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CHRONIC DISEASE MANAGEMENT: HOW IT AND ANALYTICS CREATE HEALTHCARE VALUE THROUGH THE TEMPORAL DISPLACEMENT OF CARE[1]

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The treatment of chronic diseases consumes 86% of U.S. healthcare costs. While healthcare organizations have traditionally focused on treating the complications of chronic diseases, advances in information technology (IT) and analytics can help clinicians and patients manage and slow the progression of chronic diseases to result in higher quality of life for patients and lower healthcare costs.

We build on prior research to introduce the notion of temporal displacement of care (TDC), in which IT and analytics create healthcare value by displacing the time at which providers and patients make interventions to improve healthcare outcomes and reduce costs. We propose that healthcare value is created by strategic actions taken at specific points-in-time during the treatment process. Our theoretical development identifies TDC mechanisms through which IT and analytics displace later high cost interventions in favor of earlier preventative procedures.

We test our hypotheses using four years of data on 45,000 cardio-metabolic patients from the U.S. state of Vermont, which implemented a Patient-Centered Medical Home (PCMH) program. Our study includes four cohorts with increasing levels of IT and analytics use: (1) non-PCMH practices, (2) PCMH practices with basic IT systems installed, (3) practices that completed data quality sprints (DQS) to increase use of IT systems, and (4) practices that use analytics through the Vermont Healthcare Information Exchange (VHIE).

Our results provide insights into how TDC effects develop over time. In Year 1 after implementation, the DQS cohort demonstrates a marked increase in the use of preventative procedures such as eye exams and neuropathy screenings, the increase becomes more pronounced in Years 2 and 3, and the increase is even greater for the VHIE cohort. As the use of preventative procedures increases, emergency department utilization decreases, with a more pronounced decrease for the VHIE cohort than the DQS cohort. By Year 2, the DQS and VHIE cohorts experience a decrease in total healthcare costs, with a greater decrease for the VHIE cohort than the DQS cohort. By Year 3, the healthcare outcomes indicator of Hemoglobin A1c (HbA1c) level is statistically significantly lower, with a greater decrease for the VHIE cohort than the DQS cohort. The increased use of

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low-intervention healthcare treatments earlier in the process leads to a decrease in overall healthcare costs, which then leads to an improvement in healthcare indicators.

Keywords: Temporal, displacement, care, IT, analytics, chronic, disease, healthcare, outcomes, cost

Introduction

From the early days of computing, healthcare organizations have deployed information technology (IT) to capture treatment and patient data for administrative and clinical reporting. Healthcare IT researchers have established that IT can play a role to reduce healthcare costs and improve healthcare outcomes (Devaraj and Kohli 2000; Shams et al. 2015). With advances in digitization of clinical processes, availability of longitudinal data, and analytic tools, clinicians now have an opportunity to observe patterns in outcomes for the population of patients, not just individual patients. The need to understand how clinical interventions affect a population's health is most pressing in the treatment of chronic diseases, because chronic diseases consume 86% of U.S. healthcare costs (CDC.gov). As chronic diseases progress, patient conditions become debilitating and often irreversible. IT combined with analytics can help providers coordinate and manage patient care at the population level, assist with more comprehensive screening, and support the increased use of preventive measures. These capabilities enable providers to better manage chronic disease progression, so patients can live healthier and more productive lives (Adler-Milstein et al. 2014).

Diabetes, a cardio-metabolic disease that is one of the most prevalent chronic diseases, is characterized by the inability to process carbohydrates and maintain normal blood glucose levels, which results in gradual, progressive damage to the kidneys, blood vessels, eyes, and heart. The number of people with diabetes worldwide increased from 108 million in 1980 to 422 million in 2014. Diabetes is the seventh leading cause of death in the United States (CDC.gov), and 68% of people over the age of 65 with diabetes die from complications related to heart disease. The complexity of diabetes and other cardio-metabolic diseases makes it difficult for healthcare organizations to identify and understand when to intervene or when to let patients manage the condition. The need for understanding is also important for insurance companies and state governments, who bear a large portion of treatment costs and lost productivity for sick patients. With early diagnosis, consistent treatment, and timely interventions, diabetes progression and the subsequent impact on organs is manageable. IT combined with analytics can assist clinicians and patients to better manage chronic diseases by helping to identify and track patients who need screening, preventive treatments, medication review, and community health services.

In this paper, we address how IT and analytics play a defining role in the effective management of cardio-metabolic disease by introducing the notion of temporal displacement of care (TDC). We build on prior research which indicates that organizations create business value based on the *point-in-time at which actions take place* (Lee and Tang 1997; Reed et al. 1996), to discuss the way IT and analytics create healthcare value by displacing the time at which providers and patients make interventions to improve healthcare outcomes and reduce costs. We examine patient care for the chronic condition of cardio-metabolic disease using data for patients in the U.S. state of Vermont, which implemented the Vermont Blueprint for Health (VBH) program with the objective to improve the health of its citizens while optimizing the state's healthcare expenditures.

In traditional settings, healthcare is provided in spurts. When a patient shows certain symptoms or complains of an illness, providers intervene by administering diagnostic exams, pharmaceutical therapies, surgical procedures, and rehabilitation. This care is episodic. Patients then take responsibility for their well-being and manage the condition until symptoms return. Often, patients fail to recognize the progression of chronic diseases, which causes them to delay seeking preventive care. If they delay too long, the treatments required after the onset of acute symptoms are intense, expensive, and could have irreversible and life-altering effects. Using IT and analytics, healthcare providers can identify opportunities to displace the timing of treatment such that they match care resources with patient needs to produce healthcare outcomes that are higher quality and lower cost (Bardhan and Thouin 2013). In this paper, we will show how this temporal displacement through IT and analytics creates a virtuous cycle to better match care resources with patient health conditions, to engage patients in the ownership of their healthcare (Oborn and Barrett 2016), resulting in continuous improvement of population health outcomes.

Background

After an individual is diagnosed with a chronic disease, the clinicians' objective is to manage disease state progression

because the underlying physiologic changes are often irreversible. IT and analytics provide clinicians with insights into the patient's condition that facilitate early intervention before the disease progresses to a stage where higher cost and more intensive treatments are required (Kohli and Tan 2016). For example, most complications associated with diabetes are the cumulative effect of elevated blood glucose levels. High levels of glucose cause gradual damage to blood vessels and nerves. Numerous complications result from prolonged elevated blood glucose levels, high blood cholesterol, elevated inflammatory hormones and oxidants, and vascular damage that lead to high blood pressure. High blood pressure can then lead to greater damage as the consistently elevated pressure damages the organs. Once blood vessels and nerves are damaged, tissues lose their ability to function normally. If not managed over time, the accumulated damage of these conditions leads to blindness, kidney failure, heart attacks, stroke, and the amputation of limbs. The cascading effect of diabetes on the heart and other organs is termed cardiometabolic disease.

The need to proactively coordinate and manage patient care has spurred initiatives to develop innovative new healthcare delivery models, such as the patient-centered medical home (PCMH). PCMH is a delivery model in which the primary care physician serves as both care coordinator and care provider (Rittenhouse and Shortell 2009). The objective is to closely monitor the plan of care and patient condition so that high-cost interventions, such as emergency care and hospitalization, are replaced with low-cost interventions before patient conditions deteriorate to the point where high-cost interventions are necessary. Although the PCMH model is conceptually simple, proactive patient surveillance and service integration require a complex IT infrastructure and analytics to achieve a lower cost and higher quality of clinical outcomes (Angst et al. 2012). Bates and Bitton (2010) highlight the importance of IT in treating chronic diseases:

> We believe that the development of electronic health records will be critical in seven major areas: telehealth, measurement of quality and efficiency, care transitions, personal health records, and, most important, registries, team care, and clinical decision support for chronic diseases (p. 614).

While the PCMH model mandates that physicians adopt electronic medical records (EMRs) to achieve PCMH certification, EMR adoption alone is *not* sufficient to support effective management of chronic disease. Although EMRs digitize data, they are still "encounter-oriented" in that they record the activities, interventions, and assessments of each patient visit so the records can be retrieved for review during subsequent visits. To achieve the objectives described by Bates and Benton, additional layers of IT structure and integration are required. Beyond the *installation* of IT such as EMRs, the next level of IT application is the *use* of IT for care management. Data quality and data standards are the foundation for IT use. In most EMRs, clinical encounter data and plan of care information are entered as unstructured text. Establishing data standards and recording information in a structured format enable population-level querying of the EMR so that PCMH clinicians can *use IT* to achieve better outcomes for all patients under their care. With data standards to enable system and data integration across providers, the next level of IT involves information exchange among providers and the *use of analytics* to track patients across the care delivery cycle, identify patients to displace later intensive interventions in favor of earlier preventative interventions, evaluate physician and care plan effectiveness, and measure outcomes. In Table 1 we summarize the role of IT and analytics at each level of chronic disease management.

Business disciplines have approached the notion of temporal displacement from various perspectives that share a common thread: business value is created by the firm through a combination of actions *and the point-in-time at which those actions are taken*. Temporality is an essential component of action-taking. To ground the notion of TDC, we draw on two streams of operations management research – total quality management and delayed differentiation.[2]

Total Quality Management

Total quality management (TQM) proposes that firms can achieve higher quality in products and services by taking strategic actions at an *earlier point-in-time*. Firms can improve quality by building in quality during the production process, which reduces the need for inspection, rework, and warranty costs (Deming 1986). In other words, by displacing later activities such as inspection and rework to an upfront stage, firms can achieve cost reduction by doing work right the first time (Hackman and Wageman 1995).

The premise of TQM is that firms can create business value by taking certain actions, such as developing production processes, at an earlier point-in-time, just as healthcare providers can create value by taking certain actions at an earlier point-in-time. TQM is consistent with the notion of TDC in this

[2]From the Business Strategy literature, first-mover advantage (FMA) is a stream of research that describes the impact of taking strategic actions at an earlier point-in-time (Lieberman and Montgomery 1988; Thietart and Vivas 1984). Because FMA is primarily associated with market entry rather than business processes, we believe that the total quality management (TQM) literature provides a stronger foundation for TDC in this paper.

Table 1. Constructs for the Study of TDC

Construct	Description
Temporal dimension	Temporal dimension is a given point-in-time during the patient care process. It must be possible to measure time to study TDC. The temporal dimension must consist of at least one relatively earlier time period and one relatively later time period, in order to observe the movement of some interventions from one time period to another time period.
Interventions	Interventions are actions intended to improve health outcomes. Interventions are initiated by clinicians or patients, and can involve medication, procedures, and/or lifestyle changes. There must be at least two categories of clinical interventions that range in intensiveness of effort, expertise or capital required.
Utilization	Utilization is a measure of consumption of resources and services. It must be possible to measure the utilization of a clinician or patient for an intervention, expressed as either how many times an intervention was utilized or the proportion of time an intervention is enacted compared to the number of times scheduled.
Health outcomes	Health outcomes are the change in health status resulting from an intervention. The study of TDC requires a measurable and consistent record of patient health outcomes that go beyond whether a patient utilized a high- or low-intensity intervention. For example, in this study Hemoglobin A1c (HbA1c) is a direct measure of average blood sugar levels over time. The HbA1c level indicates the health status for a patient with cardio-metabolic disease.
Cost outcomes	Cost outcomes are financial measures that result from interventions (Devaraj et al. 2013). It must be possible to measure the cost of high- and low-intensity interventions. In most cases, the cost of high-intensity interventions is higher than the cost of low-intensity interventions.

paper, where providers can deliver higher quality healthcare at lower cost by taking certain actions such as conducting regular diagnostic check-ups and ensuring adherence to prescription medications at an earlier point-in-time of the disease progression.

Delayed Differentiation

In contrast to TQM-inspired actions that confer benefits on firms that take strategic actions at an earlier point-in-time, delayed differentiation confers benefits on firms that take strategic actions at a *later point-in-time* (Swaminathan and Tayur 1998). The concept is to design the production process so the point of differentiation is delayed as much as possible. Delayed differentiation is facilitated through standardization (using common components in multiple products) and modularization (ability to assemble submodules into a complete product) (Lee and Tang 1997). Swaminathan and Tayur (1998) illustrate delayed differentiation through a case where a computer manufacturer has three different products that each contain some combination of four different components. The computer manufacturer can maintain a set of semi-finished products, called "vanilla boxes," and then perform final assembly of the products once more accurate product or market information is received. When demand is not perfectly correlated across the underlying products and when markets are not subject to significant demand shocks (Anupindi and Jiang 2008), delayed differentiation enables the firm to serve customers more effectively with higher product availability and more efficiently with lower costs.

Drawing upon this perspective, providers who treat chronic disease patients can better predict demand, preschedule services, and free resources to treat patients who need urgent care. While TQM relates to the creation of business value by taking actions at an earlier point-in-time, delayed differentiation relates to the creation of business value by taking actions at a later point-in-time. In both cases, business value is created by the action and the (earlier or later) timing of the action. In this paper, we build on these two research streams and propose that IT and analytics create healthcare value at earlier and later stages of healthcare delivery. Earlier in the patient care process, IT and analytics are used to identify patients who are "at-risk" for chronic disease and present the highest opportunity for healthcare value. Later in the process, IT and analytics are used to monitor, fine-tune, and manage healthcare delivery (Bardhan et al. 2015), which frees resources to pursue the next set of opportunities for healthcare value.

IT and analytics also play crucial roles to mitigate risk (Knight 1971) and increase coordination (Christensen et al. 2009) in the temporal displacement of care. In traditional healthcare, an individual provider is only willing to assume responsibility and risk to diagnose and treat a disease that is consistent with his/her professional credentials (Knight 1971). When risk crosses boundaries across providers, no individual

provider will be willing to assume the responsibility and risk, unless there is a mechanism to coordinate activities across providers. IT and analytics provide the coordination mechanism for providers to arrange treatment and ensure that required services are performed at the appropriate location and time (Christensen et al. 2009). This coordination optimizes care for the long-term prospects of all patients and reduces overall healthcare costs.

Temporal Displacement of Care (TDC)

We propose that healthcare organizations can create value for individuals with chronic diseases by using IT and analytics to displace the time at which clinicians and patients make interventions. Healthcare value is then measured by improved clinical outcomes and lower costs. Building on our discussion of the foundations of temporality, we propose that healthcare organizations must create IT infrastructure and processes to identify, track, and analyze patient conditions to make clinical interventions at appropriate points-in-time. Temporality is a critical element in tracking resources and activities during treatment of a chronic condition.

TDC addresses when and which resources and activities are consumed in the treatment setting of chronic care for a population, not how an individual patient is treated. Our TDC assumptions are limited to the management of chronic disease conditions, so we do not make claims about curative treatment protocols or address how to make choices among treatment options. We assume that patients with chronic conditions are willing to participate in their care program and will cooperate in the temporal interventions prescribed by clinicians. We recognize that noncompliance among diabetes patients remains an issue (Brundisini et al. 2015). We also recognize that TDC will be viewed differently by providers for whom fee-for-service has been the predominant payment model (such as in the United States and China), compared with the evolving value-based payment model in which providers share the responsibility for costs and patient outcomes.

To use IT and analytics to displace care, providers must be able to codify the time dimension, interventions, and associated cost and outcomes (we discuss interventions and outcomes in the next section). Codification is the conversion of knowledge into forms that are suitable for transfer across economic agents. Codification enables knowledge to be captured, instructions to be communicated, and data to be distributed, which expands the division of labor including coordination across stakeholders (Kotlarsky et al. 2014; Mithas and Whitaker 2007). Table 1 provides additional information on constructs for the study of TDC.

Improvements in EMR functionality, data quality, and practice connectivity result in changes to clinical practice procedures and better integration with ancillary and support providers. The changes transform care delivery from a set of activities that take place in a physician's office and are dependent on proactive patient engagement, to a set of integrated activities and processes that take place across multiple agencies. Prior research has described a similar hierarchy of primary care, in which individual providers can make some improvements to infrastructure and care activities within the practice, but where coordination and shared information across providers is necessary to maximize healthcare value (Rollow and Cucchiara 2016).

To complement the theory development in this paper and illustrate these concepts in practice, in Table 2 we provide a brief overview of how increased use of IT and analytics changes the screening, diagnosis, and treatment of a patient with Type 2 diabetes, and in Table 3 we provide a vignette to illustrate the experience of a diabetic patient and the clinical interventions used to treat the patient. The vignette contrasts traditional diabetes care with treatment in various VBH settings. We constructed the vignette based on interviews with practice managers, clinicians, and executives who had first-hand experience with chronic disease patients in VBH as well as traditional clinical settings. Our interviews included three practicing physicians, a physician assistant, a diabetes nurse educator, CEO of a community health center, COO of a medical center, director of quality initiatives for a health service area, and a VBH project administrator.

Theoretical Underpinning

Theoretical underpinning for the hypotheses includes the notions of risk developed by Knight (1971) and disruptive innovation developed by Christensen et al. (2009) and applied to the healthcare industry. We begin with the application of disruptive innovation to the healthcare industry (Christensen et al. 2009), and then incorporate theoretical risk considerations. According to Christensen et al., service firms fall into one of three categories:

(1) *Solution shops* (SS) diagnose a problem and then recommend a plan to solve the problem. Consulting firms or financial advisors are examples of SS outside the healthcare industry, and physicians are an example of SS in the healthcare industry.

Table 2. Application of IT and Analytics to Chronic Disease Management

Dimension	Description	Capability	Data Visibility	Analysis	Temporal Displacement of Care
IT Infrastructure *"What am I doing?"*	Installed base level of IT	**Non-VBH** Paper charts or basic electronic medical records (EMR).	Clinical data of individual patients for each provider. Often supplemented with non-searchable copies of fax documents. Incomplete medical record.	Paper charts: minimal analysis capability. EMR: Providers can evaluate only what is entered by the practice. Limited to patient-level trend analyses.	No ability to proactively displace care.
		VBH Practice certified as a PCMH. Meets meaningful use criteria for EMR capabilities.	Clinical data from individual patient visits in a standardized structure. Data from other providers still missing and/or poorly integrated.	Provider can conduct aggregate analyses of patients in his/her clinical practice. Providers within the same practice can share and aggregate data across patients.	No ability to proactively displace care. Provider accesses patient records as needed but will receive alerts from the EMR when certain events occur, such as a missed appointment or an abnormal lab result.
Use of IT *"Am I doing things right?"*	Data quality, processes and procedures are coded and structured to enable increased use of IT	**Non-VBH** Paper charts or basic EMR.	None, or limited EMR use of decision support tools to support evidence-based medical management.	Provider can analyze individual historical patient progress using tools provided by EMR vendors. No integration with external entities. Incomplete medical record.	Displacement of care based on conventional treatment protocols, often in response to patient complaint.
		VBH Compare 'best practices' and clinical and cost outcomes within the area and statewide.	Provider has visibility to internal practice data from actual patient visits, ability to identify additional patient visits that should have occurred, and ability to compare data across patients.	Provider can comprehensively evaluate PCMH patients, such as overall status of prescribed interventions and how well patients adhere to prescribed plan of care.	Moderate ability to displace care because provider can monitor patient outside of scheduled appointments to ensure the patient is refilling prescriptions, keeping appointments, and adhering to other maintenance procedures.
Use of analytics *"Am I doing the right things?"*	Access to external data for analytics, clinical assessment, and outcome measurement.	**Non-VBH** No integration with claims data. Sophisticated clinical practices use *ad hoc* technology to interface population management data.	Provider visibility limited to those included in vendor reporting tools. Cannot identify gaps in care.	Provider can evaluate self-reported patient adherence. No information about patient compliance with prescriptions, eye exams and flu vaccine.	Limited and local displacement by adjusting dosage, and alternative treatment plans.
		VBH Longitudinal analysis with ability to compare various treatments and outcomes.	Provider has visibility to internal practice data on patients, external data such as prescription refills and hospital visits, and benchmarking data from other practices on patients with similar conditions.	Provider can evaluate PCMH patients with a holistic view, such as a comparison of patient treatments and outcomes with other PCMH practices.	High ability to displace care because provider can draw from internal best practices and from other providers to optimize the treatment plan to minimize costs and maximize desirable health outcomes. Greater predictive ability to displace care and to refine best practices.

Table 3. Improved Patient Prognosis from Temporal Displacement of Care

Scenario: John is a 35-year-old male with a family history of diabetes. He has not seen a physician since his senior year in high school. While his body weight is within recommended range, John eats poorly and consumes substantial amounts of fast food, soda, and alcoholic beverages. He has a history of sporadic employment and is frequently laid off and unemployed for a few months at a time. John recently found a new job. His employer requires a physical and drug screening prior to beginning work, so John has scheduled a doctor visit.

Traditional Primary Care	Certified Patient-Centered Medical Home (PCMH)	PCMH after Data Quality Sprint (DQS)	PCMH after DQS, with connectivity to the Vermont Health Information Exchange (VHIE)
The physician conducts a physical primarily focused on completing the form required by John's employer. The physician does not take a health history, and orders blood and urine drug screens as the only lab work.	John's physician uses information technology in the form of electronic medical records (EMR) that meet meaningful use criteria. During John's visit, the physician performs a complete physical including health and family history. John's family history prompts the physician to perform baseline lab work. The physician notices that despite his young age, John's serum glucose levels are high. The physician prescribes a medication to lower his blood sugar, and examines his feet and cardiovascular system to determine whether any damage has already occurred. John is scheduled to return in six months. John does not keep his appointment, his record is flagged by the EMR, and the office contacts him to schedule a new appointment.	John's physician uses an EMR that adheres to a set of standardized data structures. John's initial treatment begins much as it would in a certified PCMH, but clinical and outcome data are submitted to VHIE and integrated with claims data. Practice profiles show cost of care and outcomes. John's physician is now able to see that costs and outcomes of her diabetic patients are worse than the Vermont state average, so she implements a quality improvement initiative for her practice. As a result of the quality improvement initiative, John is asked to come back four months after his initial visit for a Hemoglobin A1c (HbA1c) test, which is a better measure of long-term blood glucose control. Lab results are automatically sent to the practice EMR, and show that John's HbA1c has increased to 9.8, indicating very poor control of blood glucose levels. John admits having difficulty adhering to the plan of care, because he again recently lost his job and health insurance. The physician refers John to a care coordinator who works with John to secure insurance coverage and obtain medications through a Vermont state program. John is scheduled to return for another follow-up visit three months from now.	John's physician uses an EMR that adheres to a set of standardized data structures and is directly connected to the VHIE. Clinical and outcome data are aggregated and transferred to VHIE, integrated with claims data, and accessible by care delivery partners. Those care delivery partners also have the ability to transfer data directly to John's physician. John's physician is now able to determine whether he is complying with the treatment plan. The practice is directly connected with Community Health Team (CHT) partners that are working with John to remove any barriers he may face that might prevent him from adhering to the plan of care. John's physician receives an EMR update from a CHT member. During a wellness check, John stated he had stopped taking his oral anti-hyperglycemic medication because it was making him feel nauseous, and he could not afford the cost of the foods for the diet recommended to him. A quick field test revealed that John's blood glucose was far too high, and the CHT member scheduled an appointment for John to meet with the physician the following week. During the visit, John's physician changes his medication and sends referrals through the EMR to a dietician and community health counselor to help John find a diet that fits his income and lifestyle.

Table 3. Improved Patient Prognosis from Temporal Displacement of Care (Continued)

Traditional Primary Care	Certified Patient-Centered Medical Home (PCMH)	PCMH after Data Quality Sprint (DQS)	PCMH after DQS, with connectivity to the Vermont Health Information Exchange (VHIE)
Physician's perspective: The physician can only see what is in the individual patient record during the visit. The patient is responsible for adhering to the plan of care and following up with the physician. There are no organized community support services. The physician practice cannot evaluate or manage costs, because it can only obtain information related to claims submitted by their own practice, and is unable to obtain claims information from other providers.	**Physician's perspective**: The physician can more proactively manage care, but is not able to assess patient adherence to the plan of care. The practice can better manage quality and costs because it receives aggregate reports of total costs and outcomes relative to other practices across the state.	**Physician's perspective**: The physician can more proactively manage care, using comparative data that enable her to manage costs and benchmark against other PCMHs. The ability to aggregate and share data is a precursor to a "learning health system" where physicians are able to identify practices achieving the best outcomes and emulate their strategies. By connecting with community partners, physicians are able to treat the whole patient, not just the medical condition. However, their EMR does not contain the details of the community based efforts, and depends on phone calls and fax reports.	**Physician's perspective**: The physician can now more proactively manage care, coordinate activities with CHTs, manage costs, and share best practices by benchmarking against other PCMHs. EMR is a fully integrated system that incorporates all care partners.
Interview quotes: "We were expected to see a patient every 15 minutes, and most of that time was spent collecting data that didn't require an MD to gather." *Primary care provider, independent practice* "We have patients come back to us even though we are not the closest provider. We have patients tell us they come back because the MD at the [prestigious medical center] spends 10 minutes with them and doesn't check anything." *Diabetes educator and practice manager, medical center*	**Interview quotes:** "Reporting forced us to look at specific measures and be honest with ourselves." *Chief operating officer, medical center* "Population management is emphasized, so there is more outreach and patients are more likely to receive preventive care and better control of health drivers." *Internist, medical center* "Blueprint statewide data reports are important. They allow us to identify improvement opportunities and change how we do things." *Physician assistant and EMR director*	**Interview quotes:** "We see patients more often. If HbA1c is greater than 9.0, we schedule appointments every three months and follow-up if the patient misses the appointment." *Diabetes educator and practice manager, medical center* "We are no longer dependent on the patient to follow up. The panel coordinator is able to follow all patients." *Chief operating officer, medical center* "Social needs can be paired with other non-healthcare resources." *Internist, medical center*	**Interview quotes:** "Role of VHIE was to integrate holistic care. A care coordinator is able to exchange information with agencies to help secure food, housing, medical insurance, even employment opportunities." *Director of quality initiatives, health service area* "Integrated medical record is a one-stop shop. I can see what all care partners are doing and they can send me messages." *Internist, medical center* "If HbA1c levels are sustained over 9.0, then there is a much higher risk of neuropathy, retinopathy, decline in renal function, and damage to the circulatory system. Spending more time with patients before they progress saves money and improves the quality of their lives." *Chief executive officer, community health center* "The healthcare network is not just healthcare providers. A typical EMR doesn't let you integrate social and community support services." *Chief executive officer, community health center*
John's prognosis: While John does not feel any negative effects now, his diabetes is progressing. Irreversible damage is gradually occurring to his circulatory system, nervous system, kidneys and eyes.	**John's prognosis**: More proactive case management with emphasis on screenings enabled the physician to detect John's diabetes early. With effective management of blood glucose levels, John will experience slower disease progression, better health and well-being, and be a more productive member of society *if he adheres to the plan of care*.	**John's prognosis:** John has a better prognosis, due to proactive case management, patient engagement, and attempts to remove societal barriers that can prevent adherence to the plan of care. John is no longer left alone to adhere to the plan of care, and he is paired with additional non-healthcare resources to help him achieve clinical goals.	**John's prognosis:** With the entire care team integrated, communicating, and coordinating their efforts to help John, his prognosis is very good. The health system is proactive and responsive to any barriers John may face. Information flows in real time, enabling more rapid response to any potential medical or societal complications.

(2) *Value added providers* (VAP) take components and transform these components into complete products. Auto repair shops are an example of VAP outside the healthcare industry, and hip replacement surgical centers are an example of VAP in the healthcare industry.

(3) *Facilitated networks* (FN) enable transactions between producers and consumers. eBay is an example of FN outside the healthcare industry, and WebMD is an example of FN in the healthcare industry.

We argue that when a consumer engages in a transaction for service, the consumer transfers the responsibility to the service provider. The service provider, in exchange for a fee, takes on the risk to return quality, complete, and accurate service (Knight 1971). The provider is willing to undertake the risk only to the extent that the fee compensates for the risk.

In a SS, a physician takes the responsibility and the risk to diagnose and treat a disease that is consistent with his/her professional credentials. For example, a dermatologist will not take the responsibility to diagnose or treat allergies because this would introduce excessive risk beyond what the dermatology practice credentials can accommodate. When transaction risk crosses the boundaries of responsibility from a SS to a VAP, there must be a mechanism to coordinate activities to ensure that required services are performed at the appropriate location and time. For chronic disease patients, their health conditions can change daily, there is a critical need for a coordinating entity to monitor health conditions, assess severity, redirect care, educate patients, and arrange for follow up care. In the absence of such a coordinating entity, patients must invest resources to coordinate their own activities.

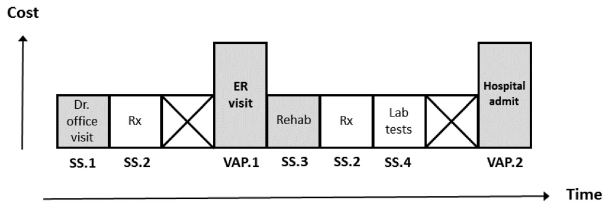
This is when an FN would emerge. However, in the U.S. healthcare system, most hospitals are SS, VAP, or a hybrid SS/VAP. As an SS, VAP, or hybrid SS/VAP, a hospital will coordinate patient care *only to the extent that it helps reduce the hospital's risk*. For example, a hospital (VAP) may request records from a physician's office (SS) to reduce the hospital's risk in treating the patient for a specific condition or event. This mixed SS/VAP model results in a reduction of patient care, because the SS and VAP coordinate primarily to reduce their own risk, not to take on more responsibility for the patient. Simultaneously, this mixed SS/VAP model and the resulting coordination result in an *increase* in cost, as shown in our empirical results.

Figure 1 illustrates how the lack of coordination between SS and VAP results in increased costs. In this figure, the patient is responsible to arrange for his/her own care. The patient begins by going for a doctor's appointment (SS) and picking up a prescription from a pharmacy (SS). However, if the patient feels fine when the prescription expires, the patient may not make it a priority to contact the doctor's office or the pharmacist to renew the prescription. Without an FN neither the doctor's office nor the pharmacist would contact the patient to renew the prescription. If the patient does not treat the chronic disease through medication for a duration of time, the disease may manifest as a negative event that requires an emergency room visit (VAP.1 in Figure 1). Of course, the cost of an emergency room visit would be much higher than the cost of a doctor's office visit or a medication prescription. The cycle would repeat when the patient has a new beginning after a rehab (SS.2 in Figure 1), receives another prescription, and gets lab tests (SS.2 and SS.4 in Figure 1), but loses momentum again and eventually needs to have an even more expensive inpatient hospital admission (VAP.2 in Figure 1).

An important feature of our research setting is that VBH is a FN that coordinates chronic disease patient care. As described above, the norm for U.S. healthcare is for patients to coordinate their own healthcare. Given the range of awareness and commitment across patients, management of chronic diseases is often sporadic and seldom effective. This is because neither SS nor VAP has the incentive to take on more patient care responsibility than is required for the fee. Their incentive to reduce risk puts the onus on the patient to bridge the gap between SS and VAP.

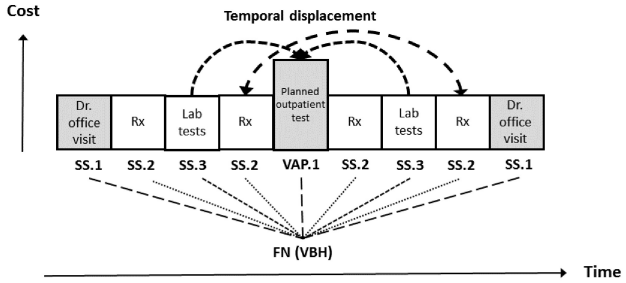
To bridge the timing and knowledge gap between SS and VAP, VBH takes responsibility by optimizing care not just for an episode but for the long-term health prospect of all patients. The state of Vermont is a payer and bears fiduciary responsibility for the well-being of its citizens. VBH, a FN created by Vermont with legal safeguards, aims to lower overall risk instead of merely transferring risk to SS and VAP (Knight 1971 p. 254). Risk theory proposes that firms can lower risk by grouping instances and by understanding differences among individuals in relation to uncertainty. This measurability is essential to grouping and requires the ability to empirically identify which instances are similar and then find the proportion of members that are expected to show one of the expected outcomes (Knight 1971, pp. 245-246).

Figure 2 shows how the coordination role of a FN helps to reduce overall cost. In this figure, VBH plays an important role to coordinate treatment for the patient. Through intervention by the FN, the patient is reminded to attend follow-up appointments with the doctor (SS.1), renew prescriptions with the pharmacy (SS.2), and have tests conducted at the lab (SS.3). As the higher-cost VAP treatments are displaced in favor of lower-cost SS treatments, the cost of treatment declines and patient condition improves.



Note: There are two reasons why this treatment pattern has a high cost. First, this treatment pattern involves six different providers (four SS and two VAP) that do not coordinate with each other. Second, the lack of coordination leads to at least two types of high-cost interventions (emergency room visit and hospital admission).

Figure 1. Cost and Treatment Pattern for SS and VAP (non-VBH)



Note: This treatment pattern has a low cost, because the VBH facilitated network (FN) plays a coordination role to ensure consistent SS follow-up over time. Low-intervention treatments are moved earlier in the process and are sustained. These low-intervention treatments are lower cost than the high intervention treatments in Figure 1.

Figure 2. Cost and Treatment Patterns for VBH as a Facilitated Network (FN)

Figures 1 and 2 directly tie with the theoretical model and constructs used in this paper (see Table 1). The temporal dimension is shown in the horizontal axis, and cost outcomes are shown in the vertical axis. Low-intervention treatments are shown in the regular size boxes, and high-intervention treatments are shown in the large boxes. High utilization is indicated when boxes are filled in, and low utilization is indicated when boxes are crossed out. The linear nature of interventions in traditional healthcare is shown in Figure 1, and the temporal displacement of care is shown by the shifting of interventions across time in Figure 2.

The IT and analytics infrastructure enable VBH to function as a FN. VBH utilizes the IT and analytics infrastructure to lower risk by grouping instances of patient conditions. Such grouping occurs because VBH captures patient health data to understand differences among chronic disease patients. VBH establishes best practices for patient groups, disseminates such best practices among physician practices, monitors compliance, and provides benchmarking to take corrective action. Grouping allows VBH practices to tailor care plans by shifting the locus of care among SS and VAP (Christensen et al. 2009 p. xxxiv), enabling the temporal displacement of high-intervention treatments in favor of low-intervention treatments. IT and analytics are the underlying mechanisms to identify, group, analyze, and monitor chronic diseases. Together, these serve as a platform to educate patients on self-care and to share insights with VBH practices. Christensen et al. endorse formation of VBH-like networks and suggest that "As these networks grow, the center of gravity for the care of any chronic diseases will increasingly shift from solution shop business models to facilitated networks" (p. xxxvi).

Hypotheses

IT, Analytics and Temporal Displacement

Scholars have emphasized the need to examine mechanisms that enable organizations to implement interventions (Hedström and Swedberg 1998), such as shifting activities from

one time period to another. Codes are one mechanism that organizations use to signify states learned from past actions, and communicate those states to actors in the present (Butler 1995). Organizational codes are generally stored and retrieved from IT systems, which economize time and space by recording an abbreviated form of past situations, actions, and outcomes (Holmer-Nadesan 1997).

At the operations level, codes specify the nature of situations and events, the level of attention that should be paid to events as they arise, and the potential actions to respond to each event. Such codes are entered in patient charts by hospital staff to document the level of care needed for patients. This documentation of codes communicates the level of care needed to transition across nursing staff when one nurse manager completes a shift to another nurse manager who begins the next shift (Zerubavel 1979). At the decision-making level, managers use treatment codes to evaluate alternative courses of action, select an action, and implement the action to produce the desired outcome (Butler 1995). The situation, action, and outcome are added to the organization's codes, which then help organizations apply knowledge from the past to make more effective decisions for the future (Gherardi and Strati 1988). As the organization expands its code base over time, it can access the expanded code base to better interpret its environment, be forewarned about complex situations, quickly perceive events, and apply the code base to understand problems, actions to address the problems, and outcomes associated with each action (Goodman 1973).

By analyzing and recombining past actions with successful outcomes, coded abbreviations of patient conditions enable organizations to displace temporal boundaries, extend present conditions, and exert greater influence over future situations through remote control and centralized planning. For example, when the United Kingdom's National Health Service (NHS) analyzes which care profiles lead to better healthcare outcomes at lower costs, clinicians can refer to these care profiles to identify the most effective and efficient treatments (Bloomfield and Coombs 1992).

As temporal boundaries are displaced and organizations achieve greater control, they are able to move events from one time period to another through scheduling, synchronization, and allocation (McGrath and Rotchford 1983). Scheduling is the time at which an event will occur, and organizations can define schedules so the desired action takes place at the desired time. Synchronization is the alignment of one action by one person with another action and/or another person, and organizations can synchronize activities to ensure that personnel work in concert to achieve the desired objective. Allocation is the assignment of priorities and resources to tasks, which increases the likelihood that tasks can be completed when desired. Codification increases the effectiveness of task identification and resource allocation across time periods (Rahmandad et al. 2009). These mechanisms enable organizations to respond to temporal pressures and problems by extracting an event from one context and relocating that event to another time. As a result "these three issues [scheduling, synchronization and allocation] are at the heart of matters of organizational efficiency, cost and productivity" (McGrath and Rotchford 1983, p. 69).

The literature in this section describes the theoretical mechanisms through which IT and analytics facilitate better healthcare outcomes at lower cost. Table 2 provides more detail on how providers can deploy and use IT. By using the codification capabilities of IT systems to capture the health status of patients, providers analyze the codes to identify the most effective treatments *at the most effective time* for each patient. IT gives clinicians greater visibility and control over the healthcare delivery process so they can displace the timing of patient procedures and schedule interventions that will have the highest impact on healthcare outcomes. They can synchronize actions with partner agencies to provide efficient and effective healthcare support and allocate human resources and financial capital to improve healthcare outcomes. Consistent with this discussion, we hypothesize:

Hypothesis 1A: The use of IT is associated with the temporal displacement of high-intervention medical procedures in favor of low-intervention medical procedures.

*Hypothesis 1B: The use of IT **and** analytics is associated with a greater temporal displacement of high-intervention medical procedures in favor of low-intervention medical procedures.*

IT, Analytics and Impacts Over Time

In addition to relocating actions from one time period to another time, codification facilitates organizational learning through the process of accumulating, encoding, and leveraging insights gained through experience over an extended period of time (Saloman and Martin 2008). Organizational learning involves the ability to recombine current knowledge with past knowledge across long time horizons, which requires that knowledge be maintained in archival databases and available for analysis and recombination (Nerkar 2003). The IT systems impact the data and associated processes that are used to identify, interpret, and learn from the data (Holmer-Nadesan 1997). For example, when an organization receives feedback about outcomes from past resource allocations, it uses that feedback to adjust future allocations, test assumptions on the relationship between actions and out-

comes, and track actions and outcomes to improve performance (Rahmandad et al. 2009). For example, the NHS uses resource management software to codify standardized care profiles, which define the tests and drug therapies for patients with a specific diagnosis (Bloomfield and Coombs 1992). Clinicians can refer to these codified care profiles to determine the course of action based on the patient diagnosis, and the NHS can use the care profiles to collect data on patient patterns and variances in resource use across patients with the same condition and over time.

Organizational learning based on codification can take the form of single-loop learning or double-loop learning (Argyres 1976). In single-loop learning, the organization uses existing codes to respond to an event with a specified action to ensure conformance to an existing performance norm, which reinforces the existing codes for that event–action sequence and timing. In double-loop learning, organizations use experience and insights to go beyond existing codes and either modify or create new codes for improved performance. In this manner, organizations use codes to absorb their previous patterns of comprehension and reweave those patterns into a new coherent system of understanding over time (Chia 2002).

Time is relevant for organizational learning. When an organization learns new knowledge, the benefits of that new learning take some time to appear (Ko and Dennis 2011). As the organization accumulates learning, it is able to recognize new knowledge, contextualize new learning, and adapt the learning to work practices to improve performance. While initial benefits may be modest, the scope and/or impact increases over time (Ko and Dennis 2011). Learning also occurs across organizations through mechanisms such as benchmarking competitors, hiring employees with in-depth industry knowledge, contracting with leading suppliers, participating in trade associations and industry conferences, and individual networking (Saloman and Martin 2008).

To the extent that codification-based organizational learning spreads across organizations, there is evidence that over time the performance of late adopters converges with the performance of early adopters (Ko and Dennis 2011). The organization science literature explains how providers can apply their codification-based learning to improve the scope and impact of healthcare value over time, and how later-adopting providers can use the IT infrastructure to catch up to early adopters in terms of healthcare outcomes. Early-adopters will use the codification-based features of IT for single-loop learning, in which they apply codes to maintain patient health at an accepted standard. In the early stages of TDC, as IT and analytics lead to the increased use of low-intervention treatments and reduced use of high-intervention treatments, it may take some time for cost savings and health benefits to materialize. As the health benefits materialize and early adopters gain experience and insights, they become more sophisticated and engage in double-loop learning where they test new assumptions, gain more knowledge, and modify codes to achieve new and higher levels of healthcare value. Through this recursive process, the code base becomes more robust for later adopters. Later adopters take advantage of the knowledge represented in the code base to advance along the learning curve more quickly and converge their performance with early adopters. Consistent with this discussion, we hypothesize

Hypothesis 2A: ***Over time****, the use of IT will be associated with an increase in displacement of high-intervention medical procedures in favor of low-intervention medical procedures.*

Hypothesis 2B: ***Over time****, the use of IT* ***and*** *analytics will be associated with a greater increase in displacement of high-intervention medical procedures in favor of low-intervention medical procedures.*

IT, Analytics and Patient Outcomes

The business value of IT literature points to the importance of use of IT artifacts to achieve productivity and other gains:

> System-use is a pivotal construct in the system-to-value chain that links upstream research on the causes of system success with downstream research on the organizational impacts of information technology (Doll and Torkzadeh 1998, p. 171).

When decision makers incorporate available information, their actions lead to appropriate solutions in pursuit of desired outcomes. Accurate and complete information about previous interventions and status gives clinicians the ability to prescribe appropriate medication so the patient does not need to make an unplanned visit to the doctor's office or emergency room. Further, when clinicians can access a list of patients who have not refilled their medication prescription, they can intervene and contact patients to ensure adherence. Inability to access past information or to identify non-adherent patients leads to expensive interventions and potential adverse health outcomes. Hospital decision makers' use of IT has been associated with lower mortality rates (Devaraj and Kohli 2003) and clinical utilization of services (Menachemi et al. 2008). Recently, use of IT is found to have spillover effects among hospitals in a region because when hospitals can access consistent, timely, and complete patient records, clinicians do not have to readminister tests and can provide prompt treatment. Prompt treatment and fewer tests lower the cost of patient

care (Atasoy et al. 2017). Consistent with this discussion, we hypothesize

Hypothesis 3A: The use of IT will be associated with reduced healthcare costs and improved patient health indicators.

*Hypothesis 3B: The use of IT **and** analytics will be associated with a greater reduction in healthcare costs and more improved patient health indicators.*

Research Setting

The Vermont Blueprint for Health (VBH) is a state-led initiative designed to transform health care delivery in the U.S. state of Vermont (Vermont Blueprint for Health 2015). VBH is organized around a network of practice facilitators, community health team leaders, local health and human services leaders, and project managers that work as a patient-centered medical home (PCMH). Each of Vermont's 14 health service areas (HSA) has an administrative entity such as a hospital or federally qualified health center that provides local leadership for project management, staffing for community health teams, and financial management. The network allows for a rapid response to the state's healthcare priorities through statewide implementation of initiatives. VBH programs are informed by comprehensive evaluations of healthcare quality and outcomes at the practice, community, and state levels. VBH is based on a three-tier strategy for IT and analytics, where each tier builds on the preceding tier. Table 4 provides more information on the three tiers.

The registry database passes the PCP core data elements and clinical data to an independent nonprofit data analytics firm that joins patient data from the registry database with cost and outcomes data from commercial insurance firms and Medicaid via the All Payer Claims Database (APCD). The APCD contains summary administrative health care claims data. By law, all major commercial insurance companies and Medicaid issuing policies in the state of Vermont must submit data to the APCD. The integrated data are analyzed, and patient-level, practice-level, and program-level results are returned to the registry database and/or disseminated to providers and public health agencies.

The analytics output supports clinical decision-making, guides activities of public health providers, and helps policy makers assess program performance. VBH uses two types of analytics capabilities: direct data measurement and analytics reports. Direct measurements are combined into recipient-specific sets to create custom reports for various stakeholders. For example, custom reports provide an update to public healthcare providers (PHP). These patient needs trigger the PHPs to proactively contact patients who may require certain preventative or maintenance services. Having information on patient needs facilitates the temporal displacement of healthcare services to occur earlier in the process so healthcare outcomes can be improved and costs reduced.

Analytics products combine direct measurements with additional analyses. For example, healthcare practice profiles and HSA profiles provide performance measurement and comparisons that benchmark each practice and HSA against other practices and HSAs. Any stakeholder can receive a combination of direct measurement data and analytics reports. For example, the VHIE sends patient-level insight and practice profiles from the registry database to the respective EMRs. In a similar manner to PHPs, PCPs can use patient-level insights to proactively engage patients at earlier points-in-time, and practice profiles to evaluate patient needs and practice performance relative to other PCP practices. Analytics reports include calculation of performance payments that are a function of cost, quality, and utilization measurements. Analytics reports are used to assess programs that span multiple HSAs and involve large numbers of practices, and to develop predictive models to estimate future costs and public health trends.

Data

Cardio-Metabolic Disease

When complications from diabetes extend to the heart and other organ systems, the patient is said to suffer from a multi-organ system suite of conditions known as cardio-metabolic disease. Table 5 provides the medically accepted list of 16 health conditions and corresponding International Classification of Diseases Ninth Revision (ICD-9) codes to indicate patients at risk of complications associated with cardio-metabolic disease. These ICD-9 codes include conditions related to diabetes, cholesterol and lipid disorders, obesity, and hypertension.

Selection Criteria

Our data sources for this study are the Vermont All Payer Claims Database (APCD) and the Vermont Health Information Exchange (VHIE), which together contain medical claims plus the utilization of health and pharmacy services, clinical outcomes, and mandatory quality reporting measures for every Vermont resident that is uninsured, covered by commercial insurance, or covered by Medicaid. Our selection criteria for the total cost of care and utilization of health services

Table 4. Vermont Blueprint for Health Tiers for IT and Analytics

Tier	Description
Tier 1 EMR Use	Supports primary care practices as they move through the PCMH certification process and EMR implementation. This involves the installation of basic EMR systems to satisfy "meaningful use" requirements established by the U.S. federal government under the HITECH Act of 2009 (Blumenthal and Tavenner 2010). EMRs enable accurate recording of information collected during each patient encounter, and support information gathering for medical claim submission. Tier 1 installation of IT applications gives the provider visibility to internal practice data from actual patient visits.
Tier 2 Data Quality Sprints (DQS)	Establishes data standards through data quality sprints (DQS) that enable data aggregation, consolidation and extraction (details in Figure 3), and are designed to enhance individualized patient care with guideline-based decision support. The data extraction and consolidation enable the provider to maximize actual use of IT, with visibility to internal practice data from actual patient visits (as in Tier 1 above), AND the ability to identify patients that should have occurred, AND the ability to compare data across patients. Also supports management of populations with flexible reporting for groups of patients and individual patients. DQS align provider data capture and adhere to Continuity of Care Record (CCR) processing using industry standard nomenclatures to improve clinical data capture. The CCR specification is an extensible markup language (XML) based standard to specify the encoding, structure, and semantics of a patient summary clinical document for exchange with other providers (Ferranti et al. 2006), which is a prerequisite for Tier 3. Data capture is based on the VBH data dictionary, which is adopted directly from national guidelines for preventive health maintenance and treatment of chronic conditions.
Tier 3 Vermont Healthcare Information Exchange (VHIE)	Extracts practice-level data, integrates claims data from payers, and provides data sharing, network-wide analysis and information dissemination through the Vermont Healthcare Information Exchange (VHIE) (details in Figure 3). VHIE provides analytical capabilities to include external data on patients such as prescription refills and hospital visits, AND benchmarking data from other practices on patients with similar conditions (shown in Table 1). Tier 3 involves extraction and integration of standardized data elements from Tier 2 for aggregation, analysis, and reporting stages. During the clinical data aggregation stage, the VHIE extracts and translates predetermined "core data elements" from EMRs into a common master database (Yaraghi et al. 2015). Information from VHIE is passed to the VBH registry database via the integration engine. Patient-level data are augmented by messages entered by four types of Vermont public healthcare providers (PHPs): support and services at home, tobacco cessation counselors, community health teams, and self-management programs. These healthcare providers work directly with patients but may or may not have direct contact with primary care providers (PCPs).

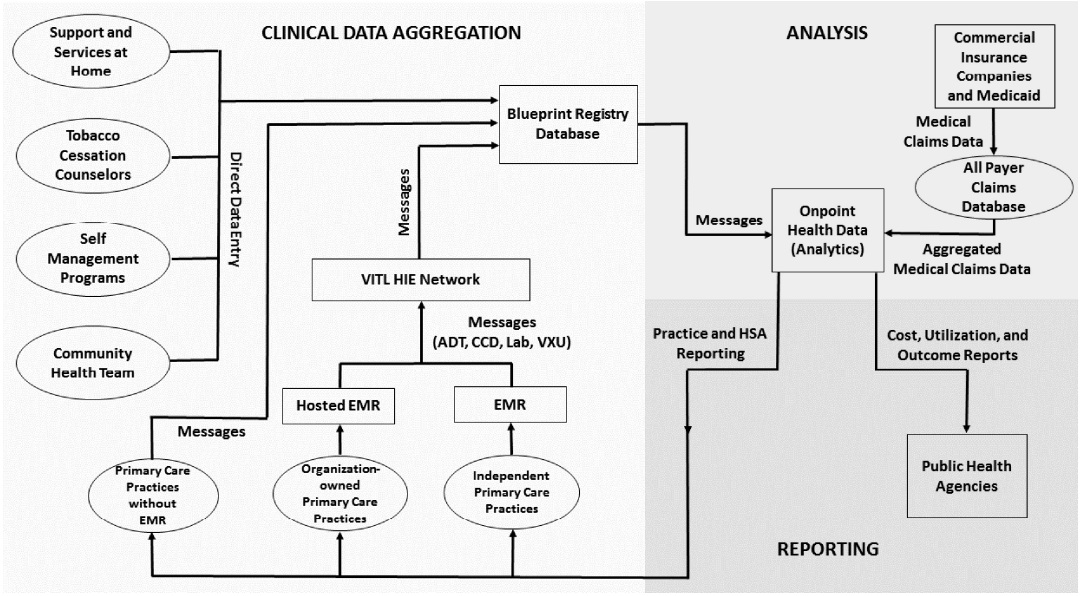


Figure 3. Data Use: Aggregation, Analysis, and Reporting

Table 5. Diagnostic Codes Related to Cardio-Metabolic Disease

Health Condition	ICD-9 Codes
Coronary arthrosclerosis, native artery	414.xx
Intermediate coronary syndrome	411.xx
Pure hypercholesterolemia	272.0x
Pure hyperglyceridemia	272.1x
Mixed hyperlipidemia	272.2x
Unspecified hyperlipidemia	272.4x
Dysmetabolic syndrome X	277.7x
Essential hypertension	401.xx
Obesity, unspecified (BMI 30.0-39.9)	278.00
Morbid obesity (BMI 40 or greater)	278.01
Overweight (BMI 25.0-29.9)	278.02
Hypertensive heart disease	402.xx
Hypertensive chronic kidney disease	403.xx
Diabetes type 2 not controlled	250.x0
Diabetes type 2 controlled	250.x2
Disorders of thyroid gland	240.xx-246.xx

are based on actual medical claims data gathered and formatted by the Vermont Department of Public Health. At the time of this study, the data sources did not include information for Vermont residents covered by Medicare or Medicare Advantage.

Our data are annual summaries of cost, quality, and utilization measures over the five-year period 2009–2013. Because not all Vermont residents entered the VBH program at the same time, we are able to compare outcomes for VBH patients and non-VBH patients with the same condition in a quasi-natural experimental setting. Our VBH data also contains the current level of IT usage for each practice (e.g., whether the practice has completed the DQS and whether the practice has established VHIE connectivity). As described in Table 4, the deployment of IT and analytics is cumulative. For example, in Tier 1 the PCMH cohort has installed EMR systems and meets federal meaningful use criteria. In Tier 2, the DQS cohort has met the same technology standards as in Tier 1 and has also completed a data quality sprint. In Tier 3, the VHIE cohort has met the same technology standards as the PCMH cohort, has completed the DQS, and has also achieved VHIE connectivity. This enables us to evaluate cost and quality measures for patients treated by PCMHs based on their level of IT and analytics usage. To examine these measures against practices that did not undertake these structured IT deployment initiatives, we divide the patients into matching VBH tiers (PCMH, DQS, and VHIE, respectively) and non-VBH (control) cohorts.

The data in this analysis were normalized to control for practice-level and payer mix effects using a methodology deployed in past research (Finison et al. 2017). Controlling for practice-level and payer mix effects eliminates specific industry practices that could bias results. For example, providers negotiate reimbursement rates with each payer separately. A payer covering a relatively small proportion of individuals in a given geographic location will have less negotiating power and therefore pay higher amounts to providers than a payer with a larger market share. Failure to account for the pricing mechanism could lead to erroneous conclusions where providers seemingly reduce total cost of care, when the reduction was actually due to payer mix factors. All cost of care measures are adjusted for the medical inflation rate calculated for the state of Vermont using data from the APCD.

To be included in a VBH cohort, patients must have 12 months of baseline data that includes treatment by a primary care practice certified as a PCMH, and 24–36 months of follow-up data where the patient is attributable to the same practice observed during the baseline period.[3] The date when care delivery was assumed by a PCMH is treated as the index date at which the patient is presumed to start benefits from the improved data and process changes facilitated by IT and analytics. A total of 22,469 patients met the inclusion criteria

[3]All subjects included in the study were at least 18 years old and had a medical claim with at least one ICD-9 code.

for a VBH cohort (PCMH 7,622 patients; DQS 9,548 patients; and VHIE 5,299 patients, respectively) for whom appropriately matched control patients were also available in the state of Vermont's dataset. While we have five years of data, not all practices adopted IT and analytics initiatives as the same point in time. Since IT and analytics adoption was spread over the time horizon of our data, our sample size (n) for the three VBH cohorts was lower by about 25% in the third year after the baseline year (Year 3 PCMH 6,264 patients, DQS 7,453 patients, VHIE 3,827 patients).

Analysis

We structured the analysis as an observational, retrospective case-control study. Retrospective case-control studies are frequently used in medical, epidemiological, and public health research when prospective and/or experimental study designs are impractical, unethical, and/or illegal. Such studies can be impractical when several years of longitudinal data are required or when the number of subjects required to discern an effect is prohibitively large. Ethical issues would include withholding a treatment for a control group patient that could be beneficial, or administering a treatment that could be harmful. Finally, laws governing patient autonomy, informed consent, and physician responsibilities can render some research questions untestable in an experimental setting. Given these practical limitations, medical and public health researchers conduct retrospective studies. In Table 6, we provide conditions where a retrospective cohort study design is required, and examples of past research studies that adopted this study design.

The studies listed in Table 6 use a retrospective cohort study design because the researchers seek to identify the effect of observed exposure to an intervention on an observed health outcome of interest. In case-control cohort studies, propensity score matching is used to construct each cohort because a number of factors can affect health outcomes. Propensity score matching controls for those effects by ensuring that subjects in each cohort are paired with a control subject that has similar covariates known to affect health outcomes. This is in contrast to a regression approach where matching variables are included as covariates in the regression. Both approaches yield similar results, but the advantage to a case-control cohort approach is that researchers can avoid over-parameterizing a regression model with covariates where the effects on the independent variable are well-established. For example, in this setting a factor such as age exerts a strong effect on measures such as cost of care or likelihood of hospitalization. However, the fact that age is a risk factor for chronic diseases already is well-established. Rather than include age and other factors *that are already known* to impact the outcomes of interest in the model, propensity score matching in the first stage of analysis ensures that we compare apples to apples with respect to the effect of treatment interventions on healthcare outcomes. For example, a retrospective case-control study design was used to establish the correlation between smoking and lung cancer (Doll and Hill 1950). More recently, retrospective case-control study designs have been used to study the effect of lifestyle choices on incidence of heart disease (Zaridze et al. 2009) and the impact of community-wide cardiovascular disease prevention programs on health outcomes (Record et al. 2015).

Finally, case-control study design is preferred over regression models because regression models control for variables in a linear fashion. For example, if we study the effect of a medication on heart failure and our treatment group consisted of only men but our control group consisted of men and women, we could use all data but could only infer the *possible* effect of women. With propensity score matching, we can directly match males with males and our study results would not apply to females.

We compose three VBH cohorts with matched control cohorts using pharmacy data,[4] medical claims data, and clinical data described above. We use nearest neighbor propensity score matching with a +/– 0.05 caliper to develop a 1:1 match of a VBH group to the control group. A sufficiently tight caliper (approximately +/– 0.20) has been shown to eliminate approximately 99% of bias due to measured confounders (Rosenbaum and Rubin 1985). While calipers of +/– 0.25 or 0.20 are generally accepted, our review of the healthcare literature finds that public health researchers often use much tighter calipers because variance is high (Austin 2011). To determine the appropriate caliper we examined the sensitivity of estimated effects to small changes in the propensity score specification (Lunt 2014). We found that results were stable with the +/– 0.05 caliper, and remained consistent with effects observed with calipers of +/– 0.10 and +/– 0.02, although the latter caliper resulted in significantly fewer matches. One concern with an extremely tight caliper is the inability to match experimental subjects with test subjects. That did not occur with this study, and the 22,469 matched individuals represents over 60% of the 36,223 individuals that met study inclusion criteria attributable to VBH practices.

[4]Our pharmacy data consists of alerts of when prescriptions were filled, and do not include the prescription details and/or instances when prescriptions were given but not filled.

Table 6. Retrospective Study Designs in Medical and Public Health Research

Motivation for Retrospective Case-Control Study Design	Study	Description	Why Retrospective Case-Control Study Is Required
Prospective study designs may be *impractical* or *infeasible*	Tzoulaki et al. 2009	Fifteen-year retrospective analysis of the effect of three types of oral diabetes medication on cardiovascular disease and all-cause mortality.	Duration of time required for observable effects makes other study designs *impractical*.
	Booth et al. 2006	Six-year retrospective analysis of relationship between age and cardiovascular disease in diabetics compared with non-diabetics.	Duration of time required for observable effects and large number of subjects makes other study designs *infeasible*.
Prospective study designs may be *unethical*	Lauffenburger et al. 2015	Retrospective cohort analysis of effectiveness and safety of blood thinning medications on patients with atrial fibrillation of the heart. This study uses a one-year baseline period and one to two years of follow-up.	Potential for life threatening effects makes assignment of patients to groups *unethical*.
Prospective study designs may be *illegal without informed consent of all subjects*	Bittner et al. 2015	Retrospective cohort study on use of non-statin lipid-lowering therapy among patients with coronary heart disease. Study compares 20 cohorts over time.	Researchers cannot make changes to pharmaceutical treatment plans without the informed consent and permission of each study subjects. A retrospective cohort study is required because experimental design would be *illegal*.
	Delea et al. 2003	Retrospective cohort study of the prevalence of heart failure. associated with an oral diabetes medication. This study uses one year of baseline data and five years of follow-up.	In addition to a large number of subjects and a long follow-up period, an experimental study design would require informed consent from each subject. This combination requires a retrospective cohort study because a prospective study would be *impractical, unethical, and illegal*.

We match subjects in each VBH cohort with control subjects based on age, gender, HSA, insurance type, baseline comorbidity index at index date as defined by Aggregated Clinical Risk Grouping (ACRG3) score, baseline comorbid conditions, baseline healthcare costs, and utilization. The patient in the control group who is matched with a VBH patient must meet matching criteria on the index date. The *p* values for post-match baseline demographic, clinical, and utilization, cost and outcome measures show that there are no statistically-significant differences between the VBH cohorts and their respective control groups for any demographic or data measure, including frequency of low-intervention treatments, frequency of high-intervention treatments, and health and financial outcomes.[5]

[5]Post-match statistics for demographic variables, utilization, cost and outcome measures are not included in the manuscript due to length restrictions, but are available from the authors on request.

Table 7. Comparison of Low Intervention Treatments for VBH Cohorts and Control Groups

Low Intervention Treatment	VBH Cohort	Year 1		Year 2		Year 3	
		VBH	Control Group	VBH	Control Group	VBH	Control Group
Physician office visits (*per member*)	PCMH	4.4	3.8	4.9*	3.8	5.0**	3.7
	DQS	5.1**	3.8	5.2**	3.8	5.2**	3.7
	VHIE	5.8***	3.7	5.8***	3.7	5.7***	3.8
Neuropathy screening (*percent of members*)	PCMH	60%	57%	67%*	57%	80%**	58%
	DQS	64%*	56%	74%***	58%	94%***	57%
	VHIE	70%***	56%	84%***	58%	95%***	56%
Eye exam (*percent of members*)	PCMH	64%	59%	73%	61%	84%**	63%
	DQS	71%*	59%	82%***	63%	93%***	64%
	VHIE	75%**	61%	87%***	62%	96%***	65%
Rx utilization (*prescription fills per member*)	PCMH	38	34	39	33	41**	34
	DQS	38*	34	41**	34	43***	33
	VHIE	41**	33	46***	33	48***	34

Difference between control group and VBH significant at *10%, **5%, and ***1%; no asterisk indicates not significant (*NS*).

Main Results

In Table 7 we provide data on the use of low-intervention treatments by the three VBH cohorts and their respective control groups for the first three years after the baseline year. For ease of exposition, we tested differences between groups using paired t-tests or McNemar tests for continuous or categorical data, respectively. Those tests provide measures of absolute risk rather than odds ratios, which are less intuitive in their interpretation. The section for each low-intervention treatment is divided into three rows, one row each for the PCMH cohort, DQS cohort, and VHIE cohort. Each year is divided into two columns, one column with data for the VBH cohort, and another column with data for the respective control group. When the difference between the VBH cohort and respective control group is statistically significant, the statistical significance is indicated by asterisks in the VBH column.

Hypothesis 1A proposed that the use of IT will be associated with the temporal displacement of high-intervention medical procedures in favor of low-intervention medical procedures. Consistent with this hypothesis, we expect displacement of low-intervention treatments to early stages, resulting in higher utilization of physician office visits, neuropathy screening, eye exams, and prescription fills per member attributable to DQS practices compared with the control group. We see this phenomenon for all four low-intervention treatments (see Table 7). Even in the first year after VBH implementation, we note early differences in the DQS cohort and PCMH cohort relative to their respective control groups. For example, in Year 1, the average number of physician office visits is 4.4 per member for the PCMH cohort (not statistically significantly (*NS*) different from control group average 3.8), while the average number of physician office visits is 5.1 per member for the DQS cohort ($p < 0.05$ difference from control group average 3.8).

We see a similar result for the other three low-intervention treatments, even in the first year after VBH implementation. In the DQS cohort, 65% have a neuropathy screening in Year 1 ($p < 0.10$ difference from control group 56%), while only 60% of the PCMH cohort have a neuropathy screening (*NS* difference from control group 57%). In the DQS cohort, 71% have an eye exam in Year 1 ($p < 0.10$ difference from control group 59%), while only 64% of the PCMH cohort have an eye exam in Year 1 (*NS* difference from control group 59%). There are 38 prescription fills per member per year in the DQS cohort ($p < 0.10$ difference from control group 34), while the difference between prescription fills per member in the PCMH cohort is *NS*.

For Hypothesis 1A to be supported, we should also see a decrease in high-intervention treatments as these treatments are subject to temporal displacement in favor of low-intervention treatments. In Table 8, we provide data on the use of high-intervention treatments by the three VBH cohorts and their respective control groups for the first three years after the baseline year. Similar to the layout of Table 7, Table 8 has three rows for each treatment, one row with data for each VBH cohort (PCMH, DQS, and VHIE) compared with their respective control group. The results for Table 8 support

Table 8. Comparison of High-Intervention Treatments for VBH Cohorts and Control Group

High Intervention Treatment	VBH Cohort	Year 1		Year 2		Year 3	
		VBH	Control Croup	VBH	Control Group	VBH	Control Group
Avoidable emergency department utilization (*number of visits*)	PCMH	20.7%	24.1%	19.7%	24.3%	21.1%	23.5%
	DQS	18.6%*	24.2%	19.0%*	24.2%	17.2%**	24.0%
	VHIE	18.0%**	24.1%	17.7%***	24.0%	16.4%***	23.6%
Number of inpatient admissions	PCMH	10.9%	11.1%	10.6%	11.1%	10.8%	11.2%
	DQS	10.7%	11.1%	10.5%	11.2%	10.3%*	11.5%
	VHIE	10.7%	11.1%	10.1%**	11.0%	10.5%***	12.4%

Difference between control group and VBH significant at *10%, **5%, and ***1%, no asterisk indicates not significant (*NS*).

Hypothesis 1A because we see a decrease in avoidable emergency department visits as early as Year 1. In Year 1, 18.6% of patients in the DQS cohort had an avoidable emergency department visit ($p < 0.10$ difference compared with control group 24.2%), compared with 20.7% of the PCMH cohort (*NS* difference compared with control group 24.1%). While we see only a minor decrease in inpatient admissions for the DQS cohort in Year 1 (10.7% *NS* compared with control group 11.1%), the decrease in emergency department visits for the DQS cohort combined with the increase in four low-intervention treatments for the DQS cohort provides support for Hypothesis 1A.

Hypothesis 1B proposed that use of IT *and* analytics will be associated with an even greater temporal displacement of high-intervention treatments in favor of low-intervention treatments, compared with the use of IT alone. Consistent with this hypothesis, we should expect to see a further increase in low-intervention treatments for the VHIE cohort (where both IT and analytics are used) compared with the DQS cohort (where IT is used), which, as discussed above, has already shown a more pronounced effect than the PCMH cohort relative to their respective control groups. The results in Table 8 confirm a greater increase in all four low-intervention treatments for the VHIE cohort compared with the DQS cohort relative to control groups, showing the incremental contribution of analytics to healthcare outcomes. In Year 1, the average number of office visits increases to 5.8 for the VHIE cohort ($p < 0.01$ difference compared with control group 3.7), greater than 5.1 for the DQS cohort. The percent of patients with neuropathy screening in Year 1 increases to 70% for the VHIE cohort ($p < 0.01$ difference compared with control group 56%), higher than 64% for the DQS cohort. The percent of patients with eye exams in Year 1 increases to 75% for the VHIE cohort ($p < 0.01$ difference compared with control group 61%), higher than 71% for the DQS cohort. The number of prescription refills in Year 1 increases to 41 for the DQS cohort ($p < 0.01$ difference compared with control group 33), higher than 38 in the DQS cohort. As shown in Table 8, even as the utilization of low-intervention treatments increases for the VHIE cohort (because high-intervention treatments are temporally displaced in favor of low-intervention treatments), emergency department utilization as a high-utilization treatment decreases with the addition of analytics capability. In Year 1, 18.0% of patients in the VHIE cohort have emergency room visits ($p < 0.05$ difference compared with control group 24.1%), lower than the DQS cohort with 18.6%. Although we see a minor decline in inpatient admissions for the VHIE cohort in Year 1 (10.7% *NS* compared with control group 11.1%), the fact that all four low-intervention treatments increase for the VHIE cohort and high-intervention treatment emergency department visits decrease for the VHIE cohort provides support for Hypothesis 1B.

Hypothesis 2A proposed that, over time, the use of IT will be associated with an increased displacement of high-intervention medical procedures in favor of low-intervention medical procedures. Consistent with this hypothesis, we should expect that the increase in low-intervention treatments for the DQS cohort in Year 1 will continue and *further* increase in Years 2 and 3. The results in Table 8 show this to be the case. For the DQS cohort, the number of physician office visits per member increases from 5.1 in year 1 to 5.2 in Years 2 and 3 ($p < 0.05$ difference compared with control group 3.7). The percent of DQS patients with neuropathy screening increases from 64% in Year 1 to 74% in Year 2 ($p < 0.01$ difference from control group 58%) and to 94% in Year 3 ($p < 0.01$ difference compared with control group 58%). The percent of DQS patients with an eye exam increases from 71% in Year 1 to 82% in Year 2 ($p < 0.01$ difference compared with control group 63%) and to 93% in year 3 ($p < 0.01$ difference compared with control group 64%). The number of prescription fills per DQS patient increases from 38 in Year 1 to 41 in Year 2 ($p < 0.05$ difference compared with control group 34) and to 43 in Year

3 ($p < 0.01$ difference compared with control group 33). Even as DQS patients increase the use of low-intervention treatments over time, they decrease the use of high-intervention treatments. This is consistent with the notion of temporal displacement and provides confidence in our claim that services displaced from high-intervention treatments result in the increase of low-intervention treatments. While there is not a decrease in percentage of DQS patients with avoidable emergency department visits from Year 1 to Year 2, there is a statistically significant decrease from 19.0% to 17.2% in Year 3 ($p < 0.05$ difference compared with control group 24.0%). Similarly, while the percent of DQS patients with an inpatient admission does not decrease at a statistically significant level from Year 1 (10.7%) to Year 2 (10.3%), the difference between the DQS cohort (10.3%) and the control cohort does become moderately statistically significant in Year 3 ($p < 0.10$ difference compared with control group 11%). For the DQS cohort, the further increase over time in low-intervention treatments and further decrease over time in high-intervention treatments provide support for Hypothesis 2A.

Hypothesis 2B proposed that the use of IT *and* analytics will be associated with a greater increase in temporal displacement of high-intervention medical procedures in favor of low-intervention medical procedures over time, compared with the use of IT alone. While the results are inconclusive for physician office visits, we do observe this phenomenon for the other three low-intervention treatments. The percent of VHIE patients with neuropathy screening increases from 70% in Year 1 to 84% in Year 2 ($p < 0.01$ difference compared with control group 58%) to 95% in Year 3 ($p < 0.01$ difference compared with control group 56%). The percent of VHIE patients with eye exams increases from 75% in Year 1 to 87% in Year 2 ($p < 0.01$ difference compared with control group 62%) to 96% in Year 3 ($p < 0.01$ difference compared with control group 65%). The number of prescription refills per VHIE patient increases from 41 in Year 1 to 46 in Year 2 ($p < 0.01$ difference compared with control group 33) to 48 in Year 3 ($p < 0.01$ difference compared with control group 34). For high-intervention treatments, while the percent of VHIE patients with emergency department visits decreases slightly from Year 1 (18.0%) to Year 2 (17.7%), it decreases further from 17.7% in Year 2 ($p < 0.01$ difference compared with control group 24.0%) to 16.3% in Year 3 ($p < 0.01$ difference compared with control group 23.6%). We see a decrease in the percent of VHIE patients with inpatient admissions from 10.7% in Year 1 to 10.1% in Year 2 ($p < 0.01$ difference compared with control group 11.0%), and a widening differential from the control group in Year 3 (10.5%, $p < 0.01$ difference compared with control group 12.4%). For the VHIE cohort, the increase in three low-intervention treatments over time and the decrease in high-intervention treatments over time provide support for Hypothesis 2B.

Table 9 provides comparative data on cost and health indicators for the three VBH cohorts and their respective control groups, for three years after the baseline year. Hypothesis 3A proposed that the use of IT will be associated with reduced healthcare costs and improved patient health indicators. Table 9 shows that while DQS patients did generate emergency department (ED) cost savings in Year 1, other cost indicators such as inpatient cost savings and total healthcare cost savings did not emerge until Year 2. We compute cost savings as the difference between the VBH expenditure and the control group expenditure. In Year 2, inpatient cost savings were \$34 (\$218 – \$174) per member per month compared with the control group ($p < 0.10$) and total healthcare cost savings were \$97 (\$741 – \$644) per member per month compared with the control group ($p < 0.05$). In Year 3, inpatient cost savings increased to \$59 (\$230 – \$171) per member per month compared with the control group ($p < 0.01$), and total healthcare cost savings remained relatively steady at \$89 (\$740 – \$651) per member per month compared with the control group ($p < 0.10$).

While these empirical results generally support Hypothesis 3A, *we observe the additional insight that there is a lag effect between the temporal displacement of treatments and the subsequent decrease in costs*. This lag effect is even more pronounced when we consider the health indicator of HbA1c levels. With the implementation of IT, we see a moderately statistically significant decrease in HbA1c levels only in Year 3 (0.82% for DQS patients $p < 0.10$). *These empirical results appear to show a pattern such that temporal displacement of care is followed by cost savings, which is then followed by health indicator improvements with a lagged effect in each relationship*. We will discuss this important insight further in the discussion section below.

Hypothesis 3B proposed that the use of IT *and* analytics will be associated with reduced healthcare costs and improved patient health indicators, compared with the use of IT alone. The pattern of empirical results for VHIE patients is similar to the pattern of results for DQS patients described above. Except for cost savings for ED visits, cost savings for inpatient visits do not occur until Year 2, which at \$53 (\$220 – \$167) per member per month for VHIE patients compared with the control group ($p < 0.05$) are higher than \$34 cost savings per member per month for DQS patients compared with the control group. In Year 3, these inpatient cost savings for VHIE patients increase to \$65 (\$227 – \$162) per member per month compared with the control group ($p < 0.05$), which are higher than DQS patient \$59 cost savings per member per month compared with the control group. Total healthcare cost savings for VHIE patients also do not emerge until Year 2, which are \$102 (\$730 – \$628) per member per month compared with the control group ($p < 0.05$). In Year 3, these total

Table 9. Comparison of Cost and Health Outcomes for VBH Cohorts and Control Group

Outcome	VBH Cohort	Year 1		Year 2		Year 3	
		VBH	Control Croup	VBH	Control Croup	VBH	Control Group
Avoidable emergency department expenditure (*per member per month*)	PCMH	$68	$81	$60*	$82	$57**	$86
	DQS	$55*	$79	$51**	$83	$55**	$88
	VHIE	$52*	$77	$49***	$82	$52**	$86
Inpatient healthcare expenditure (*per member per month*)	PCMH	$199	$202	$187	$216	$177**	$229
	DQS	$198	$200	$174*	$218	$171***	$230
	VHIE	$192	$199	$167**	$220	$162***	$227
Total healthcare expenditure (*per member per month*)	PCMH	$710	$714	$687	$732	$667**	$742
	DQS	$713	$711	$644**	$741	$651*	$740
	VHIE	$688	$715	$628**	$730	$636***	$746
Health status (*HbA1c level*)	PCMH	7.14%	7.30%	7.00%	7.28%	6.63%*	7.25%
	DQS	7.12%	7.30%	6.80%	7.26%	6.40%*	7.22%
	VHIE	6.89%	7.33%	6.66%*	7.30%	6.20%***	7.24%

$ rounded to nearest whole number.
Difference between control group and VBH significant at *10%, **5%, and ***1%; no asterisk indicates not significant (*NS*).

healthcare cost savings for VHIE patients increase to $110 ($746 – $636) per member per month ($p < 0.05$), which are higher than $89 per member per month cost savings for DQS patients compared with the control group. Just as most cost savings do not emerge until Year 2, improvements in the health indicator for VHIE patients do not emerge until Year 2 (7.30% – 6.66% = 0.64% lower HbA1c compared with control group at $p < 0.10$). This HbA1c level improves further in Year 3, reaching 1.04% (7.24%–6.20%) lower for VHIE patients compared with the control group ($p < 0.01$), even lower than the 0.82% (7.22%–6.40%) difference for DQS patients in Year 3. While these empirical results generally support Hypothesis 3B, as discussed above we believe the insight of lags from temporal displacement to cost savings and health indicators deserves special attention, which we give in the discussion section below.

Robustness Checks

We conducted several robustness checks to rule out alternative explanations for our findings. We describe each robustness check below.

Did Healthier Patients Participate in VBH?

One possible explanation for our empirical results could be that healthier patients participated in VBH. Our main analyses suggest that this was not the case. As we show in Table 9, the HbA1c levels of patients who participated in VBH are virtually identical to HbA1c levels for patients in the control group. Our propensity score matching ensures that characteristics of VBH patients and control group patients are comparable. There is no *a priori* evidence to suggest a difference between VBH and non-VBH patients.

Were VBH Patients Diagnosed with New Chronic Disease(s) *After* Propensity Score Matching?

To rule out the possibility that VBH patients were diagnosed with an additional chronic disease *after* propensity score matching, we examined data derived from medical claims to determine whether there were differences in the proportion of patients with a newly diagnosed chronic disease during the follow-up period. We find no significant difference between VBH patients and non-VBH patients. Table 10 shows the proportion of individuals in each cohort for which a claim was submitted during the follow-up period that is not associated with the condition(s) met for study inclusion. New diagnoses for five conditions are virtually identical between the VBH cohort and control group in each of the three follow-up years, adding further support to the notion that there is no inherent difference between patients in the VBH cohort and the control group.

Table 10. Proportion of Patients Receiving New Diagnosis During Follow-Up Period

	Year 1		Year 2		Year 3	
	VBH	Control	VBH	Control	VBH	Control
Coronary heart disease	1.1%	1.0%	1.2%	1.0%	1.2%	1.0%
Hypertension	1.3%	1.1%	1.2%	1.0%	1.2%	1.1%
Congestive heart failure	0.3%	0.0%	0.5%	0.3%	0.2%	0.3%
Diabetes	1.2%	1.1%	1.4%	1.1%	1.4%	1.1%
Hyperlipidemia	1.5%	1.1%	1.6%	1.0%	1.5%	1.0%

Table 11. Comparison of Cost and Health Indicators for Small and Large VBH Practices

Outcome	VBH Cohort	Year 1		Year 2		Year 3	
		VBH (Small)	VBH (Large)	VBH (Small)	VBH (Large)	VBH (Small)	VBH (Large)
Avoidable emergency department expenditure (*per member per month*)	PCMH	$67	$70	$58	$61	$59	$54
	DQS	$57	$54	$52	$50	$57	$54
	VHIE	$53	$50	$48	$51	$54	$50
Inpatient healthcare expenditure (*per member per month*)	PCMH	$198	$201	$189	$184	$175	$178
	DQS	$200	$195	$173	$180	$173	$169
	VHIE	$190	$194	$165	$168	$160	$163
Total healthcare expenditure (*per member per month*)	PCMH	$710	$714	$687	$732	$667	$742
	DQS	$713	$711	$644	$741	$651	$740
	VHIE	$688	$715	$628	$730	$636	$746
Health status (*HbA1c level*)	PCMH	7.14%	7.30%	7.00%	7.28%	6.63%	7.25%
	DQS	7.12%	7.30%	6.80%	7.26%	6.40%	7.22%
	VHIE	6.89%	7.33%	6.66%	7.30%	6.20%	7.24%

Does IT and Analytics Use Vary Among VBH Practices?

It is possible that the size of a VBH practice was a factor in the deployment of IT and analytics, because larger practices may have superior resources and could be in a better position to implement and integrate IT and analytics into practice operations. To determine practice size, we identified all patients receiving care from a VBH practice. To ensure a sufficient number of observations in each comparison group, we partitioned the practices into two groups. Smaller practices represented the bottom 50% of VBH practices in number of distinct patients seen each year (mean 1,011, standard deviation 603), and larger practices represented the top 50% of VBH practices in number of distinct patients seen each year (mean 2,581, standard deviation 1,242). We conducted this analysis among VBH practices only, because non-VBH subjects are not attributed to a specific practice in our data set. Table 11 compares cost and outcome measures for small and large VBH practices at each level of IT utilization, and shows that the cost and outcome measures are similar for small and large VBH practices.

Discussion

Previous research has proposed several approaches to contain healthcare costs and improve health outcomes. These approaches involve evidence-based medicine (EBM) that emerges from "integrating individual clinical expertise with the best available external clinical evidence from systematic research" (Sackett 1997, p. 3). EBM guidelines emerge from clinician experience combined with external sources, such as a population of patients treated by a group of practitioners in a hospital, or a large population of patients treated by providers in an integrated health system such as the U.S. Veterans Administration. Our TDC approach seeks evidence of process changes by exploring the mechanisms through which IT and analytics result in higher quality healthcare at lower cost.

By utilizing IT and analytics, clinicians can ascertain how to displace care across stages of the chronic care lifecycle. In the early stage, clinicians utilize IT infrastructure to codify and gather utilization, cost outcomes, and health outcomes data to identify promising opportunities to increase quality

and reduce cost. In the later stage, clinicians deploy analytics to understand how interventions over time influence patient status, so clinicians can advance the timing of treatments from more intensive and costly treatments (such as inpatient admissions and emergency room visits) to less intensive and less costly treatments (such as eye exams, lab tests, and prescription refills). Displacing the timing of some treatments leads to increased healthcare quality, because earlier treatments help to prevent patients from developing more severe conditions. Understanding the effectiveness of treatments through analytics also enables clinicians to delay or exclude invasive and expensive treatments that would be more effective at later stages. This creates organizational learning that clinicians can retrieve for analytics of future displacement opportunities. It is likely that accumulated evidence from process changes proposed by TDC will become a part of future EBM practices and be used in predictive analytics to identify at-risk patients.

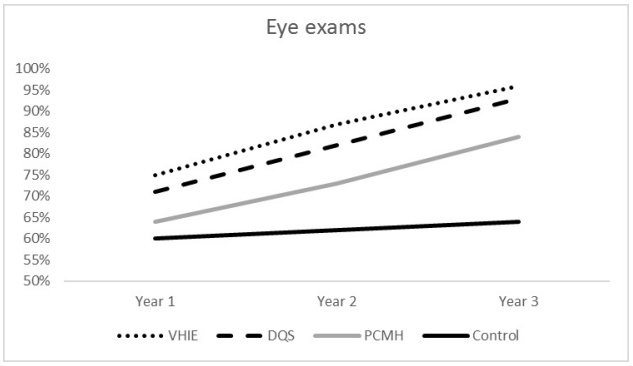
Our time-based analysis using an index date and three follow-up years provides deeper insight into the way TDC impacts develop over time. As illustrated in Figure 4 (based on empirical results in Table 7), improved disease management is associated with an immediate and sustained increase in the utilization of low-intensity health interventions such as eye exams and neuropathy screenings. By Year 1, the percent of members in the DQS and VHIE cohorts having annual eye exams and neuropathy screenings increased by between 10% and 15% above their respective control groups at a statistically significant level. This improvement continued in Year 2 and increased further in Year 3. By Year 3, between 93% and 94% of the DQS cohort and 95% and 96% of the VHIE cohort was getting regular eye exams and neuropathy screenings. The shift in utilization is important because it indicates more aggressive and consistent medical management. A larger number of office visits provides more opportunities for comprehensive physical assessment and patient education, and a larger number of prescription fills indicates more aggressive pharmacological management and/or better patient compliance. Higher rates of eye exams and neuropathy screenings enable clinicians to more reliably detect evidence of disease progression that may require changes to the plan of care.

The low-intervention treatments described above displace high-intervention treatments such as emergency department utilization as shown in Figure 5 (based on empirical results in Table 8). In Year 1, the DQS and VHIE cohorts already achieve a statistically significant reduction in emergency department utilization compared with their respective control groups. This reduction is maintained in Year 2, and by Year 3 the percent of DQS and VHIE cohort members that utilized the emergency room declined by 6% for both cohorts compared with Year 1. More comprehensive and timely medical management by displacing activities, enabled by IT and analytics, results in a greater number of low-intervention treatments in Year 1 that reduce or eliminate high-intervention treatments.

As the utilization of low-intervention treatments increases and the utilization of high-intervention treatments decreases for the VHIE and DQS cohorts, we begin to see an impact to overall healthcare costs. As shown in Figure 6 (based on empirical results in Table 9), the difference in total healthcare cost does take until Year 2 to materialize, suggesting a lag between the change in treatments and the impact to healthcare costs. This lag in improved healthcare costs suggests the need for patience to realize financial benefits from healthcare investments in IT and analytics. In Year 2, the cost per member per month is $97 lower for the DQS cohort compared to its control group, and $102 lower for the VHIE cohort compared to its control group. The improvement for the VHIE cohort continues from Year 2 to Year 3, by which time the cost per member per month is $110 lower than its control group.

Just as there is a lag between the increase (decrease) in utilization for low (high) intervention treatments and financial benefits, there is a longer lag between the increase (decrease) in utilization for low (high) intervention treatments and healthcare indicators such as HbA1c levels. Figure 7 shows the actual HbA1c level for each cohort, based on the percentage differences in cohorts shown in Table 9. By Year 2, only the VHIE cohort has a statistically significant difference compared with the control group. In Year 3, the positive difference for the VHIE cohort increases further, while the DQS cohort establishes a statistically-significant difference. This longer lag for health indicators, together with the lag in healthcare cost savings described above, shows that policy makers and healthcare institutions need to show some degree of patience for healthcare savings and healthcare indicators to improve after changing treatment plans based on investments in IT and analytics.

The sequence illustrated in Figures 4–7 above, in which utilization of preventative services increases first, followed by cost savings, followed by quality improvement, is consistent with the theoretical underpinnings of TDC that IT and analytics also play crucial roles to mitigate risk (Knight 1971) and increase coordination (Christensen et al. 2009) articulated in this paper, with additional implications discussed in the next section.



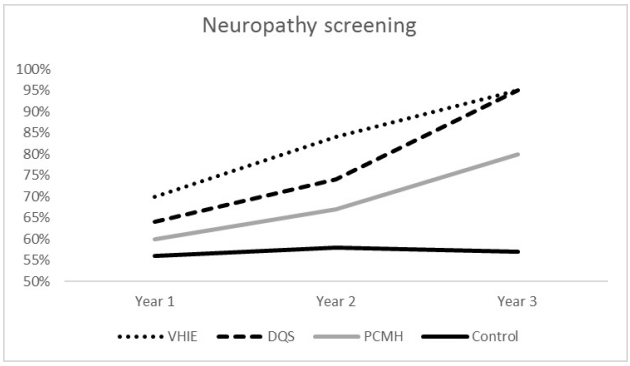


Figure 4. Frequency of Eye Exams and Neuropathy Screening by Cohort

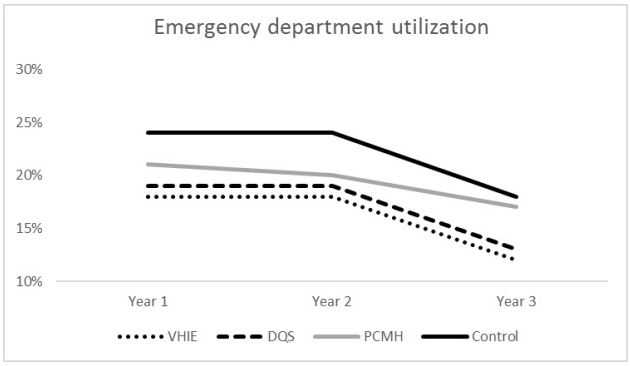


Figure 5. Frequency of Emergency Department Utilization by Cohort

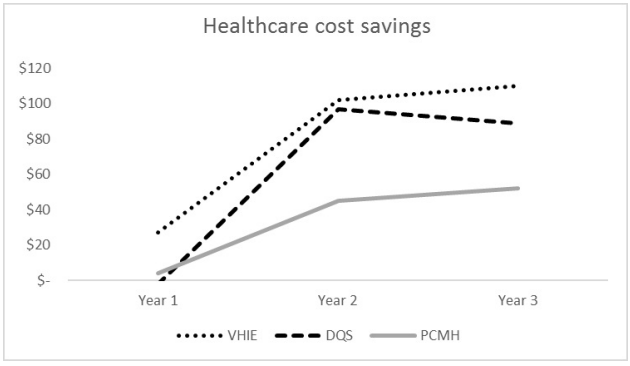


Figure 6. Total Healthcare Cost Savings by Cohort

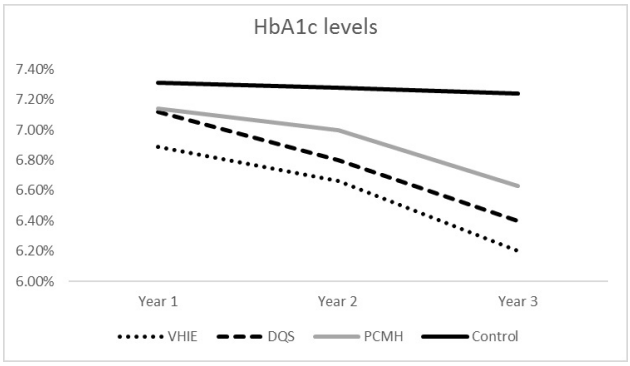


Figure 7. HbA1c Levels by Cohort

Contributions

The contribution of our research emerges from the integration of IT and analytics with the operations management literature on TQM and delayed differentiation which established the notion that business value can be created by strategic actions and *by the timing of those actions*. Prior healthcare research has established that preventative care is lower cost than curative care due to preventable hospital admissions (Kolstad and Kowalski 2012; Yach and Calitz 2014), and that patients are likely to have improved healthcare indicators if IT is used to contain the advance of acuity by enabling preventive care activities (Shih et al. 2011). Our temporal analysis involving a base year and three years of follow-up data provides insights into the way TDC impacts develop over time. It begins with a displacement of more intensive interventions in favor of less intensive treatments, which results in lower costs. As the program gains momentum, clinicians collaborate with patients to adapt their behaviors to better manage their chronic disease.

Our findings contribute to IS research by articulating the theoretical mechanisms through which the use (not just implementation) of IT and analytics leads to impacts on healthcare treatments, costs, and outcomes over time. IT infrastructure is germane to identify the nature and timing of treatments that must be displaced in the continuum of chronic disease care. We provide evidence that IT and analytics create healthcare value by identifying for clinicians which low-intervention healthcare treatments to move earlier in the process, and which high-intervention treatments to displace later in the process. The increased use of low-intervention healthcare treatments earlier in the process leads to a decrease in overall healthcare costs, which then leads to an improvement in healthcare indicators.

Implications for IS and Healthcare Research

The findings reported in this paper have significant implications for research at the intersection of IS and healthcare. We demonstrate how IT and analytics can be used to increase the volume and velocity of information available for providers to manage chronic diseases. Our theory and findings show that the impacts of IT and analytics go beyond the patient-level impacts of EMRs and extend to the management of population-level chronic care. We find it interesting that a large proportion of healthcare research is focused on new treatments, when proven existing treatments could be implemented at a much lower cost on a much larger scale through initiatives such as VBH supported by IT and analytics. Our empirical analysis suggests that massive improvements in health outcomes and reductions in healthcare costs are possible through such coordinated efforts.

Just as the treatments that will reduce the progression of chronic disease are generally known, the types of IT that can support large-scale implementation of initiatives such as VBH are also known. The importance of data quality and the prevalence of Internet technology required for healthcare exchanges have been in place for over two decades. While research into new forms of IT may not be essential to address population-level chronic disease care, what will be needed is a systematic view that integrates our findings with research into the incentives that will encourage governments and healthcare providers to implement and use the appropriate IT and analytics. What is new in this domain is the increasing availability of analytics tools and skills, and research will be needed to help organizations embed these tools into their business processes, and education will be needed to help professionals develop the relevant skills.

Our TDC approach presents a road map for researchers to identify improvement opportunities by analyzing clinical operations data to examine how variations in the type and timing of interventions lead to improvement in patient health conditions. Our findings from patients with cardio-metabolic disease can be applied to treatment of patients with other progressive chronic diseases such as primary heart disease, chronic obstructive pulmonary disease (COPD), and cancer. For example, a study of COPD can adapt our TDC framework to measure the effect of the three tiers of IT and data analytics described in Table 3. Utilization measures could include ED utilization and hospital admission rates as well as condition-specific measures of lung transplant rates and volume reduction surgery. Cost measures could also be similar to ours, such as total cost of care and condition-specific costs including cost of supplemental oxygen and continuous positive air pressure (CPAP) machines. Disease state progression could be measured through condition-specific assessments such as pulmonary function tests that measure airflow, lung volume, and lung capacity. Since effective management of many chronic diseases depends on timely diagnosis, proactive intervention, and coordination of care among different healthcare providers, our TDC approach can guide design of public health efforts for other chronic conditions such as treatment of Human Immunodeficiency Virus (HIV), chronic kidney disease, Alzheimer's and dementia, and depression. Because patients and clinicians must collaborate to generate improvements in cost and quality, and such improvements are difficult to achieve by either party alone, our findings also have implications for the co-creation of IT value (Grover and Kohli 2012).

Beyond chronic disease management, insights from TDC can extend to any setting in which conditions are progressive and return to normalcy is the exception. In such cases, preemptive actions can have a decisive impact on outcomes. For example, TDC principles of data gathering, analysis, and displacement of activities can be applied to care of complex equipment such as aircraft engines, autonomous vehicles, and electrical power grids where preventive maintenance can protect the systems while also reducing costs of catastrophic failures. Indeed, General Electric has been gathering real-time data from aircraft engines to model normal operation, and analyzing data for potential failures (Wilson 2003). With analytics, TDC principles can establish best practices for displacement of preventive maintenance activities to prolong the life of aircraft engines.

Implications for Practice

Our analysis of data from a baseline year and three follow-up years suggests that for practitioners to deliver high quality outcomes and lower costs, government agencies and healthcare systems should carefully define the metrics up front. Because providers are likely to change their actions faster than patients change their behaviors, operational costs are likely to decrease before there is a noticeable improvement in patient health outcome indicators. Although some healthcare providers may observe steady improvement, other entities might see sporadic improvement or even a decline in the early years before benefits emerge (Menon et al. 2009). Providers and patients must recognize that the financial investments required to initiate such large-scale programs can take several years to demonstrate returns (McCullough, Casey, Moscovice and Prasad 2010). Therefore, state governments, providers, and citizens should not give up on TDC initiatives if improvement in population health status takes time, even as they take actions to minimize that timeframe. Alongside financial investments, providers must be willing to make process changes and share best practices.

Further, the integration of IT infrastructure and development of analytic capabilities involve significant and sustained commitment. To achieve improvements in healthcare quality and cost outcomes, practitioners must commit resources to build and facilitate IT and analytics infrastructure. Building the IT infrastructure involves gaining consent of data owners, establishing protocols to accurately identify patients, interventions, costs, and outcomes, and then capturing and storing data in a secure environment. Providers and patients must be willing to share health data and must have the ability to choose how much data and with whom they would like to share. Protocols to identify patients requires investments in a master patient index through which longitudinal intervention and cost data from various providers are accurately combined and linked to each patient. Organizations pursuing these efforts must acquire technical competencies such as data extraction, cleansing, transformation, and loading (ECTL) to create and manage a large data warehouse. Finally, security mechanisms must be in place for access control, user authentication, and intruder detection. A stable IT infrastructure will enable practitioners to build effective analytical capability that incorporates reporting services, with "push" and "pull" data capabilities such as pushing an alert when a patient has missed a prescription and pulling updates when a patient gets immunizations or receives a therapeutic treatment at home.

While our main analysis demonstrates the creation of healthcare value over time, researchers can examine how this healthcare value is apportioned by various stakeholders (Menon and Kohli 2013). For example, when healthcare costs are reduced, do the savings improve the profitability of primary care practices that participate in initiatives such as

VBH? Do private insurers reduce the amount of reimbursements? How are the cost savings apportioned to state and federal government insurance programs? Understanding the way healthcare value is captured by various stakeholders would give a clear picture of the incentives for various stakeholders to participate in wellness programs. To the extent that appropriate incentives are lacking, researchers could identify the types of subsidies that would be necessary to make the markets for healthcare more efficient (Parker and Van Alstyne 2005). Our findings also present an opportunity for researchers to identify the pathways and mechanisms through which later adopters interact with early adopters to exchange knowledge.

Limitations and Future Research

Our data are subject to at least three limitations. First, while our unique data set includes the entire population of the U.S. state of Vermont, it is important to note that there are some aggregations in the data. For example, annual cost data for each patient is aggregated by cost category, not by individual event. While we analyze annual data for each cost category (avoidable ED expenditures, inpatient healthcare expenditures, total healthcare expenditures), we are unable to discern the specific composition of costs within each category (for example, which procedures were performed during an inpatient office visit). Our data do not include item-level pharmacy charges, comprehensive laboratory panel results, or specific information on all possible treatments and interventions. Our data do not include the sequencing of procedures, and it is possible that the sequencing of procedures among some patients may vary and have an unobserved influence on our results. Hence, while we can evaluate the results, we cannot offer patient-level clinical guidance on provider interventions that achieved the outcomes. Our data also do not include changes to health insurance benefits or co-payments that have been shown to influence patient utilization of low-intervention treatments (Chandra et al. 2010; Starc and Town 2018).

As a second limitation, although our discussions with healthcare executives provide insights on how stakeholders share best practices, our data does not record the specific communications and networking across primary care practices, public health providers, and the VBH organization. A record of the extent of networking across stakeholders could generate greater insights about the way benefits spread across practices over time. Future researchers may find these topics to be fruitful areas of study. Researchers may also explore how learning effects vary among early and late adopters of TDC practices and how best practices are shared and adopted. The participation of patients and how information helps them engage more actively in their plan of care is also a fruitful area of research that will shed light on the boundaries of provider-led initiatives.

A third potential limitation is that while our data set includes exceptional detail on the types of financial benefits that healthcare providers can achieve through the application of IT and analytics, our data does not include the upfront financial investments by the state of Vermont or by healthcare providers to become certified as a PCMH, to pass the DQS, or to be approved for the VHIE. Although our research offers important insights on healthcare IT value, further research is needed to learn more about the IT investments required to generate this value.

Given that VBH represents a network of clinicians, we would be interested to know if the time-based improvement within a clinical practice shown in our main results can extend to other practices. Are there differences in learning in the effects of temporal displacement of care between early adopters and late adopters of TDC? This presents an opportunity for researchers to study the timing of up front investments in IT and analytics, and develop insights on the matching between investments and returns.

Conclusion

We have introduced the notion of temporal displacement of care (TDC), in which IT and analytics create healthcare value by displacing the time at which providers and patients make interventions to improve chronic disease healthcare outcomes and reduce costs. Our empirical analysis involving a base year and three years of follow-up provides insights into the way such impacts develop over time by displacing later high-intervention procedures in favor of earlier low-intervention procedures. The displacement of procedures translates into lower healthcare expenses, including costs for emergency care and inpatient admissions. Only after the IT infrastructure and analytics inform displacement of procedures do cost differentials widen and chronic disease health status measures improve. Our theory and results are important for governments, healthcare systems, clinicians, and patients because they present a roadmap to use IT and analytics to improve patient health while optimizing healthcare expenditures. Chronic diseases are progressive. We can slow or halt the progression, but we cannot reverse their course. Our findings are critical for patients and healthcare providers because chronic diseases do not give second chances.

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