may provide high-quality care and also effectively use health IT, leading to confounding concerns.

To mitigate endogeneity concerns, we deploy an instrument variable (IV) approach. We utilized two instruments - the number of rural health clinics (RHC) and number of critical access hospitals (CAH). RHCs and CAHs are typically located in rural areas and may encounter difficulty in using health IT to meet MU requirements (Levinson 2019). Further, providers in RHCs are ineligible for the MU program, thus lacking incentives for effective use of health IT. Hence, ACOs that include RHCs and CAHs are likely to exhibit lower levels of MU achievement. On the other hand, the number of RHCs and CAHs may not be systematically codetermined with ACO quality for several reasons. First, ACO quality is measured based on Medicare patients, regardless of ACO location. Second, ACO quality is risk-adjusted and scaled based on historical performance, and we have controlled for population risk in our model. Further, echoing prior results (Reschovsky and Staiti 2005, Stensland et al. 2013), we conducted supplemental analyses to confirm that our IVs are not correlated with the risk, age, ethnicity, and morbidity of chronic diseases of the FFS beneficiary population in our study, as well as their access to healthcare services (e.g., inpatient, primary care, ED, and post-acute services).

To further test the validity of our IVs, we conducted two tests to examine the exogeneity and relevance assumptions. We used the Hansen-Sargan test to test for over-identifying restrictions. The Sargan statistic equals 2.20, with a p-value of 0.14. Therefore, we fail to reject the null hypothesis that our instruments are uncorrelated with the error term and are correctly excluded from the estimation equation. We also implemented the Anderson canonical correlations likelihood-ratio test, where the null hypothesis is that the instruments are weak. The test statistic equals to 15.64 with p-value < 0.01. These results suggest that our IVs are valid.

Due to the skewness of our data, we deployed a two-step Heckman approach to mitigate endogeneity concerns related to *MU Achievement* (Terza et al. 2008, Wooldridge 2010). Following Bharadwaj et al. (2007), we created a binary indicator with a value equal to one when the focal ACO exhibits a MU achievement percentage above the average level of ACOs of similar type, and zero otherwise. In the first step, we estimated a Probit selection model with a binary indicator as the dependent variable and the IVs as additional independent variables, to derive the inverse Mills ratio. In the second step, we introduced the inverse Mills ratio as an independent variable to account for unobserved variables that may bias our estimation results.

Columns (3) and (4) in Table 4 represent the results of the Heckman endogeneity correction. We observe that the coefficient of *ACO Efficiency* is negative but insignificant, which supports our earlier finding on the lack of significant association between ACO efficiency and quality. We observe positive coefficients of *MU Achievement* (coeff. = 0.031; $p < 0.10$) and the interaction term, *MU Achievement*ACO Efficiency* (coeff. = 0.315, $p < 0.05$). Hence, our results support hypotheses H2 and H3 with respect to the impact of meaningful use on ACO quality and its positive interaction effect on the association between ACO efficiency and quality, respectively. Our results also suggest that efficient ACOs do not make tradeoffs against quality, since greater ACO efficiency is not associated with lower quality.

6.4. Difference-in-Differences Analysis of Hospitals based on ACO Participation

As previously noted, ACOs are different from traditional healthcare delivery organizations due to their unique incentive structures and inter-organizational structure that requires ACO providers to collaborate across organizational boundaries to coordinate patient care for their assigned beneficiaries. To study these differences between ACOs and traditional healthcare providers, we conducted a difference-in-differences

(DID) analysis of hospitals, based on their participation in ACOs, to evaluate whether (a) ACO participation can change the association between hospital quality and efficiency, and (b) effective use of health IT can resolve quality-efficiency tradeoffs within ACO hospitals, compared to non-ACO hospitals. Note that the unit of analysis is the hospital instead of an ACO, since we study the impact of health IT use on hospitals' abilities to mitigate quality-efficiency tradeoffs after joining an ACO.

We consider hospital participation in an ACO as the treatment and implement propensity score matching (PSM) to mitigate selection concerns about ACO participation. Further details about our data collection, variable construction, PSM, and basic DID analyses are presented in Appendix C.[9] We estimate a DID model that highlights the role of ACO participation and meaningful use of health IT in resolving the quality-efficiency tradeoffs, as specified below.

$$\begin{aligned} HospPerformance_{it} &= \alpha_0 + \alpha_1 ACOPart_{it} + \alpha_2 Efficiency_{it} + \alpha_3 Efficiency_{it} * ACOPart_{it} \\ &+ \alpha_4 MU_{it} + \alpha_5 Efficiency_{it} * MU_{it} + \alpha_6 Efficiency_{it} * MU_{it} * ACOPart_{it} \\ &+ \beta X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (3)$$

where $HospPerformance_{it}$ represents three quality measures – mortality, readmission, and experiential quality – for hospital *i* at year *t*. *ACOPart* is a binary indicator with a value of one if hospital *i* participates in an ACO in year *t* and zero otherwise. It is important to note that non-ACO hospitals may practice under alternate payment incentives (such as FFS or HVBP), and hence, *ACOPart* captures the performance difference attributed specifically to the unique incentives of the ACO model. Specifically, we are interested in coefficients α_3 and α_6, which identify differences in the association between ACO efficiency and quality, and the interaction effect of MU based on hospital ACO participation, respectively. *X* represents our control variables. We include two-way fixed effects to account for time-invariant, hospital characteristics, and policy changes.

[9] Table C1 in Appendix C provides details of our PSM process based on several ACO characteristics, while Table C2 presents model-free DID analyses that shows significant differences between the control and treatment groups of hospitals. Table C3 shows the impact of hospital participation in ACOs on different measures of hospital quality.

Table 5 presents our DID estimation results. We observe that *Efficiency* is positive and significant in columns (1) and (2), indicating that efficient hospitals that did not participate in ACOs exhibited higher mortality and readmission rates. This result provides evidence of quality-efficiency tradeoffs within non-ACO hospitals, even when they participate in other incentive payment models such as the mandatory HVBP program. Next, we observe that the coefficient of *Efficiency*ACOPart* is negative and marginally significant for readmission rate, which indicates that efficient ACO hospitals exhibit lower readmission rates compared to their non-ACO hospital counterparts. Further, the insignificant coefficient of *Efficiency*MU* suggests that MU achievement does not have a significantly impact on the relationship between quality and efficiency among non-ACO hospitals. In contrast, the coefficient of *Efficiency*MU*ACOPart* indicates that effective health IT use is associated with lower readmission rates and greater experiential quality, among hospitals that participate in ACOs.

Our hospital-level DID analyses highlights the critical role of ACO participation in shaping the way that hospitals use health IT to deliver high quality care efficiently. We extend the prior literature that has primarily focused on studying the impact of health IT on hospital performance under traditional payment models. Our research based on the unique incentives in the MSSP ACO program provides a better understanding of the effective use of health IT in addressing quality-efficiency tradeoffs, where providers need to coordinate patient care across organizational boundaries.

7. Robustness Checks

In this section, we will present several robustness checks to further test the validity of our results.

7.1. Internal and External Information Integration

In order to test whether MU achievement is a useful proxy for effective health IT use, we collected additional data on hospital-level information integration from the AHA IT Supplement database. Specifically, the AHA database contains survey response data that indicates whether a hospital exchanged data on patient demographics, clinical care records, laboratory results, medication history, and radiology reports, with other ambulatory providers and hospitals, either *within* or *outside* its health system/network. We constructed two summative indices, *Internal Information Integration* and *External Information*

Integration, which take a value of one if a focal hospital shared patient health information with providers within and outside its health system, respectively. We used the list of hospital ACO participants as a crosswalk to match this data with ACO performance. We then calculated a weighted average value of *Information Integration* using the number of staffed hospital beds at the ACO level. Due to data limitations, our analysis is based on the subset of hospital-managed ACOs for the three-year period from 2014 to 2016.

The *Information Integration* (*Internal* and *External*) constructs represent alternate measures of effective use of health IT for care coordination with clinicians inside and outside the ACO. We deployed Heckman estimation with the same IVs as discussed before. The estimation results in Table 6 indicate that information integration is associated with better ACO quality and has a positive effect on the relationship between quality and efficiency, as reflected in the positive coefficients of *Information Integration* and its interaction with *ACO Efficiency*. Our results support the underlying mechanism of information integration that moderates the relationship between ACO efficiency and quality. In other words, hospital-led ACOs with greater information integration are more likely to mitigate efficiency-quality tradeoffs.

7.2. Falsification Tests

Next, we conducted a falsification test to justify the interaction effect of information sharing. While sharing patient health information across ACO providers is expected to improve the association between quality and efficiency, it is unlikely to influence clinicians' communication quality with patients. Specifically, meaningful use of EHR systems do not enable caregivers to be more compassionate or communicate in terms that patients understand (Kazley et al. 2012). Their communication style and bedside manners largely depend on providers' interpersonal skills and demeanor, rather than the extent of EHR use (McWilliams et al. 2014, Merlino and Raman 2013).

Hence, we adopted two constructs that capture provider communication behavior as reported by CMS. *Provider-patient Communication* represents how patients rate the quality of communication with their ACO providers with respect to clarity of communication, listening, and treating patients with respect. *Patient Health Education* measures the extent to which ACO providers educate their patients on health management, including preventive instructions and healthy behavior. We used these two measures as dependent variables in a falsification test. A significant coefficient of *MU Achievement**ACO Efficiency* would indicate a spurious effect of *MU Achievement* due to confounding factors, whereas an insignificant coefficient indicates that health information sharing serves as the primary mechanism to resolve quality-efficiency tradeoffs. We report our estimation results in Table B1 where we observe insignificant interaction coefficients in both models. These results mitigate potential confounding concerns and provide further evidence to support our main findings that information integration contributes to better ACO performance by strengthening the relationship between efficiency and quality.

7.3. Heterogeneity Analyses

We conducted additional heterogeneity analyses to examine which types of ACOs are likely to benefit from MU achievement. First, we categorized ACOs based on the median number of assigned beneficiaries. We estimated the fixed effects model separately for large and small ACOs and the results are shown in columns (1) to (4) of Table B2. Consistent with our main findings, we observe that *MU Achievement* is positively associated with ACO quality, and ACO efficiency is not associated with quality, regardless of ACO size. However, the interaction effect of *MU Achievement* is significant only for small ACOs, possibly because challenges in coordinating care across larger ACOs may not be addressed only through meaningful use.

Second, we studied ACO performance based on their geographic location. We note that there is no uniform approach to categorize ACOs as urban or rural because an ACO may have participants located in both areas. During our observation period, solely urban healthcare providers formed a large number of ACOs. Hence, we treat an ACO as rural if it has participants from rural communities (e.g., CAH and RHC), and urban otherwise. We present the results of our subgroup analysis in columns (5) to (8) of Table B2, and observe that, while MU achievement improves ACO quality across both types, it only has a positive interaction effect for rural ACOs. Although our classification based on size and location are somewhat ad hoc, our results suggest the need for further studies to explore the impact of IT use in small and rural ACOs.

Overall, while we observe consistent results with respect to the positive association between MU achievement and quality, our analysis indicates that interaction effects are positive for small and rural ACOs. Our findings have significant managerial implications for ongoing efforts to expand ACO coverage in rural regions through IT-enabled care coordination initiatives such as expansion of telehealth and remote patient monitoring. We also report additional robustness analyses in Appendix B. Specifically, we report the results of alternate DEA inputs and outputs in Table B3, alternate DEA model specifications in Table B4, and robustness tests for alternate dependent variables in Table B5.

8. Discussion

Our research contributes to the extant literature on business value of health IT in an emerging value-based healthcare environment. While prior research has primarily examined the performance implications of health IT at a hospital level, these studies do not examine the tradeoffs between different dimensions of performance, and their findings are not applicable under value-based payment models established by the ACA. To the best of our knowledge, our study represents the first attempt to address the broader question: *can health IT use improve organizational capabilities needed to pursue both efficiency* <u>*and*</u> *quality?*" Considering the multi-dimensional nature of healthcare performance, our study highlights the role of health IT use and its impact on the relationship between efficiency and quality, thus providing a comprehensive understanding of IT value.

The ACO program provides a unique opportunity to study the role of health IT in a value-based care setting, where participants share incentive payments based on the overall quality and efficiency of ACO providers. Drawing on theories of virtual organizations and information processing, we show that the inter-organizational structure of ACOs necessitates effective use of IT to coordinate patient care with disparate providers, across organizational boundaries. Enhanced IT-enabled integration allows ACO providers to balance tradeoffs between quality and efficiency, consequently improving their capability to pursue both dimensions simultaneously. Hence, our research highlights the role of information integration as a critical mechanism that enables healthcare providers in a value-based care environment to meet competing performance objectives. Our findings based on hospital-level ACO participation contribute to the extant literature by highlighting the importance of shared incentives in shaping the effective use of IT. While prior research has focused primarily on studying the impact of health IT on hospital performance in a FFS regime, we focus on an important, yet unaddressed empirical question related to the role of health IT use in resolving quality-efficiency tradeoffs among healthcare providers in the value-based care era.

8.1 Policy Implications

Our results have several practical implications for policymakers to develop appropriate incentives for value-based care. As the U.S. healthcare system shifts from FFS to value-based payment models, studies have documented substantial variations in the cost and quality outcomes of ACOs (Landi 2017). We propose a novel multi-dimensional framework to evaluate ACO performance, based on the efficiency of resource utilization and achievement of quality goals. Our DEA approach offers new insights for measuring ACO quality and efficiency, and can be used to identify the factors that contribute to efficient care and improvements in care quality.

In addition to the ACO program, CMS has established several value-based care initiatives, such as the HVBP program, with the goal of improving hospital quality and efficiency. Our study implies that concurrent financial incentives alone are insufficient to improve healthcare quality and efficiency. Policies to promote effective IT use should be developed to overcome systems interoperability challenges, facilitate exchange of patient information, and coordinate care across providers, in order to realize the aim of value-based care, i.e., delivering efficient and high-quality healthcare. Specifically, effective use of IT for health information integration across ACO providers should be rewarded, thereby enhancing their capabilities to improve performance.

Health IT systems have been criticized for their lack of interoperability in sharing patient health information across disparate health networks with different EHR systems. As a result, ACOs that use multiple EHR vendors often have incomplete data when their patients transition across care settings (Levinson 2019). An inability to access relevant patient health records frustrates ACO practitioners, increasing the likelihood of unnecessary procedures and medical errors, and hinders care coordination necessary for successful care management (Ayabakan et al. 2017; Lowell 2018). Our analyses also highlights the need to develop and promote universally compatible data standards, in an effort to achieve greater information integration across EHR systems (Hagland 2018).

We observe that ACO quality is negatively associated with the number of participating entities. Further, our heterogeneity analyses show that IT use is less effective in improving quality within large ACOs. Since CMS mandates a minimum enrollment of 5,000 beneficiaries for MSSP ACOs, this encourages ACOs to expand their patient populations by including more participating entities. On the other hand, larger number of entities increases the cost and complexity of care coordination due to challenges in sharing health information, treatment protocols, and performance data. This is particularly true for rural ACOs where participants are geographically dispersed and do not possess the relevant infrastructure to coordinate care. Our results suggest that larger is not always better when dealing with the current state of ACO maturity. Rather, ACOs should consider care coordination challenges when adding new beneficiaries and participants.

9. Conclusions

In this study, we demonstrate the role of effective health IT use as an enabler of health information sharing capabilities necessary to achieve competing organizational objectives with respect to the efficiency and quality of care in ACOs. To the best of our knowledge, our research represents one of the first studies to (a) evaluate *quality-efficiency tradeoffs* in the context of value-based care, and (b) highlight the importance of IT-enabled information integration in addressing these tradeoffs, thereby enhancing the organizational capabilities necessary to achieve both performance dimensions. Our empirical analyses show that effective use of health IT plays a critical role in moderating the relationship between ACO efficiency and quality. In other words, health IT strengthens this relationship within ACOs compared to its impact on traditional hospitals that do not participate in ACOs. Our research underscores the importance of well-designed incentive models to promote inter-organizational information sharing for efficient, high-quality care.

Our study does have several limitations. While meaningful use provides a reasonable proxy for effective health IT use, our data does not allow us to track the use of IT for specific care coordination practices, such as patient referral management, quality dashboards, and medication adherence. We are not aware of any longitudinal, nationally representative data on the care coordination capabilities of ACOs and acknowledge that our study provides the first step toward collecting such data for research and policymaking. Further, we recognize that several key factors may affect IT usage (e.g., complementary investments in staff training), leading to a concern of omitted variable bias. While we draw on MU achievement as a proxy for effective IT use and implemented an IV approach to mitigate this concern, future studies can draw on richer datasets on complementary organizational investments to address this issue. Third, due to changes in the ACO regulations for EHR use in 2017, our definition of health IT use spans both the MU and Advancing Care Information programs. While we observed qualitatively consistent results using data on each program separately, we acknowledge that access to a longer period of health IT use by ACOs is critical for future research. Fourth, our study is restricted to Medicare ACOs and may not be generalizable to other programs, such as ACOs for non-Medicare beneficiaries. Although the MSSP program accounts for a majority of ACOs across the U.S., there may be differences between MSSP and non-Medicare ACO programs. Examining alternate contexts to compare differences across different ACO delivery models may provide additional nuanced insights.

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Figure 1: Conceptual Research Model

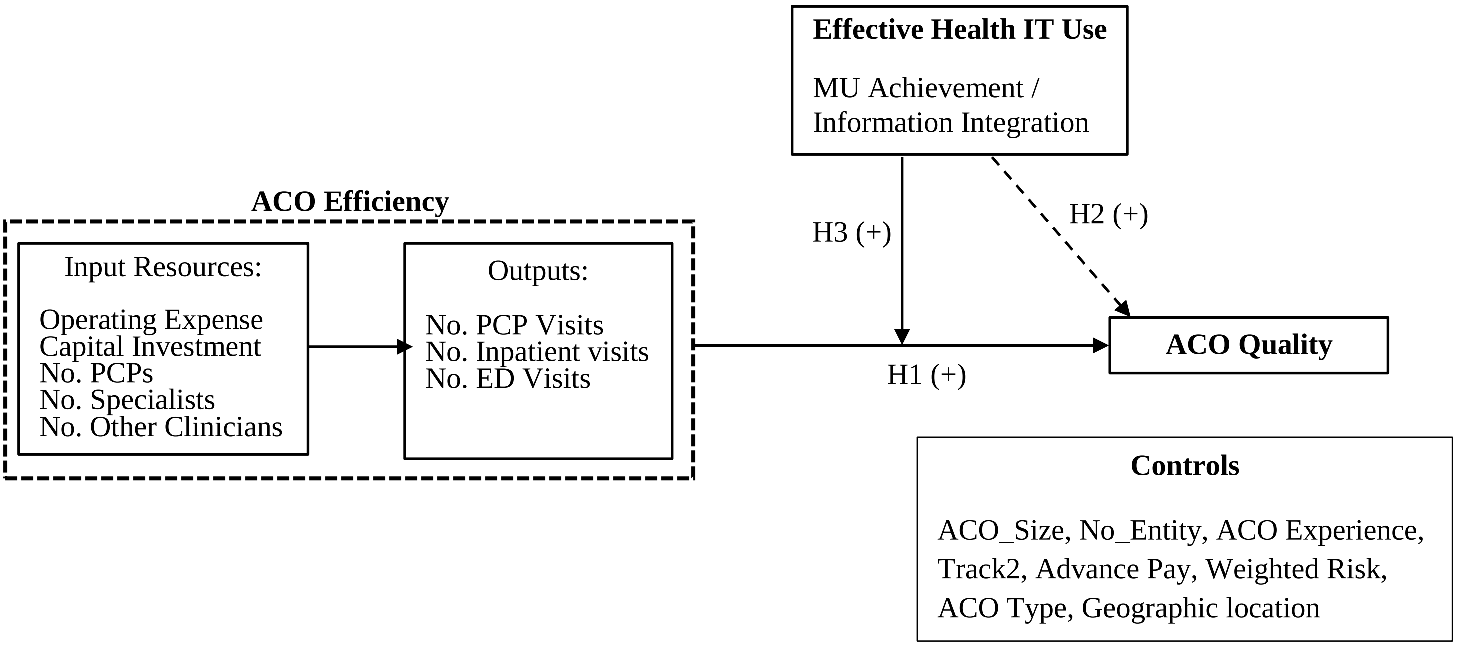
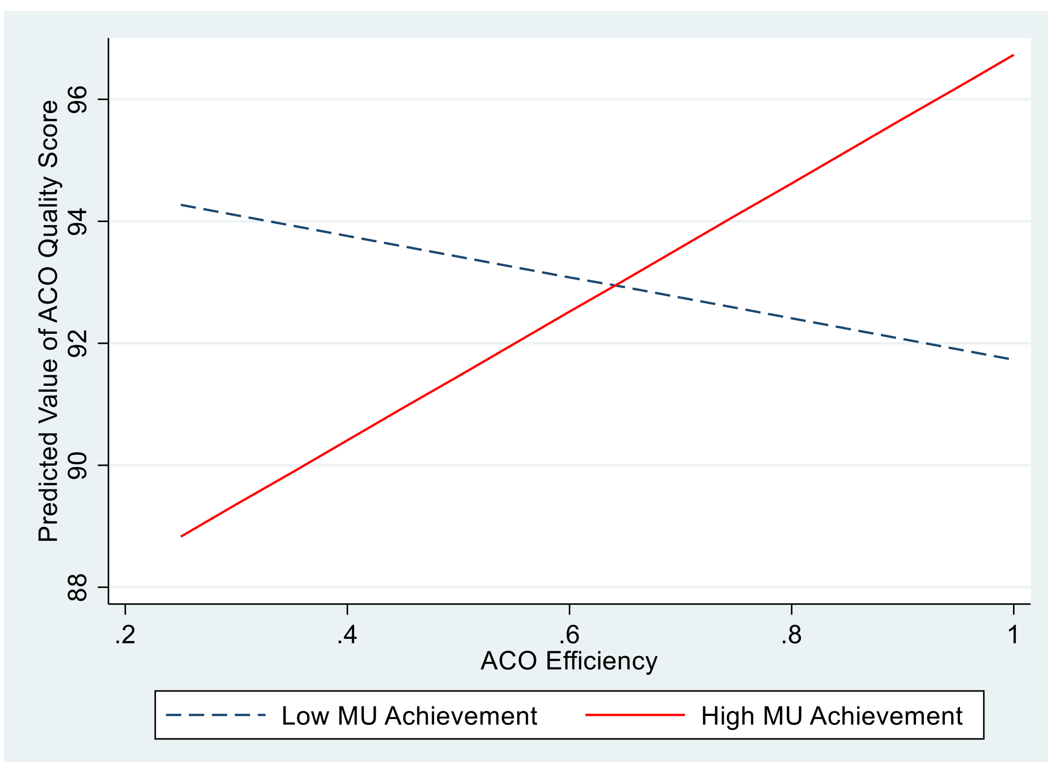


Figure 2: Quality-Efficiency Relationship for Low- versus High- Meaningful Use ACOs



Note: Other variables are at their mean values.

Table 1: ACO Variable Definitions and Descriptive Statistics

Variable	Definition	Mean (St. Dev.) N=2,140
First Stage DEA Model		
Input Resources		
Operating Expense ($)	Average expenditure per beneficiary year exclude expense for physician/supplier service and expense for durable medical equipment.	7136.163 (2048.719)
Capital Investment ($)	Average expenditure per beneficiary year for durable medical equipment.	260.326 (63.426)
No. PCPs	Number of primary care physicians per beneficiary year that reassigned billing rights to an ACO participant (198 PCPs per ACO).	0.011 (0.012)
No. Specialists	Number of specialists per beneficiary year that reassigned billing rights to an ACO participant (344 specialists per ACO).	0.018 (0.028)
No. Other Clinicians	Number of nurse practitioners, physician assistants, and clinical nurse specialists per beneficiary year (150 other clinicians per ACO).	0.008 (0.011)
Output Services		
No. PCP Visits	Number of primary care services per beneficiary year.	10.328 (1.749)
No. Inpatient Visits	Number of inpatient discharges per beneficiary year.	0.326 (0.081)
No. ED Visits	Number of emergency department visits per beneficiary year.	0.733 (0.173)
Second Stage Econometric Model		
ACO_Quality	Aggregated quality performance from individual quality indicators based on CMS quality measure benchmarks. Measured using scaling criteria from CMS based on 33 quality measurements in 2014, 33 in 2015, 34 in 2016, and 31 in 2017 and 2018.	93.221 (6.745)
MU Achievement	Percent of PCPs who qualified for EHR incentive payment based on meaningful use achievement for year 2014—2016. Percent of eligible clinicians (i.e., nurse practitioners, registered nurses, physician assistants, and physicians) who meet the Advancing Care Information base score requirements for 2017 and 2018.	87.542 (18.124)
Internal Information Integration	Summative index of information integration within the health system with respect to patient demographics, clinical care records, laboratory results, medication history, and radiology reports.	0.950 (0.133) N = 576
External Information Integration	Summative index of information integration outside the health system with respect to patient demographics, clinical care records, laboratory results, medication history, and radiology reports.	0.840 (0.228) N = 576
ACO_Size	Number of assigned beneficiaries in 1,000s.	18.350 (18.153)
No_Entity	Number of distinct organizations participating in an ACO based on taxpayer identification number.	36.743 (55.339)
ACO Experience	Number of years enrolled in MSSP program.	1.826 (1.534)
Track2	Binary indicator of the ACO model participation. 1=two-sided risk model, 0=otherwise.	0.076 (0.265)
Advance Pay	Binary indicator of participating in Advance Payment Model. 1=participant, 0=otherwise.	0.058 (0.235)
Weighted Risk	Weighted average of risk score of each beneficiary category by category population.	1.039 (0.101)
ACO Type	Binary indicator of hospital involvement in DEA model. 1=financial integrated with hospital, 0=otherwise.	0.559 (0.497)

Table 2: Sample Distribution of ACOs and Efficiency Evaluations

Year	ACO Type	No. of ACOs	DEA Efficiency Score		Mann-Whitney Test*
			Mean	(St. Dev.)	
2014	Hospital-Managed	135	.889	(0.100)	3.530 (0.000)
	Physician-Led	171	.930	(0.078)	
	All	306	.912	(0.091)	
2015	Hospital-Managed	200	.914	(0.082)	2.700 (0.007)
	Physician-Led	186	.934	(0.075)	
	All	386	.924	(0.079)	
2016	Hospital-Managed	246	.895	(0.084)	4.703 (0.000)
	Physician-Led	182	.932	(0.072)	
	All	428	.910	(0.081)	
2017	Hospital-Managed	279	.893	(0.094)	4.989 (0.000)
	Physician-Led	193	.936	(0.068)	
	All	472	.911	(0.087)	
2018	Hospital-Managed	337	.879	(0.094)	6.425 (0.000)
	Physician-Led	211	.930	(0.072)	
	All	548	.899	(0.090)	
Overall	Hospital-Managed	1197	.893	(0.092)	10.322 (0.000)
	Physician-Led	943	.932	(0.073)	
	All	2140	.910	(0.086)	

Note: *: p-values (two-tailed test) are included in the parentheses for the Mann-Whitney tests (Wilcoxon rank-sum tests).

Table 3: Correlation Matrix

	Variables	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
V1	ACO_Quality	1										
V2	MU Achievement	0.21*	1									
V3	Int. Info. Integr.	0.07*	0.11*	1								
V4	Ext. Info. Integr.	0.11*	0.18*	0.32*	1							
V5	ACO Efficiency	0.01	-0.18*	-0.07	-0.04	1						
V6	ACO_Size	0.02	0.19*	0.06	0.001	-0.25*	1					
V7	No_Entity	-0.16*	-0.21*	-0.004	-0.04	-0.11*	0.45*	1				
V8	ACO Experience	-0.43*	0.09*	0.11*	0.17*	-0.04	0.11*	0.13*	1			
V9	Track2	0.02	0.08*	0.03	0.07	-0.08*	0.04*	0.08*	0.14*	1		
V10	Advance Pay	-0.10*	-0.10*	-0.22*	-0.13*	0.10*	-0.13*	-0.08*	0.14*	0.03	1	
V11	Weighted Risk	-0.08*	-0.29*	-0.09*	-0.15*	-0.18*	-0.06*	0.10*	-0.04	0.06*	0.15*	1
V12	ACO Type	0.09*	0.28*	n/a	n/a	-0.20*	0.32*	0.09*	-0.09*	0.06*	-0.25*	-0.19*

Note: * indicates statistically significant at p=0.05. Correlations for Internal and External Information Integration are based on the sub-sample of hospital-managed ACOs.

Table 4: Estimation Results for Baseline Model and Heckman Estimation

DV: *ACO_Quality*	(1)	(2)	(3)	(4)
Model Specification	Baseline OLS		Heckman Model	
MU Achievement	0.048***	0.034**	0.050***	0.031*
	(0.013)	(0.014)	(0.019)	(0.019)
ACO Efficiency	-4.664	-4.488	-4.630	-4.532
	(3.699)	(3.608)	(3.675)	(3.597)
MU Achievement*ACO Efficiency		0.309**		0.315**
		(0.144)		(0.142)
ACO_Size	0.002	0.004	0.002	0.004
	(0.017)	(0.017)	(0.017)	(0.017)
No_Entity	-0.012**	-0.012**	-0.011**	-0.013**
	(0.005)	(0.005)	(0.005)	(0.005)
ACO Experience	-1.462***	-1.408***	-1.470***	-1.397***
	(0.165)	(0.166)	(0.174)	(0.176)
Track2	2.395***	2.415***	2.399***	2.411***
	(0.770)	(0.744)	(0.770)	(0.744)
Advance Pay	0.669	0.459	0.666	0.460
	(1.701)	(1.756)	(1.700)	(1.759)
Weighted Risk	-3.660	-3.205	-3.633	-3.233
	(4.728)	(4.717)	(4.734)	(4.716)
ACO Type	-1.468	-1.149	-1.482	-1.123
	(1.116)	(1.132)	(1.117)	(1.135)
Inverse Mills Ratio			-0.060	0.083
			(0.328)	(0.321)
Constant	98.726***	97.908***	98.717***	97.906***
	(5.143)	(5.172)	(5.148)	(5.169)
Observations	2,122	2,122	2,122	2,122
R-squared	0.266	0.270	0.266	0.270
ACO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes

Note: Standard errors are clustered at the ACO level. *p < 0.1; **p < 0.05; ***p < 0.01 (two-tailed test).

Table 5: Difference-in-Differences Analysis of Hospitals based on ACO Participation

DV	(1) Mortality Rate	(2) 30-day Readmission Rate	(3) Experiential Quality
ACOPart	-0.074	-0.028	0.107
	(0.096)	(0.050)	(0.153)
Efficiency	0.414**	0.210*	-0.151
	(0.194)	(0.117)	(0.357)
Efficiency*ACOPart	-0.346	-0.251*	0.210
	(0.519)	(0.141)	(0.440)
MU	0.077	0.035	0.287*
	(0.061)	(0.055)	(0.158)
Efficiency*MU	-0.025	0.208	-0.198
	(0.231)	(0.205)	(0.599)
Efficiency*MU*ACOPart	0.439	-0.554**	1.693*
	(0.523)	(0.263)	(0.921)
Urban	-0.518**	-0.509*	1.196**
	(0.203)	(0.270)	(0.609)
Teaching	-0.619**	-0.194	0.257
	(0.241)	(0.135)	(0.363)
Chained	-0.158	-0.246***	0.090
	(0.157)	(0.089)	(0.282)
NonForProfit	-0.049	-0.337***	0.868**
	(0.309)	(0.114)	(0.344)
Governmental	-1.299*	0.861*	-1.610
	(0.777)	(0.457)	(1.280)
Beds	-0.000	0.000	-0.000
	(0.001)	(0.000)	(0.002)
CMI	-0.587	0.067	-0.090
	(0.450)	(0.207)	(0.559)
WageIndex	-0.181	1.238**	-2.461
	(1.000)	(0.517)	(1.594)
Constant	15.056***	14.547***	75.012***
	(1.297)	(0.675)	(1.943)
Observations	2,025	3,209	3,105
R-squared	0.128	0.134	0.115
Marginal Product: Efficiency (ACOPart=1)	0.068	-0.041	0.059
Marginal Product: Eff*MU (ACOPart=1)	0.414	-0.345*	1.494**
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Propensity Score Matching	Yes	Yes	Yes

Note: Standard errors are clustered at the hospital level. *p < 0.1; **p < 0.05; ***p < 0.01 (two-tail test).

Table 6: Impact of Information Integration across hospital-led ACOs

DV: *ACO_Quality*	(1)	(2)	(3)	(4)
	Internal Info Integration		External Info Integration	
Information Integration	0.511*	0.661**	3.207*	4.128***
	(0.263)	(0.256)	(1.632)	(1.578)
ACO Efficiency	-5.884	-6.673	-5.872	-6.680
	(6.402)	(6.396)	(6.398)	(6.388)
Information Integration*ACO Efficiency		4.798***		29.849***
		(1.793)		(11.172)
ACO_Size	0.011	0.007	0.011	0.007
	(0.032)	(0.032)	(0.032)	(0.032)
No_Entity	-0.040***	-0.037***	-0.040***	-0.037***
	(0.012)	(0.012)	(0.012)	(0.012)
ACO Experience	0.384	0.369	0.384	0.369
	(0.350)	(0.344)	(0.350)	(0.344)
Track2	3.974***	3.920***	3.980***	3.914***
	(1.399)	(1.391)	(1.398)	(1.389)
Advance Pay	3.563	5.874	3.569	5.874
	(10.220)	(10.050)	(10.220)	(10.052)
Weighted Risk	-4.773	-4.562	-4.765	-4.549
	(2.912)	(2.969)	(2.914)	(2.975)
Inverse Mills Ratio	-0.616	-0.715	-0.624	-0.724
	(0.545)	(0.534)	(0.543)	(0.531)
Constant	89.311***	87.214***	89.293***	87.199***
	(10.763)	(10.598)	(10.762)	(10.600)
Observations	576	576	576	576
Observation Period	2014-2016		2014-2016	
R-squared	0.146	0.160	0.139	0.142
ACO FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Geographic Control	Yes	Yes	Yes	Yes
ACO Type	Hospital-Managed		Hospital-Managed	

Note: Standard errors are clustered at the ACO level. *p < 0.1; **p < 0.05; ***p < 0.01 (two-tail test).