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Research article

An exploratory study of the growth of the Accountable Care Organization and its impact on physician groups' profit: a complex adaptive system approach

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ABSTRACT

The emergence of Accountable Care Organizations (ACOs) in the landscape of the U.S. healthcare system marks a paradigm shift in healthcare operations. The potential impact of ACOs has been a topic of intense debate. Traditional analytical approaches do not lend themselves to examining the complex phenomenon of the emergence and growth of ACOs in the healthcare network. We adopt a complex adaptive system lens to examine the growth of ACOs among physician groups and explore factors that influence this growth. We also discuss the impact of ACOs on the profit of physician groups. An agent-based model was built to simulate physician groups' ACO entrance and exit based on a set of simple rules and their complex interactions with other agents. Based on the simulation results, we derive patterns of ACO expansion and contraction, following four stages of wait-and-see, rollercoaster, fast growth, and stabilizing. Findings suggest that the growth of ACOs is sensitive to the initial state of ACO membership. When the initial size of ACO membership increases, it helps to eliminate the rollercoaster stage. In addition, the growth of the ACO varies depending on the cost–quality tradeoff. When both cost and quality objectives can be met simultaneously, the growth of ACO membership follows wait-and-see and fast growth stages followed by a different stage that we term sticky state. The impact of ACOs on physician groups' cumulative profit varies by the service quality level of the physician group. Physician groups affiliated with insurance companies charging the lowest or the highest level of health insurance premiums are worse off with the ACO option. However, the ACO benefits physician groups affiliated with an insurance company charging a moderate level of premiums.

1. Introduction

The emergence of Accountable Care Organizations (ACOs) is a nascent yet influential event in the evolution of the U.S. healthcare system. Understandably, there has not been any consensus reached over ACOs' impacts on the healthcare network (Gamble, 2013; Gold, 2011; Muhlestein, 2013). In fact, since the inception of ACOs at the national level in 2012, there have been fierce debates over the ability of these organizations to meet their performance goals, as well as any unintended consequences that could adversely impact members of the health supply network (Dove et al., 2009; Numerof, 2011).

One of the factors contributing to the debate is that it is extremely difficult to realistically assess the effects of ACOs, due to the inherent complexity of the U.S. healthcare system (Burns et al., 2002). A healthcare supply network is comprised of numerous entities/organizations (such as patient groups, physician groups, and insurance companies; Burns and Pauly, 2002). In order to provide healthcare services to patients, these entities engage in complex relationships to allocate resources and simultaneously compete with other healthcare providers in the region (Plsek, 2001). Further, these entities are self-regulating

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(Anderson et al., 2003) and they learn and adapt to changes in the environment (Wilson and Holt, 2001). Their adaptive behaviors present a significant challenge in understanding the implications of ACOs using a conventional model that is based on the assumption of central planning at the network level (Pathak et al., 2007).

However, where conventional models have failed, we believe the complex adaptive system (CAS) approach will work. A complex adaptive system is a theoretical framework that embraces complexity and views organizations as living, adaptable, changeable systems (Choi et al., 2001). If we view the healthcare supply network as a CAS, then a single change in the environment, such as the creation of ACOs, could have complex ripple effects when traveling through the myriad relationships within a healthcare supply network. In addition, the CAS perspective allows agents such as physician groups to learn and adapt to changes in the environment, which provides a realistic representation of the complex dynamics among healthcare supply networks. In this research, we use the CAS lens to examine the growth of ACOs, a pressing issue in healthcare. Accordingly, we present our first research question: How does ACO membership expand and contract over time?

Because one defining characteristic associated with a complex system is its sensitivity to initial conditions (Kolen and Pollack, 1990), we also set out to discover whether different levels of participation by physician groups at the onset of ACO formation will impact the development stages of the ACO. In addition, as scholars have long observed the quality and cost tradeoff in various disciplines such as manufacturing (Farooq et al., 2017), project management (Khang and Myint, 1999), and mathematics and computation (Tareghian and Taheri, 2006), we investigate how the quality and cost tradeoff impacts the expansion and contraction of ACOs. Thus, our second research question is: What factors impact the expansion and contraction patterns of ACOs?

Lastly, we investigated the impact of ACOs on physician groups' profit and delineated this effect at the service quality level. This finding helps health service providers to make strategic decisions on whether or not to join an ACO. Here, we formally put forward our third research question: How does the creation of ACOs impact the profit of physician groups? And how does this impact vary among different physician groups?

By answering these three questions, our research provides policy guidance on the ACO, its deployment strategy, and its potential impact. This policy guidance is much needed in this very early stage of implementing ACOs and could potentially shape the U.S. healthcare supply network. Specifically, we modeled the responses of supply network agents (i.e., patients, physician groups, and insurance companies) to changes in the environment (i.e., the formation of ACOs), the complex interactions created by their responses, and the impact of these complex interactions on the expansion of ACO networks as well as on the profit generation of physician groups. In addition, we examine factors that can impact the growth of ACOs. Understanding these factors can assist policy makers to design and adjust program parameters in order to better deploy ACOs.

Besides significant policy guidance, by applying the CAS perspective our research, makes important theoretical contributions to supply network research, especially research in healthcare supply networks. First, we extend our understanding of the behaviors of the healthcare supply network as a CAS, which responds to calls from Operations and Supply Chain Management (O&SCM) scholars (Carter et al., 2015; Pathak et al., 2007) to take a more realistic look at the complex nature of supply networks. Second, we create a stage model and derived patterns of expansion and contraction of ACOs, which is novel in healthcare supply network research.

The rest of the paper is divided into the following sections. Section 2 provides background information on the formation of ACOs in the context of the U.S. healthcare service supply network and explains how the CAS lens offers a superior theoretical framework to investigate dynamics within this complex healthcare supply network. Section 3 explains the methodology. Section 4 sets up the agent-based model. Section 5 presents findings and discussion. Section 6 provides conclusions, implications, and future research directions.

2. Research background

2.1. Accountable Care Organizations

The healthcare delivery system of the United States has traditionally been thought of as independent systems (Rice et al., 2013), where "care has been delivered by multiple providers with little or no coordination" (Barnes et al., 2014). This fragmentation leads to issues with high healthcare cost and low quality (Barnes et al., 2014). In an attempt to solve these issues, the Affordable Care Act passed in 2010 funded the establishment of ACOs. These organizations are "groups of doctors, hospitals, and other healthcare providers, who come together voluntarily to give coordinated high quality care to the Medicare patients they serve" (CMS.gov). The emergence of ACOs in the landscape of U.S. healthcare marks a paradigm shift in healthcare operations (Bohmer and Lee, 2009; Song et al., 2012). Projections call for more than 50% of U.S. hospitals to be participating in the ACO model, representing a dramatic increase from 5% in its inception year of 2012.

Moving away from the traditional pay-for-service model, the ACO is a payment and care delivery model that attempts to explicitly connect provider reimbursements to quality metrics and reductions in the total cost of care for a population under consideration. The motive behind the establishment of ACOs is cost savings for Medicare services (Fisher et al., 2009). If an ACO can meet the cost-saving goals, then physician groups affiliated with the ACO will be awarded a percentage of the savings (CMS.gov) by the Federal government of the United States. The savings are calculated by the Center of Medicare Services, a branch of the U.S. Federal government, based on historical benchmark to an ACO's per capita expenditures during the performance year. To qualify for the savings, an ACO must meet or exceed a predetermined cost saving as well as quality criteria. Thus, there is a direct incentive for physician groups to improve quality of care and reduce total cost of care. It is hoped that such an alignment of goals between the healthcare system and the payer (e.g., Government for Medicare) will result in a more effective and efficient system. Operationally, the ACO model requires physician groups and other healthcare providers to come together to provide coordinated care to patients. The ACO assumes financial risk for some part of patient care and gets rewarded with a bonus if the cost of providing care is below budget while meeting certain quality requirements.

With the increased awareness of ACOs, there have been calls for using analytics to help healthcare suppliers use healthcare resources "as efficiently as possible in a population perspective" (Terry, 2013). Our research answers this call. We examine the growth of the ACO and its impact on members of the healthcare supply network. We believe that in order to realistically model this phenomenon and understand its implications, it is important to adopt a CAS perspective for the following reasons. First, an ACO is embedded in a web of agents in a healthcare supply network such as insurance groups, patients, and physician groups. These agents have their own sets of attributes, goals, and behavioral rules, resulting in a rugged landscape (Kauffman and Levin, 1987; Pathak et al., 2007) that cannot be studied in a well-organized linear manner. Second, an ACO is made up of physician groups that interact directly and indirectly with other agents in the healthcare system and it is difficult to decompose these effects into linear terms due to the varying actions of the agents. Third, the ACO represents a key change to the environment of U.S. health systems, and agents such as physician groups observe, learn, and adapt to this change. This type of learning and adaptation behavior cannot be modeled using a conventional linear approach (Dooley, 1997). The CAS lens adds realism and practicality to a research model that captures such learning and adaptation behavior.

2.2. Healthcare supply network as a complex adaptive system

The envisioning of a supply network—whether it is a physical material supply network or a healthcare service supply network—as a CAS, is relatively new in O&SCM (Carter et al., 2015; Pathak et al., 2007). The study conducted by Choi et al. (2001) was one of the first to suggest a shift of research paradigm from an organized view of supply networks to one that incorporates complexity. They argue that supply networks emerge rather than being planned by a single entity. Therefore, managers should balance the need for control with the need to allow the supply network to emerge through processes of self-organization and adaptation.

Many researchers have joined in promoting the use of a CAS perspective in supply network issues. Notably, Pathak et al. (2007) reviewed an extensive list of peer-reviewed journals and identified developments in theory, methodology, and techniques used in CAS research. They also noticed that most of these developments were outside the domain of O&SCM. They subsequently addressed opportunities and challenges of applying CAS to O&SCM. Focusing the application of CAS on the specific area of disaster relief, Day (2014) explained why CAS might be the most appropriate theoretical framework to guide the understanding of supply network operation in the event of disasters, and set forth propositions on how to improve supply network resilience. Most recently, Carter et al. (2015) recognized the lack of theoretical development in supply chain management and proposed a framework to conceptualize the supply chain domain. In their effort, the CAS lens was used as the foundational premise for conceptualization of the supply chain.

Besides addressing CAS in O&SCM conceptually, various researchers have ventured to apply the CAS lens to a specific supply network phenomenon, notably in the area of inter-firm collaboration. For example, Holweg and Pil (2008) conducted case studies to examine the complex nature of supply chain coordination and found that the CAS lens complements findings derived from other competing theories. Nair et al. (2009) simulated supply chain coordination with an agent-based model and put forth propositions regarding cooperative relationship development in a supply network. Kim (2009) examined trust at the local agent level and its impact at the system level. A recent research by Li et al. (2021) studied buyer firm's financial squeeze and its impact on the buyer's extended supply network, via complex interactions. Besides inter-firm collaboration, scholars have also examined the effect of supply chain complexity on plant performance (Bozarth et al., 2009), mutual influences between properties of human agents and properties of supply chain systems (Tangpong et al., 2014), abnormal flow patterns in supply streams (Sawaya et al., 2015), and the relationship between learning and adaptation in supply networks located within industrial districts (Giannoccaro, 2015). Table 1 summarizes key research in supply network as a CAS.

As shown in Table 1, we are not aware of any supply chain research that applies the CAS lens to the growth of ACOs in the healthcare domain. The lack of research in this area is perhaps due to the nascency of the ACO concept and how little is known about its effectiveness. In addition to the novelty in the ACO context, we note that few existing studies address the evolutionary aspect of the supply network (Yan et al., 2021). By examining the growth patterns of ACO members, we trace the expansion of ACO networks over several years and portray the stages of ACO network growth. In this regard, our research is theoretically new and exciting, and enhances understanding of the evolution of healthcare supply networks.

3. Methodology

Our research was executed in two steps. In step one, we constructed an empirically based healthcare supply network and worked with healthcare providers to understand tradeoffs of joining an ACO and the reasons behind the tradeoffs. In step two, we built an agent-based model, based on the healthcare supply network, to simulate the growth of the ACO and its impact on the cumulative profit of healthcare supply network members. We outline these two steps in detail below.

Table 1
Summary of research in supply network as a complex adaptive system.

Author (year)	Methodology/type	Findings
Choi et al. (2001)	Conceptual	The first paper to envision supply networks as CAS.
Pathak et al. (2007)	Conceptual	Identify challenges and opportunities of applying CAS in supply network research.
Holweg & Pil (2008)	Case study	CAS helps to explain supply chain coordination and complements findings supported by other competing theories.
Nair et al. (2009)	Agent-based modeling	Offered propositions regarding cooperative relationship development in supply networks.
Kim (2009)	Agent-based modeling	Trust in local agents and its impact at system level.
Bozarth et al. (2009)	Survey research	Empirical examination of supply chain complexity on plant performance.
Day (2014)	Conceptual	Examination of disaster relief with CAS lens.
Tangpong et al. (2014)	Survey and experiments	Examination of the mutual influences between properties of human agents and properties of supply chain systems.
Sawaya et al., 2015	Time series modeling in combination with adaptive limit process charts	Identification of abnormal flow patterns in supply streams.
Carter et al. (2015)	Conceptual	Theorization of supply chain as a CAS.
Giannoccaro (2015)	Agent-based modeling	Investigated the relationship between learning and adaptation in supply networks located within industrial districts.
Li et al. (2021)	Agent-based modeling	Examined the impact of financial squeeze on buyer's extended supply network.

3.1. Empirical data on healthcare supply network

Because the ACO was pioneered in 2012 and subsequently opened up to all healthcare facilities in 2013, we traced back to the 2012 HIMSS Analytics™ Database (HIMSS) to define structures of the healthcare supply network and derive cost and quality parameters for physician groups belonging to an ACO. The HIMSS database compiles annual surveys of care delivery organizations across the United States. The survey items cover a wide range of U.S. healthcare suppliers' characteristics and operational practices. We linked this dataset to the 2013 Hospital-Compare database published by Medicare.gov. HospitalCompare captures healthcare providers' performance data such as quality of service and patient satisfaction. We chose to construct network-level data based on data collected in year 2012 and lag our performance variables by one year, because research has shown that the effects of organizational changes are likely to manifest in subsequent years (Devaraj and Kohli, 2003). In addition, because the development of a complex adaptive system is sensitive to initial conditions (Kolen and Pollack, 1990), it is imperative that we model the structure of the network based on data from the inception of the ACO in 2012.

Based on the HIMSS data, we mapped a healthcare supply network located in the Midwest region of the United States. We chose the Midwest region to represent a generic healthcare system in the United States, as healthcare systems in the East or West regions of the country may be confounded by other factors such as a diverse population profile, which may lead to healthcare disparities (Riley, 2012), as well as different trajectory of healthcare-related technologies (Feibus, 2015). We noted

Table 2
Key parameters used in the base scenario.

Parameter	Setting
Patient base	200,000
Total number of physician groups	60
Initial percentage of physician groups in an ACO	5% (or 3 out of 60)
Penalty parameter for service quality (applies to ACO members only)	0.92
Administrative cost associated with joining ACO	$20,000

Table 3
Means and standard deviations of service quality levels: ACO members vs. non-ACO members.

Type	N	Mean	Standard deviation	Standard error mean
Non-ACO members	2,763	71.39	5.16	0.10
ACO members	198	69.78	5.28	0.38

the number of physician groups, the number of ACO groups, and the patient base in the region. More importantly, we examined empirically the cost–quality tradeoff for healthcare providers that have joined the ACO. Although the stated objective for ACOs is to cut costs while improving quality, research shows mixed results of ACOs' impact on quality (Kelleher et al., 2015). In order to realistically model the supply network dynamics, we analyzed empirical data to derive a realistic parameter for cost–quality tradeoff for healthcare suppliers affiliated with ACOs.

Based on the empirical data, we noticed that there are 60 physician groups in the Midwest region we modeled, serving the needs of a 200,000 patient base. Initially 5% of the physician groups joined an ACO. We used these parameters to set up our agent-based model. Table 2 summarizes these parameters.

3.2. Cost–quality tradeoff

In the next step, we first analyzed the empirical data to derive the cost and quality tradeoff associated with joining an ACO group and then interviewed subject matter experts (SMEs) in this region to understand the reasons behind the cost and quality tradeoffs. When analyzing the cost–quality tradeoff associated with ACO membership, we compared mean values of service quality across two groups: ACO members and non-ACO members. Results of mean comparison for service quality levels across these two groups are reported in Table 3. We then conducted two independent sample *t*-tests using SPSS version 20. Results of the *t*-tests are reported in Table 4.

Empirical data support service quality degradation for members of the ACO. As indicated in Table 3, the mean value and standard deviation of service quality for non-ACO members is 71.387 (standard deviation = 5.157) and for ACO members is 69.778 (standard deviation = 5.283). The mean value of service quality is higher for non-ACO members than for ACO members.

Based on Table 4, Levene's Test for Equality of Variance did not reject the assumption of the equality of variance. Therefore, we proceeded with interpreting results based on an equality of variance assumption. Results show a statistically significant difference in the mean values of service quality across the two groups. The p-value is < 0.001. The confidence interval is (0.864, 2.355) and does not contain the value of 0. Both the p-value and the confidence interval validate that the difference in mean value is statistically significant. Thus we conclude there is a quality tradeoff for healthcare providers that are members of an ACO. Even though improving quality is stated as part of the goals of ACOs (CMS.gov), there is degradation in service quality for ACO members.

3.3. Interview with physician groups

We worked with local healthcare providers and physician group administrators to examine the reasons behind the quality and cost tradeoffs. We chose these SMEs based on their tenure, area of expertise, and job functions. Specifically, we interviewed SMEs from two sides of the ACO to provide a comprehensive understanding: the healthcare administrator's side and the healthcare worker's side. From the administrator's side, we interviewed one healthcare executive who helped to establish numerous ACO groups. From the healthcare workers' side, we interviewed a surgeon who is also the head of a physician group, as well as a registered nurse. All SMEs are fully cognizant of ACO formation and have on average over 30 years of experience in the medical field. They provided validation of our results and cited reasons for the reduction of service quality as the limitation of treatment options for patients and reduction in treatment flexibility.

Based on our interviews with medical professionals, once physician groups joined an ACO, physicians are taking more and more risks with the patient base. "If there is a medical loss from a group of patients, the doctors basically have to pay back some of the money," stated one medical professional during our interview. As a result, doctors are exercising tighter control in their referral patterns in order to reduce costs and meet cost targets. For example, a general surgeon noted that "in this day and age of ACOs, I am doing less hernia surgeries than I used to." He attributed the reason for the reduction of surgery to the change of referral patterns from the primary care doctors, who are now the gatekeepers of patient problems. "The patients still have the same complaints that 'Hey, I got hernia and I want to get it fixed.' Now they are told in a higher percentage that you don't need to get it fixed. Don't worry about it." The patients were told to put off a hernia operation in order to reduce the amount of this surgery and the associated costs. This limitation of treatment options reduces patient satisfaction.

A similar story was shared on knee and hip replacements. Because of the high costs associated with these surgeries (a quote was given during our interview that "those are $50,000 operations"), if too many of these surgeries are allowed, "that is going to show up negatively on your bottom line." As a result, patients must go through a series of less expensive treatments before they are allowed to get a replacement. Thus, there is a decrease in treatment flexibility. One physician observed that "there is a decrease in services that patients are used to and coming to expect, which results in decrease in patient satisfaction." Interview

Table 4
Comparison of mean values of service quality levels: ACO members vs. non-ACO members.

	Levene's test for equality for variances		*t*-Test for equality of means						
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean difference	Standard error difference	95% confidence interval of the difference	
								Lower	Upper
Equal variances assumed	0.13	0.72	4.24	2959	0.00	1.61	0.38	0.86	2.35
Equal variances not assumed			4.15	224.75	0.00	1.61	0.39	0.84	2.37

protocol, interview questions, and resporesponses are available upon request.

With this empirical validation, we then proceeded with an estimation of the degree of quality degradation for members associated with an ACO. Here we regressed ACO membership on service quality, and the resulting model was statistically significant at the $p < 0.001$ level. We relied on the coefficient of correlation, r, to estimate the degree of quality degradation. The r value was 0.08 and we therefore factored in an 8% quality degradation for ACO members for the base scenario. We later varied this parameter to perform subsequent what-if analysis.

3.4. Agent-based model

An agent-based model (ABM) is a type of computational model that simulates the actions and interactions of autonomous agents with a view to assessing their effects on the simulated system as a whole. It allows direct representation of individual entities (as agents) and their interactions in a system. ABMs have applications in diverse real-world problems, and have become increasingly popular as a modeling approach in many disciplines of research. Table 5 provides examples of ABMs used in a variety of disciplines (Arifin et al., 2016).

Table 5
Applications of agent-based models (ABMs)[a].

Category	ABMs
Commerce Industry Business Enterprise	Stock market management (Arthur et al., 1997)
	Software agents (shopbots and pricebots) (Kephart et al., 2000)
	Supply chains management (Macal et al., 2004; Swaminathan et al., 1998; Julka et al., 2002)
	Intelligent manufacturing (Shen and Norrie, 1999; Shen et al., 2006)
	Credit risk analysis (Yan et al., 2021)
	Wholesale electricity market (Sueyoshi and Tadiparthi, 2008)
	Operational risk and organizational design (Bonabeau, 2002)
	Consumer purchasing behavior (North et al., 2010)
	Enterprise environments management (Bolloju et al., 2002)
Computing Internet Artificial life Decision support systems Economics	Product development on the Internet (Holweg and Pil, 2008)
	Robot control, robot manufacturing, computer graphics, entertainment, games, music, economics, Internet, information processing, industrial design, electronics, security, data mining, telecommunications, etc. (Macal, 2009; Kim and Cho, 2006)
	Control systems (Jennings and Bussmann, 2003)
	Social computing and social intelligence (Wilson and Holt, 2001)
	Decision support systems (Bui and Lee, 1999; Power and Sharda, 2007; Angehrn, 1993; Foster et al., 2005; An, 2012)
	Economics (Tesfatsion, 2002)
	Finance (LeBaron, 2000)
Ecology	Ecology (general) (Grimm and Railsback, 2013)
	Predator-prey relationships (killer whales and sea lions/ sea otters) (Testa et al., 2012)
	Land use (Matthews et al., 2007; Castella et al., 2005)
	Forest ecosystem management (Nute et al., 2004)
Environment Infrastructures	Environmental health impact (Sokolova and Fernández-Caballero, 2009)
	Critical infrastructures modeling (Rinaldi, 2004; Dudenhoeffer et al., 2006)
Natural disaster management	Hurricane evacuation (Chen et al., 2006; Dow and Cutter, 2002)
	Flood management (Dawson et al., 2011)
	Earthquake and tsunami management (Mas et al., 2012)
Transport and travel	Transport logistics (Davidsson et al., 2005)
	Travel behavior (Pel et al., 2012)

Source: Arifin et al., 2016 with permission from the source.
[a] References for papers cited in this table can be found in Arifin et al. (2016).

In O&SCM, the ABM technique has been applied to modeling the supply network as a CAS (Giannoccaro, 2015; Kim, 2009; Nair et al., 2009; etc.). An ABM offers several advantages over other modeling techniques. For one, it allows researchers to link behavioral rules resulting from the interactions of individual agents to aggregate or complex patterns, and to capture the emergent phenomena at the macro or network level (Bonabeau, 2002). In addition, an ABM can accommodate heterogeneity in that each agent can operate according to its own preferences or its own rules of action (Marchi and Page, 2014). The third advantage of an ABM is that it can simulate learning at both the agent level and the network level. In a CAS, agents can be adaptive in their actions and interactions with other agents (Macy and Willer, 2002). For example, agents adapt by imitating and/or replicating. These adaptive behaviors cannot be modeled by a conventional linear model (Pathak et al., 2007), as a linear model does not allow the continuous adjustments of independent constructs in response to changes in dependent constructs. Finally, in general, an ABM offers the most natural way for describing and simulating a system composed of behavioral entities, offering a closer representation of reality. This holds true for most of the applications of ABM presented in Table 5 and is one of the major reasons for the choice of ABM over other modeling techniques in our study.

In the healthcare context, the use of agent-based modeling is rapidly growing, and scholars have recognized the suitability of adopting ABM in healthcare research (Barnes et al., 2013). For example, Kanagarajah et al. (2010) adopt ABM to demonstrate the complications of healthcare system improvement in the context of an emergency department. Their work proves the nonlinear behaviors of healthcare service delivery and showcases the applicability of ABM in evaluating healthcare services. Similarly, Xie and Peng (2012) use ABM to investigate the reduction in waiting time and improvement in resource utilization of the operating room in a hospital. They model patients in the healthcare system as agents with autonomous and adaptive behaviors. Their findings validate the effectiveness of utilizing ABM in improving decision making in the healthcare context. ABM has also been applied to the spread of infectious disease (Laskowski et al., 2011; Xie and Peng, 2012), calculation of healthcare return on investments (Blachowicz et al., 2008; Kruzikas et al., 2014), and discovering interventions to increase population wellness (Silverman et al., 2015). For an extensive review of the application of ABM in various healthcare contexts, please refer to Barnes et al. (2013).

4. Modeling the healthcare supply network with ABM

4.1. Empirically based ABM

We model the evolution of ACO formation in a region in the Midwest part of the United States (Region S). Region S's healthcare supply network is characterized by a 200,000 patient base, three insurance groups, and 60 physician offices, 5% of which participate in an ACO.

4.2. Model architecture

In general, the three major components of an ABM are agents, environment, and rules. Agents can be individual or collective entities (such as organizations or groups). Each agent represents an actor in the simulated (virtual) environment in which it interacts with other agents. Employing a set of rules, agents individually assess the environment and make decisions. As a whole, the set of agents, the environment, and the rules, with their clearly defined boundaries, inputs, and outputs, compose the ABM (Arifin et al., 2016).

The ACO ABM consists of four major agent types: *Patients*, *Physician Groups*, *Insurance Companies*, and *Accountable Care Organizations*. Each *Patient* agent is connected to a *Physician Group* agent and an *Insurance Company* agent. An *Insurance Company* agent can have multiple *Physician Group* agents, each of which can potentially be connected to an

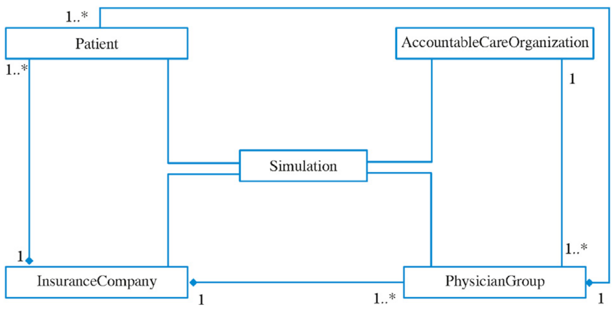

Fig. 1. A simplified class diagram of the model architecture in the ABM. Legend: "1 and 1..*" signify one-to-many relationships among network agents.

Accountable Care Organization agent. A simplified model architecture for the ABM is shown in Fig. 1.

4.3. Agents' attributes

In this section, we describe the attributes of *Patient*, *Physician Group*, and *Insurance Company* agents in the healthcare supply network. Below we describe attributes associated with each agent in the healthcare supply network.

Patient Agent. First, we examine the *Patient* agent. Our ABM accommodates the creation of 200,000 patients. At the beginning of the simulation, each patient is randomly assigned to an insurance group and a physician group that is affiliated with that insurance group. In addition, a patient is randomly assigned a wealth level as well as a binary indicator for whether a patient is price sensitive or not. The wealth level is a measurement of the income level of a patient. Once it is randomly assigned, it will remain with the patient until the end of the simulation. Importantly, at the beginning of the simulation, a patient is also randomly assigned a set level of service expectation. Service expectation represents the quality level of service that the patient is expecting from a physician group. Table A1 in the appendix provides more detail on the *Patient* agent.

Physician Group Agent. Next, we describe the *Physician Group* agent. A *Physician Group* agent has a set capacity and level of service quality that it provides to its patients. A Boolean indicator (*inACO*) describes whether a *Physician Group* is a member of the ACO and this indicator changes in response to the changes in the environment, based on a set of behavioral rules that will be described later in the manuscript. We also track the number of patient visits, and the group's yearly profit as well as cumulative profit. Table A2 in the appendix provides more detail on the *Physician Group* agent.

The computation of a *Physician Group's* yearly profit, *profitYearly*, depends on its ACO status. For non-members, the computation of $profitYearly_{nonACO}$ follows the following formula:

$$\text{profitYearly}_{\text{nonACO}} = \text{revenueYearly}_{\text{nonACO}} - \text{costYearly}_{\text{nonACO}} \tag{1}$$

Where:

$$\text{revenueYearly}_{\text{nonACO}} = \text{perVisitRevenueConstant}_{\text{nonACO}} * \text{numVisits} \tag{2}$$

$$\text{costYearly}_{\text{nonACO}} = \text{fixedCost}_{\text{nonACO}} + (\text{unitCostConstant}_{\text{nonACO}} * \text{numVisits}) \tag{3}$$

$$\text{fixedCost}_{\text{nonACO}} = \text{fixedCostConstant}_{\text{nonACO}} * \text{Capacity} \tag{4}$$

The cumulative profit, $profitCumulative_{nonACO}$, is the summation of $profitYearly_{nonACO}$ over the years.

For ACO members, the computation of $profitYearly_{ACO}$ follows the following formula:

$$\text{profitYearly}_{\text{ACO}} = \text{revenueYearly}_{\text{ACO}} - \text{costYearly}_{\text{ACO}} + \text{costSharingConstant} * \text{numVisits} \tag{5}$$

Where:

$$\text{revenueYearly}_{\text{ACO}} = \text{perVisitRevenueConstant}_{\text{ACO}} * \text{numVisits} \tag{6}$$

$$\text{costYearly}_{\text{ACO}} = \text{fixedCost}_{\text{ACO}} + (\text{unitCostConstant}_{\text{ACO}} * \text{numVisits}) \tag{7}$$

$$\text{fixedCost}_{\text{ACO}} = \text{fixedCostConstant}_{\text{ACO}} * \text{Capacity} \tag{8}$$

The cumulative profit, $profitCumulative_{ACO}$, is the summation of $profitYearly_{ACO}$ over the years.

Table 6 reports the initial values used to set up the *Physician Group* agent. Note here that we assume that by joining an ACO, on average, a physician group will achieve a cost reduction of $20/patient visit. Further, our model assumes that by joining an ACO, a member physician office will share a portion (50%, or $10/patient visit) of the cost savings. These are reasonable assumptions based on ACOs' cost-saving goals and reward structure (CMS.gov).

Insurance Company Agents. There are three *Insurance Company* agents. The first one, *AffordMe*, has the lowest premium and consequently, *Physician Group* agents associated with *AffordMe* on average offer the lowest service quality. The second one, *BetterLife*, has a slightly higher premium than *AffordMe* and on average offers a slightly higher service quality to its patient base. The last one, *CareTop*, has the highest premium, and physicians associated with *CareTop* on average offer the highest service quality. The differentiation among three insurance agents mimics a common practice in Region S, where insurance premium ranges from the least expensive group with the most restrictive healthcare supplier selection, i.e., managed care health insurance; to the moderately

Table 6
Initial parameters for physician groups: ACO vs. non-ACO group.

Name	Description	Non-ACO group	ACO group
joiningCostConstant	Administrative cost associated with joining ACO.	$0	$20,000
perVisitRevenueConstant	Average revenue received by *Physician Groups* at each patient visit.	$250	$250
unitCostConstant	Average cost incurred at *Physician Groups* at each patient visit.	$50	$30
costSharingConstant	A cash rebate received by ACO members for reaching cost reduction targets.	$0	$10/Visit
fixedCostConstant	Average overhead per capacity.	$20	$20
Capacity	Capacity of a *Physician Group*.	Uniform distribution (2000, 6000)	
ServiceQuality	Service quality level at each *Physician Group*.	Normal distribution with a mean of (2.5, 3.0, 3.5) and standard deviation of (.5, .5, .5) for *Physician Groups* affiliated with insurance group *AffordMe*, *BetterLife*, and *CareTop*, respectively.	Similar to non-ACO members except with a 0.08 reduction in ServcieQuality (i.e., 0.92*ServiceQuality of non-ACO members).

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expensive group with a wider range of selection of healthcare providers, i.e., Preferred Provider Organizations; to the most expensive group with the widest selection of healthcare providers, i.e., indemnity coverage. For a discussion on the different types of health premiums and their clinical quality performance tradeoffs, please refer to Robinson (2003). In general, a wider selection of healthcare providers is related to higher service quality, as highly qualified doctors tend to accept premium health insurance and reject low premium insurance (Galewitz, 2020).

Service quality is modeled on a [0, 6] continuous interval, with zero representing the lowest and six representing the highest service quality. This allows a 7-point scale. Research shows that having more scale points improves precision, yet there is a diminishing return if too many scale points are used (Nunnally, 1994). A 7-point scale is more discriminative than a 5-point scale and is a happy medium, as it does not require the maintenance of too many response categories. Service quality of physician groups affiliated with *AffordMe* follows a normal distribution with a mean of 2.5 and a standard deviation of 0.5. Service quality of physician groups affiliated with *BetterLife* follows a normal distribution with a mean of 3.0 and a standard deviation of 0.5. Service quality of physician groups affiliated with *CareTop* follows a normal distribution with a mean of 3.5 and a standard deviation of 0.5. Because *CareTop* charges the highest premium, if the service levels from *BetterLife* or *AffordMe* do not meet the expectations and patients are wealthy enough, patients may consider switching from *BetterLife* or *AffordMe* to *CareTop* and its affiliated physician group. Table A3 in the appendix provides more detail on the *Insurance Company* agent.

4.4. Environmental change

The introduction of an ACO is considered an environmental change. It imposes cost and quality implications to network agents. As we mentioned earlier, physician groups that are members of an ACO incur a lower cost for each patient visit—and at the end of the year, the physician groups share 50% of the cost savings. At the same time, ACO membership also incurs a quality penalty of 8%, as supported by empirical data. This means that once a physician group joins an ACO, its service level is automatically reduced to 92% of its previous level. This penalty is lifted once a physician group exits an ACO.

4.5. Behavioral rules

The *Patient* agent exhibits switching behavior where the patient switches to a different physician group if he or she is not satisfied with the quality received. For a given physician's office visit, if the service level received is equal to or exceeds the patient's expectation, then the patient will continue to stay with the physician's office. However, if the service level is below the patient's expectation, then the patient will decide on whether to switch physician groups or not, depending on the patient's wealth level. If the patient is wealthy enough (or is price insensitive) and is not satisfied with the service experience, the switch flag will be turned on and the patient will switch to a different insurance group and, via the different insurance group, switch to a new set of physicians. This switch only happens once at the end of the year, simulating what happens in real life, i.e., switching insurance group is an infrequent event and typically is only allowed during the yearly open enrollment period.

The *Physician Groups* decide to join or exit an ACO based on rules stated in Table 7. As a general principle, a physician group that is a member of the ACO will stay in the ACO, if the average profit of ACO members exceeds that of non-ACO members. The opposite scenario will decrease the physician group's probability of staying in the ACO. On the other hand, a physician group that is not a member of the ACO will increase its probability of joining, if the average profit per physician group is higher for ACO members than for non-ACO members. Otherwise, it will decrease its probability of joining. Table 7 also accommodates situations where the ACO profit is negative.

4.6. Scenario/experiment design

We created a base scenario to simulate the growth of an ACO. The parameters used in the base scenario are depicted in Table 2. We ran the base scenario 10 times and the outputs represent the average of the 10 simulations.

In order to examine factors that influence the growth of the ACO, we contrasted the base scenario with additional experiments. First, research shows that the behavior of a complex system is sensitive to initial conditions (Kolen and Pollack, 1990). As mentioned earlier, our base scenario is based on an empirical dataset collected in the Midwest region of the United States, which revealed a participation rate of approximately 5% in the starting year of ACOs. To investigate the impact of varying level of initial participation rates on the long-term development of ACOs, we varied the initial percentage of ACO membership by doubling and tripling the percentages to 10% (Experiment 1 or E1) and 15% (Experiment 2 or E2) of the physician group base, or 6 (and 9) out of 60. We reran each scenario 10 times and computed the average. Second, we were interested in the discrepancy between ACOs' official objectives (i.e., improving both cost and quality) and the quality degradation supported by empirical data. We ran a what-if analysis by removing the quality penalty parameter from the base scenario (Experiment 3 or E3), rerunning the simulation 10 times, and computing the average. Third, to

Table 7
Physician groups' decision rules for joining ACO.

	#	PhysGrpProfit (X) Sign* of X	AvgACOProfit (Y) Sign of Y	X/Y (R)	Prob of joining ACO (P)
If X is not a member of ACO Initial P = 0.5					
	1	+	+	R > 1	P=P-R
	2			R<=1	P=P + R
	3	–	+	N/A	P = 1 (join)
	4	+	–	N/A	P = 0.5
	5	–	–	R > 1	P=P + R
	6			R<=1	P=P–R
If X is a member of ACO Initial P = 1					
	7	**PhysGrpProfit (X) Sign of X**	**AvgNonACOProfit (Y) Sign of Y**	**X/Y (R)**	**Prob of joining ACO (P)**
	8	+	+	R > 1	P = 1.0
	9			R<=1	P=P–1+R
	10	–	+	N/A	P = 0.5 (drop from ACO)
	11	+	–	N/A	P = 1
	12	–	–	N/A	P = 0.5

Note: Sign* refers to the sign of the value, i.e., positive or negative.

Table 8
Experiments.

	ACO at initiation (%)	Quality penalty	Existence of ACO	Findings
Base scenario	5	0.08	Yes	ACO membership goes through 4 stages: Wait-and-see→rollercoaster→steady growth→stabilizing
Experiment 1 (E1)	10	0.08	Yes	ACO membership goes through 3 stages:
Experiment 2 (E2)	15	0.08	Yes	Wait-and-see→explosion→stabilizing. Elimination of Rollercoaster stage.
Experiment 3 (E3)	5	0	Yes	ACO membership goes through 3 stages: Wait-and-see→explosion→steady state. Elimination of rollercoaster stage.
Experiment 4 (E4)	0	0	No	Compared to no ACO, physician groups associated with *BetterLife* stand to gain by joining ACO. Physician Groups associated with *AffordMe* and *CareTop* are worse off.

realistically understand ACOs' impact on physician groups' profit, we simulated an environment where no ACO is allowed (i.e., the probability of ACO is set to 0; Experiment 4 or E4). Again, we reran the simulation 10 times and computed the average. Table 8 summarizes the four experiments.

4.7. Output measures

We report both textual and graphical outputs from the simulation runs. The yearly output tracks the attributes of each agent. For example, for the physician group, we track its annual number of patient visits, cost structure, revenue and profit (both annual and cumulative), its ACO membership status, etc.

In addition, we also report graphical outputs from the simulation runs. For each year, a single yearly graph depicts the dynamic network that connects all physician groups to their corresponding insurance companies, and also shows which of the physician groups are currently members of the ACO. As a result of the dynamic interaction between the patients, physician groups, insurance companies, and the ACO, patients switch insurance companies as well as physician groups. Depending on the yearly cost, revenue, and profit, each physician group, at the end of every year, may join or leave the ACO. The yearly graph accordingly portrays these dynamic changes for each year. Fig. 2 provides an example of the evolution of ACO membership for one simulation over the course of 10 years (we report results at the end of odd years only in order to fit all graphs into one page).

All graphical information was first saved in the DOT format, which is a plain-text graph description language. Then, each DOT file was visualized by an open-source graph visualization software called Graphviz (http://www.graphviz.org/).

4.8. Model features, assumptions, and simulations

We assume the presence of one ACO, three insurance companies, 60 physician groups, and 200,000 patients. All agents are non-spatial (i.e., they do not possess any explicit spatial information). The ABM is implemented as discrete-event computer simulations in the Java programming language. Time is modeled in yearly time steps, with each simulation running for at least 10 years. A sample simulation run takes about 10 min to output 10-year results data on a 2.8 GHz Intel Core i7 Apple Macintosh computer with 16 GB of memory.

5. Results and discussion

5.1. The expansion and contraction of ACO networks

5.1.1. The base scenario

First, we report the simulation results on the expansion and contraction of ACO membership in the base scenario. In the base scenario, the initial probability of a physician group belonging to an ACO, P_{ACO}, is set at 5%, following our empirical findings in Region S. Fig. 3 below depicts the growth of ACO membership throughout the 10 simulation periods.

As shown in Fig. 3, in the initial state, three out of 60 physician groups joined the ACO. This number increased to 27 at the end of the simulation. When we examined the evolution of the ACO, we noted four distinctive stages. In period 1 to period 2, we first experienced a "wait-and-see" stage in which the number of physician groups in the ACO remained small (<1%). However, this stage passed quickly. Between period 2 and period 5, we witnessed a "rollercoaster" stage where we saw first a rapid expansion of ACO membership (from 3 to 17 and then to 19), representing approximately 10%–400% of positive growth rate, which was then followed by a fast decline (from 19 to 11) in period 5, representing approximately 43% negative growth rate. The third stage was a "steady growth" stage where the number of physician groups in the ACO increased gradually, at a rate of over 10%. Finally came stage four, the "stabilizing" stage where the number of physician groups in an ACO remained steady, with approximately 10% or less fluctuations. Table 9 below summarizes these stages, their defining characteristics, as well as growth rate.

Because physician groups make the decision to join an ACO based on their peers' performance, the initial adoption of ACO is somewhat slow, as very few members are part of the ACO and the probability of these members outperforming a great majority of the other physician groups is slim. Therefore, a large number of physician groups are in the wait-and-see mode. Then, as the cost savings for ACO members starts to take effect, other physician groups observe the benefit of the ACO and decide to join. We see a fast increase in membership. However, while ACO membership can potentially save costs and share savings for physician offices, it also brings with it a penalty associated with quality degradation, which results in a great reduction in patient visits (and thus revenue generation). Therefore, we start to see a rollercoaster effect as existing members exit the ACO right after a large amount of new physician offices enter the ACO. This stage allows the best-fit physician office to remain in the ACO and screens out ill-fitting ones so we see a steady growth thereafter. Eventually, the system seems to stabilize over the long run.

We also noticed, through our iterations of simulations, that during the 10-year evolution of the ACO network, if at any year, the number of physician groups in an ACO reaches 60, or 100%, then this number will remain for the rest of the 10 years. Similarly, if at any year, the number of physician groups in an ACO is 0, or 0%, then this number will also remain for the rest of the 10 years. The extreme cases seem to have invoked a swarming effect (Reynolds, 1987). In the case of full participation in ACO, because all physician groups are a part of the ACO, there is no benchmark information available for physician groups not in an ACO in a particular region. Therefore, the situation deters the exit of physician groups from the ACO. Similarly, when there is no physician group entering the ACO, there is no benchmark information for ACO members, and physician groups tend to remain non-ACO.

5.1.2. Sensitivity to initial state

Next, we investigated the impact of initial conditions on the evolution of the ACO. In the follow-up scenario (E1), we varied the parameter of P_{ACO} to 10%, doubling the base scenario. On average, there were 6 out of

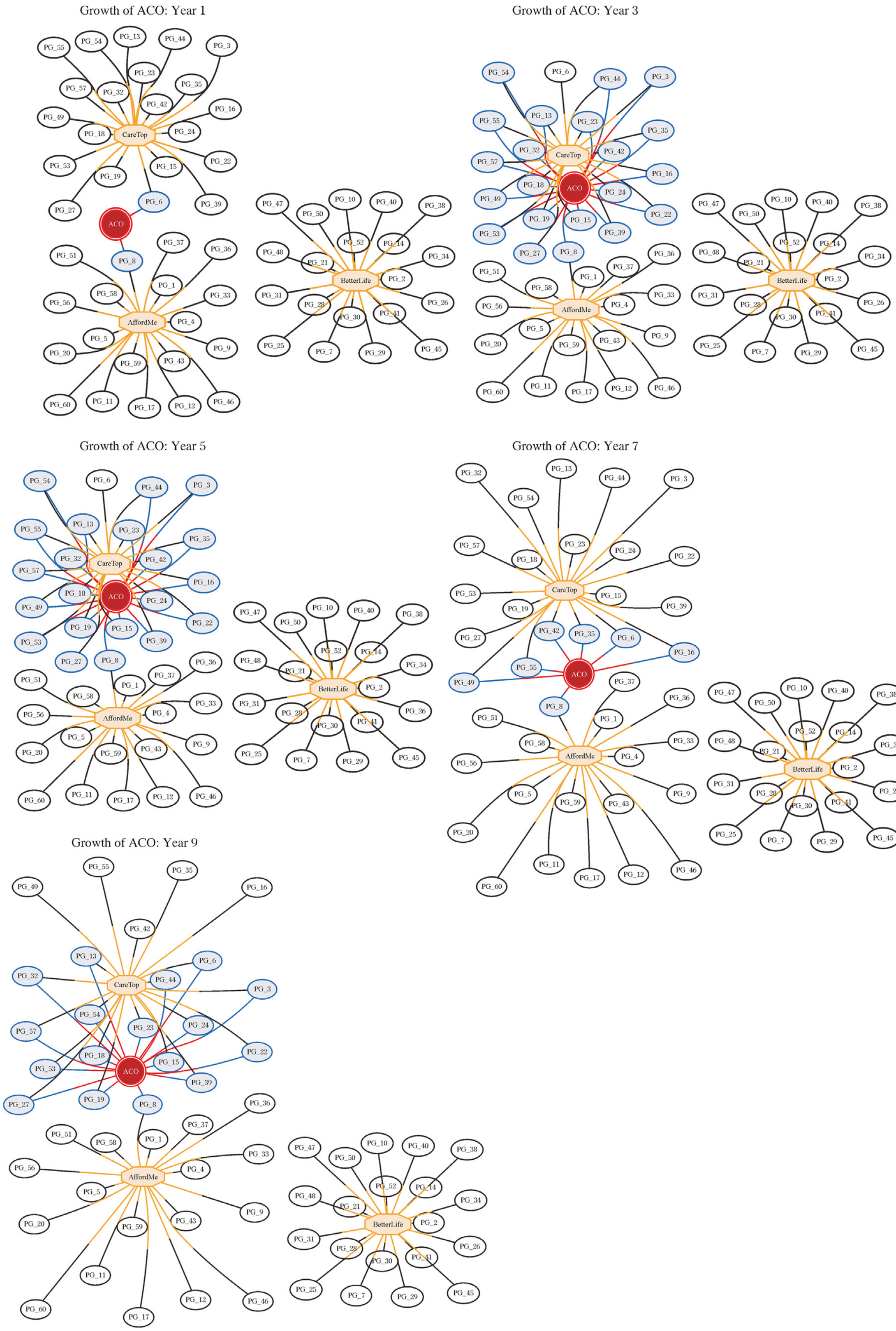

Fig. 2. A graphical representation of expansion and contraction of ACO.

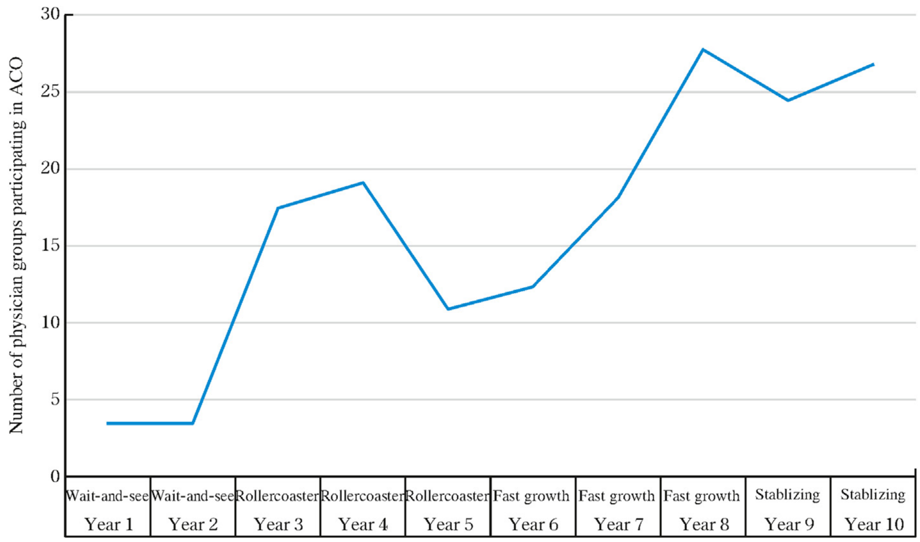

Fig. 3. Growth of ACO (base scenario $P_{ACO} = 5\%$).

60 physician groups belonging to an ACO at the initiation of the simulation. Results of the simulation for E1 are reported in Fig. 4.

Compared to Fig. 3, Fig. 4 shows a much steadier trend of expansion of ACO size. Here we see three distinctive stages. Similar to the base scenario, in period 1 to period 2, we first experience a "wait-and-see" stage in which the number of physician groups in the ACO remains small and constant. This stage passes quickly. The second stage can be seen as "fast growth" where the number of ACO membership increases from 5 to 40 (in period 3) and then to 53 (in period 4). In the third stage, which lasts from periods 5 to 10, we witness a "stabilizing" stage where the number of ACO members largely remains stable.

Table 9
Description of stages.

Stage Name	Characteristics	Growth rate	Experimental settings
Wait-and-see	Initial state with very low enrollment.	<1%	Base Scenario; ACO at 10%; no quality penalty.
Rollercoaster	State of volatility, with alternate stages of high levels of positive growth rate, followed immediately by a high level of negative growth rate.	[-43%, 400%]	Base scenario
Fast growth	Consecutive states of positive, high growth rate.	>= 10%	Base scenario, ACO at 10%; no quality penalty
Stabilizing	Consecutive states of positive, low growth rate.	<10%	Base scenario; ACO at 10%.
Sticky state	Alternate states of low to moderate levels of positive growth rate, followed immediately by a low to moderate level of negative growth rate.	[-21%, 27%]	No quality penalty

This suggests that the evolution of ACO membership is subject to initial state. If there is a relatively large presence of ACO membership at the beginning of the simulation, it is likely to have included a balanced mixture of physician groups at different service quality levels. This helps to set a more realistic baseline for ACO members. When non-ACO members decide to join or not to join the ACO, they compare their own cost attributes to this baseline. This helps to recruit physician groups that are a good fit with ACO cost and quality profiles. This in turn fuels a steady growth of best-fit members and avoids a turbulent rollercoaster state (as depicted in Fig. 3) where a large number of physician groups are entering and exiting the ACO.

We varied the parameter of P_{ACO} to 15% in Experiment 2, tripling that of the base scenario. This resulted in a pattern very similar to that of 10%. We witnessed the same stages of growth and similar number of physician groups in each stage.

5.1.3. The quality and cost tradeoff

Although the official objective of ACOs is to save healthcare costs while maintaining a high level of healthcare service quality (CMS.gov), the second

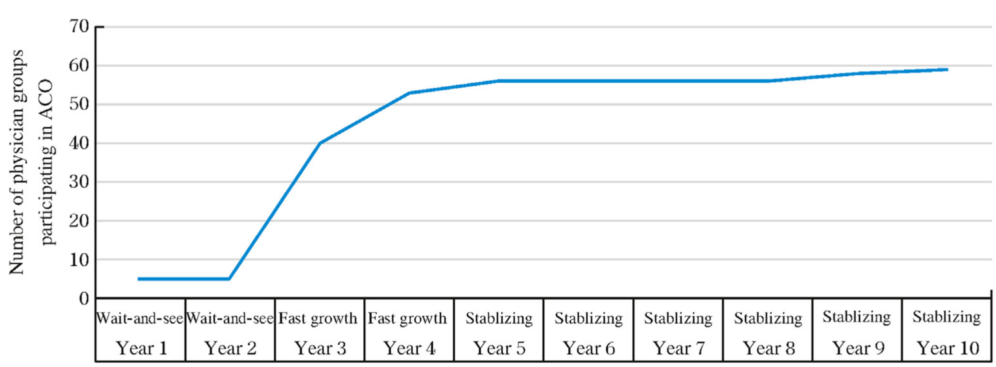

Fig. 4. Growth of ACO membership ($P_{ACO} = 10\%$).

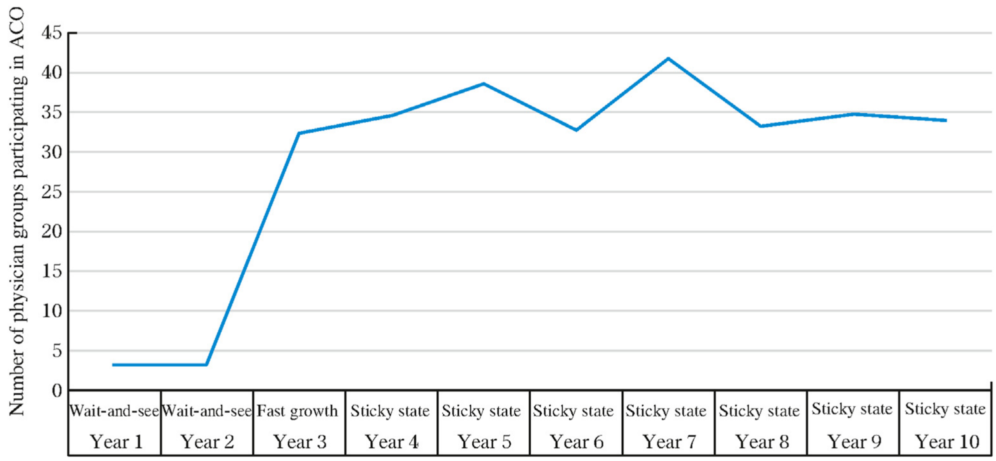

Fig. 5. Growth of ACO membership without quality penalty.

objective has been questioned (Kelleher et al., 2015). In our base scenario, we apply a quality penalty parameter, P_p, to physician groups that are a member of the ACO and set the P_p value to 0.92, based on empirical data. But what if members of ACO are able to meet both objectives? Next, we contrast the base scenario with E3 that removes the penalty parameter associated with ACO members. The result is reported in Fig. 5.

After removing the quality penalty parameter, the pattern of ACO growth reveals three stages. Periods 1 and 2 depict the "wait-and-see" stage, which is similar to the previous scenarios. Then a "fast growth" stage was seen to occur in period 3. What is interesting is that after the fast growth stage, we encountered a new stage we term as "sticky state" where the number of physician groups in an ACO fluctuates up and down; a small expansion will be followed by a small contraction and vice versa. Overall, there is no huge increase or decrease in the membership.

Because of the removal of quality penalty, compared to the base scenario, we do not see the rollercoaster effect where a massive amount of physician groups with lower service quality exit the ACO. The resulting ACO is comprised of physician groups with a variety of cost and service levels. The sticky state reflects slight increases and decreases of ACO membership due to random variation of patients' experience.

5.2. The impact of ACO on physician groups' cumulative profit

For the base scenario, we computed the cumulative profit ($Profit_b$) at the end of Year 10 for each of the 60 physician groups. Physician groups in the base scenario have the option of joining the ACO. We then created a contrasting scenario where the ACO is not an option and computed cumulative profit for each of the 60 physician groups ($Profit_c$). Next, we conducted two-tailed two-sample t-tests to compare the difference in cumulative profits across the two scenarios for physician groups affiliated with each of the three insurance companies: *AffordMe, BetterLife*, and *CareTop*. *T*-tests are commonly used in experimental design to detect the differences in mean values between base groups and experimental groups (Brown and Melamed, 1990). Here we use t-tests to detect the differences in mean cumulative profits between ACO member physician groups and non-ACO member physician groups. Results of the t-tests are reported in Table 10.

As shown in Table 10, there are statistically significance differences (at the $p < 0.001$ level) in the cumulative profits of physician groups affiliated with each of the three insurance companies. Specifically, for physician groups in the *AffordMe* category, the mean cumulative profit for non-ACO members is 15816726 and for ACO members is 12830478. The difference is statistically significant at the $p < 0.001$ level. This finding suggests that ACO membership leads to a deterioration of

Table 10
Comparison of cumulative profit: ACO option vs. no ACO option.

	AffordMe	BetterLife	CareTop
Mean value (ACO option = Yes)	12830478	18071294.12	9179104
Standard deviation	301319	349320	328214
Sample size	25	17	18
Mean value (ACO option = No)	15816726	11773208	9818500
Standard deviation	342367	259935	219905
Sample size	19	25	16
p-value for t-Test	$p < 0.001$	$p < 0.001$	$p < 0.001$

cumulative profit for physician groups within the *AffordMe* category. Similarly, there are statistically significant differences between ACO and non-ACO physician groups in *CareTop* and *BetterLife* categories, where physician groups in *CareTop* encounter a deterioration in cumulative profit under ACO and physician groups in *BetterLife* receive higher cumulative profit under ACO. These findings suggest that physician groups affiliated with both *AffordMe* and *CareTop* were worse off with the ACO option. However, the ACO option benefitted physician groups affiliated with the *BetterLife* insurance company.

Physician groups affiliated with *AffordMe* have the lowest average service quality level. Due to the quality–cost tradeoff, participation in ACO will deteriorate service quality even further. We then witness a large number of patients switching to other healthcare providers with higher service level. This results in a decrease in the number of visits (and thus revenue) for *AffordMe* physicians. For this group of physicians, the loss in revenue exceeds gain in cost savings, which results in a reduction in profit.

Physician groups affiliated with *CareTop* have the highest average service quality. However, service quality degradation impacts *CareTop* as well. On average, patients in the *CareTop* group have the highest service expectations among all patients. If they are not satisfied, they will move away from *CareTop* and reduce the number of patient visits (and thus revenue). Further, the *CareTop* group is also associated with the highest healthcare premium. If a patient from a less expensive insurance group is not satisfied with the service experience and is ready to switch, *CareTop* may not be an option for them due to their wealth level.

Physician groups affiliated with *BetterLife* benefit most from ACO formation. Although *BetterLife* suffers from quality degradation as well, it is in a strategic position where it can receive new patients switching from *CareTop* as well as from *AffordMe*. For patients switching from *AffordMe*, *BetterLife* is a more attractive choice due to its lower healthcare premium compared to that of *CareTop* and higher service quality. For patients switching from *CareTop*, *BetterLife* is also a more attractive choice due to its higher service quality compared to that of *AffordMe*. Thus, *BetterLife* stands to gain most from ACO due to the increased number of patient visits and subsequent revenue and profit increases.

6. Conclusions, implications, and future research directions

The emergence of ACOs is a relatively new phenomenon in the U.S. healthcare network. While many believe this might save the healthcare system, others opine that the prospects look bleak—but there is a consensus that data-driven analysis is warranted (Terry, 2013). We argued that traditional analytic methods fail to capture the complexity of the healthcare network and the interactions amongst the agents. We proposed a CAS approach as being more realistic in representing this phenomenon.

Our research examined a pressing issue in the healthcare supply network, the establishment of the ACO, its expansion, and its impact on physician groups' profit. We found that the evolution of an ACO goes through different stages, and the pattern of growth is influenced by both its initial condition and the cost and quality tradeoff. When an ACO contains a small percentage of physician groups at initiation, it will experience a period of fast growth followed by a fast decline, as non-members are first attracted by the cost savings experienced by the initial few members and are then turned off by patient deflection due to service quality degradation. However, when an ACO contains a relatively large percentage of physician groups at initiation, it is likely that there is a basket of physician groups with varying levels of service quality. In such a case, the growth of the ACO is based on comparison to a stable base of quality and cost indicators and therefore we are likely to see stable growth. Thus, one factor that facilitates ACO growth is to include a larger number and variety of physician groups at initiation.

Both joining and rejoining an ACO cost money and resources. There are administrative costs associated with membership, such as the training of personnel to be in compliance with ACO rules, which occur both at the physician group as well as at the healthcare administrative agency. This is a manifestation of the classic network externality issue where the value derived from a network and thereby its success critically depend on the number of participants in the network. Therefore, it is more prudent for policy makers to promote a stable increasing trend of ACO membership. Our results suggest that policy makers should encourage a greater number of physician offices to be pioneers of ACO programs. In addition, we encourage a variety of physician offices of different cost and quality profiles to be included in the initial pioneering organizations to set up a more realistic benchmark baseline. A proactive approach in rewarding such pioneering organizations might go a long way in the eventual success of ACOs.

We also addressed the quality and cost tradeoff and showed that if cost savings associated with ACOs can be reached without sacrificing quality, the adoption pattern is more stable. While our results were an offshoot of the settings of our CAS based on empirical data, this nevertheless suggests that policy makers should design incentives and promote higher quality services for ACO members.

Finally, we examined the impact of ACOs on physician groups' profit. We found that ACO benefits accrue most for middle-tier physician groups that offer a relatively good quality service at a relatively reasonable cost. Physician groups at different quality levels should be made aware of the impact of ACO membership on their patient flow, revenue, and profit. For example, our research suggests that at the current state of ACO development, physician groups that offer superior services at a premium cost should use caution before joining ACOs. The cost and quality tradeoff that is evident in empirical data suggests a detrimental effect on the service quality offered by these premium physician groups. As a result, simulation analysis shows a degradation on cumulative profit. However, if in the future, ACOs could achieve their stated objectives, i.e., saving cost while improving service quality, then it will be more advantageous for these high quality physician groups to join an ACO. In general, physician groups should only make the entrance decision after carefully conducting a cost and benefit analysis.

Our research examined the growth of the ACO and investigated its impact on the healthcare supply network. We used the CAS perspective to simulate agents in the healthcare supply network and the learning and adaptation behavior of agents in response to changes in the environment. As such we were able to derive patterns of ACO evolution and offer managerially relevant insights to physician groups as well as policy makers.

From a managerial and practitioner perspective, we hope our study will spur further analysis of the assumptions and behavior of the various stakeholders in a healthcare system that will continue to see increased participation in ACOs. The introduction of ACOs in the U.S. healthcare network is a very significant innovation to the system. However, it remains to be seen whether it will be successful or not. The call of the hour is certainly to look at data and analysis and provide information to the participants to help them be successful in this new environment. If this does not happen, there is a real risk that the fate of ACOs will go the same way as another healthcare innovation not too long ago—HMOs or health maintenance organizations. HMOs are now widely considered to be a failure largely due to the lack of data availability to make sound decisions in that environment. We hope our study will spawn further analysis using multiple analytical lenses to inform how ACOs will play out in the healthcare system. The more data analysis and insight generated, the better the chance that ACOs will be successful.

One of the main obstacles to the success of ACOs is the level of participation by various providers to form or join an ACO. Given the uncertainty around the measures and financial incentives, it is possible that many providers may stay away from ACOs. To address this critical issue, our results offer some preliminary evidence about the participation level of physician groups.

While the CAS perspective offers an interesting and appropriate approach to capture the complex nature of the emergence of ACOs, our study constitutes a small first step in that direction. There are several opportunities and avenues to expand our research. First, the formation of ACOs is at its initial stage and there exists a certain degree of vagueness associated with ACO rules. A follow-up model could incorporate the U.S. government as an agent and examine different incentive designs that could impact the adoption of ACOs and operation performance of physician groups. For instance, these incentive programs could incorporate an exit penalty, design varying levels of cost saving structures according to ACO developmental stages, or design varying levels of cost saving structures according to tenure within an ACO. Second, our research shows that the initial number of physician groups in an ACO matters to the pattern of adoption. A follow-up study could incorporate other aspects of the initial state such as the composition of ACO members, and examine how their quality level impacts the expansion of the ACO. Third, we based our research on the regional healthcare network in an area located in the Midwest of the United States. Future research could develop supply networks based on other regions, especially metropolitan areas, to see if different patterns of adoption emerge. Lastly, given that our qualitative interviews revealed limitation of treatment options and reduction in treatment flexibility as two potential factors to explain quality tradeoff, a future study might extend the existing model, which is profitability driven, to incorporate social welfare. An interesting extension of this model is to maximize the overall social welfare from a policy maker's perspective.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dsm.2021.05.003.

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