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Assessing the relationship between pharmacy quality and healthcare cost for a commercially insured population

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ASSESSING THE RELATIONSHIP BETWEEN PHARMACY QUALITY AND HEALTHCARE COST FOR A COMMERCIALLY INSURED POPULATION

by

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PH.D. THESIS

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To Katie

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SCIENTIFIC ABSTRACT

Background: In response to high cost and inadequate quality, the healthcare system is in the midst of a transition from paying for volume to paying for value. Billions of dollars could be saved through more effective medication use, and evidence supports the role of the community pharmacist in lowering healthcare cost and improving healthcare quality through medication optimization. Despite this, value-based payment models for community pharmacies are rare, and those that do exist have not been critically evaluated and implementation in a commercially insured population is rare.

Objective: The first objective was to design and test a conceptual model of pharmacy value. The second objective was to evaluate variation in the value community pharmacies provide a commercial insurer by assessing the relationship between attributed patients' healthcare quality and cost.

Methods: This study used prescription and medical claims data for 2012 and 2013 from a large commercial insurer in Iowa and South Dakota. Patients were attributed to the pharmacy filling the majority of their prescriptions. Pharmacies' weekly prescription volume and Sunday prescription filling behavior were used as structural measures of healthcare quality. Percent of days covered (PDC) metrics for beta-blockers, statins, renin-angiotensin system antagonists and non-insulin diabetes agents were used as process metrics. Pharmacies were excluded if the denominator for any PDC metric was less than 15. Outcome metrics consisted of a non-trauma, non-cancer, unplanned hospitalization rate and a non-trauma ED visit rate. Cost impact was categorized into pharmaceutical, medical, and total cost of care. High quality pharmacies with typical or low associated costs or low cost pharmacies with typical to high quality were identified as high value and vice versa for low value. All metrics were risk-adjusted using mixed effect models with a random pharmacy intercept. The ratio between observed and expected quality scores was used for

quality scoring. Quality outliers were identified by comparing the 95% CI around pharmacies' risk-adjusted scores to the all-pharmacy risk-adjusted score mean. A t-test was used to assess variation in pharmacy value.

Results: There were 171 pharmacies and 74,581 patients eligible for scoring on all quality metrics. Mixed effects models observed a small but significant impact of pharmacy on process and outcome healthcare quality. No relationship between structures and processes, processes and outcomes was detected. Ten pharmacies were scored as high quality and nine as low quality. Similar numbers were identified for cost outliers, and significant variation in value was detected.

Implications/conclusions: Results support the hypothesis that high and low value pharmacies exist. A well-designed value-based payment model could be used to create incentives for pharmacists to enhance care for commercially insured patients, but validation is needed to ensure that incentives are aligned appropriately.

PUBLIC ABSTRACT

Every consumer wants to get their money's worth out of the things they buy. Unfortunately, in healthcare, it's too often true that patients, insurers and the government are spending too much and getting too little in return. In short, the US healthcare system lacks value.

One opportunity for improving healthcare quality and reducing the cost of healthcare is optimizing how medications are used. Hundreds of billions of dollars can be saved every year by using medications better and more optimal use of medications can keep patients healthier longer.

Pharmacy, the profession most closely aligned with medication use, has been shifting the focus of pharmacists' work away from dispensing medications towards improving patients' health through closer oversight of medication use. Evidence suggests that there are community pharmacists who, through the course of their normal work, are making a difference in their patients' health.

This study sought to identify pharmacies where pharmacists are adding value to the healthcare system by improving their patients' health as well as pharmacies where pharmacists could be doing a better job. Using advanced statistical methods and insurance billing information, the results found that high value and low value pharmacies exist. This variation in pharmacy value could be used to create new payment models that reward pharmacists for a job well done, but more work is needed to ensure that systems to assess value are accurate.

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CHAPTER I
INTRODUCTION

1.a Cost and Quality in the US Healthcare System

US healthcare costs far exceed that of any other nation, nearly $3 trillion in 2014 alone (Centers for Medicare and Medicaid Services, 2015q). Only the UK, Germany, Japan and China have GDPs greater than the cost of US healthcare (Centers for Medicare and Medicaid Services, 2015q; The World Bank, 2015). The 17.5% of the US GDP consumed by healthcare is far more than any other industrialized nation, and the $9,523 in per-capita spending is more than twice the average American's annual spending on food (OECD, 2013; United States Department of Agriculture Economic Research Service, 2014).

Healthcare expenditures in the US are large, and rising faster than other segments of the economy. Expenditures are expected to rise 1.3% faster than GDP between 2015 and 2025, resulting in more than 20% of the economy devoted to healthcare spending by the end of 2025 (Keehan et al., 2016). Currently, $297.7 billion, or 9.9% of national health expenditures, is spent on outpatient prescription drugs (Centers for Medicare and Medicaid Services, 2015q). Prescription drugs are expected to be one of the fastest growing national healthcare expenditure categories through 2025 (Keehan et al., 2016).

US healthcare costs are enormous and growing larger. Might this level of cost be justified, though, if those paying for healthcare and health insurance received the best quality care? One does not typically complain about the cost of a luxury car. The quality is worth the price; a luxury car is a good value. One certainly would complain, however, about spending enough money to buy a luxury car and getting a lemon instead. Therefore, to fully understand if the cost of the US healthcare system is too high, the relationship between quality and cost must be considered.

1.a.1 Lower than Expected Healthcare Quality

Quality divided by cost is one way of conceptualizing value (Porter, 2010a). Despite incredibly large healthcare costs, if US citizens were receiving the best healthcare in the world, one could argue that there would be no need for the system to address costs because of the high quality received for dollars spent. Unfortunately, this is not the case.

The US ranked 37th in health system performance in the 2000 World Health Organization global rankings (World Health Organization, 2000). Reports from the Commonwealth Fund from 2004 comparing the US to its industrialized peers find that the US consistently ranks last on aggregate measures of healthcare quality (Davis, Stremikis, Squires, & Schoen, 2014). Comparisons from the Organization for Economic Cooperation Development (OECD) find that on basic measures of health, such as life expectancy at birth and hospitalizations from diabetes, asthma and COPD, the US ranks below most other OECD nations (OECD, 2013). Concurring with these reports, the National Research Council and Institute of Medicine report from 2013 comparing the US to 16 other industrialized, Western nations finds that in nearly every category of quality and performance assessed the US falls short. The US does tends to rank better on experience of care measures (availability of healthcare resources, short wait times, etc.) but the only category where the US consistently ranks first is healthcare expenditures per capita and as a share of GDP.

1.a.2 Efforts to Create More Value in the Healthcare System

Clearly, the healthcare system provides lemon quality at a luxury price. The diversity of metrics on which the US falls short suggests that no single strategy can correct the imbalance

between healthcare quality and cost and thereby increase value. In response to this problem, the Centers for Medicare and Medicaid Services (CMS) has created several initiatives to increase value and expects by 2017 to have 90% of Medicare payments tied to value (Burwell, 2015). The Patient Protections and Affordable Care Act contained several provisions aimed at improving value in the healthcare system and the CMS Innovation Center has been testing new models of care delivery for Medicare beneficiaries (Centers for Medicare and Medicaid Services, 2015g).

CMS's efforts to improve value are numerous. Accountable care organizations (ACOs), designed to improve quality while decreasing costs through better care coordination, have reported modest savings in the first round of public and private experiments (Centers for Medicare and Medicaid Services, 2015o; Des Moines Register, 2015; Iowa Department of Human Services, 2015). The Star Rating system for Medicare Part C and D plans displays quality scores on the Medicare Plan Finder website and provides payment bonuses to Part C plans with exceptional quality (Centers for Medicare and Medicaid Services, 2015f, 2015l, 2015n). The CMS value-based payment modifier for 2016 creates opportunities for high quality and low cost groups of 10 or more physicians to earn bonuses on the Medicare Physician Fee schedule (Centers for Medicare and Medicaid Services, 2015i). Commercial insurers are also experimenting with provider-oriented efforts to improve healthcare quality and reduce costs (Blue Cross and Blue Shield Association, 2014; Blue Cross and Blue Shield of Michigan, 2015c), although limited information is publically available. All of these programs demonstrate the serious commitment by the federal government and insurers to use novel payment models to address the lemon-luxury problem.

1.a.3 Creating Additional Value by Optimizing Use of Medications

Despite these efforts, unnecessary, avoidable costs and insufficient quality remain a frustration for patients, healthcare practitioners, health insurers and government officials. Substantial research has shown that optimizing the use of medications can reduce overall healthcare expenditures and increase healthcare quality. The IMS Institute for Healthcare Informatics estimates that savings from optimizing medication use could have totaled $213 billion in 2012, with nearly half ($105.3 billion) of these savings coming from improved adherence alone (IMS Institute, 2013). Roebuck and colleagues found that adherent patients spent significantly less on healthcare than their non-adherent peers (Roebuck, Liberman, Gemmill-Toyama, & Brennan, 2011). Annual estimated savings from medication adherence for congestive heart failure, hypertension, diabetes, and dyslipidemia patients total $8,881, $4,337, $4,413 and $1,860 respectively. Adverse drug events, defined by the Agency for Healthcare Research and Quality (AHRQ) as "an injury caused by medical care related to a drug" (AHRQ), create an estimated 3.5 million physician office visits and 1 million emergency department visits each year and are most common in the elderly (Harris et al., 2015).

Despite these opportunities, few of the value-oriented strategies currently pursued by CMS and major commercial insurers involve those professionals most aligned with overseeing medication use—community pharmacists. CMS Healthcare Innovation Center awards have been given out to three ongoing projects which include community pharmacists (Centers for Medicare and Medicaid Innovations, 2013, 2014). Awarding grants for these demonstration projects suggests CMS is interested in investigating the role of the community pharmacist in reducing healthcare costs while improving quality, and results from these projects are not yet available. Managed care organizations are also beginning to experiment with creating incentives to enhance pharmacy value (Deninger, 2015; Hosford, 2015; Inland Empire Health Plan, 2014; Trygstad, 2015). These community pharmacy-focused efforts are mostly pilot projects with limited scope.

1.a.4 Pharmacists Can Optimize Medication Use and Increase Healthcare Value

Pharmacy's history over the last 60 years suggests pharmacists are ready to take on larger roles in the healthcare system. Pharmacists in the 1950s began to rebel against the expanded merchandising in pharmacies and created a new philosophy of practice focused on ensuring that patients received the most appropriate medications (White, 1965). This philosophy expanded through the 1970s and in the 1980s and resulted in the first community pharmacy residencies (American Pharmaceutical Association, 1986; Sasich, 1983; Wenzloff, 1987). At the 1989 "Pharmacy in the 21st Century Conference" this philosophy was termed "pharmaceutical care" and it was declared to be the dominant philosophy of practice for all pharmacists (Hepler & Strand, 1989). The evolving clinical orientation to community pharmacy practice and the universal PharmD requirement of 2000 means that all recent pharmacy graduates were taught that pharmacists are clinically oriented healthcare professionals responsible for their patients' health. This suggests that there are community pharmacists ready and able to provide patient care services that can optimize medication use and therefore increase value in the healthcare system.

As part of practicing pharmaceutical care, community pharmacists have been conducting formal, structured medication reviews in pharmacies since the mid-1990s. Codified in the 2003 Medicare Prescription Drug, Improvement and Modernization Act as medication therapy management (MTM), these reviews are mandated to be available to all eligible enrollees in Medicare Part D (Centers for Medicare and Medicaid Services, 2015a). Studies on the impact of MTM have so far been highly varied in design, setting and outcomes (Viswanathan et al., 2015) but the program has been shown to improve outcomes and reduce costs (Perlroth et al., 2013).

Medication therapy management in the community setting requires significant time for pharmacists to sit down with patients, review all of their medications and associated conditions,

create a list of medications for the patient and send recommendations for medication changes to the patient's prescribing healthcare provider (American Pharmacists Association & National Association of Chain Drug Stores Foundation, 2008). An alternative design, stratifying patients by risk of nonadherence and providing brief, 2-5 minute adherence related consultations found that community pharmacists working in chain settings could improve adherence and reduce healthcare expenditures for patients taking oral diabetes medications and/or statins (Pringle, Boyer, Conklin, McCullough, & Aldridge, 2014). Another study suggesting community pharmacists can impact measures of healthcare quality took place within CVS pharmacies serving employees of a Midwest manufacturing facility (Brennan et al., 2012). The aims of this cohort study were to increase adherence to oral diabetes medications and initiate new statin or ACE-I/ARB prescriptions for patients with diabetes. Study researchers found that community pharmacists succeeded in achieving both aims and were more effective than their mail order peers.

The clinically oriented philosophy of practice that has developed over the last 60 years and evidence from the MTM program and other shorter, targeted interventions in large chain pharmacies suggests that, when given the opportunity, community pharmacists can impact process measures of healthcare quality and create savings. Unfortunately, the current structure of community pharmacy practice makes even brief interventions difficult to implement. Results from the National Pharmacist Workforce Survey reveal that workload for more than three-quarters of pharmacists working in mass merchandiser and chain settings has increased vs. a year prior and is rated by pharmacists as high or excessively high (Doucette WR, 2014). These percentages are greater than those reported in previous workforce surveys (Doucette WR, 2014). Also, investigations by the California Board of Pharmacy have found that pharmacists employed by Rite Aid, CVS and Walgreens have all failed to uphold their duties to counsel patients on new or changed prescriptions (San Diego County Office of the District Attorney, 2015). Comments

from CEOs of pharmacy benefits managers considering prescriptions a commodity and downplaying the impact of community pharmacies on patient care suggest a potentially common line of thinking among payers (National Community Pharmacists Association, 2011, 2012b). Pharmacy chains that do try to innovate are criticized for taking pharmacists out of typical dispensing roles (Change to Win, 2013). Despite these constraints and criticisms, there is no doubt that some pharmacists operate innovative pharmacies and provide exceptional patient care regardless of their environment. To expand the number of innovative pharmacies, incentives are needed for pharmacists to change their practice and focus on value.

1.a.5 Value Based Payment Models for Pharmacy: An Underexplored Opportunity to Improve Healthcare System Value

To create the most value possible from medications, the healthcare system should engage those most closely aligned with medication use: community pharmacies and community pharmacists. Federal efforts to improve pharmacy quality through Medicare and Medicaid are hindered by the programs' designs. When creating incentive programs for outpatient healthcare providers under Part B, Medicare can directly modify payments through the physician fee schedule (Centers for Medicare and Medicaid Services, 2015i). Medicare is more limited in its policy options for incentivizing quality through Medicare Parts C and D as these programs are operated by private insurers receiving funds from Medicare.

The Medicare Star Rating system creates incentives for Part C and D plans to maximize the quality of their provider network, and some Part C and D plan sponsors have begun to measure pharmacy quality (Express Scripts, 2015). These efforts are too limited and nascent to impact current practice, however. One independent community pharmacy owner, for example,

calculated that if he received value bonuses from a certain Part D plan sponsor for all eligible patients, the bonus would only come to a maximum of $20 per patient-year (Deninger, 2015).

Medicaid has experimented with pharmacy-based case management programs (American Society of Health-System Pharmacists, 2008), but these programs are limited in scope. Also, dual eligible patients, the patients responsible for the highest share of healthcare expenditures within Medicaid, are ineligible because of the Medicare MTM benefit. Inland Empire Health Plan (IEHP), a private Medicaid plan operated in California, has since 2013 been working on a value-based payment model (VBPM) for pharmacies (Inland Empire Health Plan, 2014, 2015b). This model rewards pharmacies for achieving quality benchmarks for process measures of care including adherence, medication appropriateness and generic drug use. It is not reported how this program influences payments received by pharmacies, but analysis by IEHP does indicate that there is substantial variation in pharmacies' ability to meet quality targets (Inland Empire Health Plan, 2015a). The North Carolina State Medicaid program provides payment bonuses for pharmacies meeting generic dispensing targets (Centers for Medicare and Medicaid Services, 2015m), and Community Care of North Carolina, a non-profit Medicaid managed care organization, incorporates pharmacies in their medical home model using a novel VBPM (Trygstad, 2015). The expanding privatization of Medicaid prescription drug benefits may allow the creation of novel programs designed to leverage community pharmacies' impact on healthcare quality to reduce cost of care (Menges, Batt, Mouna, Pantaleo, & Singh, 2015), but privatization also makes payment mechanisms for pharmacies more difficult to discern by outside entities. It is clear that value-based payment models for pharmacies are being created; it is less clear how they are being designed and implemented.

To guide in the creation of quality metrics for private and public insurers, the Pharmacy Quality Alliance (PQA), a multi-stakeholder organization established in 2006 for the purpose of creating medication related quality metrics, has created and endorsed 17 medication related

quality metrics (Pharmacy Quality Alliance, 2015). Of these metrics, four are included in the measurement of medication related quality within Medicare Parts C and D (Centers for Medicare and Medicaid Services, 2015n). Pharmacy Quality Solutions (PQS), a PQA spin-off, operates a platform called the "Electronic Quality Improvement Platform for Plans and Pharmacies" (EQuIPP) which allows pharmacies and plans to observe measurements of medication related quality (EQuIPP, 2016). EQuIPP has experienced incredible growth since its inception in 2013 and now evaluates quality for nearly 90% of all community pharmacies (EQuIPP, 2015b, 2016). Third party payers are beginning to use PQA metrics included in the EQuIPP platform to evaluate pharmacy quality and there is strong potential for EQuIPP's use in future VBPMs (Inland Empire Health Plan, 2014).

A fundamental and unanswered question is whether the metrics commonly used to evaluate community pharmacy practices are sufficient to create a system of measurement that can encourage pharmacists to modify pharmacy practice in a way that improves quality and decreases costs, thereby adding value to the healthcare system. If one pharmacy's adherence scores are higher than another pharmacy's, is this because of actions by the pharmacists at that pharmacy, or are there other patient factors that are confounding the measurement? PQA provides no guidance on risk adjustment (Pharmacy Quality Alliance, 2015). Dharmarajan and colleagues found case-mix adjustment significantly improves identification of high and low value pharmacies (Dharmarajan, Bentley, Banahan III, & West-Strum, 2014). PQS's own work has suggested a need for risk adjustment of quality metrics (Desai, Nau, Conklin, & Heaton, 2016). Without some form of adjustment, it could be that pharmacies identified as high quality are simply lucky. IEHP also does not appear to risk adjust their pharmacy benchmarks (Inland Empire Health Plan, 2014). IEHP makes an implicit assumption that pharmacies with more adherent patients deserve to be paid more because of some actions by pharmacists which result in improved adherence (Inland

Empire Health Plan, 2015b). Unfortunately, there is little empiric evidence to support this assumption.

If a system can be developed to use administrative claims data to measure the impact of pharmacies on healthcare cost in a way that more accurately identifies high performing pharmacies, these pharmacies could be rewarded for their impact on healthcare value. Better identification lays the foundation for financial rewards to high value pharmacies and encourages other pharmacies to pursue changes to practice that will increase value. Only by assuring that financial rewards are provided to high value pharmacies can a VBPM be effective in increasing value for health insurers.

1.b Dissertation Aims

Other studies have attempted to create high value pharmacies by instituting practice changes intended to increase healthcare quality and simultaneously decrease costs (Brennan et al., 2012; Pringle et al., 2014). Rather than trying to implement a pilot program to change practice and create high value pharmacies, this project assumes that high value pharmacies exist and seeks to identify them. High value pharmacies will be those that differentiate themselves from their peers by being 1) high quality and associated with average healthcare costs, 2) of equal quality but cost saving, or 3) have both high quality and cost savings. This project's long term goal is to validate these findings by investigating characteristics that differentiate high value from low value pharmacies and create a VBPM for pharmacies.

The first step of creating a VBPM for pharmacies is to broadly measure pharmacy quality and relate quality to healthcare cost. This dissertation has two specific aims for accomplishing this goal:

1. Design and test a conceptual model of pharmacy quality.
2. Assess pharmacy value by evaluating the relationship between patients' healthcare costs and the quality of pharmacies from which they receive medications.

1.c Theoretical Framework

Approaching a problem this complex requires a theoretical framework. Pharmaceutical care, the clinically oriented practice philosophy adopted by the profession in 1989, is defined as the "responsible provision of drug therapy for the purpose of achieving definite outcomes that improve a patients' quality of life (Hepler & Strand, 1989)." Outcomes under the original paradigm were defined as curing or slowing the process of disease and preventing, eliminating or reducing patients' disease symptoms. Pharmacists accomplish these outcomes by identifying and resolving actual and potential drug therapy problems. The central idea of pharmaceutical care is that pharmacists can and should not simply dispense medications but practice in a way to improve their patients' health and quality of life.

Donabedian's structure, process, outcomes (SPO) theory of healthcare quality creates a useful framework for guiding this inquiry (Donabedian, 1988). Structure is broadly defined as the attributes of the setting in which care has occurred. Process denotes the way in which these attributes are used to create quality. Finally, outcomes relates to the impact of care on patients' health. Measuring outcomes should be the focus of any inquiry into healthcare quality (Porter, 2010a) and aligns with the aim of pharmacists providing patient care under the pharmaceutical care paradigm. Despite this, few studies have used quality metrics to evaluate the impact of community pharmacists on outcomes of healthcare. The most common metrics used to evaluate pharmacies are process metrics: medication appropriateness, medication adherence, etc. These metrics are not outcomes of care; no patient takes a medication for the purpose of taking a

medication. Patients take medications to improve or maintain their health. Pharmacies can be evaluated on their ability to improve process measures of care, but to evaluate the impact of pharmacists on healthcare quality, outcomes must be assessed.

As considered by Donabedian in his original 1988 publication, healthcare quality must be evaluated in the context of healthcare cost. Some features of healthcare quality, like hospital admissions, can be reduced to both increase quality and decrease the cost of healthcare. Others, including measures of medication adherence, when optimized, may increase healthcare cost while increasing healthcare quality. The US healthcare system can no longer afford interventions that substantially increase the cost of healthcare without regard to quality. Therefore, to assess the value of pharmacies for commercial insurers, one must consider healthcare cost as well as healthcare quality.

1.d Innovation

This dissertation innovates in several ways. First, data used in this project come from a commercial insurer. Most previous administrative claims studies assessing pharmacy quality have used Medicare claims data. Private, commercial insurers are responsible for nearly as much healthcare expenditure as Medicare and Medicaid combined (Centers for Medicare and Medicaid Services, 2014), yet assessment of pharmacy quality for commercially insured patients is lacking.

Second, the most common measurements of pharmacy quality in administrative claims studies are process measures of care including drug interactions, use of high risk medicines and medication adherence. Indeed, none of the quality metrics endorsed by the Pharmacy Quality Alliance are outcomes metrics. This study evaluates the impact of pharmacists on their patients' probability of hospital admission and ED visits using a novel approach to eliminate those events

least likely to be related to care by pharmacists. Unnecessary hospital admissions and ED visits are a major driver of healthcare costs, and pharmacists can create substantial value by reducing their patients' probability of an admission or visit.

Finally, this study combines measurements of pharmacies' impact on healthcare quality and cost to assess the value pharmacies in a commercial insurers' network provide to that insurer. This dissertation will lay the foundation for a future VBPM that measures and rewards pharmacies for the value they create for the healthcare system.

1.e Significance

The cost of healthcare in the United States is unsustainable and healthcare quality for US citizens is lacking. A substantial portion of unnecessary and avoidable healthcare expenditures is related to suboptimal medication use. Pharmacists have the ability to work with patients to optimize medication therapy, yet lack of incentives limits their ability to provide high value services. A value-based payment model for pharmacies could create rewards for high value pharmacies, but the knowledge as to how high value pharmacies can be accurately identified is lacking. This dissertation fills this critical gap by creating a comprehensive method to identify high value pharmacies which, once validated, can lay the foundation for a future VBPM. This new model will incentivize pharmacists to optimize medication therapy and create needed value in the healthcare system.

CHAPTER II
LITERATURE REVIEW

2.a Healthcare Quality, Cost and Value: Differentiating Terms

This dissertation explores the value pharmacies provide to a commercial insurer. Before the investigation can begin, however, one must have an understanding of what is meant when referring to healthcare quality, cost, and value. Quality is a quite nebulous concept but the concept of cost is more concrete. Value is measured by relating quality to cost. Therefore, to explore value, one must first have an understanding of what is meant by quality and cost.

2.a.1 What is Healthcare Quality?

Every major report assessing health quality approaches the concept differently. *Crossing the Quality Chasm*, a seminal report on healthcare quality issued by the Institute of Medicine, suggests that a high quality healthcare system should be safe, effective, patient-centered, timely, efficient, and equitable (Institute of Medicine, 2001). Within this framework, a system lacking quality is deficient on one of these six dimensions. Safety and effectiveness in this framework suggests that a high quality system lacks injuries from healthcare related services, applies services to all who would reasonably expect to receive benefit, and avoids use of services in those who would not benefit. The patient-centered concept suggests that care delivered should be allowed to vary according to patients' preferences, and patient autonomy should be respected. Timeliness and efficiency dimensions focus on reducing wait times and delays as well as avoiding waste. The dimension of equitability suggests that care should not vary according to personal characteristics that lack a necessary relationship to health, such as geography, socioeconomic status, gender, race/ethnicity, etc.

The term "performance," used when describing the healthcare system in reports by the World Health Organization (WHO) and the Commonwealth Fund (Davis et al., 2014; World Health Organization, 2000), is a broader term than quality. Quality measurement is one element of healthcare system performance. Achieving high levels of health is measured with two domains—health and responsiveness. Maximizing health is the main objective of the healthcare system and is assessed in the WHO report using measures of mortality and life expectancy, adjusting for level of disability in society. Responsiveness is how well the system responds to the non-healthcare needs of the population. Examples of these needs are patients' perceptions of how well the healthcare system treats them with respect, wait times for needed services, etc. and is analogous to the need for patient-centered care concept from the *Crossing the Quality Chasm* report.

Mirror, Mirror on the Wall: How the Performance of the U.S. Health Care System Compares Internationally, a report by the Commonwealth Fund, compares the performance of the US healthcare system with that of ten other industrialized countries (Davis et al., 2014). Performance is measured on dimensions of quality, access, efficiency, equity and healthy lives. Evaluation of quality is subdivided into four categories: effective care, safe care, coordinated care and patient-centeredness. Effective care is divided into two categories, prevention and chronic care, and is defined by the extent to which patients receive services that can prevent or treat illness. In assessing effective care, this report ranks the US well compared to other industrialized nations on providing preventive care but no better than average for chronic care. Safe care is defined as avoiding patient injuries when providing care that is intended to help them and care coordination measures the exchange of information between primary care physicians, specialists, and other members of the healthcare team. Finally, patient-centeredness contains three subdomains: 1) communication, 2) continuity and feedback, and 3) engagement and patient preferences. Communication measures patients exchanging information with the healthcare team

while continuity and feedback assess physicians' understanding of patients' medical history and feedback on their care experiences. Engagement and patient preferences measures patients' autonomy and ability to guide their own care. This four factor framework provides an extensive set of measures to evaluate the quality of the US healthcare system as part of a broader assessment of performance as contained in the report. The US is ranked last on performance, but ranked 5th out of eleven countries on healthcare quality. The performance of the US healthcare system falls short on measures of efficiency, equity and healthy living.

The Centers for Medicare and Medicaid Services (CMS) has also developed a quality strategy (Centers for Medicare and Medicaid Services, 2015h) that aligns with and expands the National Quality Strategy (Department of Health and Human Services, 2011). Unlike the WHO and Commonwealth Fund reports, the CMS Quality Strategy is a strategic plan to improve the organization's healthcare quality. It is designed with action and planning in mind, not measuring and comparing internationally the quality of the US healthcare system. The CMS Quality Strategy consists of six goals: 1) make care safer by reducing harm caused in the delivery of care, 2) strengthen person and family engagement as partners in their care, 3) promote effective communication and coordination of care, 4) promote effective prevention and treatment of chronic disease, 5) work with communities to promote best practices of healthy living, and 6) make care affordable. This is a very broad definition of quality, encompassing some elements, like cost of care, considered to be separate measures of healthcare performance in other reports (Davis et al., 2014; World Health Organization, 2000). Although not one of the six main goals, CMS does address the idea of equity by considering the elimination of racial and ethnic disparities as a foundational principle that guides CMS when pursuing each of the broad goals. In discussing reduction of healthcare costs, CMS considers value-based payment programs that promote quality, error reduction, and greater care coordination to be strategies that reduce healthcare costs. In this way, CMS directly links quality improvement to cost reduction.

A balanced, multi-pronged approach to improving healthcare system performance comes in the form of the Triple Aim, an initiative of the Institute for Healthcare Improvement (Berwick, Nolan, & Whittington, 2008; Institute for Healthcare Improvement, 2015a). Similar to the CMS Quality Strategy, the Triple Aim is a call to action. Its purpose is to redesign the healthcare system, not just to highlight problems. The core idea of the Triple Aim is a concomitant pursuit of improvements in population health, care experiences, and a reduction in per capita healthcare costs. Population health contains a broad set of measures of health—disease burden, life expectancy, and health related quality of life (Institute for Healthcare Improvement, 2015b). Patient experience includes both patients' perception of healthcare quality and their personal experiences with care as well as process and outcome measures of healthcare quality. Per capita costs are defined both as the total cost of care per member per month and hospital and emergency department use, two services that are high cost and potentially avoidable.

These frameworks for evaluating quality and performance vary in the concepts they contain, but share a common theme: Evaluating quality is complex and multifaceted. When evaluating a healthcare system, it is insufficient to assess health quality alone. All frameworks contain measures of quality, defined as achieving optimal health, as well as some measures of patient experiences and healthcare costs. Some reports consider patient experience to be a part of quality, others consider it a separate domain. The same is true with measures of healthcare cost and resource use. There is no universal definition for healthcare quality. Any effort to measure quality should understand that focusing on provider quality alone leaves out important aspects of healthcare system quality.

2.a.2 What is Pharmacy Quality?

At its most basic, pharmacy quality can be defined as achieving a degree of excellence by providing pharmacy services which maximize the probability of positive outcomes and minimize the probability of negative outcomes (Shaw Phillips & Chisholm-Burns, 2014; Warholak, 2012). More detailed elements of pharmacy quality include practice which corresponds with current medical best practices and guidelines and offers services to meet the patient's wants and needs (Warholak, 2012). Therefore, as with healthcare quality more generally, quality measurement for pharmacies should encompass broad elements of quality. Despite this, studies on pharmacy quality estimate pharmacies' impact on process measures of care (Brennan et al., 2012; Fischer et al., 2014; Pringle et al., 2014) but ignore impact items like responsiveness, patient-centeredness, timeliness and efficiency. These concepts are important for a deeper understanding of the impact of pharmacies on healthcare quality, but cannot be measured easily using administrative claims databases and are not included in current pharmacy quality measurement systems (Deninger, 2015; EQuIPP, 2015a; Inland Empire Health Plan, 2014; Mascardo, 2016; Trygstad, 2015). There is room in the literature for a better understanding of the broader impact of pharmacies on healthcare quality.

2.a.3 How Are Cost and Spending Defined?

The terms healthcare spending and healthcare cost are often used interchangeably. Indeed, it is common to refer to National Healthcare Expenditures as a measure of the cost of healthcare in the United States (Institute for Healthcare Improvement, 2015a; Kaiser Family Foundation, 2015; Munro, 2015). Spending is perhaps a more precise way to describe dollars exchanged in the healthcare system as the term suggests a summation of dollars exchanged only

after negotiations have taken place and payment is made. Cost, on the other hand, can refer to notoriously inflated sticker prices for healthcare goods and services.

Cost can be measured objectively in terms of absolute or relative dollars spent for a given item, or subjectively with items like perceived affordability (Zeithaml, 1988). Objective measurement of healthcare cost is surprisingly complex. To use the cost of pharmaceuticals as an example, the list price for a drug is often far above what is actually paid for the drug after insurers and pharmacy benefit managers negotiate with pharmacies and pharmaceutical manufacturers. A brand name statin drug's list price may be $250 per month, but after insurance company negotiations, the pharmacy is ultimately paid $200. Suppose there is a generic statin that only costs $4. The cost of the brand name drug can be stated in several ways—$200/month, 50 times more expensive than the generic, or $196 more than the generic. All of these could be ways to evaluate costs and compare costs between two items.

When assessing costs, it is also important to consider the perspective one is taking. The negotiated payment for the brand name statin is $200/month, but insurance may reduce beneficiaries' costs to $20. Therefore, if you were to ask consumers what the cost of their statin is, they only have enough information to say $20 a month. In this scenario, the cost to the insurance company is $180 a month because the beneficiary pays 10% of the cost of the drug. An insurer could reduce their costs by increasing their beneficiaries' cost sharing, and a patient could reduce their costs by switching to an insurance plan with a lower cost sharing. The broadest measure of healthcare costs commonly available is the sum of insurers' and patients' payments for a given item. This measure facilitates comparison of costs across insurance products by ignoring the impact of cost sharing on payments by any one party.

2.a.4 How does Value Relate to Quality and Cost?

Marketing literature defines value as the benefit received from a good or service relative to what is given in return (Alston & Blizzard, 2012; Zeithaml, 1988). Porter uses a similar definition when defining value as dollars spent per outcome achieved (Porter, 2010a). Translating this trade-off into health policy, Secretary of HHS Sylvia Burwell describes CMS's efforts to improve value in the healthcare system as building a system that "delivers better care, that is smarter about how dollars are spent, and that makes people healthier (Burwell, 2015)." This relates closely to the Blue Cross and Blue Shield Association's description of value-based programs as those which help beneficiaries receive "safe, high-quality, coordinated and affordable care (Blue Cross and Blue Shield Association, 2014)." Finally, the Institute for Healthcare Improvement refers to the triple aim of better care for populations, better care experiences and reducing per capita costs of healthcare as both improving performance and improving value (Berwick et al., 2008; Institute for Healthcare Improvement, 2015a). All of these ways of defining value refer to the same basic trade-off of achieving healthcare quality relative to healthcare costs. There is a suggestion that value cannot be achieved without some minimum achievement on quality, but value can generally be increased by 1) holding quality constant and reducing cost, 2) increasing quality while holding cost constant, or 3) increasing quality while simultaneously reducing cost.

2.b Improving Value: A Focus on Optimizing Medication Use

Avoidable costs and insufficient quality remain a frustration for patients, healthcare practitioners, health insurers and policymakers. CMS recognizes that focusing on improving the value provided by medications is a yet-to-be-explored opportunity for the healthcare system (Centers for Medicare and Medicaid Services, 2015s). For the purposes of this study, medication optimization

encompasses all care processes that are intended to enhance medication use, which in turn improves health outcomes. Hundreds of billions of dollars could be saved every year by using medications more optimally. The IMS Institute for Healthcare Informatics estimates that optimizing medication use could have saved $213 billion in 2012 (IMS Institute, 2013). Analysis by the New England Healthcare Institute finds that suboptimal medication use resulted in unnecessary morbidity and mortality and created $289 billion in excess healthcare cost for 2008 (New England Healthcare Institute, 2009). Addressing nonadherence is consistently the largest source of potential savings across studies of medication optimization. Focusing only on diabetes, hypertension and dyslipidemia, a study by Nasseh et al. found that medication nonadherence alone was associated with $105.8 billion in unnecessary healthcare cost in 2010 (Nasseh, Frazee, Visaria, & Vilahiotis, 2012). This study also found that for Iowa the cost of nonadherence was nearly $1 billion, or $398.08 per adult resident. A disease-state-specific assessment for the impact of adherence on healthcare cost by adults finds that the cost of medical care for adherent adults with congestive heart failure, hypertension, diabetes, and dyslipidemia was, respectively, $8,881, $4,337, $4,413 and $1,860 less than nonadherent patients (Roebuck et al., 2011). A similar analysis assessing savings related to adherence and controlling for the possible unobserved relationship between adherence and underlying health behaviors found that patients adherent to ACE-I/ARB and oral antidiabetic drugs had $4,920 and $3,033 fewer annual medical expenses (Stuart, Dai, Xu, Loh, & Dougherty, 2015). For this study, medication adherence is defined as patients taking their medications as prescribed. This definition is consistent with other published work (Osterberg & Blaschke, 2005), matches with common methods used to assess adherence using claims data, and encompasses the definition of persistence: continuing to take a medication for some fixed time period.

Avoidable hospitalizations are consistently the largest source of avoidable medication related healthcare cost. The IMS Institute study found $140 billion could be saved annually from

unnecessary hospitalizations (IMS Institute, 2013) while the New England Healthcare Institute found $197.8 billion in savings (New England Healthcare Institute, 2009). Investigating the relationship between medication use and hospitalization for a non-elderly adult population, Sokol and colleagues found that greater adherence to medications for diabetes, hypertension, dyslipidemia and congestive heart failure was associated with reduced hospitalization risk (Sokol, McGuigan, Verbrugge, & Epstein, 2005). Roebuck's 2011 study finding thousands of dollars in per-patient healthcare savings for adherent patients also found potential annual hospital days for adherent patients with CHF, hypertension, diabetes and dyslipidemia to be 6, 3, 3, and 2 days fewer than their nonadherent peers (Roebuck et al., 2011). The study found no difference in ED visits and a slight increase in outpatient doctor visits. A second study by Roebuck and colleagues using data from a Medicaid-only (non-dual eligible) population found that increasing prescription drug utilization reduced total healthcare costs, and that these reductions were driven by a decrease in inpatient costs (Roebuck, Dougherty, Kaestner, & Miller, 2015). Further support for the hypothesis of more optimal medication use decreasing hospital related healthcare costs comes from an elegant study by Stuart et al. which used data from the 1999-2000 Medicare Current Beneficiary Study and an instrumental variable approach with prescription drug coverage as the instrument (Stuart, Doshi, & Terza, 2009). The study found that, for an elderly population with diabetes, increases in the count of prescription drugs filled significantly decreases hospital costs but only has a small negative effect on the probability of hospital admission. This adds nuance to the relationship between prescription drugs and hospitalizations. It may be that even if optimal medication use can't keep a patient out of the hospital, it could reduce the care that is needed when in the hospital. For payers that reimburse based on diagnosis related group or a similar method, they could receive savings through reduced acuity on admission.

Recognizing this body of evidence, the Congressional Budget Office (CBO) in November, 2012 updated their legislative scoring to account for the value of prescription

medication use (Congressional Budget Office, 2012). The CBO procedures now calculate that for every 1% increase in projected prescription drug utilization, the cost of medical care will decrease by 0.2% and vice versa. This assumption validates the idea that optimal use of medications can reduce medical costs, although the CBO's 0.2% offset may underestimate the true effect (Roebuck, 2014). Assessment of a subset of data from Roebuck and colleagues' 2011 study found that medical cost offsets across the 4 included disease states ranged from 0.63% for dyslipidemia to 1.17% for hypertension, a 3-6 fold difference from the CBO's medical offset estimate (Roebuck, 2014). Assessment of adult Medicaid enrollees also found a consistent relationship between increasing prescription drug use and decreased total nondrug healthcare costs for hypertension and gastroesophageal reflux disease (GERD) (Roebuck et al., 2015). For every 1% increase in prescription medication use by patients with Medicaid, hypertension costs decreased by 0.032% to 0.074% and GERD costs decreased by 0.032% to 0.062%. These results suggest that the relationship between medication use and total nondrug cost offsets vary by condition and population, but there is strong evidence to suggest that greater use of prescription drugs can decrease the cost of healthcare.

This extensive body of literature suggests that optimizing medication use can decrease the cost of healthcare, and that this decrease is driven primarily by reduced hospitalization costs. The effect estimates vary by study design, population, and disease states considered, but results consistently suggest that medication optimization can save health insurers money. The main ways this can be accomplished are through reducing nonadherence and underprescribing. There are 2 types of nonadherence, primary nonadherence and secondary nonadherence. Primary nonadherence is defined as patients never starting a medication that is prescribed for them (Pharmacy Quality Alliance, 2013). Secondary nonadherence occurs when a patient fills a medication that has been prescribed for them, but does not take it as directed (IMS Institute, 2013; Osterberg & Blaschke, 2005). Underprescribing occurs when a practitioner fails to

prescribe a medication that is appropriate for the patient's condition(s) according to current standards of practice and accepted guidelines (IMS Institute, 2013).

2.b.1 Primary Medication Nonadherence

Primary medication nonadherence has been studied less frequently than secondary nonadherence. Primary nonadherence cannot be accurately evaluated using administrative billing claims (Pharmacy Quality Alliance, 2013), therefore primary nonadherence is much more difficult to study than secondary nonadherence and studies on primary nonadherence have only become common now that e-prescribing has gained popularity. PQA has established a metric for evaluating primary nonadherence that uses a combination of prescription dispensing and electronic prescribing data (Pharmacy Quality Alliance, 2013).

Estimates for rates of primary medication nonadherence (PMN) range from single digits to nearly 25% (Cheetham et al., 2013; Fischer et al., 2011; Fischer et al., 2014; Fischer et al., 2015; Jackson et al., 2014; Raebel et al., 2012; Shin et al., 2012). These estimates are for medications used to treat diseases including asthma, diabetes, hypertension, dyslipidemia and other conditions. Methods to evaluate PMN typically use e-prescribing data (Fischer et al., 2011; Fischer et al., 2014; Fischer et al., 2015; Jackson et al., 2014; Pharmacy Quality Alliance, 2013), but some studies have used prescribing and dispensing data from integrated care settings (Cheetham et al., 2013; Raebel et al., 2012; Shin et al., 2012). Estimates do not vary systematically over source of prescription data. Variation does exist in the definition of what constitutes a new prescription, with studies requiring no identical or same-class prescription at either 180 days (Fischer et al., 2011; Fischer et al., 2014; Jackson et al., 2014; Raebel et al., 2012) or 365 days (Cheetham et al., 2013; Fischer et al., 2015; Shin et al., 2012) prior to an index prescription date. Studies also vary in the time window used to evaluate whether or not a

prescription was picked up, with some studies using 14 days (Raebel et al., 2012; Shin et al., 2012), others 30 days (Fischer et al., 2014; Fischer et al., 2015) and some 90 days (Cheetham et al., 2013; Jackson et al., 2014) or "never filled" (Fischer et al., 2011). The development of a standard measure for PMN with a 180 day look-back period and a 30 day definition for an unfilled prescription should increase consistency of methods used in PMN studies (Pharmacy Quality Alliance, 2013).

Patients with PMN are, in general, more likely to be poorer and younger than their peers (Cheetham et al., 2013; Fischer et al., 2011; Fischer et al., 2015; Jackson et al., 2014; Raebel et al., 2012; Shin et al., 2012). Studies had inconsistent results with respect to influence of comorbidities and other measures of health status on PMN and most studies found substantial variation in PMN across the categories of medications assessed. Many studies use logistic models to assess predictors of PMN, but the models generally have poor discriminatory power with c statistics only around 0.6.

To date, there are no studies evaluating the impact of PMN on healthcare outcomes. However, as the C. Everett Koop quote goes, "Drugs don't work in patients who don't take them." There is a strong likelihood that increased rates of PMN result in diminished clinical outcomes. PMN remains difficult to measure but is nonetheless an important opportunity for medication optimization leading to improved value for the healthcare system.

2.b.2 Secondary Medication Nonadherence

Unlike PMN, there is substantial evidence for a relationship between secondary medication nonadherence and healthcare outcomes. Decades of evidence suggest that patients who do not take their medications as prescribed have poorer outcomes and cost the healthcare

system more than their adherent peers. A World Health Organization (WHO) report finds that nonadherence is a global problem with adherence rates in developed countries averaging only around 50% and rates for developing countries even lower (World Health Organization, 2003). Adherence rates are lower for patients with chronic conditions and vary across disease states (Osterberg & Blaschke, 2005). For example, there is evidence to suggest that half of all patients taking statins discontinue the medication with the first 6 months (Osterberg & Blaschke, 2005). For patients with diabetes, estimates for the percent of time patients are adherent range from 36% to 93%, with most studies finding adherence rates in the 75-85% range (Cramer, 2004). The Dartmouth Atlas of Prescription Drug Use confirms that there is substantial variation in medication adherence and persistence for Medicare beneficiaries (The Dartmouth Institute, 2013). Six months following a myocardial infarction, persistence rates for β-blockers vary across hospital referral regions from just over 60% to more than 90%, and persistence rates for statin medications were as low as the mid-40s (The Dartmouth Institute, 2013). Adherence rates vary substantially by number of daily doses, population observed, condition studied, and other variables (Osterberg & Blaschke, 2005). Nonadherence is a complex behavior and remains a frustration for healthcare practitioners, health insurers and policymakers. Over half of the $200 billion in potentially avoidable, medication related healthcare costs identified by the IMS Institute comes from adherence related opportunities (IMS Institute, 2013). This estimate does not differentiate between primary and secondary nonadherence, but it is clear that nonadherence creates a substantial and unnecessary burden on the US healthcare system.

Assuming that the prescription is appropriate for the patient's condition, not taking the medication as prescribed increases the likelihood of poor clinical outcomes. Medications are the mainstay of long term control for chronic diseases and many studies have assessed the relationship between nonadherence and adverse health outcomes. A 2002 meta-analysis of the impact of adherence on healthcare outcomes found 44 studies on medication adherence that

included ten different condition categories: cancer, hypertension, dyslipidemia, arthritis, intestinal disease, heart disease, otitis media, transplant, ulcers, and venous disease (DiMatteo, Giordani, Lepper, & Croghan, 2002). The studies measured adherence in different ways and had different outcomes, but pooling the estimates together, the authors find that patients with high adherence were 21% more likely to experience a favorable treatment outcome than their less adherent peers. Consistent with these findings, a 2013 literature review of studies of adherence in patients with coronary artery disease found that for all 25 of the studies reviewed there was at least some evidence that increasing adherence improved health outcomes (Bitton, Choudhry, Matlin, Swanton, & Shrank, 2013). The literature shows that although estimates of the relationship between adherence and outcomes are wide ranging and the methods to assess the relationship are highly variable, the association between better adherence and favorable outcomes is consistently positive.

2.b.2.1 Healthy Adherer Bias Inflates Estimates of Impact of Secondary Medication Nonadherence

Although observational studies have found an association between adherence and favorable healthcare outcomes, observational studies cannot establish causality. Evidence from clinical trials, reinforced by observational studies and recommendations from nationally recognized guidelines, suggests that taking medications more appropriately should produce better healthcare outcomes. This suggests a causal relationship between adherence and outcomes, but it could be that the observed relationship between better medication adherence and positive outcomes results from unobserved variables that are strongly correlated with both adherence and health outcomes. One potential source of this endogeneity is the patient's underlying orientation towards healthcare. If the patient takes their health more seriously, they may be more likely to

both take their medications more often and perform other healthy behaviors which would reduce their healthcare resource utilization and negative healthcare outcomes. In the adherence literature, this is often referred to as healthy adherer bias (HAB). Recognizing this potential, researchers have attempted to control for HAB using novel datasets (Stuart et al., 2015), variables indicative of orientation towards preventive health (Brookhart et al., 2007; Choudhry et al., 2014) and advanced statistical methods (Roebuck et al., 2015; Roebuck et al., 2011).

The primary assertion in the healthy adherer explanation for the link between adherence and outcomes is that patients who are more adherent are more likely to seek other preventive healthcare services. The level of granularity needed to assess HAB is typically not available in secondary datasets, but one study using the Medicare Current Beneficiary Survey (MCBS) linked survey responses on items including marital status, education, income, self-reported health status, self-reported limitations on daily activity, and measures of good and poor health habits to Medicare claims for patients with diabetes (Stuart et al., 2015). The study found that many of the MCBS variables, including fair to poor health status, were associated with higher medical and drug costs. When controlling for the MCBS variables believed to correlate with both adherence and healthcare costs, the authors found that estimates for the magnitude of the effect of adherence on healthcare savings were lower. Although controlling for HAB shifted estimates towards the null for all classes of medications assessed, there was no significant change in estimates of adherence on healthcare savings for models controlling for HAB for statins and oral antidiabetic medications. There was, however, a 23% reduction in the estimated savings from adherence to ACEI/ARBs. The effect for all classes was diminished but not entirely eliminated.

An alternative approach to controlling for HAB is to include covariates that are available in most administrative claims databases and are also correlated with a patient's desire for preventive services. A study of low income Medicare beneficiaries with newly initiated statin therapy found that those who persisted with therapy by filling more than one statin prescription

were more likely to be screened for mammograms and receive prostate-specific antigen tests, fecal occult blood tests, influenza vaccinations and pneumonia vaccinations (Brookhart et al., 2007). This suggests that an unobserved factor, such as HAB, creates correlations between statin adherence and use of other preventive services. Using the same dataset, researchers found that statin use in the 30 days following a hospital discharge for coronary artery disease reduced the hazard of developing atrial fibrillation (HR 0.90, CI 0.85-0.96) in models adjusting for patient and hospital characteristics but not HAB, and that a model controlling for these characteristics and HAB had nearly identical results (HR 0.90, CI 0.85-0.94) (Kulik, Singh, Levin, Avorn, & Choudhry, 2010). Adapting this method to a commercially insured population, a post hoc analysis of the MI-FREEE trial assessing the relationship between adherence and a second major cardiovascular event following a discharge for a myocardial infarction found that controlling for HAB made no difference in the estimate of the effect of adherence for any of the three medication classes studied (statins, β-blockers and ACEI/ARBs), and the hazard of a major cardiovascular event (Choudhry et al., 2014). A correlation likely exists between adherence and seeking other preventive health services, but controlling for this effect may either not be a sensitive enough measure to sufficiently control for the impact of HAB on estimates of the relationship between adherence and clinical outcomes or HAB may not significantly bias the relationship.

The third way in which researchers have controlled for HAB is through the inclusion of patient-level fixed effects in a longitudinal analysis of the relationship between adherence and outcomes of interest. This controls for patient-related effects that do not vary with time. A patient's underlying desire to receive healthcare services is one type of these effects and is hypothesized to create HAB. Roebuck has included this method in two different studies, one for Medicare patients and the other for Medicaid. For Medicare enrollees, Roebuck and colleagues found that, compared to ordinary least squares models that did not include patient-level fixed effects, models that included fixed effects resulted in smaller yet still statistically significant

estimates for the relationship between adherence and annual total cost of healthcare for CHF, hypertension and diabetes (Roebuck et al., 2011). Interestingly, controlling for HAB using fixed effects resulted in a greater estimate of savings for patients adherent to medications for dyslipidemia. Roebuck and colleagues used the same method to control for HAB when assessing the relationship between Medicaid enrollees' use of prescription drugs and cost of medical care, and found that there were consistent offsets for prescription drug use and healthcare costs for hypertension and GERD (Roebuck et al., 2015). No sensitivity analysis for the inclusion of patient-level fixed effects was reported for this study but prescription drug use for many of the studied conditions was not associated with healthcare cost offsets. Consistent with the previous two methods, controlling for patient-level fixed effects appears to diminish, but not entirely eliminate, the effect of adherence on healthcare outcomes and cost.

Healthy adherer bias complicates the relationship between adherence and healthcare outcomes. Failure to control for HAB biases estimates of the effect of adherence away from the null. There are a variety of methods for controlling for HAB, and all seem to reduce the estimates of the impact on adherence on outcomes but no method finds that the impact completely disappears. Therefore, it appears that the impact of adherence on healthcare quality and outcomes persists even when controlling for HAB. This supports the hypothesis that increasing medication adherence increases healthcare quality and reduces healthcare costs.

2.b.3 Underprescribing

Patients can't be adherent to a prescription that was never written. Underprescribing occurs when current standards of practice and the medical literature recommend that a medication should be prescribed, but isn't. Deriving estimates of the impact of this opportunity for medication optimization is difficult. Administrative datasets that are usually used to evaluate

healthcare quality lack enough data to make detailed assessments of patients who should be receiving a given prescription. Take, for example, ACEI/ARBs. These medications have long been recommended for patients with diabetes to protect kidneys and treat hypertension (American Diabetes Association, 2015), yet not all patients with diabetes are prescribed an ACEI/ARB. Is it patient resistance, prescriber incompetence, or prescribers picking the best therapy based on a holistic assessment of patients' needs? One reason for this apparent underprescribing is that it is not all patients can safely take ACEI/ARBS. Contraindications include allergic hypersensitivity reactions, angioedema, and history of ACEI/ARB related renal damage. There is no way to know which patients do not have a prescription for an ACEI/ARB because of error or negligence by the prescriber or the careful consideration of the potential negative impact of an ACEI/ARB on a patient's overall health.

A further exploration of this question using data from Medicare patients discharged from the hospital following a myocardial infarction comes from Schroeder et al. The authors discovered that only 62% of Medicare patients discharged from the hospital after an acute myocardial infarction had filled a statin medication within 30 days of discharge (Schroeder, Robinson, Chapman, & Brooks, 2015). This is surprising, considering that statins are recommended for prevention of a second myocardial infarction (S. C. Smith, Jr. et al., 2011). The Schroeder study found the fill rates were normally distributed across patients and that rates varied systematically by patient specific factors, including age, sex and comorbidities. Assessment of physician effects didn't find substantial differences by physician type. This suggests that there are not characteristics of physicians (i.e. high quality vs. low quality) which systematically cause any large group of physicians to prescribe at a different rate, calling into question whether or not the 62% fill rate was suboptimal.

Nevertheless, the accumulation of data from clinical trials and observational studies suggest that at least some portion of the patients who do not receive evidence-based therapy

would benefit from that therapy. Hospitals are chaotic environments, and even with the best intentions, mistakes are made. It could be that the mistakes are randomly distributed over physician type, lowering the prescribing rate in a nonsystematic, difficult-to-detect way. Primary care physicians may lack the time to make optimal prescribing decisions, or they may believe in error that they sent an order through their electronic medical record (EMR). Mistakes happen, and in a field as complicated as healthcare, mistakes happen often. Underprescribing is a difficult-to-detect yet important source of lost medication related healthcare system value.

2.b.4 Further Opportunities for Medication Optimization

Addressing primary medication nonadherence, secondary medication nonadherence and underprescribing are not the only opportunities to improve the use of medications and thereby add value to the healthcare system. Of the $200 billion in potentially avoidable, medication-related healthcare expenses identified by the IMS Institute, these three types of opportunities total $140 billion in potential annual savings (IMS Institute, 2013). Beyond adherence and underprescribing, there are numerous other ways that medications can be used more effectively. Antibiotic misuse, for example, is a $35.1 billion dollar annual opportunity for savings (IMS Institute, 2013). Use of antibiotics for viral infections or insufficiently tailored antibiotic therapy increase the rates of antibiotic resistance and can lead to super infections including *C. difficile*, which alone is responsible for half a million annual infections and up to $4.8 billion in avoidable annual expenditures (Centers for Disease Control and Prevention, 2015b). To combat the 20-50% of all antibiotics that are prescribed inappropriately, hospital-based antibiotic stewardship programs have become common (Centers for Disease Control and Prevention, 2015a). These programs, and analogous efforts in primary care, seek to ensure that the healthcare system is getting the most value it can out of antibiotics.

Another significant area of medication-related concern is preventable adverse drug events. Not all adverse drug events are preventable, but research suggests that some classes of medications are more prone to preventable adverse events than others. To address this issue, the Department of Health and Human Services created the National Action Plan for Adverse Drug Event Prevention (Office of Disease Prevention and Health Promotion, 2014). The initial targets of the report are three medication classes: 1) anticoagulants, 2) diabetes agents and 3) opioids. Inappropriate use of these medications can cause, respectively, bleeding, hypoglycemia and overdoses and contribute disproportionately to the more than a quarter million adverse drug event related hospital admissions each year (Office of Disease Prevention and Health Promotion, 2014) and $20 billion in avoidable annual costs (IMS Institute, 2013).

These opportunities for quality improvement and savings add to the potential value that can be created by improving adherence and prescribing of recommended treatments. Other important opportunities include maximizing the use of generic drugs, ensuring that patients are taking the right dose of medications, and many more. In all of these ways, optimizing the use of medications creates value for the healthcare system.

2.c The Evolving Clinical Role for Pharmacists and The Opportunity of Medication Optimization

As the previous section posits, medication optimization adds value to the healthcare system. The most studied opportunity for optimization is improving secondary medication adherence. Although estimates in the literature are likely inflated because of inadequate controls for healthy adherer bias, getting patients to take their medications as prescribed can improve healthcare outcomes and decrease costs. Improving primary medication adherence likely has a similar effect, but there are no studies linking primary medication adherence to changes in healthcare outcomes.

Reducing underprescribing of beneficial medications, the third major opportunity for medication optimization, helps patients receive medications that research and guidelines suggest will improve or maintain their health. Implementing strategies to improve the use of medications can create value through better healthcare quality and reduced healthcare costs.

As medication experts, pharmacists are uniquely qualified to engage in medication optimization strategies. With the exception of mail order and physician administered drugs, patients encounter a pharmacist every time they receive an outpatient medication. The PharmD standard of education equips all pharmacists with the clinical knowledge to make an assessment of medication appropriateness for their patients and to work with patients and other healthcare professionals to improve quality and outcomes and decrease costs.

The changes that have taken place in pharmacy practice since the 1950s also support the concept of community pharmacists working directly with patients to add value to the healthcare system through oversight of medications. From Eugene White's innovation to transform his pharmacy into a healthcare center in the 1950s (White, 1965) to more current developments including Hepler and Strand's conception of pharmaceutical care as the dominant practice philosophy for the clinically-oriented profession of pharmacy (Hepler & Strand, 1989) and the creation of the medication therapy management (MTM) as a standard benefit within Medicare Part D (Centers for Medicare and Medicaid Services, 2015a), pharmacists have been transitioning their role from one focused on products to one focused on patients.

There are a variety of non-dispensing functions a pharmacist can perform to improve their patients' care, ranging from short counseling sessions across the counter at prescription pick-up to sit-down, hour long MTM sessions. In the most recent National Pharmacist Workforce Study, community pharmacists reported 10-13% of their time was spent performing patient care services not associated with dispensing (Doucette WR, 2014). These activities specifically

exclude patient counseling associated with a prescription or an OTC product. No statistical comparison was made, but this was an increase by a couple of percentage points compared to the 2009 survey. Depending on setting, 24-42% of community pharmacists said they spent more time on non-dispensing related patient care services in the survey year compared to the previous year.

Pharmacy has changed significantly in the last 50 years. The American Pharmacists Association (APhA), through their publication "Pharmacy Today," frequently features pharmacists who provide innovative patient care services (American Pharmacists Association, 2015). The National Community Pharmacists Association (NCPA) blog also features stories of noteworthy community pharmacies that provide similar services (National Community Pharmacists Association, 2015). Organized pharmacy's lobbying for further involvement of pharmacists in patient care is longstanding and current efforts have coalesced around the drive for provider status (Patient Access to Pharmacists' Care Coalition, 2016). Chain pharmacies are also advocating for pharmacists' role in improving health (Shrank, Sussman, & Brennan, 2014). Pharmacy education, practice philosophy, work settings and pharmacy advocacy organizations are all moving pharmacy from a profession focused on products to one focused on patients. Within this transition, though, there are still two important questions: Can community pharmacists make a difference in their patients' health? Are community pharmacists making a difference in their patients' health?

2.c.1 Can Community Pharmacists Impact their Patients' Health?

Before assessing the impact that pharmacists are making on their patients' health, it is necessary to ask whether or not it is possible for pharmacists to make this impact. If no evidence supports the idea that community pharmacists can add value to the healthcare system, it is illogical to evaluate variation in pharmacy value. For variation in healthcare value observed at the

pharmacy level to be attributed to actions by pharmacists, there has to be evidence of pharmacists' ability to create value.

2.c.1.1 CMS' Experience with Medicare Part D Suggests Programs to Optimize Medication Use can Create Value

As described in section 2.b, substantial improvements in healthcare quality and cost savings can result from medication optimization. Recognizing this possibility, the crafters of the Medicare Prescription Drug, Improvement and Modernization Act of 2003 included medication therapy management (MTM) as a standard benefit for qualifying enrollees in the Part D program (Centers for Medicare and Medicaid Services, 2015j). This program was not the first insurance-sponsored program to address suboptimal medication use, but it is the largest. For 2016, Part D plan sponsors are required to create programs which address suboptimal medication use for plan enrollees with a minimum of two to three chronic conditions, two to eight chronic medications and projected annual pharmaceutical costs of at least $3,507 (Centers for Medicare and Medicaid Services, 2015j). Although not required for delivery of the benefit, all Part D MTM programs include pharmacists (Centers for Medicare and Medicaid Services, 2015a). Requirements for the program include an annual comprehensive medication review (CMR), quarterly targeted medication reviews (TMR) and outreach to prescribers. The CMR is designed to be an all-encompassing review of patients' medications, focusing on opportunities to improve drug therapy. TMRs are more specific; they can be used as follow-up from a CMR, part of a drug utilization review process, or other targeted medication quality initiative.

CMS believes the MTM program is essential for controlling healthcare costs in the Medicare program and has taken steps to increase the quality of the benefit and the number of qualifying enrollees. These steps include a recent initiative to encourage better use of the program

by standalone Part D plan (PDP) sponsors by loosening regulatory requirements, sharing Part A and B data, and providing additional payments to plan sponsors which can improve healthcare quality (Centers for Medicare and Medicaid Services, 2016c). In assessing the impact of the traditional MTM benefit, a CMS-commissioned report took advantage of the benefit's flexible requirements by comparing beneficiaries that were not eligible in their specific plan but would have been if they had been enrolled in a different plan to MTM-eligible enrollees (Perlroth et al., 2013). This helps to eliminate some of the selection effects that would occur if the MTM eligible population was compared against the general enrolled population. Statistical adjustment was also made to account for differences between patients and between Part D plans. Enrollees with diabetes, CHF and COPD were included in the analysis and drug therapy outcomes assessed were adherence, quality of prescribing and drug safety. Outcomes for resource utilization were hospitalizations and ED rates as well as costs from drugs, hospitalizations and ED visits.

Acumen found that there was substantial variation in the outcomes of MTM across the eight Part D plans assessed, but that overall the MTM benefit improved medication adherence and quality of prescribing for diabetes, CHF and COPD (Perlroth et al., 2013). The odds ratio of adherence vs. nonadherence (using an 80% threshold) across all medication classes for an MTM population receiving a CMR ranged from 0.99 to 1.43, with a mean odds ratio of 1.23. The benefit did not have a long term impact on drug safety. Estimates of program benefits for those enrollees who received CMRs were greater than for enrollees who did not receive CMRs. One must be cautious, however, in assigning this effect entirely to CMRs as beneficiaries could choose to opt out of CMRs, thus indicating that the population choosing not to opt out may have a greater orientation towards receiving healthcare services. Considering the aforementioned concern with healthy adherer bias (Section 2.b.2.1), this could account for some portion of the impact of CMRs on beneficiaries' nonadherence and underprescribing.

The MTM benefit did not have as consistent effects on resource utilization. Eligible enrollees who received CMRs were less likely to be hospitalized and visit the ED than the comparison population for all three conditions studied. Also, for patients with diabetes and CHF, enrollees who received a CMR had substantially less hospital cost than the comparator group and the MTM eligible population that did not receive a CMR. Results of resource utilization analysis among those who were MTM eligible but did not receive CMRs were not as consistent, and never showed any savings on hospital costs. This suggests that CMRs may be driving the benefits received by CMS from the MTM program.

In summary, the MTM benefit is the largest program of its type which focuses on medication optimization as a tool for improving health quality and decreasing costs. Results vary by condition and by Part D plan sponsor. Some sponsors operate highly successful programs; other programs fail to produce any successful results. Use of community pharmacists to provide the MTM benefit is not mandatory, but those plans operating highly successful MTM benefits cite community pharmacist involvement as a key to their success (Perlroth et al., 2013).

2.c.1.2 Many Studies of Community Pharmacists' Impact on Patients' Health Suffer from Serious Design Flaws

Organized pharmacy has long advocated for the idea that pharmacists can make a difference in their patients' health and has funded research that demonstrates positive results from community pharmacist involvement in patient care. The APhA Foundation's Project ImPACT series and Ten City Challenge, for example, have studied community pharmacists' impact on depression, diabetes, dyslipidemia and osteoporosis (Bluml, McKenney, & Cziraky, 2000; Fera, Bluml, & Ellis, 2009; Finley, Bluml, Bunting, & Kiser, 2011; Garrett & Bluml, 2005; Goode, Swiger, & Bluml, 2004). The NACDS Foundation has taken a slightly different tack,

investigating community pharmacists' impact on broader aspects of healthcare, including primary medication nonadherence, involvement in emerging models of care delivery, transitions of care, and point of care testing (National Association of Chain Drug Stores Foundation, 2015).

APhA holds the results of its foundation's studies up as undeniable proof that pharmacists can make a difference in their patients' health, but all of these studies have serious design flaws. All studies promoted on the APhA Foundation's website use a single cohort pre-post design to evaluate community pharmacists' impact on patients' health (Bluml et al., 2000; Fera et al., 2009; Finley et al., 2011; Garrett & Bluml, 2005; Goode et al., 2004). Patients voluntarily enrolled in the studies and could typically self-refer for participation. The studies that reported economic outcomes did so using projections from previous years' claims, not actual difference within the group or a differences-in-differences comparison with a matched cohort (Fera et al., 2009; Finley et al., 2011; Garrett & Bluml, 2005). These projections may not reliably measure potential savings. Also, the APhA Foundation attributes the positive results to the actions of the pharmacist, but with potential selection effects, regression to the mean and historical effects that plague studies with these designs, this assignment of causation cannot be made with confidence. These studies are useful as demonstrations of practice redesigns aimed at increasing pharmacists' interactions with patients, but the APhA Foundation studies provide only weak evidence that community pharmacists can impact their patients' health.

Another praised-yet-flawed series of studies evaluating community pharmacists' impact on patients' health are from the Asheville Project. Began in 1996, the Asheville Project was an experiment by the City of Asheville and Kerr Drug to engage pharmacists in meeting with city employees with diabetes for the purpose of improving health outcomes and quality for employees and decreasing healthcare costs for the city (The Asheville Project Web Site). Later, employees from Mission Hospital were included in the project. This was a pharmacist-driven effort, but the intervention offered to employees also included other inducements to improve care: a free

glucose meter, waiver of copayments for testing supplies and medications, and the ability to meet with a certified diabetes educator (CDE) (Cranor, Bunting, & Christensen, 2003; Cranor & Christensen, 2003). Although only 85 patients were included in the first two studies reporting results from the project, researchers found a statistically significant reduction in A1c after only seven to nine months of follow up (Cranor & Christensen, 2003) that moderated yet persisted over time (Cranor et al., 2003). The authors report that the intervention did not significantly increase the cost of healthcare, and conclude that pharmacists engaged in the Asheville Project produced clinically relevant changes in employees' health and saved money for the city over the long term (Cranor et al., 2003; Cranor & Christensen, 2003). This suggests that community pharmacists are capable of addressing medication related health concerns for patients with diabetes and thereby add value to the healthcare system. A further evaluation using the same design and setting but for employees with hypertension, dyslipidemia and asthma came to roughly the same conclusions (Bunting & Cranor, 2006; Bunting, Smith, & Sutherland, 2008).

One aspect that sets all of these studies apart from the previously mentioned APhA Foundation studies is the use of medical and pharmacy claims to calculate real differences from baseline instead of reporting differences with projected costs. Furthermore, they are good examples of how a service can be implemented in a community pharmacy. For these reasons, they do make a substantial contribution to the literature. One cannot, however, read the studies and be assured of the link between the changes to outcomes and actions by the pharmacists involved. First, the studies all employ a quasi-experimental design with two intervention cohorts and no control group. To increase power, results from both cohorts are pooled even though the cohorts differ with respect to age, gender mix and educational status and were first eligible for enrollment in different years (Cranor & Christensen, 2003). This is less of concern in the short term as the clinical and economic results are more or less an averaging of the effect of the intervention across the two cohorts. However, with the different starting times for the enrollment

period, the right-truncated design of the long term outcomes study means that as time progresses, the make-up of the eligible set for each time is made up more and more of the City of Asheville cohort. If the City of Asheville differed from the Mission Hospital cohort with respect to any of the outcomes, this would bias the interpretation of results over time.

Furthermore, lack of a control group leaves the studies open to substantial sources of bias. First, this study was likely implemented in reaction to the employers' observation that their costs for their employees with diabetes had increased substantially in the years leading up to the study. This leaves open the possibility of regression to the mean as costs for care of employees with diabetes returned to baseline levels. Also, lack of a control fails to account for any historical effects that could influence the population's care independent of the study intervention. This effect is somewhat mitigated through the two year time offset between cohorts, but the possibility remains. Selection effects may also plague this study, as results are only reported for those employees with diabetes that chose to enroll in the intervention. These employees likely differ systematically from their diabetic peers with respect to desire to control their disease and receive healthcare services. This could independently impact their clinical and economic outcomes.

Finally, the intervention was not a pharmacist-only intervention, yet the results are ascribed to the impact of community pharmacists alone. In addition to access to pharmacist provided MTM, the intervention included access to a CDE, a free blood glucose meter, and free medications (Cranor et al., 2003; Cranor & Christensen, 2003). Economic theory and several studies of value based insurance designs suggest that reducing copayments increases medication adherence (J. L. Lee, Maciejewski, Raju, Shrank, & Choudhry, 2013). Better medication adherence, as described in section 2.b.1, improves clinical outcomes. This occurs independent of the effect of pharmacists. A better design for the purposes of identifying pharmacist effect would have been enrollment and randomization to one arm with a CDE, free glucose meter and free medication section and another arm with the elements of the first arm plus meetings with a

pharmacist. This would give a clearer picture of the impact of pharmacists on healthcare quality and costs, although larger enrollment would have been required to achieve sufficient power.

Flaws in the design of these studies of employees with diabetes are also found in the Asheville Project studies on employees with hypertension, dyslipidemia and asthma (Bunting & Cranor, 2006; Bunting et al., 2008). These studies are considered by some in the profession to be the final word on pharmacists' impact on patients' health, yet issues with the design and evaluation of the intervention make it difficult to parse out pharmacists' impact from that of other elements of the intervention and to separate the effect of the intervention from potential sources of bias. Thankfully, there is other literature relevant to answering the question.

2.c.1.3 Evidence from Well Designed Studies is Sparse but Generally Positive

Most outpatient studies of US pharmacists' impact on their patients' health are conducted using pharmacists in ambulatory care clinics (Cutrona et al., 2010; Santschi, Chiolero, Burnand, Colosimo, & Paradis, 2011; Viswanathan et al., 2015; Wang, Yeo, & Ko, 2015). These studies typically conclude that pharmacists are effective in improving patient care, but few pharmacists work in ambulatory care and the work environment for ambulatory care pharmacists is very different than for community pharmacists (Doucette WR, 2014). Some well-designed studies evaluate community pharmacists' skills, but create such unique study environments that it is unlikely the results are valid for community pharmacists practicing in a typical setting (e.g., Chrischilles et al. (2014)). Others are useful for guiding the implementation of pharmacists services but assess subjective, surrogate healthcare outcomes like the medication appropriateness index (Hanlon & Schmader, 2013) and include no randomization or relevant control group (e.g., Witry, Doucette, and Gainer (2011), Doucette, McDonough, Klepser, and McCarthy (2005), Chrischilles et al. (2004)). These studies are useful for pharmacists implementing services but are

less useful for answering the question of whether or not community pharmacists can improve their patients' health.

To investigate the impact of pharmacist-provided MTM in the outpatient setting, the Agency for Healthcare Research and Quality commissioned a systematic review of the literature (Viswanathan et al., 2015). The authors included all studies of pharmacist-provided MTM as of January 4th, 2014 and excluded any condition-specific studies (e.g. studies only including patients with diabetes focusing on lowering A1c) and found 44 studies that met their criteria. Of these, only nine showed conclusive benefit from MTM interventions by pharmacists for outpatients and none of these nine studies included community pharmacists exclusively. One of the studies suggesting benefit was the previously reviewed study of MTM commissioned by CMS (Perlroth et al., 2013). Viswanathan and colleagues found substantial heterogeneity between the studies, but were still able to conduct a meta-analysis using the results of six studies and found that there was no pooled impact of pharmacists on outpatient visits or hospitalizations. There was, however, found to be some effect of pharmacist-provided MTM on adherence, quality of prescribing and hospitalizations in results of some single studies but no effect on patient satisfaction and health-related quality of life. The authors attempted to evaluate other medication and health related outcomes of pharmacist-provided MTM, but concluded that studies were insufficient to provide evidence according to the authors' standards.

This report suggests that there isn't sufficient evidence to conclude that community pharmacists can impact their patients' health via comprehensive MTM. The report is not all-inclusive, however, and excludes several studies involving pharmacists focused on specific conditions (J. K. Lee, Grace, & Taylor, 2006; Nola et al., 2000; Planas, Crosby, Farmer, & Harrison, 2012; Zillich, Sutherland, Kumbera, & Carter, 2005), two studies assessing effectiveness of appointment based medication synchronization (D. Holdford & Saxena, 2015; D. A. Holdford & Inocencio, 2013), a study on transitions of care (Luder et al., 2015) and several

more recent, large trials of community pharmacists providing abbreviated MTM interventions (Brennan et al., 2012; Fischer et al., 2014; Pringle et al., 2014). These studies have more rigorous designs than the APhA Foundation's Project ImPACT and Asheville Project studies and find favorable evidence for the impact of pharmacists on their patients' health.

In a 6 month randomized control trial, Nola et al. (2000) evaluated a community pharmacist's impact on LDL, HDL, and cardiovascular risk factors for 51 outpatients with risk factors for coronary artery disease and elevated LDL. The intervention took place at one community pharmacy. All patients received a cholesterol test performed by a licensed nurse before and after the intervention period. The 26 patients randomly selected for the intervention group also received education on lifestyle modifications, an additional cholesterol check at the study's midpoint, physician referrals for pharmacist-determined changes in drug therapy, and monitoring of any newly started medications. The researchers found that, compared to patients in the control group, patients in the intervention arm after the study had no significant differences in their LDL, HDL or risk factor score but did have greater rates of initiation for new therapy. It is possible that the study period was not long enough and the sample not large enough to detect the impact of the pharmacist's intervention, but the most straightforward interpretation of the results is that this six month intervention was not successful in improving meaningful health outcomes.

Another condition-specific randomized control trial, this time studying patients with hypertension, was conducted by Zillich et al. (2005). A convenience sample of twelve pharmacies was chosen for the study and pharmacies were randomized to high-intensity (HI) and low-intensity (LI) intervention arms. The HI arm consisted of four pharmacist-patient visits over three months wherein pharmacists provided education about hypertension, how to measure blood pressure, lifestyle modifications to lower blood pressure, and made recommendations for changes to therapy to better control blood pressure. Sessions lasted 15-60 minutes and pharmacists faxed physicians recommendations for medication changes. All patients in the HI arm were also

provided a free blood pressure cuff. For the LI arm, patients met with pharmacists to measure blood pressure three times in three months, didn't received enhanced education, and were told to talk with their physician about any abnormal blood pressure results. LI patients were not provided with a free blood pressure monitor. Primary outcomes for the study were changes in systolic and diastolic blood pressure. Secondary outcomes were medication additions and dose changes.

Pharmacists enrolled 58 patients into the HI and 80 patients into the LI arm. One patient dropped out of the HI arm and no patients dropped out of the LI arm. At the end of the study period, the HI group's diastolic blood pressure was significantly lower than the LI group's but systolic blood pressure was not. Patients in the HI group also had substantially more medications started and dosages increased than patients in the LI group. Findings from this study suggest that community pharmacists can significantly reduce patients' diastolic blood pressure through medication optimization. This was a shorter intervention period than the Nola et al. study, but effects on blood pressure control do not take as long to manifest as changes in cholesterol levels.

A three phase randomized control trial involving federal outpatient pharmacists working at the Walter Reed Medical Center was more ambitious in scope than the previous two studies and engaged a very different patient population (J. K. Lee et al., 2006). Patients were required to be elderly and on multiple chronic medications to be considered for the study. During the two month run-in phase, patients' baseline blood pressure, LDL and adherence were evaluated. For the six month phase one, medications for all patients were confiscated by the study team and bubble-packed such that each day's medications were included in a separate compartment designed to be punched out of a card. Also, all phase one participants met with a clinical pharmacist for 30-60 minutes every two months. At the conclusion of the phase one, patients were randomized to continue enhanced care for an additional six months or switch back to usual care. A total of 200 patients were recruited into the run-in phase, 174 continued to phase one and 159 were randomized in phase two with 76 patients assigned to usual care and 83 to continue

advanced pharmacy care. Outcomes for the study were medication adherence, blood pressure control and LDL.

The study found that, compared to the run-in phase, adherence increased significantly for all patients in phase one. For the patients reassigned to usual care for phase two, adherence returned to baseline but higher adherence was maintained for patients in the continued intervention arm. Systolic blood pressure was also improved between run-in and phase one, as well as between phases one and two. There was no difference between phase one and phase two for diastolic blood pressure and LDL. These results suggest that there is benefit from an intervention consisting of an adherence aid (bubble packed medications) and counseling by pharmacists, but that effects on adherence from this intervention, when delivered for only six months, do not persist. This study adds further evidence that pharmacists can impact their patients' health, but a significant flaw is that pharmacist counseling was never evaluated separately from the adherence aid. Therefore, it is impossible to say which intervention had a more significant impact on adherence.

A fourth study included pharmacists working for a small chain of pharmacies in Oklahoma who participated in a nine month randomized controlled trial evaluating pharmacist management of patients with diabetes (Planas et al., 2012). There were 27 patients randomized to the control arm, consisting of baseline, three, six and nine month evaluations by pharmacists of the patients' A1c, blood pressure and LDL. The intervention arm included 38 patients and consisted of monthly visits wherein pharmacists evaluated A1c, LDL, blood pressure, addressed drug therapy problems when appropriate and provided education on disease states and lifestyle modifications. To prepare for the intervention, study pharmacists received three days of training. Primary outcomes of interest were changes to and clinical goal attainment for A1c, LDL and blood pressure. Univariate assessment of differences between control and intervention cohorts found that the pharmacist intervention significantly lowered systolic blood pressure and A1c as

well as increased the percent of patients at goal for both markers. Substantial demographic differences existed between control and intervention cohorts, however, and the small sample size did not allow for statistical adjustment. Therefore, although these results are positive, little evidence useful for answering the primary question can be gleaned from this study.

Another study involving chain pharmacists tested an intervention aimed at reducing hospital readmissions through MTM sessions provided at the time of care transition from the hospital to home (Luder et al., 2015). Nine Kroger pharmacists from around Cincinnati were trained to provide targeted MTM sessions to patients discharged within 72 hours from one of two small, regional hospitals. Patients could choose either pharmacist care or usual care, and by the end of enrollment 30 patients chose the pharmacist and 60 chose usual care. The intervention and control were relatively well balanced, and in a multivariate assessment of readmission at 30 days, patients enrolled in the pharmacist arm had significantly lower odds of readmission (OR 0.072, CI 0.008-0.628). Odds of a 30-day ED visits and a composite hospitalization and ED visit measure were not significantly different. The lack of randomization is concerning, as the possibility exists that the results are confounded by more engaged patients opting to engage in the pharmacist intervention, but the results nevertheless show promise for the possibility of pharmacists to lower readmission rates.

The numbers of patients enrolled in the previous studies ranged from 51 to 200 and took place in independent community pharmacies or small to medium sized pharmacy chains. These studies provide examples of pharmacists' impact on their patients' care, but they do not provide strong evidence that the average pharmacist, through the course of their typical day, can positively impact their patients. All of these interventions required some level of training for pharmacists, who then in turn provided a specific advanced service to patients. This has shown benefits, but the time it takes to provide these services remains a persistent barrier to uptake. To help create better opportunities to provide services, a practice concept called appointment-based

medication synchronization (ABMS) has been developed. ABMS involves identifying an anchor prescription around which fills for all other prescriptions are aligned (D. A. Holdford & Inocencio, 2013; National Community Pharmacists Association, 2013). Once the date has been set and fills adjusted, the patient then has a once a month or once a quarter appointment at the pharmacy to receive medications and discuss any medication related concerns. The patient-pharmacist conversation can either be casual and unstructured, similar to a typical prescription pick up counseling session, or a more formal MTM session aimed at identifying and resolving drug therapy problems. ABMS is often facilitated by commercial software, such as Simplify My Meds, that help to with fill synchronization and patient management (National Community Pharmacists Association, 2013).

Two studies by Holdford suggest that ABMS can be effective in improving adherence and persistence. The first, taking place among Thrifty White pharmacies in the upper Midwest, matched patients opting to enroll in ABMS with patients not enrolled in ABMS between June 30, 2011 and October 31, 2012 (D. A. Holdford & Inocencio, 2013). The aim was to assess the impact of ABMS on adherence, using the 80% PDC cut-off, and nonpersistence, identified as gaps in therapy greater than 30 days. Adherence and nonpersistence were compared across six drug classes, and the number of ABMS-enrolled and not enrolled patients with fills in each class ranged from 47 – 564. Odds of adherence for patients enrolled in ABMS were 3.4 – 6.1 times greater than patients not enrolled in ABMS and hazard ratios for time to nonpersistence were 0.27 – 0.48, depending on drug class. All comparisons were significant at $p<0.01$.

A second study by Holdford comes to similar conclusions on the effectiveness of ABMS using pharmacists from a different chain and patients with chronic medications (D. Holdford & Saxena, 2015). This study assessed adherence and persistence to chronic medications resulting from an ABMS program implemented by Ohio pharmacists under the employ of Discount Drug Mart, Inc. The analysis period ran between March 1, 2013 and February 28, 2014 and included

patients who had opted in to ABMS before March 1, 2013. Across six medication classes assessed, sample sizes for ABMS enrolled patients ranged from 140 to 600 and matched comparators ranged from 418 to 1,133. Researchers found that odds of adherence for patients enrolled in ABMS were 2.3 – 3.6 times greater than matched comparators and hazard ratios for time to nonpersistence ranged from 0.39 – 0.67, with all comparisons significant at $p<0.01$.

Results from ABMS studies suggest that pharmacies can revise their workflow to support greater adherence and persistence. Some concern does exist for the potential of selection effects relating to patients opting in to ABMS services, but it is hard to conceive of how this could be avoided. A larger concern for interpreting these results is that benefits of ABMS on adherence and persistence due to synchronization cannot be disentangled from effects due to enhanced counseling and MTM. Indeed, it is entirely possible to implement ABMS and maintain usual care for prescription counseling. As evidence of this, Holdford's second study refers to counseling as an opportunity to "speak with the pharmacist as needed (D. Holdford & Saxena, 2015)." Synchronization alone could improve adherence and persistence, and as such one should be cautious and not over-emphasize the effect of the pharmacist in results from ABMS implementation.

The next three cohort studies reviewed are much larger, include pharmacist-focused interventions, take place in large chain community pharmacies, and include 5,123 to 121,155 patients in the intervention arm (Brennan et al., 2012; Fischer et al., 2014; Pringle et al., 2014). In the first study, CVS/Pharmacy used prescription claims to identify employees of a Midwest manufacturer who, in 2009, had filled a prescription for a medication used to treat diabetes (Brennan et al., 2012). The intervention arm included twelve CVS pharmacies and a mail order pharmacy. Matched with these intervention patients was a cohort of patients who also used CVS community or mail order pharmacies but were not employed by the manufacturer. The six month intervention was analogous between community and mail order pharmacies and included a

welcome letter announcing to employees that they were enrolled in the program, an offer of a free glucose meter, a call from a pharmacist if they were late on a refill, counseling about starting an ACEI/ARB or statin if the patient didn't have a fill history for either of those medications, a contact to the doctor about starting the medication (if the patient consented), and counseling and later follow-up if a new prescription was written. There were 1,101 patients in the community pharmacy cohort and 4,022 in the mail order pharmacy cohort. Outcomes for the study were adherence to diabetes medications and initiation rate of new ACEI/ARB and/or statins.

The study found that the intervention significantly improved adherence by 2.6% during the six months it was active, and that the mean adherence remained greater than the control group for six months following the intervention. There were also significant positive effects on ACEI/ARB and statin initiation with rates in the intervention group exceeding controls by 39% and 22% respectively. Effects on adherence were more than twice as large for community pharmacists as they were for mail order (3.9% difference vs. 1.7% difference). Also, the ACEI/ARB initiation rates for the community pharmacy intervention cohort were 68% higher than community pharmacy controls, and statin initiation was 67% higher. Initiation rates for mail order pharmacies were only 31% and 9% higher than controls. This suggests that a structured, focused intervention by community pharmacists can impact patients' health, and that a face-to-face intervention involving a community pharmacist may be more effective than an intervention involving a mail order pharmacist.

A second study conducted with CVS pharmacists focused on reducing primary medication nonadherence (PMN) (Fischer et al., 2014). CVS implemented two interventions to address PMN. The first consisted of an automated system with reminders for medication pick up and, if the first intervention was not successful, a call from a pharmacist eight days after the initial fill for a new prescription. The intervention and control groups were drawn from patients at any CVS pharmacy who also had Caremark for a pharmacy benefits manager. The control group

was comprised of patients with one of eight randomly chosen birthdates who never received the intervention. The intervention was applied to all other patients who failed to pick up a new prescription eight days after filling. The authors found that of the prescriptions left unfilled at eight days, 36.9% were eventually abandoned (returned to stock) for the intervention group compared to 41.7% for the control group. This difference was statistically significant, and the greatest significant difference within medication classes was for β-blockers, followed by diuretics. Training for pharmacists to provide this intervention was minimal and the intervention was incorporated into the pharmacists' daily work routine. Unfortunately, no long term follow up was performed, but this provides further evidence that a brief intervention by pharmacists may improve patients' health.

Importantly, these CVS/Pharmacy interventions were conducted with pharmacists as a part of their normal, daily routines. Significant differences were found without requiring a pharmacist to sit down with patients for 15-60 minutes and review the complete medication profile. A similar philosophy of intervention and practice change was employed in a study of pharmacist interventions at Rite-Aid pharmacies in Pennsylvania (Pringle et al., 2014). In this twelve month cohort analysis, 107 Rite-Aid pharmacies from a district in Pennsylvania were chosen for an intervention and 111 pharmacies were chosen from a geographically distant Pennsylvania district to serve as comparators. To enhance comparability, propensity score matching was used to match patients on a 1:1 basis. Patients receiving one of five medication classes, calcium channel blockers, oral antidiabetic drugs, statins, β-blockers and ACEI/ARB, at intervention pharmacies were screened for potential nonadherence using an adherence estimation instrument. If the potential for nonadherence was discovered, patients were engaged in a 2-5 minute adherence-focused conversation that used principles of motivational interviewing. Study coordinators taught the regional managers who in turn taught the pharmacists in the intervention group how to deliver the brief screening and intervention. To track their progress, pharmacies

were given online access to their own scores for adherence calculated using PQA's metrics for percent of days covered. The main outcomes of the intervention were 1) patient achievement of the 80% threshold for adherence using PQA's PDC metric and 2) healthcare costs using sums of allowable charges over the year-long study period.

The screening and brief intervention successfully improved adherence for all medication classes over the year-long course of the study. The smallest change was observed for β-blockers where 3.1% more patients met the 80% PDC threshold in the intervention group compared to controls. Oral antidiabetic drugs had the largest increase at 4.8%. In a sub-analysis, the authors found that approximately 75% of the observed difference in adherence for the intervention group vs. control was from non-adherent patients crossing the 80% threshold. The remaining 25% of the difference was from more patients in the intervention group staying adherent than in the control group. Per-patient healthcare annual costs remained unchanged for calcium channel blockers, β-blockers and ACEI/ARB, but were $241 lower for patients taking statins and $341 lower for patients taking oral antidiabetic drugs. Differences in costs for drugs across all five classes were minimal, and savings were driven by reductions in emergency department and inpatient costs for statins and emergency department savings for oral antidiabetic drugs. Although more than 40% of patients enrolled had commercial insurance, no breakdown was given for results by insurance type.

Results from the CVS and Rite-Aid studies are important for answering the question of whether pharmacists can impact their patients' health. Large chain community pharmacies employ more community pharmacists than any other setting and are the most stressful, busiest work locations with the fewest average opportunities for clinical patient care services (Doucette WR, 2014). Despite this, pharmacists in these settings were able to add a service that created observable differences in adherence, the addition of beneficial medications, and the cost of healthcare. Evidence from smaller studies is also important as it suggests that more advanced

services can also be implemented and improve patients' health, but results from these studies are less generalizable.

The evidence to answer the primary question of this section, "Can community pharmacists impact their patients' health?" is neither plentiful nor universally positive, but it is sufficient to suggest that, at the least, when the intervention is structured appropriately and the environment is supportive, community pharmacists have the ability improve their patients' health. The next question to ask is, "Are pharmacists improving their patients' health?" To assume that a system of quality and cost assessment can appropriately identify high value pharmacies, one has to know that there are pharmacists actively creating value for insurers.

2.c.2 Are Community Pharmacists Impacting their Patients' Health?

Evidence from the preceding section suggests that, given the right circumstances, pharmacists can positively impact their patients' healthcare quality and reduce the cost of healthcare. Results from smaller trials suggests that if pharmacists receive enhanced training and provide 15-60 minute long MTM-like sessions, programs can be implemented which show positive results on surrogate healthcare outcomes in less than a year. Evidence from larger trials in chain pharmacies suggests that these longer sessions and enhanced training may not be necessary for the pharmacist to impact nonadherence and underprescribing. Combined, this evidence suggests that pharmacists *can* create value in the healthcare system, but a more important question remains—*are they*? At a basic level, accurate checking and dispensing of medications adds value, but is this beyond that which a mail order robot adds? Phrased differently, are there pharmacists going above and beyond minimum legal and societal expectations by providing exceptional patient care, optimizing medication use and creating value by improving healthcare quality and reducing costs?

Doug Hepler, reflecting on his and Linda Strand's idea of pharmaceutical care, in his 2010 Whitney Lecture called the goal of universal clinical practice of pharmacy the profession's "dream deferred (Hepler, 2010)." In many ways, pharmaceutical care of the 1990s created more excitement than lasting change. There are examples, some of which are described in the preceding section, by which pharmacists changed their practice in response to and in accordance with this new philosophy. All in all, however, the goal of transforming every pharmacist's primary work function to be to improve patients' quality of life has not been attained. OutcomesMTM, a major payer for pharmacist-provided MTM services, had more than 2.4 million claims in 2015 (OutcomesMTM, 2016). This impressive figure is larger than years prior (OutcomesMTM, 2015), but is still less than a claim a week for the 50,000 pharmacists actively engaged in the OutcomesMTM network. Although the percent of time spent in patient care services is growing, less than 15% of the average community pharmacists' time is spent providing clinical services not associated with dispensing (Doucette WR, 2014). The typical community pharmacist still spends the vast majority of his or her time fulfilling basic medication dispensing tasks. One study described the usual practice of pharmacy thusly:

> "Standard care consisted of accurate interpretation and filling of prescriptions *and infrequent, nonsystematic counseling* on the medication *that might address* drug-drug interactions, preventing adverse events, encouraging appropriate medication use, and counseling on the disease state." (Pringle et al. (2014), emphasis added)

Consistent with this description, the California Board of Pharmacy found that pharmacists employed by Rite Aid, CVS, and Walgreens have all routinely failed to uphold their duties to counsel patients on new or changed prescriptions (San Diego County Office of the District Attorney, 2015). If this is the standard of practice for most pharmacists, are pharmacists providing value beyond fulfilling a dispensing role? Suggesting not and supporting the idea of

limited pharmacy networks, in 2012 George Paz, former CEO of Express Scripts stated the following:

> "At the end of the day…Nexium is Nexium, Lipitor is Lipitor, drugs are drugs and it shouldn't matter that much who is counting to 30." (Express Scripts, 2012)

The National Association of Chain Drug Stores and the National Community Pharmacists Association both issued comments opposing this remark, emphasizing pharmacists' role in patient care and questioning the value of pharmacy benefits managers (PBMs) like Express Scripts (National Association of Chain Drug Stores, 2012; National Community Pharmacists Association, 2012b). This is a necessary role for these organizations. They serve as advocates for what pharmacy wants to be, but not necessarily what pharmacy is.

Nevertheless, community pharmacists do have the ability to impact patients' health and increasingly pharmacies are reorganizing to facilitate advanced pharmacist-patient interactions. The desire to help others is a major motivator for pursuing a PharmD (Keshishian, 2010), and assuming this desire is not eliminated by the time pharmacists enter practice, the average pharmacists' satisfaction depends in part on their ability to help their patients. There is little doubt that the trajectory of pharmacy practice is towards a universal clinical approach, but the slope of the curve is not as steep as previously thought.

The accumulated literature and changes to pharmacy education and practice suggest that it is extremely likely there are pharmacists who, through medication optimization, improve their patients' health and create value for the healthcare system. As described above, however, pharmacists making this difference are likely to be in the minority. As a part of healthcare modernization, there is a call by healthcare practitioners and policymakers to reward healthcare practitioners for the value that they create. This call has also been issued by pharmacists for pharmacy (Brown, 2009). If there are pharmacists providing exceptionally valuable services and

making a difference in their patients' health, they should be rewarded for their efforts. These rewards also provide incentives for other pharmacists to enhance their service offerings. Before such a system can be created, though, one must first understand the variation in value that currently exists. For non-pharmacist healthcare providers, this is accomplished by systems of value assessment using quality metrics.

2.c.2.1 Measuring Value for Non-pharmacist Healthcare Providers.

By 2018 CMS plans to transition 90% of all fee-for-service payments to quality or value modified systems of reimbursement and 50% of all payments to alternative payment models, including accountable care organizations and bundled payments (Burwell, 2015). Value modified payment models do not attempt to prescriptively change the way care is delivered to increase value in the healthcare system; they recognize that variation in value exists and reward high performers to incentivize change among lower performers. Alternative payment models are important tools in enhancing value in the healthcare system, but this section focuses on quality or value modifications to fee-for-service systems that are being used to adjust payments to primary care physicians. As pharmacies are paid fee-for-service for dispensing medications, a discussion of these quality or value modified systems is more germane to this dissertation than a broad discussion of alternative payment models.

In 2015, CMS created the value-based payment modifier (VBPM) for Medicare payments to physicians. In establishing this new program to incentivize quality, CMS built upon the existing physician quality reporting system (PQRS) under which eligible healthcare practitioners and group practices send quality related information directly to CMS. Eligible practitioners include physicians, nurse practitioners, physician assistants, physical therapists and other ancillary health professionals but not pharmacists (Centers for Medicare and Medicaid Services,

2015d). Only physicians are eligible for the VBPM, however. The PQRS began as a pay-for-reporting system in 2007 under the label "physician quality reporting initiative" (Stulberg, 2008) and has evolved to encompass nearly 200 metrics from which individual practitioners and group practices can choose to report quality information to CMS (Centers for Medicare and Medicaid Services, 2016b). Requirements vary by individual vs. group practice but all participants must report nine metrics covering at least three National Quality Strategy domains for at least half of eligible Medicare patients (Centers for Medicare and Medicaid Services, 2015b). Failure to participate in 2015 results in a 2% decrease in reimbursement for CMS for payments to be made in 2017 (Centers for Medicare and Medicaid Services, 2015r).

The VBPM only applied to physician groups of 100 or more for CY 2015, but by 2017 all physicians except those enrolled in Medicare sponsored ACOs will be included in the VBPM (Centers for Medicare and Medicaid Services, 2015i). Physician value is assessed by measuring quality and cost. The highest value physicians are those who, compared to their peers, have significantly higher quality and lower associated healthcare costs. Moderately high value physicians have either higher quality and average costs or average quality and lower costs. The lowest value physicians have significantly lower quality and higher costs, and moderately low value physicians have either lower quality and average costs or average quality and higher costs. This trade-off system is an example of balancing cost and quality to measure value. Differences between cost and quality categories are defined by standard deviation above or below the group mean for composite quality and cost scores (Centers for Medicare and Medicaid Services, 2015k).

For 2016, the lowest quality physician groups will face a 2% reduction in Medicare payments and moderately low quality physicians a 1% reduction (Centers for Medicare and Medicaid Services, 2015i). To maintain budget neutrality, penalties applied to lower value physician groups will be used to fund bonuses to higher performing groups. An adjustment factor

is calculated to distribute payments between higher value providers, and the highest value providers—those with high quality and low costs—receive their normal payments plus two times the adjustment factor. Moderately high value providers will receive a bonus of one times the adjustment factor.

Under the VBPM, each year's quality bonuses are based on clinical information from two years prior. For 2015, physician groups could elect either a neutral evaluation option wherein they received no penalties or bonuses based on value, or a full risk model where payment could be adjusted up or down (Centers for Medicare and Medicaid Services, 2015c). There were 691 group practices with more than 100 physicians that participated in the PQRS in 2013 that were therefore eligible for participation in the full risk VBPM model for 2015. Of these, 106 groups elected the full risk model, and 14 had above average value and 11 were below average. The adjustment factor for payments made to higher value groups was 4.89, meaning that these groups received a 4.89% payment bonus. There were no group practices in the highest value group. Opting out of the full risk model is not an option for groups with 100 or more physicians for 2016. It is too soon to evaluate the impact of this system on physician quality, but CMS is clearly hoping that incentives as large as those being given out for the VBPM program will push physician group practices to improve quality and lower cost.

CMS's efforts are being mirrored in the private sector, but information on programs from private insurers is much more difficult to find and details are sparse. A large initiative in California coordinates pay-for-performance incentives for seven commercial health plans representing nearly 10 million lives and has paid out more than $450 million in incentive payments since 2004 (Kessell et al., 2015). Michigan Blue Cross Blue Shield (BCBS) is partnering with nearly 20,000 physicians to create the Physician Group Incentive Program (PGIP), an initiative to increase quality and decrease cost (Blue Cross and Blue Shield of Michigan, 2015c). Michigan BCBS modified its fee-for-service system such that all participating

physicians give a portion of their income to a central pool, and disbursements from this pool are made according to physicians' ability to improve quality and lower costs. Quality is measured using a combination of nineteen quality metrics, ranging from measures on control of chronic disease to adherence and prevention (Blue Cross and Blue Shield of Michigan, 2016). The incentive program is cost neutral for Michigan BCBS and the entire value based program, of which the PGIP is a part, is purported to have saved $1.4 billion in healthcare expenses between 2005 and 2015 (Blue Cross and Blue Shield of Michigan, 2015a). Other BCBS plans, including Iowa's Wellmark BCBS, are also implementing quality measurement programs for physicians (Blue Cross and Blue Shield Association, 2014; Wellmark Blue Cross and Blue Shield, 2016). Some states are even crafting state-wide initiatives and bringing together health plans, medical groups and hospitals to focus on increasing healthcare value within the state (Dade, 2015). As a part of moving away from a pure fee-for-service system, value based payment models are becoming more common for physicians in both public and private plans.

2.c.2.2 Measuring Value Created by Community Pharmacists

There is increasing recognition in the healthcare system that the variation in value between healthcare practitioners can be measured and that incentives can be created for practitioners to improve their practice and contribute more value. Large initiatives as described above hold promise in bending the cost curve and putting the cost and quality of the US healthcare system in greater alignment with that of other industrialized nations, but all of these large initiatives leave out community pharmacies. The potential quality improvement and savings from more optimal medication use is substantial, yet pharmacists are almost never included in value-based systems. Where pharmacist inclusion does exist, it often is in the form of new hires

working in ambulatory care clinics (Blue Cross and Blue Shield of Michigan, 2015b; M. Smith, Bates, Bodenheimer, & Cleary, 2010).

CMS does not have the same ability to incentivize pharmacies to improve value as they do for physicians. CMS does not directly pay pharmacies through Medicare but works through private intermediaries which operate Part D prescription drug plans. CMS has created the Star Rating system of quality evaluation for Part C and D plans, but putting pressure for quality improvement on private intermediaries cannot be as effective as directly modifying reimbursement through the fee-for-service payment system as CMS has done through Part B.

As previously described, it is more difficult to discover details of value-based programs for private insurers than it is for public insurers. Nevertheless, there is some information available on the nascent value-based payment models for community pharmacies. Nearly all private insurers that operate Part C and D plans are subject to quality measurement by CMS, and this creates incentives for these private plans to maximize the value created by their community pharmacy network. In 2016, Part C plans without an associated drug plan have 32 quality metrics, and Part C plans with drug plans (MA-PD) have an additional fifteen metrics (Centers for Medicare and Medicaid Services, 2015p). Part D standalone plans (PDP) have fifteen quality metrics. New for 2016, the completion rate of comprehensive medication reviews as a part of the MTM program is included as a quality metric for MA-PD and PDP plans. Scores on these metrics are aggregated into a 5-star rating system which is displayed on the Medicare Plan Finder web site when seniors make plan decisions for Part C and Part D plans. Additionally, attaining a star level of 4 or greater results in bonus payments for Part C plans.

The Star Rating system creates incentives for Part C and D plans to increase quality, and there is a recognition that community pharmacists may be able to improve ratings (Academy of Managed Care Pharmacy & American Pharmacists Association, 2014). The Part D star rating

metrics with the largest weights were all developed by the Pharmacy Quality Alliance (Centers for Medicare and Medicaid Services, 2015n) and are incorporated in Pharmacy Quality Solution's (PQS) Electronic Quality Improvement Platform for Plans and Pharmacies (EQuIPP) platform (Academy of Managed Care Pharmacy & American Pharmacists Association, 2014; EQuIPP, 2016). Created as a part of the Pennsylvania Project with Rite-Aid pharmacies (Pringle et al., 2014), EQuIPP tracks prescription claims data for more than 55% of Medicare beneficiaries and, in some states, more than 80% of enrollees in MA-PD plans (EQuIPP, 2015b). Nearly 90% of all community pharmacies in the US are EQuIPP subscribers.

MA-PD and PDP plans are using EQuIPP data to track pharmacy quality and reward high performing pharmacies. In a blog post, an independent community pharmacist described a pay-for-performance system used by a PDP to evaluate and reward quality at his pharmacy (Deninger, 2015). The pharmacist was enthused to see that his pharmacy beat many of the benchmark scores on EQuIPP, but disappointed to see that the quality bonus payment received by the pharmacy only amounted to $20/patient-year. Complementing a bonus payment strategy, one may soon see a preferred network strategy based not on a prescription cost reduction strategy with pharmacies pay plan sponsors to be in the network but on a quality maximization strategy wherein higher quality pharmacies are preferred over lower quality pharmacies (Nau, 2015). Some MA-PD and PDP plans believe that community pharmacies are providing exceptional value to their beneficiaries and payers are interested in creating quality bonus systems (Academy of Managed Care Pharmacy & American Pharmacists Association, 2014; Nau, 2015). Express Scripts, for example, has collaborated with a MA-PD plan sponsor to create a pay-for-performance pharmacy network and touts benefits including reduction in high-risk medications, improvements in delivery of guideline recommended care for diabetes and adherence (Express Scripts, 2015). Unfortunately, details are only available in the form of a $337 report (Atlantic Information Services, 2016). If this network were implemented by CMS instead of a private intermediary all

information would be more freely available. There is potential for high quality networks in Medicare, but the rollout has been slow, specifics scarce, and payments meager.

Medicaid programs are also starting to experiment with evaluating and rewarding pharmacy quality. A rudimentary program operated by Sunflower Health Plan, a Medicaid managed care plan out of Kansas, recently started rewarding pharmacies accredited through the Center for Pharmacy Practice Accreditation with a $0.50 greater dispensing fee on every prescription (Sunflower Health Plan, 2016). A more robust design implemented in 2013 by another Medicaid managed care plan, Inland Empire Health Plan (IEHP), uses six PQA metrics and generic dispensing rate to evaluate and reward value provided by all 1,904 pharmacies in its network with annual prescription volumes greater than 1,000 (Inland Empire Health Plan, 2014, 2015a). Pharmacies receive payment bonuses based on a star rating system, and IEHP is creating a high-performing network with its top providers starting 2016.

Another Medicaid managed care organization, Community Care of North Carolina, has created a high performing pharmacy network. Funded by a $15.1 million grant from the CMS Innovations Center, CCNC has developed one of the most robust pharmacy value based payment models in the country (CMS Innovations Center, 2016; Trygstad, 2015). CCNC connects high performing pharmacies with a medical neighborhood for the purpose of improving quality and decreasing costs for its members (Trygstad, 2015). In exchange for participating in the network, pharmacies receive small, fixed capitated per member per month (PMPM) payments in addition to fee-for-service payments for MTM-like visits and an additional quality modified capitated rate. There were 255 pharmacies participating in the network as of 10/1/2015 and CCNC has observed substantial decreases in hospital admissions, readmissions and emergency department visits as a result of the program. No peer reviewed studies have yet been published on the results of this pharmacy VBPM. CCNC's system of evaluation and rewards for pharmacy quality is closer than

any other to the highly complex and comprehensive systems of provider reimbursement used by CMS.

Private payers are also experimenting with pharmacy VBPMs. The Wisconsin Pharmacy Quality Collaborative (WPQC), a group of 377 pharmacies in Wisconsin, has partnered with at least five commercial insurers with the aim of improving healthcare quality and decreasing total healthcare costs (Johnson, 2013; Trapskin, Johnson, Cory, Sorum, & Decker, 2009; WPQC, 2016). Boasting a 2.5:1 to 43:1 ROI, pharmacies are paid for providing two levels of service. Level 1 consists of short, specific medication conversations (Johnson, 2013) that are analogous to the interventions from the Pennsylvania Project (Pringle et al., 2014). Level 2 interventions are full MTM visits, similar to those provided through MA-PD and PDP plans. Payment is fee-for-service, and therefore not tied to pharmacy value, but the creation of network and payer partnerships suggests that payers are beginning to consider the value that community pharmacies provide.

Wellmark BCBS, the largest commercial health insurer in Iowa, is creating a high performance network that uses value-modified capitation payments to supplement prescription revenues for a small group of pharmacies that can demonstrate that they are improving health quality for Wellmark's members (Hosford, 2015). Asthma, diabetes, dyslipidemia and depression are disease targets for the initial phase of the project (Iowa Pharmacy Association, 2015). Scoring for this VBPM is broken down into chronic disease state management (twelve points), ED visits (three points), hospitalizations (three points) and total cost of care (six points) (Mascardo, 2016). Patients with at least one chronic medication are attributed to a pharmacy that fills the majority of their prescriptions. If no pharmacy fills a majority, they are dropped from the dataset. Disease state management metrics represent a mix of process and surrogate outcome measures and ED visit rates, hospitalization rates and total cost of care measures are all risk adjusted. Wellmark's network experiment is intriguing and results will be of interest.

There is a dearth of publically available literature on creating and testing potential systems that can be used for pharmacy VBPMs. Medicare's structure makes information on value related efforts for pharmacies difficult to obtain, and Medicaid is no better. When Medicare innovates on payment models for physicians and hospitals, the details of the new payment models are publically available. When private insurers innovate, these initiatives are considered proprietary. Examples of value-based payments for Medicaid do exist, but those are also operated through private insurers and therefore opaque. Commercial insurers like Wellmark have started to create VBPMs for pharmacies, but progress is limited. Any value based payment model for pharmacy relies on a system of metrics that effectively estimates the quality of care provided by pharmacies. The Pharmacy Quality Alliance has been developing metrics for quality evaluation, but these are standalone metrics and must be aggregated to provide a full picture of pharmacy quality. There is substantial opportunity, especially within the commercial health insurance industry, to create a system of quality measurement and evaluate the relationship between quality and cost to estimate pharmacy value. To ensure that this system accurately measures quality, a guiding theory is needed.

2.d Theoretical Framework

Pharmacies create value in two ways: product dispensing and healthcare service delivery. Determining quality of pharmaceuticals, although quite complex, is fairly straightforward. Drug products are approved by the FDA, and production of these products must adhere to strict quality standards set by the U.S. Pharmacopeial Convention and published in the U.S. Pharmacopeia (USP). As long as a product adheres to USP standards, it is high quality. USP creates the universal standard against which the quality of a pharmaceutical can be compared. Because of the tight regulatory oversight, there is not substantial variation in the quality of products dispensed.

Determining quality of healthcare services is much more nebulous. As observed in section 2.a, no two reports on healthcare system performance and quality use the same framework for evaluating the healthcare system. Assessing quality of services provided within the healthcare system is even more difficult to define. Service quality is influenced by the perceptions of the consumers that receive the service (Parasuraman, Zeithaml, & Berry, 1985), and therefore no universal, USP-like standards for service quality can exist. Variation in pharmacy value does not occur because a pharmacy dispenses higher quality pharmaceuticals; variation occurs because some pharmacists are providing patient care services that improve healthcare outcomes and decrease healthcare costs.

To propose a set of metrics that can be used to estimate quality of pharmacies, a guiding theory is needed. Before deciding on a theory, it is important to understand the paradigm under which this research is being conducted. This research has three paradigmatic axioms derived from Section 2.c:

1. Substantial opportunity exists to improve medication related healthcare quality.
2. Pharmacists, through medication optimization, can add value to the healthcare system.
3. There are observable differences in the value pharmacies add to the healthcare system.

Acknowledging these axioms, two types of quality theories can be used to explore pharmacy value: marketing theories and patient safety/healthcare quality theories. Marketing theories describe the relationship between the service provider and a consumer of the services. Patient safety/healthcare quality theories take a more holistic view of the healthcare system and describe the relationship between care delivery and healthcare outcomes.

2.d.1 Marketing Theories: Gap Theory and SERVQUAL

Investigations on consumer perceptions of service quality began in the 1970s and 1980s as the focus of the economy shifted from manufacturing to service. One of the foundational theories coming out of this exploration is gap theory (Parasuraman et al., 1985). Developed through a series of focus groups with executives and consumers in retail banking, credit cards, securities brokering, and product repair and maintenance, the theory posits that consumer perceptions of quality are a function of the size and direction of gap between service expectations and service performance. The original theory described ten determinants of quality (Table 1).

These ten determinants shape the consumers' service expectations and are evaluated when a service is performed. In addition to these ten determinants, service expectations are also influenced by word of mouth, personal needs, and past experience. According to gap theory, customers with lower initial expectations of service quality will perceive a given level of service performance to be of greater quality because the calculated gap between expectations and quality is smaller. In the context of this theory, perceived service quality is thought to be formed not over a single transaction but to slowly evolve like an attitude (Parasuraman, Zeithaml, & Berry, 1988).

Table 1. Determinants of Service Quality According to Gap Theory(Parasuraman et al., 1985)

Determinant of Service Quality	Description
Reliability	Consistency of performance and dependability. The firm performs the service right the first time.
Responsiveness	Willingness or readiness of employees to provide services. Employees are prompt and conduct business with a sense of urgency.
Competence	Possession of required skills and knowledge to perform service.
Access	Approachability and ease of contact. Hours are convenient, wait times are short and personnel can be reached when needed.
Courtesy	Politeness, respect, consideration and friendliness of contact personnel.
Communication	Keeping customers informed in language they can understand and listening to them. Relates to appropriately varying service conversation for different customers and explaining the cost and benefit clearly.
Credibility	Trustworthiness, believability, honesty of the service provider. The provider should have the customer's best interests in mind.
Security	Freedom from danger, risk or doubt. Physical, financial and confidentiality all important aspects of safety.
Understanding/Knowing the Customer	Making the effort to understand the customer's needs. Includes recognition of the customer.
Tangibles	Physical evidence of the service, including facilities, appearance of personnel, items used to provide the service, etc.

To test their gap theory, Parasuraman et al. (1988) created SERVQUAL, an instrument to evaluate consumer perceptions of service quality. Originally containing 97 items over the ten gap theory domains, the survey was reduced to 22 items across five domains through a survey validation process. Of these five domains, three are original to gap theory: tangibles, reliability and responsiveness. The other two domains are combinations of gap theory domains. Assurance is a combination of communication, credibility, security, competence and courtesy. Empathy is a

combination of understanding/knowing customers and access. Each of the 22 items on the survey has two related questions, one for service expectations provided before the encounter and the other for service performance provided after the encounter. For example, the first item of the original SERVQUAL instrument's pre-service experience survey asks the respondent to rate the extent to which they agree with the following statement: [The firm] should have up-to-date equipment. The corresponding performance measure is: [The firm] has up-to-date equipment. Differences in ratings on expectations and performance are used to calculate gap scores for determining perceived service quality.

The original SERVQUAL instrument has been used to assess quality in many different service industries, including healthcare. In a survey of service quality at a multi-specialty Midwestern medical clinic, Headley and colleagues adapted SERVQUAL for medical use (Headley & Miller, 1993).They sent expectation assessment surveys to 967 patients scheduled to receive appointments, of which 244 were returned (25.2% response rate) and 159 service performance surveys were matched with respondents after their scheduled appointment. The authors used the same items as the original SERVQUAL survey, but found slightly different clustering for items and revised the domains by keeping reliability, responsiveness, empathy and tangibles but dropping the label assurance and adding the labels dependability and presentation. The authors found that patients with higher service quality scores had slightly higher intentions to return for additional services and that higher scores in domains of dependability, reliability and empathy were most closely associated with these behavioral intentions.

In response to criticism about the cumbersome nature of the dual-instrument design and lack of validity for gap scores in predicting consumer behavior (Cronin & Taylor, 1992), Parasuraman and colleagues published a revised SERVQUAL instrument in 1994 (Parasuraman, Zeithaml, & Berry, 1994). This revision simplified the scale to one survey, and asked customers about the performance of the service provider relative to their expectations (i.e. the service

provided greatly exceeded my expectations, somewhat exceeded my expectations, etc.). Validity of the revised instrument was assessed using 162 young adults enrolled in an undergraduate marketing course (Kaldenberg, Becker, Browne, & Browne, 1997). Participants were asked to use the SERVQUAL instrument to rate the quality of service provided by their last visit to the dentist. The authors found that the variance in responses to the SERVQUAL instrument could be useful for evaluating service quality deficits for dental practices.

SERVQUAL has also been used to study differences in perceived service quality between family members and residents of nursing homes and found that residents' expectations of service quality were less than that of their family members (Duffy, Duffy, & Kilbourne, 2001). A study of quality using SERVQUAL in cancer clinics at M.D. Anderson Cancer Center found that across the four clinics studied, performance was relatively consistent but expectations varied and billing accuracy and wait times were deemed to be the biggest problems (Anderson & Zwelling, 1996). These studies further suggest that SERVQUAL can be used to measure perceived service quality in healthcare settings.

From the accumulated literature, it seems that gap theory and SERVQUAL are useful in evaluating service quality, but the question remains: Is the measurement of quality as determined by these surveys relevant to the aims of this project? Marketing theories treat patients as customers. Goals of service in this context are typically repeat purchasing of the service. Items on the SERVQUAL instrument align closely with notions of care experiences from healthcare system performance reports described in Section 2.a. The use of SERVQUAL is not common in current healthcare settings, but the instrument was reviewed along with many other instruments in the development of the hospital version of the Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey (Centers for Medicare and Medicaid Services, 2003). CAHPS surveys are frequently used to assess patient perceptions of hospital quality and results are used in

quality assessment of Medicare Shared Savings Programs ACOs (Centers for Medicare and Medicaid Services, 2015e).

Marketing theories are useful in measuring aspects of care experiences, but cannot measure variation in service outcomes. The subjective nature of these instruments was emphasized in Parasuraman and colleague's original 1988 SERVQUAL paper:

> "In absence of objective measures, an appropriate approach for assessing the quality of a firm's service is to measure consumers' perceptions of service quality."
>
> Parasuraman et al. (1988)

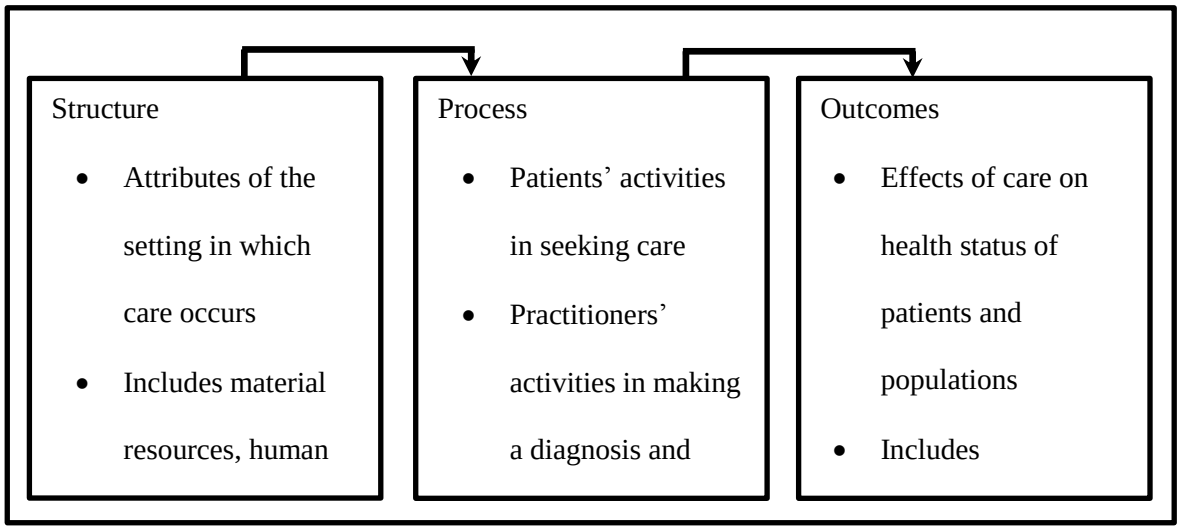
Today's healthcare system has the ability to objectively assess quality. As described in section 2.a.3, definitions of pharmacy quality often refer to pharmacies' impact on healthcare outcomes and current value-based payment models for pharmacies focus on variation in healthcare quality related to pharmacies. Payers care more about a pharmacy's ability to improve objective quality scores and reduce the cost of medical care than they do about patients' subjective perceptions of quality. Therefore, gap theory and SERVQUAL are insufficient guiding theories for creating a set of metrics that can be used for evaluation of pharmacy quality and value.

2.d.2 Healthcare Quality Theories: SPO and SEIPS

Quality assessment and improvement efforts arise naturally from the desire of healthcare practitioners to provide the best possible care to their patients. Given this desire and the unique nature of healthcare it is not surprising that quality assessment and improvement in healthcare as a separate discipline arose in the middle of the 20th century (Donabedian, 2005).

Avedis Donabedian, the father of quality assurance (Best & Neuhauser, 2004), created one of the earliest and most well-known theoretical frameworks for assessing healthcare quality when he divided influences on healthcare quality into three categories: structure, process, and outcomes (SPO) (Donabedian, 2005) (Figure 1). SPO is all but ubiquitous in discussions of healthcare quality. Some sources, when describing healthcare quality, even fail to mention Donabedian in association with the SPO framework, instead describing structures, process and outcomes as elements of fact in the same way one would describe the parts of a computer (Shaw Phillips & Chisholm-Burns, 2014). Nevertheless, it is useful to review SPO as originally described by Donabedian.

Figure 1. Structure, Process Outcomes Theoretical Framework of Healthcare Quality (Donabedian, 1988)



According to SPO, high quality outcomes are the result of high quality processes which are the result of high quality structures (Donabedian, 1988, 2005). These interrelated elements of healthcare quality must all be considered when assessing a healthcare system. SPO recognizes that linkages exist and suggests that process measures be used which have a theoretical linkage to healthcare outcomes. Furthermore, SPO considers both provider and patient care processes. Although SPO includes structural elements to be important influences on care processes and

therefore healthcare outcomes, Donabedian considers measurement of structures to be of lesser importance and more tangentially related to healthcare outcomes than measurement of process.

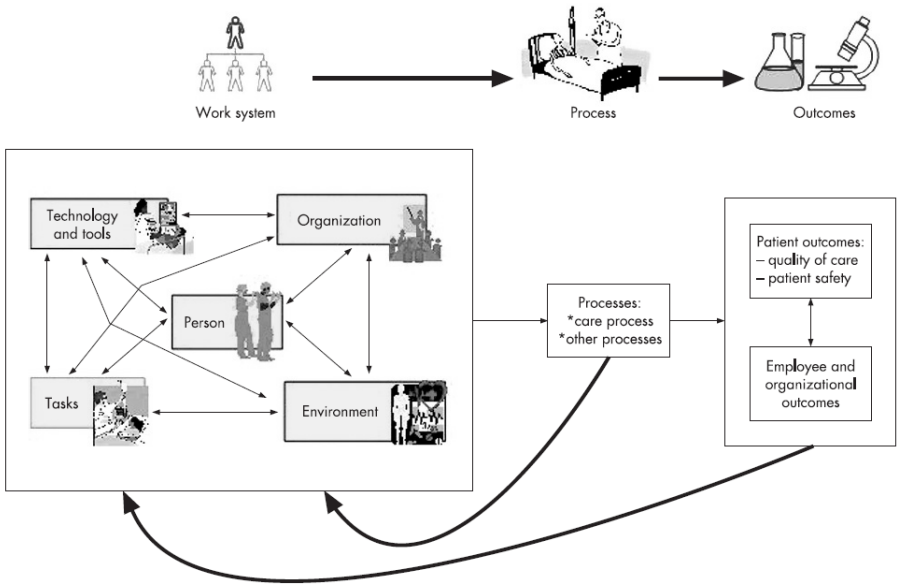
In response to SPO's lack of focus on structural elements of healthcare quality, experts with experience in human factors engineering created the Systems Engineering Initiative for Patient Safety (SEIPS) framework for healthcare quality assessment (Carayon et al., 2006). This framework expands on the SPO framework and replaces Donabedian's concept of structures with a work system comprised of five elements (Table 2).

Table 2. Description of SEIPS Work System Elements (Carayon et al., 2006)

SEIPS Element	Description and Attributes
Person	• Encompasses patients, healthcare professionals, janitors or anyone else in the healthcare work system. • Attributes include physical and psychological characteristics, demographics, training
Organization	• Coordination, collaboration and communication among team members, social relationships, systems which reward performance, work schedules
Technologies and tools	• Information technologies, medical devices, ergonomic features of tools used in environment
Tasks	• Task variety, autonomy/independence in work, job related stressors
Environment	• Layout, noise, lighting, temperature and humidity, design of work station

To emphasize the relationship between these elements, Carayon suggests that, "a person performs a range of tasks using various tools and technologies…within a certain physical environment and under specific organizational conditions." (Carayon et al., 2006) These elements fit into an expanded SPO model with enhanced descriptions of processes and outcomes (Figure 2).

Figure 2. Conceptional Model of SEIPS (Carayon et al., 2006)



Although SEIPS does expand upon SPO's descriptions of processes and outcomes and includes feedback loops between outcomes, processes and structures, the main difference between the theories is SEIPS's expanded focus on work systems. A newer version of the SEIPS model, SEIPS 2.0, has been created to expand the ability of SEIPS to explain the complexities of healthcare quality (Holden et al., 2013). Key changes of 2.0 compared to the original model include dividing the environment into internal and external domains and recognizing that persons include both patients and healthcare providers simultaneously. Additionally, 2.0 suggests that components of the work system do not act independently to create high quality care processes but that components interact and it is through the configuration of the interactions that high quality processes are created. SEIPS 2.0 also recognizes differences in levels of engagement between persons in the work system and dynamic adaptation of systems as new technologies emerge, health statuses change and patients adapt to their health challenges. These changes are interesting additions to the original SEIPS model, but SEIPS 2.0 lacks sufficient evidence to compel its consideration in this evaluation of the relevant quality theories.

2.d.2.1 Adaptability of SPO and SEIPS to Pharmacy Practice

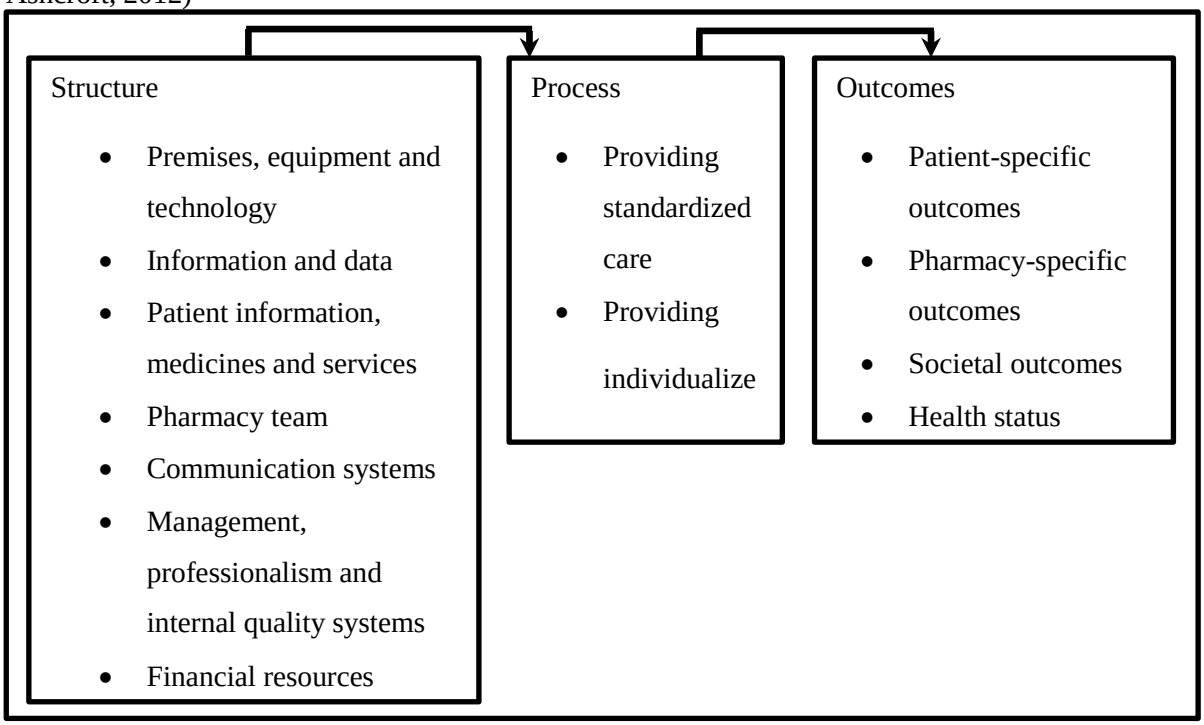
As described in Section 2.a.2, pharmacy quality is defined as achieving a degree of excellence by providing pharmacy services which maximize the probability of positive outcomes and minimize the probability of negative outcomes. Both SPO and SEIPS could be used to explore pharmacy quality pursuant to this definition as it refers to care processes—providing pharmacy services—that achieve optimal healthcare outcomes. The lack of emphasis on structures within this definition of pharmacy quality does not preclude the use of SEIPS, although expanded assessment of structures is the primary differentiator between SEIPS and SPO.

An exploration of the literature finds that both SPO and SEIPS have been used to evaluate pharmacy quality. A 2006 white paper from the American College of Clinical Pharmacy suggests that board-certification can be considered a structural element of healthcare quality (Saseen et al., 2006). The paper describes the need for board-certification and calls for all faculty and residency preceptors to receive the clinical credential. SPO is cited to undergird the argument that the enhanced structures represented by the board-certification credential lead to enhanced care processes and therefore improved outcomes. SPO has also been suggested as a framework to improve outcomes from practice by enhancing patient care processes pursuant to the philosophy of pharmaceutical care (Galt, 2000). According to SPO, higher quality processes should correlate with higher quality outcomes. MA-PD plans use medication related process and intermediate outcome metrics to evaluate plan quality for patients with high blood pressure, high cholesterol and diabetes. Assessing the linkage between these measures, Ta and colleagues found that MA-PD plans with PDC process scores in the top quartile were more than four times more likely to have related intermediate outcome metric scores in the top quartile, confirming the theoretical linkage between the metrics (Ta, Erickson, Qiu, & Patel, 2016). At the core of SPO is the concept

that enhancing structures enhances processes which lead to optimal outcomes, and these papers describe specific areas of pharmacy practice that follow this linkage.

A more holistic use of SPO to evaluate pharmacy quality comes from a study of pharmacy practice in the UK (Halsall, Noyce, & Ashcroft, 2012). The authors included patients, pharmacists, pharmacy support staff, and members of regional healthcare financing organizations (primary care trusts, PCTs) in a series of SPO-guided focus groups evaluating pharmacy quality. The authors found common themes among the participants that fit within the SPO framework and supported the structures→process→outcomes linkage (Figure 3.).

Figure 3. Structure, Process Outcomes Theoretical Framework of Pharmacy Quality (Halsall, Noyce, & Ashcroft, 2012)



Participants' background influenced the structures identified as important for high quality pharmacy care. Participants with pharmacy work experience suggested that structural elements which supported an increase in patient care capacity, such as communication technology and computer systems, were important for high quality pharmacy services. As prescription volumes

increase, these systems help pharmacists maintain service quality. Patients and members of the regional financing organizations emphasized elements that were more linked to the experience of care. Evaluation of care processes identified two types: standardized and individualized. Standardized care is providing care in a way that matches some objective standard. Examples include zero dispensing errors and zero clinically significant drug interactions. Individualized processes were more nuanced and are akin to practicing personalized medicine and are most often seen in American pharmacies through deliberate medication analyses, such as MTM. There is an acknowledgement by the authors that what is right for the average patient isn't necessarily right for all patients and that patients' needs for standardized vs. individualized care may not be consistent from visit to visit. Finally, the most important outcomes identified were those that led to patient satisfaction and maintained and improved individuals' health status.

Although the evidence is not plentiful, several papers reference SPO when discussing elements of pharmacy quality. The thorough qualitative study by Halsall et al. creates a framework for pharmacy quality that supports the use of SPO for this project. Two studies have also used SEIPS to evaluate pharmacy practice. The first assessed work system factors influencing delivery of cognitive pharmaceutical services (CPS) by pharmacies participating in the Wisconsin Pharmacy Quality Collaborative (WPQC) (Chui, Mott, & Maxwell, 2012). The WPQC has been previously described in Section 2.c.2.2 Measuring Value Created by Community Pharmacists. Semistructured interviews were conducted with eight pharmacists from six WPQC pharmacies that were successful in revising their practices to provide more CPS. Themes were identified and placed within the structure of SEIPS work systems (Table 2).

The authors found items related to each of the five work-system elements that influenced pharmacists' ability to provide CPS. The element mentioned most often which related to persons in the work system was communication between physicians, patients and pharmacy staff. Job content was mentioned more than any other task in the environment and job content variation

linked to provision of CPS included delegating responsibility for service delivery and management, initiating services, tracking paperwork, data entry and data mining. The most common environmental factor was access to a patient counseling space that facilitated private, high-level medication counseling sessions. The electronic pharmacy dispensing system and paper tools were both important and frequently mentioned tools/technology and the most important organizational factor was found to be culture. Participants stated that the culture had to be one of making provision of CPS part of the normal duty of the pharmacist. Items discovered by the authors fit well within the SEIPS structure. This finding, and the utility of SEIPS in discovering a variety of factors that influence delivery of CPS, suggests that SEIPS can be useful in exploring pharmacy quality.

A second paper using SEIPS to explore pharmacy quality evaluated work system elements that contributed to the detection and correction of e-prescribing errors (Odukoya, Stone, & Chui, 2015). Unlike the delivery of CPS, which is a process of care, prescribing errors are a sign of poor care processes with a clear link to negative outcomes. Therefore, this study has the potential to use SEIPS to evaluate pharmacists' influence on healthcare processes and outcomes. To explore e-prescribing, Odukoya and colleagues spent time in pharmacies collecting field notes on how pharmacy staff detected and corrected e-prescribing errors and used this experience to subsequently conduct focus groups with 13 pharmacists and 14 technicians. In a similar fashion to the Chui et al. (2012) study, Odukoya found items that impact detection and correction of e-prescribing errors related to each of the 5 work system elements. More experience and training on e-prescribing systems and more drug knowledge for technicians were found to be important person-level factors. Interruptions were found to be important task elements which slowed responses to e-prescribing errors. For the physical environment, a noisy, small and uncomfortably warm or uncomfortably cold environment was found to negatively influence detection and correction. Insurers' payment and formulary policies were the most important element of the

external environment. Like the Chui et al. study, the computer system was found to be the most important tool/technology and participants specifically mentioned the utility of the clinical decision support system within the dispensing system. For the organization domain of the work system, participation, communication, training, and staffing levels were all important elements that influenced response to e-prescribing errors. Although the identified factors were in some ways different than the Chui et al. (2012) study, it logically follows that they should be different given the different types of problems assessed. Importantly, although the Odukoya et al. (2015) study included an element of pharmacy quality that could easily be linked to healthcare outcomes, the study focused on the relationship between elements of the work system and the process by which pharmacists and technicians responded to the errors, not on the actual rate of errors that reached the patient.

Results from analysis of SPO and SEIPS literature suggests that both can be adapted for use in pharmacy practice to evaluate pharmacy quality. The SPO study from Halsall et al. (2012) described a holistic framework for assessing pharmacy quality that linked structures to processes to outcomes. The two studies using SEIPS didn't explore linkages between process and outcomes, and this may not be a limitation of the studies but a limitation of the theory itself. At the least, it is a limitation of how the theory has been applied in studies to date. SEIPS was founded on a criticism of SPO in that SPO didn't focus enough on important elements of structure (Carayon et al., 2006), but the theory may go too far in that it focuses on structures at the expense of outcomes. SEIPS is most useful when assessing work system redesigns focused on solving problems like prescribing errors that have clear links to outcomes. Unfortunately, Section 2.b finds that prevalence of and potential savings for nonadherence and underprescribing are far larger than prescribing errors. Both theories can be adapted to pharmacy practice, but until linkages between pharmacy structures and outcomes are better explored, SPO may be a better

theory for evaluating pharmacy value. To evaluate differences further, the utility of these theories in measuring healthcare quality will be explored.

2.d.2.2 Usefulness in Measuring Healthcare Quality

The second aim of this dissertation is to evaluate a system to measure pharmacies' impact on healthcare quality and cost. To accomplish this, a quality theory is needed which can both be applied to pharmacy practice and is useful in guiding the measurement of quality. As described in Section 2.a, healthcare cost is a fairly straightforward concept but healthcare quality is highly complex and can be approached in many ways. The comparison of SPO's and SEIPS' adaptability to pharmacy practice finds that both can be adapted but that SPO may be better for evaluating pharmacies' impact on healthcare outcomes. Nevertheless, both theories have potential for use in assessing pharmacy quality. As suggested by Donabedian (1988), quality can be measured implicitly and explicitly. Implicit measures of healthcare quality rely on expert judgment and are analogous to the individualized patient care processes described by Halsall et al. (2012). Implicit judgments of quality are commonly used when healthcare practitioners provide expert testimony during a malpractice trial and when hospital physicians conduct morbidity and mortality conferences. The medication appropriateness index is also considered an implicit measure of healthcare quality (Spinewine et al., 2007). These measures are subjective but allow the expert to view the entirety of a patient's case in making a judgment. By contrast, explicit measures are objective and analogous to Halsall's description of standardized care processes. Current value-based payment models all use explicit measures of healthcare quality. Explicit metrics can be created from healthcare claims data or medical record abstracts and allow for quick, low-cost comparison of quality across a broad set of providers.

SPO is commonly used to define explicit measures of healthcare quality. The National Quality Forum (NQF), a source for healthcare metrics and a national leader in quality metric development, uses Donabedian's SPO framework's original three domains plus patient experience and composite metrics (The National Quality Forum, 2010) to categorize its 625 different metrics (The National Quality Forum, 2015). The National Quality Measures Clearinghouse also uses SPO to differentiate between the hundreds of metrics in its measure database and adds patient experience and access categories to the original three domains (Agency for Healthcare Research and Quality, 2016b). The SPO framework, with the addition of patient experience measures, was also found to be useful for describing metrics to evaluate quality for public and private care quality initiatives (Kessell et al., 2015). The authors found that all public and private initiatives assessed quality using a mix of process and outcome measures.

Although the inclusion of patient experience variables are considered by the organizations above to be a modification to the original SPO framework (Kessell et al., 2015), Donabedian himself called for measurement of patient experience as a part of SPO:

> "It is futile to argue about the validity of patient satisfaction as a measure of quality. Whatever its strengths and limitations as an indicator of quality, information about patient satisfaction should be as indispensable to assessments of quality as to the design and management of health care systems."
>
> Donabedian (1988)

Adding patient experience to the SPO framework is not a departure from the original theory but only a departure from how the theory may have been used to study quality in the past. Patient experience, according to Donabedian, is simply another form of outcome.

SPO is also used by researchers to create or identify quality metrics. A study of measures of medication appropriateness in the elderly used SPO to evaluate the types and usefulness of current metrics (Spinewine et al., 2007). A study of healthcare quality in primary care clinics used SPO to suggest a link between nontechnical, personal aspects of care quality (communication, care continuity, etc.) and outcomes (Hsiao & Boult, 2008). The study found modest support in the literature for this theoretical link. Quality indicator development is of international interest, and an Australian review article proposing a method to select quality metrics for Australian physicians suggested using SPO to identify metrics (Evans, Lowinger, Sprivulis, Copnell, & Cameron, 2009). A systematic review of the literature assessing the relationship between structure and process metrics and outcomes for diabetes care found limited support for the link between structures and outcomes but some support for drug therapy process measures and outcomes (Sidorenkov, Haaijer-Ruskamp, de Zeeuw, Bilo, & Denig, 2011). These studies suggest that SPO can be used to create systems of quality measurement and that although SPO is a broad theoretical framework, it can still create testable hypotheses.

Unlike SPO, there has been no evaluation of the use of SEIPS in creating or identifying explicit measures of healthcare quality. The link between structures and outcomes has been found to be somewhat weak (Sidorenkov et al., 2011), and the existing studies on pharmacy quality using SEIPS are not sufficient to suggest specific items in the work system that, if improved upon, could create better outcomes of care. There is a movement underway to establish an accreditation process for community pharmacies, but this effort has struggled to find success and the formation of its structural requirements for pharmacies to be accredited does not have a clear theoretical basis (Center for Pharmacy Practice Accreditation, 2013). Only nineteen community pharmacies have been accredited through CPPA as of August, 2016 (Center for Pharmacy Practice Accreditation, 2016a). Kroger pharmacies make up fifteen of accredited pharmacies, and these were added only in March of 2016 (Center for Pharmacy Practice Accreditation, 2016c).

Recently, Sunflower Health Plan did recognize CPPA accreditation for community pharmacies by giving accredited pharmacies a $0.50 larger dispensing fee, but no other insurers have likewise recognized CPPA accreditation (Center for Pharmacy Practice Accreditation, 2016b; Sunflower Health Plan, 2016). Evidence from the lack of enthusiasm in the payor community over an accreditation process designed to ensure high quality structures is concerning when considering usefulness of a structures-focused theory like SEIPS in creating a value-based payment model.

SEIPS is best used when there is a clear outcome that can drive changes to a work system. This is not the case with efforts to engage community pharmacies in optimizing medication therapy and add value to the healthcare system. If it were known which elements of the environment clearly enhanced pharmacies' value, this could be used for a SEIPS-based quality metric creation process. Eventually, this may be the case, but that time is not now. Furthermore, studies in large chain community pharmacies have found that pharmacists can influence process measures of care without significantly changing structures (Brennan et al., 2012; Fischer et al., 2014; Pringle et al., 2014). Therefore, because SPO is adaptable to pharmacy practice, has proven useful in categorizing elements of healthcare quality, and creates testable hypotheses, SPO will be used to guide this dissertation's creation of a system to evaluate pharmacy quality and value.

2.d.3 Conceptual Model

The purpose of this conceptual model is to facilitate commercial health insurers' selection of quality metrics useful for evaluating the value that its network pharmacies provide. The framework of quality attributes developed by Halsall et al. (Figure 3) is useful for conceptualizing pharmacy quality but less useful for selecting quality metrics (Halsall et al., 2012). Therefore, a new conceptual model, based on SPO, must be created for this dissertation.

Unfortunately, it is not well understood how variation in structures influences pharmacies' impact on healthcare outcomes. A simplistic way to differentiate between community pharmacies is to create two broad categories: independent pharmacies and chain pharmacies. Independent pharmacies are a throwback to when nearly all pharmacies were owned by pharmacists, not by a Fortunate 500 company. Independent pharmacy ownership is promoted as allowing the pharmacist-owner to create personalized services for patients, carry out their own grand vision of pharmaceutical care, and be a positive force in their community (McKesson, 2016; National Community Pharmacists Association, 2016). In this straw man dichotomy, pharmacists employed by large chain pharmacy corporations can be thought of as interchangeable, anonymous figures behind the counter churning out massive numbers of prescriptions to patients/customers with whom they have no real relationship. This is supported by evidence from assessments of differences in earnings for male and female pharmacists. Thankfully, there is little difference in salaries for male and female pharmacists and little penalty on an hourly basis for part time vs. full time work (Goldin, 2015). Unfortunately, Goldin suggests that this is because pharmacists employed by large chain pharmacies are nearly perfectly interchangeable—any given pharmacist can perform the work of another pharmacist equally as well (Dubner, 2016). This supports the concept of chain pharmacists as anonymous figures dispensing high volumes of medications, unable to enact their own patient care initiatives.

Is the distinction between these two practice settings as stark as the preceding paragraph suggests? Likely not. Regardless, evidence for this stereotypical, but useful, division across pharmacies can be seen by the differences in busyness and patient care services from the most recent National Pharmacist Workforce Survey (Doucette WR, 2014). Chui and colleagues also found strong influences of organization culture on the ability of pharmacists to provide cognitive pharmaceutical service (Chui et al., 2012). Interestingly, an assessment of pharmacy quality metric scores for Medicare beneficiaries finds independent pharmacies were consistently worse

performers on quality metrics than chain pharmacies with OR for low performance ranging from 1.23-1.68 across four common PQA-sponsored quality metrics (Desai et al., 2016). This adds counterbalancing evidence to the suggestion that performance of independent pharmacies exceeds that of chain pharmacies. Lack of time and inadequate staffing are frequently cited barriers to delivering medication therapy management services in community pharmacies (Bright, Lengel, & Powers, 2009; Law, Okamoto, & Brock, 2009; Lounsbery, Green, Bennett, & Pedersen, 2009), but this could be overcome with corporate support for targeted, brief interventions like those of the Pennsylvania Project (Pringle et al., 2014).

Are there systematic differences between pharmacy structures that allows one set of pharmacies to have a stronger probability of positively influencing their patients' health than another set of pharmacies? The answer to this question is unclear, but there is enough of a reason to believe that systematic differences compel the inclusion of structures in this investigation of pharmacy quality. Studies using the SEIPS framework highlight the complexity of the pharmacy work system and suggest that many elements may influence pharmacy quality. Evidence from studies on ABMS suggest that by modifying structures through the use of systems that help to synchronize medication fills, pharmacists can create an environment that better facilitates enhanced care processes (D. Holdford & Saxena, 2015; D. A. Holdford & Inocencio, 2013), but evidence from large studies on pharmacists' influence on process measures suggests that structures may not substantially influence quality (Brennan et al., 2012; Fischer et al., 2014; Pringle et al., 2014). Interventions to improve pharmacies' impact on process measures of care in chain pharmacies specifically sought not to substantially change the pharmacies' work environment but instead facilitated enhanced care processes through electronic prompts and higher expectations (Pringle et al., 2014). True, these prompts and expectations can be considered changes to tools/technology and the organization's culture, but these are relatively minor changes to structures that still indicate only a limited impact of changes to structure on care processes.

Regardless, it is likely that there is some, if only minor, impact of pharmacy structures on the ability of pharmacists to provide high quality care. Therefore, the conceptual model will include measures of ownership type, organizational culture, and store busyness. These concepts are measurable, fit within the SPO definition of structures and are common between the SEIPS and Halsall et al. descriptions of structural influences on pharmacy quality.

Donabedian divides process of care measures into patient and practitioner measures (Donabedian, 1988). This division is also supported by work from Halsall et al. (2012). Furthermore, every large study in Section 2.c.1 controls for differences between patients when assessing effects of pharmacists on process measures, implicitly acknowledging the patients' influence on care processes and outcomes. Therefore, the conceptual model will contain two broad categories of process measures: patient care processes and pharmacist care processes.

Lastly, Donabedian's SPO theoretical framework suggests that pharmacies with high quality care processes should create high quality outcomes of care. As previously mentioned, Donabedian's framework discusses both clinical and patient experience outcomes. Frameworks to analyze healthcare quality from Section 2.a.1 consider important the analysis of patient experience as do systems of healthcare quality assessment used by the federal government (Kessell et al., 2015).

Traditionally, SPO models do not include cost as an explicit outcome, but cost can be considered when assessing what the optimal level of healthcare quality should be (Donabedian, 1988). As described in Section 2.a.4, this dissertation assesses costs as a way to measure value. This is supported by Porter's definition of value as outcomes per dollars spent (Porter, 2010a). Value increases when costs decrease and quality is maintained, when costs are maintained and quality increases, or when costs decrease and quality increases. In this way, costs are essential to this model and separate from quality measurement.

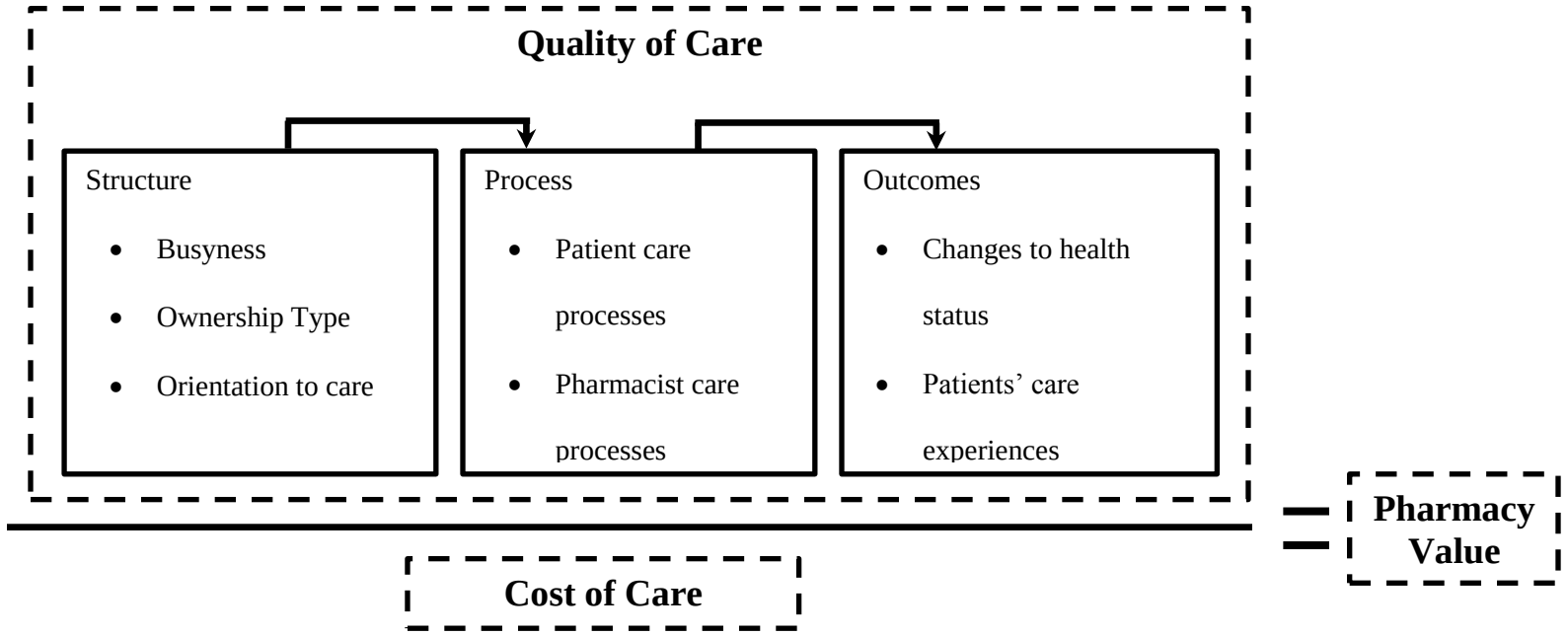
A final question remains for this conceptual model: Why include both process and outcome measures? Donabedian's framework suggests that high quality processes lead to high quality outcomes, therefore if there is a well understood link between a given process and a given outcome, is it necessary for the conceptual framework to include both? First, to address the concept of a strong linkage between process and outcome variables, it is not entirely clear that high quality pharmacy processes lead to high quality outcomes. The link between processes and surrogate clinical outcomes such as blood pressure and LDL has been established in small studies of enhanced pharmacist care, and larger studies find links between enhanced care and reductions in nonadherence and underprescribing, but these are process measures. There was one study which found a link between enhanced pharmacist care, emergency department visits, and inpatient admissions, but this effect was inconsistent across medication classes (Pringle et al., 2014). As discussed in Section 2.b.2, a strong theoretical link exists between nonadherence and poorer outcomes, but healthy adherer bias (Section 2.b.2.1) inflates these estimates.

Second, even if there were a strong theoretical link between a given high quality process and high quality outcome, Donabedian suggests that both process and outcome metrics be included in a system of quality measurement. Process metrics in this context are designed to measure the care provided by pharmacists, and are thus closely linked to variation in practice. It is this variation in practice that is thought to drive the differences in observations of value expected under Axiom 3 in Section 2.d. These process metrics do not reflect the goals of payers, however. Porter argues that process measures are useful for internal efforts to track quality, but the goal of the healthcare system should be to produce optimal, patient-relevant outcomes (Porter, 2010a). Indeed, if a process metric is adherence, this is antithetical to a payer's goals in that improvements in adherence increase a payer's drug costs. Using Porter's conceptualization of value, improving adherence only creates value insofar as the improvement decreases the rate of negative healthcare outcomes and creates healthcare savings. Variation in negative healthcare

outcomes is not only linked to the process metric assessed, though, but may be due to patients' and other healthcare providers' care processes. This more tenuous link to practice means pharmacists could be unfairly punished for variation in outcomes outside their control if outcomes were the only type of metric used to assess quality. Therefore, it is important to include outcome metrics in a system of assessment along with process metrics.

Figure 4 contains the conceptual model that will be used in this dissertation. It reflects the SPO framework's linkage between structure, process and outcome domains while emphasizing measurement of process and outcome metrics. This is not comprehensive and not intended to be a theoretical model of pharmacy quality; rather, it is intended to guide assessment of pharmacy quality from the perspective of a commercial insurer.

Figure 4. Conceptual Model for Measuring Value Pharmacies Provide to Insurers



2.e Gap and Significance

International comparisons suggest that there is substantial opportunity for the US healthcare system to reduce cost while improving or maintaining care quality. To accomplish this, there is a movement towards a focus on value provided instead of volume of services delivered. Inevitably, value-based payments will be used to reimburse pharmacies. The method by which these VBPMs will be applied to pharmacy payments is unknown, but the first step in creating any value-based pharmacy payment model is a reliable method of identifying high and low value pharmacies. Currently, Medicare Part D plans and private Medicaid plans are experimenting with value-based pharmacy payment models, but there is no publically available information on commercial insurers' efforts to create VBPMs. This dissertation fills this critical gap by testing a method for evaluating pharmacies' impact on healthcare quality and cost to create a measure of pharmacy value for a commercially insured population. This method could serve as the basis for a future value-based pharmacy payment model.

2.f Hypotheses

The aims of this dissertation are to test a conceptual model of pharmacy value and assess the variation in pharmacy value across a commercial insurer's network. A fundamental component of the SPO framework is a causal link between high quality structures, processes, and outcomes. The first set of hypotheses tests this assumption within the conceptual model described in Section 2.d.3:

Hypothesis 1.1: There is a direct relationship between the quality of a given pharmacy's structures and the quality of care processes delivered by pharmacists at that pharmacy.

Hypothesis 1.2: There is a direct relationship between care process quality at a given pharmacy and healthcare outcomes for patients receiving care from that pharmacy.

The second set of hypotheses tests for the presence of pharmacies that provide exceptionally high value or low value to commercial insurers. Value, according to the conceptual model, is measured by a pharmacy's impact on healthcare quality relative to the pharmacy's impact on healthcare cost. Not all commercial insurers bear risk for the same types of cost, therefore it may be true that not all insurers would rate the value of pharmacies the same. Furthermore, evidence from Section 2.b suggests that medication optimization has different effects on the cost of medical care than it does on pharmaceutical costs. Therefore, the hypotheses for evaluating pharmacy value are:

Hypothesis 2.1: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on pharmaceutical cost.

Hypothesis 2.2: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on medical cost.

Hypothesis 2.3: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on the total cost of care.

CHAPTER III
METHODS

3.a. Design

This retrospective, observational study aims to: 1) test a model of pharmacy quality by examining linkages between pharmacy structure, processes and outcomes and 2) assess pharmacy value by evaluating the relationship between patients' healthcare cost and the quality of pharmacies from which they receive medications. Small group and individual medical and prescription claims from a large commercial insurer in Iowa were used to explore these aims. Models to evaluate pharmacy quality are used by Medicaid managed care organizations (Inland Empire Health Plan, 2014; Trygstad, 2015), at least two Medicare Part D plan sponsors (Deninger, 2015; Express Scripts, 2015), and at least one commercial insurer (Mascardo, 2016). More is known about pharmacy quality efforts among Medicaid managed care organizations and Part D plans, but these insurers cover populations with substantially different health concerns than commercially insured populations and their examples are too few to establish an industry standard for pharmacy quality evaluation. Therefore, a new model for evaluating pharmacy value for a commercially insured population was created for this dissertation. This project tested the extent to which metrics within the model conform to the linkages between structures, processes and outcomes as proposed by Donabedian and assessed variation in the value pharmacies provide to a commercial insurer.

3.b. Data Source and Inclusion/Exclusion Criteria

Data for this project came from the Wellmark Database managed by the Center for Public Health Statistics within the College of Public Health at the University of Iowa (Center for Public Health Statistics, 2016). These data are comprised of medical and prescription claims from beneficiaries

enrolled in the small group and individual market of plans offered by Wellmark Blue Cross and Blue Shield (Wellmark). Wellmark is the dominant commercial health insurer for Iowa and South Dakota. The dates for claims included in this project ranged from 1/1/2012 to 12/31/2013, the two most recent years included in the Wellmark Database when the application for data use was submitted. Claims from the 2013 calendar year were used to calculate quality scores and sum healthcare costs. Claims from 2012 aided in identifying chronic conditions.

Patients were included if their age was greater than 17 and less than 65 for the entire two year study period, if they filled at least one prescription, if they were recorded as residing in the state of Iowa or South Dakota for the entire two year study period, and if they were alive and had continuous coverage the entire two years. Continuous coverage was identified by Wellmark's indicator for the number of months a member was enrolled. If 12 months of enrollment were indicated for 2012 and 2013, the patient was considered to be continuously enrolled. For reasons explained in Section 3.d.2.2, if a patient gave birth in 2013 they were excluded from analysis. Further exclusion criteria applied for specific metrics, and this is described in Sections 3.d.2.3 and 3.d.2.4. Pharmacies are eligible for inclusion if they are located in Iowa or South Dakota and if they meet additional inclusion criteria as described in Section 3.d.2. Student t-tests and chi-square tests were used to assess for the impact of pharmacy exclusion criteria on attributed patients' demographics.

3.c. Variables

Data were divided into two files, a de-identified member information file and a claims file which contained claim and provider information. Variables from both files were needed for this analysis. A full description of the variables included in this project is found in Appendix A. Variables were selected based on data needed for inclusion and exclusion criteria as well as an

assessment of the data requirements for process and outcome metrics described in sections 3.d.2.3 and 3.d.2.4 as well as cost variables described in section 3.d.3.

3.d Operationalizing the Conceptual Model

Donabedian describes two types of quality measures: implicit and explicit. As described in Section 2.d.2.2, the ability to standardize explicit measures and use them to quickly and easily compare care across settings has resulted in explicit measures gaining favorability over implicit measures. The challenge of this section is to describe the way in which the conceptual model (Section 2.d.3) was transformed into a set of explicit measures that can be evaluated using data commonly available to commercial insurers.

There are several attributes to consider when evaluating quality metrics. First, a metric should measure an element of the healthcare system that is of interest to insurers, and in the context of this project, susceptible to intervention by pharmacists (National Quality Measures Clearinghouse, 2015). A good metric should also be related to a condition that has either high prevalence, high incidence, or has a significant effect on burden of illness and for which the practice characteristic measured has strong clinical evidence linking changes in the metric to changes in the condition (National Quality Measures Clearinghouse, 2015). Additionally, the measure must be reliable, in that it can be measured in multiple settings, valid, in that it actually measures what it claims to measure, and able to be risk adjusted to fit a variety of populations (National Quality Measures Clearinghouse, 2015). Finally, Pillittere-Dugan, Nau, McDonough, and Pierre (2009) suggest that for pharmacy quality metrics, metric attainment rates should vary substantially from pharmacy to pharmacy and there should be room for metric improvement across pharmacies.

As a result of these considerations, this study used, wherever possible, metrics that have already been established by national healthcare quality organizations to be reliable, valid, and useful for measuring healthcare quality. When preexisting measures sufficient to operationalize the conceptual model do not exist, evidence from Chapter II was used to create new, pharmacy practice relevant metrics. The first section, structure, required the creation of new metrics. Process metrics specifications were obtained from the Pharmacy Quality Alliance. Outcome metrics were comprised of a novel non-cancer, non-trauma, unplanned hospitalization metric and a novel non-trauma ED visit metric.

3.d.1 Structure

The conceptual model suggests three categories of structure variables that influence pharmacies' patient care processes: 1) ownership type, 2) organizational culture, and 3) store busyness. These concepts are potentially interrelated latent variables that must be explicitly measured in some way for the insurer to be able to assess the effect of these variables on care processes, but there aren't established methods for estimating these effects using claims data. Additionally, the data available for this project do not include the name of the pharmacy. Without this information, ownership type is difficult to discern. The same is true for organizational culture. An opportunity for further research is a survey that measures pharmacists' perceptions of their pharmacy's culture. This could be included as a structural covariate and related to process measures of care.

Therefore, effort was made to identify variables in secondary databases that correlate with ownership type and organizational culture. A strong theoretical candidate is the presence of prescriptions on Sundays. The average independent pharmacy is only open six days a week (National Community Pharmacists Association, 2012a), whereas the average large chain, mass

merchandiser or supermarket pharmacy is open every day. Additionally, the presence of Sunday prescriptions suggests that the organization's culture is one that favors convenient prescription pickups, therefore suggesting that pharmacies open on Sundays have lower quality. It may be, however, that rural independents are more likely to be open on Sundays regardless of their convenience vs. quality culture because of the lack of alternative sources for prescriptions in their community and the possibility that nursing facility filling business contracts may require Sunday dispensing. It is not clear, though, that independent pharmacies are more likely to have higher quality than other pharmacy types. A study using EQuIPP scores found that independent pharmacies were less likely than chain pharmacies to have above average PDC scores (Desai et al., 2016) and the ability of chain pharmacies to impose system-wide quality improvement efforts may make measured quality among chain pharmacies better than the average independent.

Using Sunday prescriptions to estimate ownership type and organizational culture is a reasonable proxy for these two constructs that can be derived from claims data. The presence of prescriptions on a Sunday was calculated by identifying the dates for all Sundays in 2013 and summing the total prescriptions filled across all Sundays for each pharmacy. There were three categories of Sunday filling pharmacies: pharmacies that never fill on Sundays, pharmacies that fill regularly on Sundays, and pharmacies that rarely fill on Sundays. It was assumed that pharmacies in the first category were closed on Sundays and pharmacies in the second were open. For the third category, pharmacies had small volumes of fills on occasional Sundays, and it is assumed that they were closed but a pharmacist opened the pharmacy to fill a prescription for a needy patient or family member. To differentiate these pharmacies from those that were clearly open, an assessment was made of pharmacies' Sunday prescription fill count as a percent of total annual prescriptions and the frequency of Sunday fills. Based on an analysis described in Appendix B, it was determined that pharmacies filling more than 0 but less than 0.1% of annual prescriptions on Sundays were considered a marginal Sunday filling pharmacy. All three

categories for Sunday filling pharmacies were assessed independently. ANOVA was used to compare differences in prescription volume across Sunday filling pharmacy categories.

Busyness was estimated by calculating average weekly store volume as observed in the data available. Busyness and the related concept workload are complex concepts that relate both to objective measures like prescription volume and subjective measures including perceived work volume and demands of the job (Chui & Mott, 2012). Additionally, pharmacies with equivalent prescription volumes may have differing busyness due to variation in staffing levels. As previously stated, this project used explicit, objective metrics as these can be consistently and accurately measured across a large set of pharmacies. Prescription volume has been commonly used to describe influences on store busyness and to differentiate between busy and less busy pharmacies. A study assessing pharmacists' ability to detect drug-drug interactions found that drug-drug interactions increased with greater numbers of prescriptions per pharmacist hour and pharmacy staff hour (Malone et al., 2007). Another study assessing variation in primary medication nonadherence within one pharmacy chain used raw weekly prescription volume and found that stores with greater volume were associated with lower rates of PMN (Jackson et al., 2014). A study using EQuIPP's database found that higher volume stores, defined as stores with Medicare Advantage patient load greater than the median, performed better on the EQuIPP's high-risk medications metric compared to lower volume stores (Desai et al., 2016). There were no differences when higher and lower volume stores were compared on PDC metrics.

This suggests that a raw measure of prescription volume may correlate with busyness which in turn influences pharmacists' ability to provide quality care, but that the relationship may be inconsistent across care process measures. The unobserved variation in staffing and technology likely confound the relationship between prescription volume and busyness, but the theoretical relationship between busyness and care quality and empirical evidence finding a relationship between quality measures and measures of busyness suggests that the effects of

busyness should be assessed as a structural determinant of quality. The most common explicit measure of busyness available in data typically used by commercial insurers is prescription volume. For this study, average weekly volume was calculated by summing all prescriptions dispensed at a pharmacy during 2013, dividing by 365 and multiplying by 7. A sensitivity analysis using average daily volume was performed to account for some pharmacies not being open 7 days a week. This volume only measures some fraction of the total prescription volume at the pharmacy, but insofar as the proportion of total prescriptions dispensed to patients with small group or individual coverage from Wellmark is consistent across pharmacies this assumption is acceptable. There is bound to be variation, though, especially for pharmacies in communities with a high percentage of self-funded employers and/or a high percentage of patients with government sponsored insurance that wouldn't be included in this dataset. For this study, weekly prescription volume was coded as a raw figure, log of weekly prescription volume, and weekly prescription volume squared. Model selection techniques described in Section 3.e.2 were used to find the form of prescription volume most strongly correlated with each process and outcome measure.

3.d.2. Process and Outcome

Process and outcome metrics of healthcare quality focused on pharmacists' influence on care quality, not on patients' care processes or experiences. Although patients' role in healthcare quality is essential for study when assessing healthcare systems, data to evaluate explicit measures of healthcare quality for patients are typically not available to insurers. Some insurers construct explicit measures of care experiences through tools like CAHPS surveys, but the insurer supplying these data did not survey patients to gather pharmacy care experiences.

Because patients' care processes and care experiences cannot be directly observed with claims data, this project operationalized the conceptual model by assessing explicit measures of pharmacists' care processes and changes to patients' health. There are three essential steps to operationalize these two categories of health quality: 1) patient attribution to pharmacies, 2) disease state targeting, and 3) metric selection and creation.

3.d.2.1. Attributing Patients to Pharmacies

The first step in creating a system to measure pharmacy value is determining the method to attribute patients to pharmacies. The goal of attribution in the context of quality measurement is to assign patients to providers for whom there is a reasonable expectation of influencing care quality while retaining enough of the population to keep a statistically useful sample and not induce selection effects (Knudson & Heim, 2016). Multiple methods for attribution exist (Knudson & Heim, 2016; Pantely, 2011; Pillittere-Dugan et al., 2009), but the most straightforward and practical method is to attribute patients to a single pharmacy using prescription fills. To do this, counts for all prescriptions filled at each pharmacy where the patient received prescriptions in the calendar year 2013 were calculated. The pharmacy at which the patient filled the most prescriptions was the patient's attributed pharmacy. In the case of ties, the pharmacy that filled prescriptions for the patient last was the attributed pharmacy. This is a commonly used method of tie breaking when patients are attributed to primary care physicians (Knudson & Heim, 2016).

The total count of annual prescriptions filled was also calculated. The count of prescriptions filled at the attributed pharmacy was divided by the total count of annual prescriptions to yield the maximum percent of prescriptions filled at the pharmacy from which the patient received the most prescriptions. The purpose of attributing patients to a single pharmacy

was to identify a pharmacy that was most likely to influence their medication related healthcare quality, but a question remains: If a patient receives prescriptions from any one pharmacy no more than a very small percentage of the time, is it reasonable to expect that any one pharmacy in the patients' network has influence on their medication related healthcare quality? This problem is frequently addressed through the use of minimum attribution thresholds whereby a patient not filling some minimum percent of prescriptions at the pharmacy where they receive prescriptions most is dropped from the dataset (Pantely, 2011). Some attribution systems set a minimum attribution threshold somewhere in the 25-35% range (Pantely, 2011). Other systems of attribution require the majority or even super majority of care provided to be from a single provider in order for a patient to be attributed to that provider.

Little precedence exists for deciding minimum attribution thresholds for pharmacy quality measurement systems. EQuIPP, the industry leading pharmacy quality platform used by payers and pharmacies, attributes patients to pharmacies on a metric by metric basis (Dorich, 2016). Under this method, eligibility criteria for each metric is applied to a set of patients, then the pharmacy with the majority of prescriptions filled that are used to calculate the metric is assigned to the patient. If a patient filled hypertension medications at one pharmacy and dyslipidemia medications at another, they would be attributed to a different pharmacy for a metric assessing hypertension medication adherence than they would for dyslipidemia medication adherence. IEHP's pay for performance model uses EQuIPP's platform and presumably the built-in attribution methodology (Inland Empire Health Plan, 2014). CCNC's method of attribution is not specified, but the use of non-prescription-related metrics suggests that patients are prospectively or retrospectively assigned to single pharmacies (Trygstad, 2015). A single-pharmacy attribution method was also used for a paper assessing risk adjustment methods for adherence metrics which retrospectively assigned patients a single pharmacy filling at least 75%

of their prescriptions (Dharmarajan et al., 2014). Wellmark's high performing pharmacy network uses an attribution threshold of 50% (Mascardo, 2016).

Given the lack of a standard for a minimum attribution threshold, a preliminary analysis was conducted using this study's data which found that increasing attribution thresholds from 50% to 90% significantly improved pharmacies process and quality scores and substantially reduced the number of patients and pharmacies eligible for the study (Urick & Urmie, 2016a, 2016b). These results suggest that using more restrictive attribution criteria can create selection effects which positively bias pharmacies' observed quality. Because of this concern and in light of the lack of a standard for attribution, this study used a 50% minimum attribution threshold. See Appendix C for details on minimum attribution threshold selection.

3.d.2.2. Targeting Specific Medication Optimization Sensitive Conditions

The second step in creating a system to measure pharmacy value is targeting. The goal of targeting is to identify the conditions for which medication optimization by community pharmacists can yield the greatest value to insurers. Conditions that fit this description must create substantial expenditures for a commercial insurer and have evidence supporting the link between medication optimization and value.

The Medical Expenditure Panel Survey (MEPS) can be used to address the first criteria. Table 3 contains a list of the top ten most expensive conditions across all privately insured, non-elderly adults, the estimated annual amount spent on those conditions, and the annual prevalence of each condition within the cohort.

Table 3. Total Expenses and Prevalence for Costliest Conditions for Privately Insured, Non-elderly Adults

Condition Category	Total Expenses (millions)†	Prevalence (millions)‡
Cancer	$32,382	4.9
Trauma-related disorders	$26,861	15.8
Heart conditions	$25,809	6.2
Normal birth/live born	$25,057	4.1
Osteoarthritis and other non-traumatic joint disorders	$23,958	15.1
Mental disorders	$19,211	20.0
COPD, asthma	$19,088	17.2
Diabetes mellitus	$15,733	8.4
Back problems	$14,026	10.7
Skin disorders	$13,285	11.1

†Data extracted from Agency for Healthcare Research and Quality (2016a), selecting only those with private insurance

‡Data extracted from Agency for Healthcare Research and Quality (2016a), for individuals with any private insurance receiving any service in each condition category

There are several key points from these data. First, the most expensive conditions are not necessarily the most prevalent. Cancer and births are in the top five most expensive conditions, but estimated prevalence for a privately insured, non-elderly adult population is relatively low. Additionally, medications do not necessarily modify outcomes for all top ten conditions. Outcomes from trauma, for example, are likely not related to medication use and medications play little role in prevention of trauma.

To address the second criteria—for targeted conditions there should be a clear link between optimal medication use and outcomes—one can revisit evidence from Section 2.b and

Section 2.c. The strongest evidence for a link between medication optimization by community pharmacists and outcomes from Section 2.b exists for hypertension (DiMatteo et al., 2002; IMS Institute, 2013; Nasseh et al., 2012; Roebuck, 2014; Roebuck et al., 2015; Roebuck et al., 2011; Sokol et al., 2005), dyslipidemia (DiMatteo et al., 2002; IMS Institute, 2013; Nasseh et al., 2012; Roebuck, 2014; Roebuck et al., 2011; Sokol et al., 2005), diabetes (IMS Institute, 2013; Nasseh et al., 2012; Office of Disease Prevention and Health Promotion, 2014; Roebuck et al., 2011; Sokol et al., 2005; Stuart et al., 2015) and heart failure (IMS Institute, 2013; Roebuck et al., 2011; Sokol et al., 2005). Some studies find a link between better medication use and care improvements for coronary artery disease (Bitton et al., 2013; DiMatteo et al., 2002) and GERD (Roebuck et al., 2015). Studies of the impact of pharmacists on disease states commonly find evidence for effectiveness of pharmacists in addressing medication related concerns for hypertension (J. K. Lee et al., 2006; Planas et al., 2012; Pringle et al., 2014; Zillich et al., 2005), dyslipidemia (J. K. Lee et al., 2006; Nola et al., 2000; Planas et al., 2012; Pringle et al., 2014), and diabetes (Brennan et al., 2012; Planas et al., 2012; Pringle et al., 2014).

Hypertension, dyslipidemia and diabetes are common disease states for which there is evidence that more optimal medication use can improve care and outcomes and for which there is evidence that pharmacists can improve care and outcomes,. These are also significant sources of expenditures for privately insured, non-elderly patients. Diabetes alone is the 9th ranked condition by expenditures, with nearly $16 billion spent annually for 8.4 million patients. Although hypertension and dyslipidemia are not in the top 10 most expensive conditions, the purpose of treating these conditions is to reduce the risk of cardiovascular disease, and heart disease is the 3rd most expensive condition category. These three conditions comprise the targeted conditions for process metric selection.

Osteoarthritis (OA), a prevalent condition for the non-elderly privately insured, was not targeted for this project. There isn't sufficient evidence from studies of opportunities for medication related healthcare savings nor studies of pharmacists' impact on healthcare quality

and cost for there to be a compelling reason to include OA as a targeted disease. Furthermore, the initial therapy recommendation for OA is the use of over–the-counter oral acetaminophen, oral NSAIDs, topical NSAIDs or topical capsaicin (Hochberg et al., 2012). Therefore, any patient attributed to a pharmacy for the filling a prescription for treatment of OA will be in the later stages of disease and not representative of the general OA population.

Other options that could have been considered are asthma/COPD and depression. Asthma/COPD, the 7th most expensive condition and the 2nd most prevalent in the top 10, has some empirical evidence for the role of community pharmacists in improving quality (Bunting & Cranor, 2006), and has PQA endorsed quality metrics (Pharmacy Quality Alliance, 2016) but a preliminary assessment of the prevalence of asthma/COPD among patients eligible for this study found that there weren't enough patients to reliably execute any of PQA's COPD/asthma related metrics. Depression, a subset of the mental health disorders which is the a prevalent and expensive condition category, is included as a targeted disease state in Wellmark's high performing pharmacy network, and is the focus of one of the Asheville project related studies (Finley et al., 2011). Medication related explicit measures of depression quality are not endorsed by PQA (Pharmacy Quality Alliance, 2016) and the highly individualized nature of the disease and diversity of available therapies makes explicit measures more difficult to develop for depression than for other diseases. Therefore, depression was not targeted for this study.

Patients experiencing a birth in 2013 were also be excluded from this analysis. Births are the least prevalent of the top 10 most expensive conditions (4.1%) but have the 2nd highest associated per-condition cost ($6,111). Additionally, pregnancy is not a chronic disease, therefore systems to classify chronic conditions such as Charlson and Elixhauser do not control for the influence of pregnancy on healthcare cost. Also, it is entirely possible that pharmacies located in neighborhoods that happen to be attractive to young couples would have a disproportionately higher share of pregnancies and assigning responsibility to the pharmacy for the substantial costs

of pregnancy would be unfair. Finally, with the possible exceptions of encouraging the use of prenatal vitamins and evaluating interactions between drugs and pregnancy, there is little a pharmacist can do to reduce costs and improve healthcare quality associated with pregnancies. To exclude pregnant patients, any patients with claims in 2013 including a primary or secondary ICD-9-CM code that falls into CCS categories 180-196 with the exception of 189 (previous C-section) were eliminated.

3.d.2.3. Process Metric Selection

As described in Section 2.d.3, medication optimization encompasses the processes through which pharmacists provide care that improves health outcomes. Evidence from Section 2.c.1 suggests that the two major opportunities for medication optimization to create value for the healthcare system come from reducing nonadherence and underprescribing. Other opportunities for optimization, such as making dose adjustments and screening for drug interactions exist, but there is less evidence to support community pharmacists' ability to impact these opportunities and potential savings from these opportunities are much less than potential savings from nonadherence and underprescribing (IMS Institute, 2013). As described in Section 2.c, results from studies assessing community pharmacists' impact on care processes are mixed, but there is enough evidence to suggest that it is highly likely that there are some pharmacies delivering high quality care that makes a measurable difference in process measures of healthcare quality.

The best studied opportunity for medication optimization to improve value by reducing healthcare costs is improving medication adherence. PQA has developed and endorsed metrics to evaluate these areas of medication related healthcare quality and others (Pharmacy Quality Alliance, 2015). PQA's adherence metrics and use of high risk medications in elderly patients metric are used to evaluate quality for MA-PD and PDP plans (Centers for Medicare and

Medicaid Services, 2015n) and these measures are calculated for nearly all pharmacies in the US via the EQuIPP platform (EQuIPP, 2015b). This makes PQA-developed metrics a clear first choice for evaluating pharmacy quality related to the targeted disease states.

PQA's metrics for nonadherence for drugs used to treat diabetes, dyslipidemia, and hypertension were used as process metrics for this dissertation. It is recognized that process metrics besides adherence are useful when evaluating pharmacy quality, but many of the commonly used measures, such as high risk medications in the elderly, are clinically misaligned with the non-elderly adult population or are so specific that measurement on a relatively healthy population may not be possible (Pharmacy Quality Alliance, 2014). To test feasibility of process metrics besides adherence, algorithms to execute PQA's Diabetes: Appropriate Treatment of Hypertension, Drug-drug Interactions and Cholesterol Management in Patients with Coronary Artery Diseases metrics were created and executed. The drug treatment metrics required patients to have two chronic diseases, and the prevalence of patients with these combinations were so low that there weren't enough patients meeting the denominator to allow for assessment over a broad set of pharmacies. For drug-drug interactions, the rate of numerator flags was so low that the measure could not be reliably assessed. PQA's metric technical specifications document from 2014 was used to calculate 2013 metrics (Pharmacy Quality Alliance, 2014). The medication classes assessed as separate adherence metrics for this dissertation are: β-blockers, HMG CoA-reductase inhibitors (statins), renin-angiotensin system antagonists (RASA), and non-insulin diabetes agents (NIDA) (Table 4).

Table 4. PQA Metrics Used to Measure Pharmacy Care Processes

Metric Class	Numerator	Denominator*
Adherence to noninsulin diabetes agents**	All patients in the denominator with at least 80% PDC in 2013	All patients filling at least two prescriptions for noninsulin diabetes agents on at least two unique dates, excluding patients with end stage renal disease and/or insulin use.
Adherence to renin-angiotensin system antagonists (RASA)	All patients in the denominator with at least 80% PDC in 2013	All patients filling at least two prescriptions for a renin-angiotensin system antagonist on at least two unique dates, excluding patients with end stage renal disease.
Adherence to statins	All patients in the denominator with at least 80% PDC in 2013	All patients filling at least two prescriptions for a statin medication on at least two unique dates
Adherence to β-blockers	All patients in the denominator with at least 80% PDC in 2013	All patients filling at least two prescriptions for a β-blocker on at least two unique dates

*ESRD was identified with any diagnosis code on any claim for ICD-9 585.6.

**Includes biguanide, sulfonylurea, thiazolidinedione, DPP-IV inhibitor, incretin mimetic, meglitinide, and SGLT2 inhibitor

PQA's endorsed metrics use prescription claims to estimate secondary nonadherence. This is not the only method for evaluating nonadherence, but it is among the easiest to implement and measure across a broad set of secondary datasets (Osterberg & Blaschke, 2005). The most accurate approaches are direct observation of medication taking or tracking of drug levels in the blood, but these methods are expensive and not useful for insurers tracking adherence across a population. The PQA metrics for secondary nonadherence estimate adherence using the percent of days covered (PDC) method with a cut-off for nonadherence at 80%. This method is more conservative than the alternative mean-possession-ratio method of calculating adherence in administrative claims data (Nau, 2012), and with the inclusion of PQA's metrics in Part D plan

quality measurement and EQuIPP, PDCs have become the industry standard for adherence measurement.

The standard use of the 80% PDC measure for adherence is not without criticism (Roberto & Onukwugha, 2015), but there is evidence that patients in the 80-100% adherence range have better health outcomes than do patients with less than 80% adherence (Nau, 2012; Sokol et al., 2005). Furthermore, studies finding benefit from improving adherence on healthcare outcomes and cost (Choudhry et al., 2014; Roebuck et al., 2011; Stuart et al., 2015) as well as studies on pharmacist impact on nonadherence (J. K. Lee et al., 2006; Perlroth et al., 2013; Pringle et al., 2014) all use 80% as the nonadherence threshold to create a binary adherent-nonadherent measure. PDCs with an 80% cutoff for nonadherence vs. adherence was used for evaluating adherence in this dissertation.

The PDC for this project were calculated following the method described by Nau (2012) and in the PQA technical specifications document (Pharmacy Quality Alliance, 2014). The first step was to calculate the measurement period, which for this project begins with the first fill of the 2013 calendar year and ends on December 31st, 2013. An adjustment to the measurement period was made to account for any days spent in hospitals as it was assumed that the patient received prescriptions from the hospital and stockpiled previously received medications. Each patient's total annual hospitalized days occurring after the index date were subtracted from the measurement period. The second step was to, for each drug in the relevant metric, count the days over which patient was "covered" by the drug in the class, i.e. the fill date for the claim plus the days supplied by the prescription. Under the PDC method, if a subsequent fill for the same medication (same generic ingredient) overlapped with a previous fill, the start date and days supplied that follow were adjusted to the day after the previous medication's days supplied were finished. For example, a patient taking atorvastatin would receive a correction if atorvastatin prescriptions overlapped, but would not receive a correction if they switched from atorvastatin to

rosuvastatin. In this way, the PDC was adjusted for early fills and assumed that a patient finished all of a previous fill before beginning the next medication. The total days covered by medications calculated in the second step was summed. The third step was to divide the covered days by the total number of days in the measurement period and multiply by 100 to get the PDC for each patient. Finally, to calculate the 80% PDC score for a pharmacy, the total number of patients achieving an 80% threshold was divided by the total number of patients eligible for the metric.

It is statistically necessary to include a minimum number of patients for each process metric's denominator. PQA recommends a minimum denominator of 30 (Pharmacy Quality Alliance, 2014), but preliminary analysis of denominators found that denominators as low as 15 could be used without substantially influencing the coefficient of variance across the metrics (Appendix D.). Therefore, to reduce the chance of type II error, this study broke with PQA's recommendation and used a denominator of 15 instead of 30.

3.d.2.4. Outcome Metric Selection and Creation

One can conceive of health outcomes in a variety of ways—health status, survival, recovery, patient safety, and more (Porter, 2010a). Commercial insurers could measure health status via changes in quality of life and clinical markers of disease, but this would require significant effort to survey the entire enrolled population or establish data collection methods to gather information on clinical markers from healthcare professionals. Data available in every administrative claims database are hospitalizations, emergency department visits, and other records of healthcare resource use related to outcomes. Some hospitalizations are necessary and part of a normal disease process, other hospitalizations are avoidable and representative of negative health outcomes. Even when a hospitalization is necessary, this may be a sign that a patient's health status has fallen to a point so low as to require a hospitalization, and this could

have been avoided with better preventive care. Furthermore, the possibility of nosocomial infections makes any visit to the hospital at least somewhat risky and therefore unnecessary hospitalizations should be minimized. Although Porter argues for disease state specific outcomes, disease prevalence and small sample size limits the ability to implement explicit, specific outcome measures for this study's commercially insured population (Porter, 2010a). An attempt was made to use Agency for Healthcare Research and Quality's Quality Indicators Software (Agency for Healthcare Research and Quality, 2015) to assess hospitalizations related to diabetes and hypertension, but it was discovered that the eligible hospitalizations were far too rare for specific hospitalization metrics to be used. Therefore, a broader hospitalization metric was used.

Emergency department visits are also likely linked to low quality care processes, but patients may also use the emergency department for nonemergent reasons. For example, a study of emergency department visits by commercially insured patients found that nearly 25% of visits were unnecessary and 40% were for conditions that could have been treated in a primary care setting (Truven Health Analytics, 2013). Much has been made about unnecessary emergency department visits, and it could be that pharmacists' actions could reduce emergency department visits through improvements in health and coaching on best sources of primary care. Therefore, a reduction in ED visit use could represent both a high quality outcome and a direct cost savings with no change to health.

Claims associated with a hospitalization were identified using Wellmark's coding scheme for place of service and type of business operation (Appendix A). When the place of service indicates that the claim originated from an inpatient unit and the trend line of business confirmed the claim not to be from a practitioner or from the drug benefit, the claim was considered to indicate a hospitalization. Identifying ED visits through Wellmark's coding scheme was not as straightforward because the ED as a place of service was not broken out in the claims description. Therefore, CPT codes numbered 99281 – 22985 were used to identify claims originating from the

emergency department. These codes are specific to services delivered in the emergency department (American Medical Association, 2012) and appeared as facility and practitioner procedure codes in Wellmark's coding scheme. These codes are recommended by ResDAC for identifying ED visit claims (Research Data Assistance Center, 2012) and have been used in previous literature to identify ED visit claims (Kaskie et al., 2010). ED visits requiring critical care services could be coded using special critical care codes that supersede ED visit codes, but delivery of critical care services to commercially insured patients in the ED is likely to be rare.

To identify a subset of hospitalizations and ED visits large enough to allow for measurement in a relatively healthy, commercially insured population yet specific enough to chronic use of medications, this study excluded any hospitalizations with an associated diagnosis code for cancer, trauma or a planned procedure. ED visits were eliminated if they were associated with a diagnosis code for trauma. To avoid double-counting an outcome event, if a hospital admission coincided on the same day as the ED visit, the ED visit was not counted. Hospitalizations associated with cancer or a planned procedure were excluded following the algorithm used by CMS to exclude readmissions from the Risk Standardized All Condition Readmission metric used to evaluate ACO quality (Centers for Medicare and Medicaid Services, 2016a). Cancer diagnoses were identified using CCS classification categories 11-45. Any claim associated with a hospitalization that had an ICD-9-CM code within these CCS categories resulted in the exclusion of that hospitalization from the associated patient's hospitalization count. Planned procedures were divided into always planned and potentially planned categories. Always planned hospitalizations were any hospitalization with an ICD-9-CM code in CCS procedure categories, 65, 105, 134, 135 and 176 or CCS diagnosis categories 45, 194, 196 and 254. Potentially planned admissions were those with an ICD-9-CM code falling into one of many CCS procedure categories related to many types of surgical procedures that were also not associated with a diagnosis code for an acute illness. For example, if a patient's hospital stay

included an ICD-9-CM procedure code for coronary artery bypass graft (CABG), the admission would be considered planned and therefore excluded as long as there wasn't also an ICD-9-CM code corresponding to an acute myocardial infarction (AMI). For more details on the algorithm see appendices A and B in CMS's technical paper on the ACO metric used in this study (Centers for Medicare and Medicaid Services, 2016a). Trauma visits were CCS categories identified by AHRQ as trauma-related: 225-236, 239, 240, and 244 (Uberoi & Yeh, 2012). If any claims associated with a hospitalization or ED visit had an ICD-9-CM code in any of the trauma CCS categories, the hospitalization or ED visit was eliminated.

After hospitalizations and ED visits were eliminated, the remaining non-cancer, non-trauma, unplanned hospitalizations and non-trauma ED visits were summed for each eligible patient. The total number of attributed patients comprises the metric denominator, and the number of attributed patients with at least one hospitalization or one ED visit comprise the respective metric's numerator. Patients with more than one hospitalization/ED visit were not counted more than once. This ignored the effect of pharmacies on hospital readmissions, but readmissions are much less likely to occur for a commercially insured population than for a Medicare population (Wier, Barrett, Steiner, & Jiang, 2011).

Because the expected event rates for hospitalizations and ED visits was expected to be quite low, it was necessary to use some way to limit metric-eligible pharmacies to only those for which there is a reasonable assurance of metric reliability. One option was using a minimum denominator and estimating a priori the expected rate of hospitalizations to limit the set of pharmacies to only those that have an expected event count in excess of 1-5 events per year (Ash, Shwartz, Pekoz, & Hanchate, 2013). There is little objective basis for this cut-off, though. Instead, outcome metrics were applied to all pharmacies for which all four of the process metrics can be measured.

3.d.2.5. Quality Scoring for Pharmacies

To aggregate measures of process quality to a more usable number that potentially correlated with the pharmacy's underlying care-process quality, a single process quality score was created. Following the method used by Dharmarajan et al. (2014) and Li, Cai, Glance, Spector, and Mukamel (2009) and described more fully in sections 3.e.3, 3.e.5 and 3.e.6, high quality pharmacy outliers for a given process metric received a score of +1 and low quality outliers received a score of -1. Scores were summed across the four quality metrics and the resulting Process Quality Score had a potential range from -4 to +4.

The same method used to create the Process Quality Score was used to evaluate pharmacies' outcome quality. Pharmacies received a -1 or +1 depending on their outcome quality achievement for the two outcome metrics. This total was added to the Process Quality Score to yield a single Combined Quality Score with a potential range of -6 to +6. A fuller description of the scoring process is found in Section 3.e.5.

3.d.3. Cost of Care

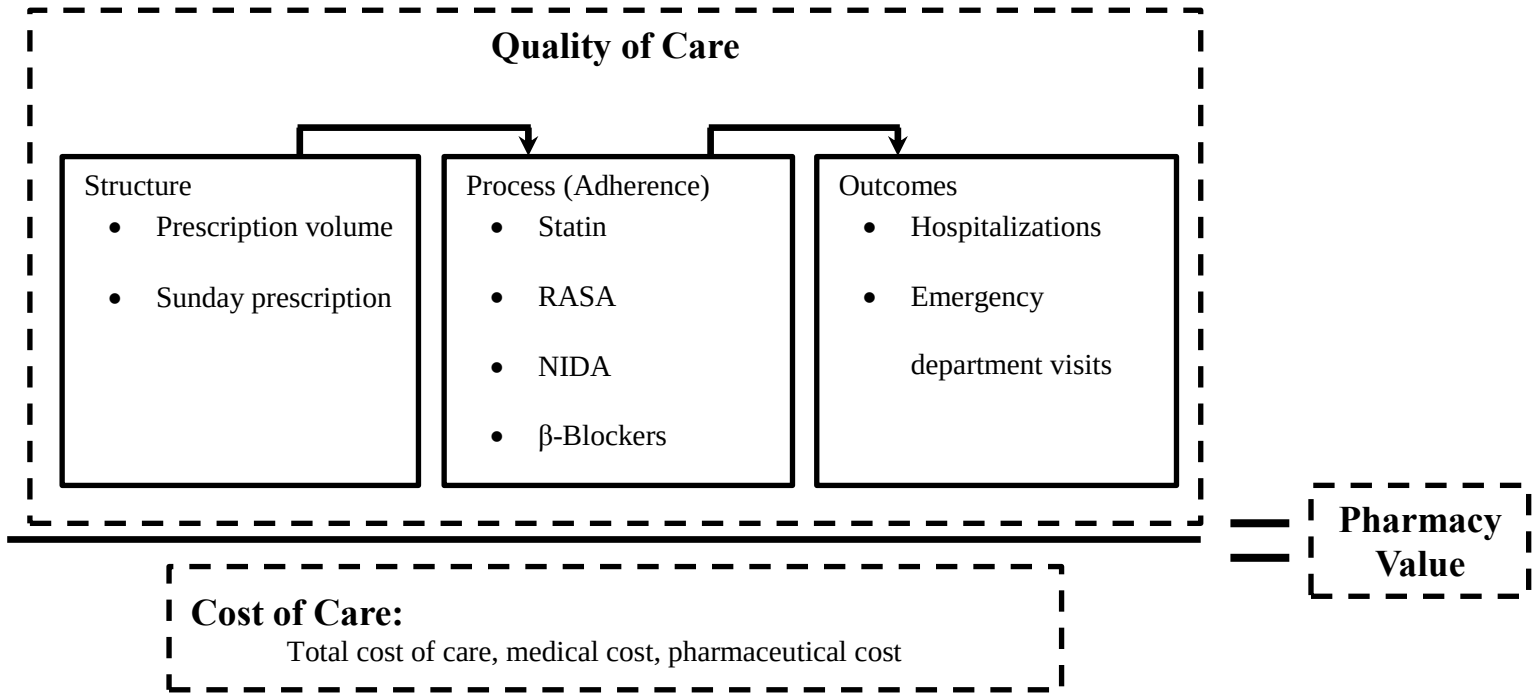
The conceptual model divides pharmacy quality by cost of care to estimate pharmacy value. Evaluation of hypotheses 2.1-2.3 necessitates inclusion of three types of costs into the model: total cost of care, medical cost, and pharmaceutical cost. Each patient's pharmaceutical costs were calculated by summing all allowable charges for 2013 for claims originating from a pharmacy. This measure of costs encompasses the patient's copayment/coinsurance amount as well as payments made by the insurer. Medical costs were the sum of allowable charges for all other claims and total cost of care is the sum of pharmaceutical and medical costs. Not all claims

with NDCs were considered in the pharmaceutical cost category because physician administered drugs were included in the cost of medical care. Allowable charges may have been inflated above the actual amount spent for a good or service, but this is the most accurate cost estimate available in the data and has been used by other authors to estimate costs (Pringle et al., 2014). Healthcare cost sums for patients with annual medical cost, pharmaceutical cost, or total cost of care in excess of two standard deviations above population averages on the log scale were right-truncated. Compared to eliminating patients, this method avoided potential selection effects while still improving model fit and reducing the risk of an exceptionally expensive patient poses to their attributed pharmacy's cost impact scores. This truncation method has also been used elsewhere in total cost of care measures (HealthPartners, 2016).

3.d.4. Operationalized Conceptual Model

The preceding sections described the measures that were used to adapt the conceptual model of the value that pharmacies provide insurers for this project. Figure 5 below shows how the conceptual model was transformed.

Figure 5. Operationalized Model for Measuring Value Pharmacies Provide to Insurers



3.e. Statistical Analysis and Modeling

The unit of observation for this project was the pharmacy, and pharmacy quality scores were calculated using patient-level data from each pharmacy's attributed population. This nested data structure is common to all healthcare quality scoring systems which compare quality across different providers, pharmacies, hospitals, etc. Although classic regression models have been commonly used to adjust for variation in case-mix and produce estimates of quality (Li et al., 2009), these models assume homoscedasticity in the variance of outcome probability across patients. Expected outcome probabilities were then often averaged across each provider's attributed population and analyzed to detect systematic differences in the effects of providers on their patients (Li et al., 2009). If differences were found, this suggests heteroscedasticity of outcome probability variance. To avoid this logical inconsistency and explicitly model the effects of providers on attributed patients for purposes of quality measurement, researchers investigating variation in quality have used more advanced hierarchical modeling techniques (Ash et al., 2013; Dharmarajan et al., 2014; Li et al., 2009).

A common approach for risk adjusting quality scores for providers is to model the provider as a random effect in a hierarchical model that also includes case-mix adjustment variables to control for differences across attributed patients (Ash et al., 2013; Dharmarajan et al., 2014; Li et al., 2009). For binary patient-level outcomes, expected provider scores can be estimated as the average of the predicted outcome event probability for the attributed population. A risk-adjusted score can then be calculated by dividing the observed rate of outcome occurrence by the expected rate of occurrence, and then multiplying this ratio by the average rate of occurrence across all providers (Ash et al., 2013; Dharmarajan et al., 2014; Li et al., 2009). An analogous approach is used to evaluate quality for continuous response variables. See sections 3.e.2, 3.e.4 and 3.e.7 for further description of this method of producing risk adjusted scores.

Aim two and corresponding hypotheses 2.1, 2.2 and 2.3 require that the relationship between quality and cost be evaluated. Creating a point system to grade provider quality is an extremely common way to compare quality among providers. Points are used in CMS's Nursing Home Compare initiative (Li et al., 2009), Medicare Part D (Centers for Medicare and Medicaid Services, 2015p), Inland Empire Health Plan's pharmacy quality initiative (Inland Empire Health Plan, 2014), Wellmark Blue Cross and Blue Shield's high performing pharmacy network (Mascardo, 2016; Swenson, 2016), and the initiative by Community Cares of North Carolina (Trygstad, 2015). There is substantial variation, however, in how scores for providers are calculated. Some systems use a "fence" derived from the standard deviation around a mean provider performance score (Ash et al., 2013) or specific percentage point cut-offs (Dharmarajan et al., 2014; Li et al., 2009) to create thresholds above and below which the pharmacy is considered a quality outlier. Although straightforward to conceptualize and implement, comparing the distribution of risk-adjusted scores to a confidence interval around a mean risk-adjusted score ignores the confidence with which the provider's risk adjusted point estimate was calculated and forces any pharmacy outside of the fence to be categorized as a high or low performer. Therefore, this method can be prone to over-identification of outliers (Ash et al., 2013) and increases the likelihood of type 1 error when evaluating the presence of pharmacies with high or low value.

An alternative system involves creating confidence intervals around each provider's risk adjusted score, and comparing this to a measure of centricity as a means of differentiating high and low quality outliers (Ash et al., 2013; Li et al., 2009). This method of creating confidence intervals around risk adjusted scores derived from random effects models has been used previously to calculate pharmacy quality using PDC measures (Dharmarajan et al., 2014) and supports the inclusion of patient level case-mix adjustment variables without risking over-identification of pharmacies caused by artificial statistical fences. The next section describes the

selection of case-mix adjustment variables, and is followed by sections detailing the statistical methods to implement a method for creating confidence intervals around risk adjusted scores that were used for quality scoring and hypothesis testing.

3.e.1. Case-Mix Adjustment

As described in the conceptual model, there are many influences on care process metrics and outcomes beyond the effects of pharmacists. Within the conceptual model, it is acknowledged that patients directly influence nonadherence and other care processes. Furthermore, pharmacists are only one of many health care practitioners that influence patients' nonadherence, hospitalizations and emergency department visits. Adjusting for variation in case mix is especially necessary for outcomes, because of the substantial influence of patient-level factors on outcome measures (Porter, 2010b).

To account for this, many studies evaluating the effects of medication optimization on outcomes of care and variation in pharmacy quality use risk adjustment methods to adjust for variation in outcomes resulting from differences in case-mix. Age and sex are used as covariates in every claims study evaluating pharmacy quality included in Chapter II (Brennan et al., 2012; Dharmarajan et al., 2014; Fischer et al., 2014; Jackson et al., 2014; Pringle et al., 2014). Studies also control for effects of income by including into their statistical models the low income subsidy (Dharmarajan et al., 2014), median household incomes by ZIP code (Brennan et al., 2012; Desai et al., 2016; Pringle et al., 2014) or median household incomes by "pharmacy neighborhood" (Jackson et al., 2014). Many studies also use some measure of comorbidity. Dharmarajan et al. (2014) used the RxRisk category system to impute health conditions from the patients' medication record. Brennan et al. (2012) uses the proprietary Ingenix pharmacy risk score. HealthPartner's risk adjusted total cost of care metric also uses age, sex and a measure of

clinical risk related to diagnosis (Knudson & Heim, 2014). EQuIPP uses benchmarking to vary quality metric targets by pharmacy, but the process for adjusting benchmarks is unclear. It is not clear what risk adjustment method CCNC uses. The value-based payment modifier used by CMS employs a complicated risk adjustment method that varies by metric but consistently uses age and some measure of clinical complexity (Centers for Medicare and Medicaid Services, 2015t).

Another variable available in the data that may be useful in risk adjusting is the patient-level count of annual prescription fills. The goal of case-mix adjustment is to control for differences in patient characteristics that influence the outcome of interest independent of provider effects (Ash et al., 2013). For models estimating the probability of adherence and outcome events, prescription count was included because of its theoretically inverse relationship with the latent variable health status that is itself correlated with patients' adherence, hospitalization rate and ED visit rate. For models predicting cost, there is still likely to be the relationship with health status, but prescription count is also directly correlated with annual pharmaceutical cost and the total cost of care. Additionally, pharmacists may create value through reducing the annual prescription count, and modeling this covariate may create misspecification of pharmacies' quality status. Therefore, annual prescription count was used in case-mix adjustment for quality measures and assessed as both a raw count of prescriptions and the log count of prescriptions, but was not included in cost prediction models.

This project included age, sex, comorbidity count, and annual prescription count as covariates to adjust for variation in case-mix. Age, calculated as the difference between the birth year and study year, and sex were included in the Wellmark database's member file. Annual prescription count was calculated by summing all prescriptions filled by the patient at any pharmacy over the calendar year. Comorbidities were assessed using the Elixhauser method as adapted from AHRQ's SAS program developed for use in HCUP data (Healthcare Cost and Utilization Project (HCUP), 2015). The Elixhauser method uses ICD-9-CM diagnosis codes to

create 30 different condition categories, which is a much more manageable set of comorbidities than the CCS's more than 250 different conditions. Compared to the Charlson comorbidity index (CCI), there some research has shown that Elixhauser has superior predictive validity for outcomes associated with hospitalizations (Chu, Ng, & Wu, 2010). Elixhauser is also endorsed by AHRQ for use in risk adjustment with HCUP data and includes more conditions than the CCI, which may be of benefit in a relatively healthy population. Elixhauser is updated periodically, but no updates have occurred since 2012 (Healthcare Cost and Utilization Project (HCUP), 2015). Following the method used by Kuntz, Chrischilles, Pendergast, Herwaldt, and Polgreen (2011), a patient was considered to have an Elixhauser condition if a corresponding diagnosis code was associated with any inpatient visit in 2012 or an outpatient visit in 2012 and a subsequent outpatient visit at least 30 days later in 2012 or 2013. An initial assessment of disease prevalence found that nearly two-thirds of eligible patients had no Elixhauser conditions. Therefore, because of low frequencies across many disease categories, comorbidities were assessed as a count of all conditions, and data were coded as a set of variables with different top-out counts (i.e. 2+, 3+, 4+) as the largest category. This simple method of summing comorbid conditions has been shown to predict healthcare costs in primary care (Brilleman et al., 2014) and is a reasonable choice for a relatively healthy population.

Income was not included in this model. Other literature including income had a more heterogeneous population with respect to income than this study's population which receives insurance either through an employer or is self-insured. This project used the patient's age, sex, annual count of prescriptions and Elixhauser comorbidities to correct for some of the sources of bias and confounding obscuring the relationship between pharmacy quality and process and outcome metrics. These were entered as covariates in hierarchical models predicting the probability of a patient meeting the numerator specification for each quality metric and in mixed models predicting patients' healthcare related cost.

3.e.2. Testing Hypothesis 1.1

Hypothesis 1.1: There is a direct relationship between the quality of a given pharmacy's structures and the quality of care processes delivered by pharmacists at that pharmacy.

As described in Section 2.d.3, high quality structures lead to high quality processes which lead to high quality outcomes. Hypotheses 1.1 tests the linkage between structures and processes. There were two structure variables included in this model: weekly prescription volume and Sunday prescriptions. The effect of these variables on the probability of a patient meeting or exceeding the 80% PDC threshold for any of the four medication classes was estimated using hierarchical logistic regression with a random intercept for pharmacy and case-mix adjustment variables:

Equation 1.

$$\log\left(\frac{p_{ijq}}{1-p_{ijq}}\right) = \alpha_j + Structures\left(\beta_1 x_{1j} + \beta_2 x_{2j}\right) + Case\ Mix\left(\beta_3 x_{3ij} + \beta_4 x_{4ij} + \beta_5 x_{5ij} + \beta_6 x_{6ij}\right) + State\ \left(\beta_7 x_{7j}\right)$$

The form of the model in Equation 1 predicts the probability that patient *i* attributed to pharmacy *j* meets the numerator specification for quality metric *q*. The random intercept for the effect of pharmacy, α_j, was assumed to follow a normal distribution. Structure variables x_1 and x_2 represent weekly prescription volume and Sunday prescription category. The case mix variables represent covariates for age, gender, count of Elixhauser conditions and annual prescription count. The need to include the pharmacy state variable was assessed using the variable's p-value.

The variable is not necessary per the conceptual model, therefore its elimination was considered in an effort to create a more parsimonious model.

The variance-covariance matrix was assumed to be compound symmetric, whereby variance estimates were allowed to differ between pharmacies but were constant for patients nested within the pharmacy (Kincaid, 2005). This specification is supported by the data structure and results in more parsimonious models compared to assuming an unstructured variance-covariance matrix. The adaptive Gaussian quadrature approximation was used to estimate maximum likelihoods. Compared to alternatives, the Gaussian quadrature enables the calculation of true AIC values, produces accurate estimates of fixed effects, and is available in SAS through PROC GLIMMIX (Capanu, Gonen, & Begg, 2013). Relative predictive ability of candidate models was compared using the AIC and discrimination ability was assessed using the c-statistic. The residual intraclass correlation coefficient was used to estimate the percent of total variance in outcome probability explained by the pharmacy to which a patient was attributed. A Wald test was used to evaluate the significance of the inclusion of the random effect for pharmacy.

To create a fully specified model that also fits the data well, weekly prescription volume, age, Elixhauser condition count and annual prescription count were tested using permutations as described in sections 3.d.1 and 3.e.1. First, the pool of eligible case-mix variables was assessed for inclusion in a base hierarchical model that included only the random pharmacy intercept. The candidate independent variable most strongly correlated with the dependent variable was chosen for inclusion in the model. If there were permutations of the included variable, they were not included in the next round of variable selection. For the next round, the variable that produces the lowest overall AIC was chosen. If, across the four PDC models, there was disagreement on the next variable to be added but the AIC values were similarly small for a variable in the majority of models, that variable was chosen as the next variable for every model. In this way, a consistent model was created. Each additional round proceeded similarly, and the need for interaction terms

was assessed with each successive variable addition. After adding all case-mix variables into the model, permutations of structure variables were similarly tested. Pharmacy state was added last and included if the p-value was less than 0.2 over the majority of models. There was no elimination of variables, except for pharmacy state, and the final model was fully specified according to the conceptual model.

Hypothesis 1.1 was tested using the associated p-value for structural variables in the fully specified model resulting from the aforementioned variable selection process. Strong correlations between both structure variables and each PDC measure fully support rejecting the null hypothesis; mixed results were considered as providing partial support for rejecting the null.

3.e.3. Calculating Process Quality Score

The Process Quality Score (PQS), used to test hypotheses 1.2, 2.1, 2.2 and 2.3 was calculated using results from Equation 1, but with the structure variables removed. The purpose of calculating risk adjusted scores, which were in turn used to calculate the PQS, was to control for differences in patient mix across pharmacies that affect outcome probability independent of pharmacy effect (Ash et al., 2013). Therefore, including variables related to the quality of pharmacy structures may unfairly penalize pharmacies that change their structures to support higher quality care processes. The quality score calculation followed the outlier identification methods used by Li et al. (2009) and Dharmarajan et al. (2014) which create confidence intervals around risk adjusted scores and compare these intervals to a population mean.

First, the observed rate was calculated as follows:

Equation 2.

$$O_{jq} = \frac{1}{n_{jq}} \sum_{n=1}^{n_{jq}} m_q$$

Where O represents the observed percentage patients attributed (*n*) to pharmacy *j* eligible for metric *q*'s denominator meeting the metric's numerator specifications *m*. O_{jq} is equivalent to the observed quality indicator score for pharmacy *j* and metric *q*.

The expected quality metric score for each pharmacy, E_{jq} was calculated as follows:

Equation 3.

$$E_{jq} = \frac{1}{n_{jq}} * \sum_{n=1}^{n_{jq}} p_{ijq}$$

Where n_{jq} represents the total number of patients attributed to pharmacy *j* who meet denominator specifications for metric *q* The variable p_{ijq} was the expected probability of meeting the numerator specification for patient *i* at pharmacy *j* for metric *q* and was derived from the transform of expected odds resulting from Equation 1, without structural variables.

A risk adjusted score was calculated as follows:

Equation 4.

$$\frac{O_{jq}}{E_{jq}} * \frac{\sum_{j=i}^{N_q} O_{jq}}{N_q}$$

Where *N* represents the total number of pharmacies included for metric *q*. A kernel density plot of risk adjusted scores overlaid with observed scores was used to visualize the relationships between the two distributions (SAS Institute Inc., 2015). A 95% confidence interval around the risk adjusted score was calculated using the standard error of probability estimates for the pharmacy's attributed population and the normal approximation of the binomial distribution:

Equation 5.

$$\frac{O_{jq}\left(1.96 \pm \frac{\sqrt{\Sigma_{i=1}^{n_{jq}}\left(\hat{p}_{ijq}(1-\hat{p}_{ijq})\right)}}{n_{jq}}\right)}{E_{jq}} * \frac{\Sigma_{j=1}^{N_q} O_{jq}}{N_q}$$

The upper and lower bound of the risk adjusted confidence intervals were compared to the mean observed PDC score for all eligible pharmacies. If the adjusted 95% CI included the mean observed PDC score, the pharmacy was considered to be of typical quality. If the entirety of the 95% CI was above the mean observed score, the pharmacy was considered to be a high quality outlier and if below, a low quality outlier. A low quality categorization received a score of -1, typical quality 0 and high quality +1. These scores were summed to produce the Process Quality Score with a potential range from -4 to +4 and was used to test the impact of a pharmacy's care process quality on its patients' health outcomes. A comparison of risk adjusted score distribution and outlier scores was made between a hierarchical model using a random intercept for pharmacy and a generalized linear model estimated with the same technique but lacking the random intercept term.

3.e.4. Testing Hypothesis 1.2

Hypothesis 1.2: There is a direct relationship between care process quality delivered at a given pharmacy and healthcare outcomes for patients receiving care from that pharmacy.

Equation 1 without structural variables but with the addition of the PQS score was used to test hypothesis 1.2. Donabedian suggests that structures relate much less strongly to outcomes than to processes (Donabedian, 1988), and hypothesis 1.2 focuses specifically on the relationship

between process and outcome quality. The variable selection method as described in section 3.e.2 was also used for hypothesis 1.2. The test for the null hypothesis for 1.2 was the p-value associated with the Process Quality Score.

3.e.5. Calculating Outcome Quality Score and the Combined Quality Score

The calculation for the Outcome Quality Score (OQS) proceeded the same as the calculation of the PQS, except that probability of hospitalizations and ED visits rates were used as outcome variables instead of the probability of adherence. The OQS had a potential range of -2 to +2. The Combined Quality Score was calculated by summing the OQS and PQS and had a potential range of -6 to +6.

3.e.6. Calculating Cost Impact Score

Hypothesis 2.1: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on pharmaceutical costs.

Hypothesis 2.2: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on medical costs.

Hypothesis 2.3: There is variation in pharmacy value as calculated by pharmacies' impact on healthcare quality relative to pharmacies' impact on total cost of care.

Hypotheses 2.1, 2.2 and 2.3 evaluated pharmacy value using three different types of cost: pharmaceutical cost, medical cost, and total cost of care. Value, according to the conceptual model, is determined by the relationship between pharmacies' impact on healthcare quality and pharmacies' impact on the cost of healthcare. The previous section described the calculation that created the Combined Quality Score to measure pharmacy quality; this section calculates the Cost Impact Score which measures pharmacies' impact on healthcare cost. Consistent with hypotheses 2.1 – 2.3, the Cost Impact Score was calculated for each of the three healthcare cost categories. The calculation of each of the scores was conducted using the same method, which was adapted from the method used to separate pharmacies by impact on healthcare quality.

The patient-level dependent variable for calculating cost, the sum of annual cost, was found to be lognormally distributed. Each pharmacy's observed mean cost for attributed patients was calculated by taking the log of the average of patients' cost in each category:

Equation 6.

$$O_{jd} = \frac{1}{n_{jd}} \sum_{n=1}^{n_{jd}} \log(C_{obs\,d})$$

Where observed mean log cost O for pharmacy j and category d was calculated by taking the average of log cost C_{obs} by attributed patients.

A hierarchical linear model was used to account for the impact of pharmacy on the log of attributed patients' cost. The model's explanatory power was evaluated using R^2_1 as described by Snijders and Bosker (2012) and the residual intraclass correlation coefficient. R^2_1 compares the change in explanatory power as variables were added into the model against a base model with only a random intercept for pharmacy. Compound symmetry and the adaptive Gaussian

quadrature were used to estimate model parameters. A Wald test was used to evaluate the significance of including the random effect for pharmacy. The form of the model was as follows:

Equation 7.

$$\log(C_{exp\ ijd}) = \alpha_j + Case - Mix(\beta_3 x_{3ij} + \beta_4 x_{4ij} + \beta_5 x_{5ij})$$

Where log expected cost, C_{exp}, for patient *i* attributed to pharmacy *j* in cost category *d* was a linear combination of the random intercept for pharmacy α_j and case-mix variables x_3 (age), x_4 (gender) and x_5 (comorbidity count). The process for calculating the observed, expected, and risk adjusted scores using hierarchical linear models was analogous to that for hierarchical logistic models. To create the Cost Impact Score for each of the three cost categories necessary to test hypotheses 2.1-2.3, the expected cost values were calculated by summing the expected cost for each patient, *i*, over the attributed pharmacy *j*.

Equation 8.

$$E_{jd} = \frac{1}{n_{jd}} * \sum_{n=1}^{n_{jd}} \log(C_{exp\ ijd})$$

Risk adjusted scores were created in the same way as Equation 4., substituting expected cost for expected adherence and outcome event probability:

Equation 9.

$$\frac{O_{jd}}{E_{jd}} * \frac{\sum_{j=i}^{N_d} O_{jd}}{N_d}$$

The same method of scoring pharmacy outliers that was used for quality metrics was used for cost. The adaptation of the formula for calculating risk adjusted confidence intervals for continuous outcomes was as follows:

Equation 10.

$$\frac{O_{jd}\left(1.96 \pm \sqrt{\Sigma_{i=1}^{n_{jd}} \frac{\left(E_{jd} - \log\left(C_{exp\ jd}\right)\right)^2}{n_{jd} - 1}}\right)}{E_{jd}} * \frac{\Sigma_{j=1}^{N_d} O_{jd}}{N_d}$$

Cost scores were created in the same way as quality scores. If the upper bound of the confidence interval from Equation 10 for cost category *d* and pharmacy *j* was below the mean cost across pharmacies, then pharmacy *j* received a Cost Impact Score of -1 for metric *d*. If the opposite was true, the pharmacy received a CIS score of +1 and if the risk adjusted confidence interval contains the mean across all pharmacies, the pharmacy received a score of 0. CIS vales were calculated for each cost category separately.

3.e.7. Testing Hypotheses 2.1, 2.2 and 2.3

To test hypotheses 2.1, 2.2 and 2.3, contingency tables were constructed which compared variation in pharmacies' impact on the cost of healthcare to pharmacies' impact on healthcare quality. To make for a more interpretable table and to aid hypothesis testing, the Combined Quality Score (CQS) was divided into three categories labeled low quality, typical quality and high quality based on the distribution of quality scores across all pharmacies. If a pharmacy's CQS was below 0, it was labeled a low quality pharmacy. If the pharmacy's CQS was above 0, it was labeled high quality. Each pharmacy was also labeled low cost, typical cost and high cost for each of the CIS categories according to the calculations in Section 3.e.6. This created nine

possible categories for pharmacy value for each of the three cost measures, and the possible relationships between the nine categories is shown in Figure 6.

Figure 6. Value Matrix for Comparing Impact on Cost and Quality to Determine Value

Low Cost	4	2	1
Typical Cost	7	5	3
High Cost	9	8	6
	Low Quality	Typical Quality	High Quality

In the value matrix, low value pharmacies appear in cells 7-9 and high value pharmacies appear in cells 1-3. For purposes of testing the value hypotheses, pharmacies in cells 1-3 receive a value outlier score of 1 and 7-9 received a value outlier score of -1, suggesting that they have either high or low value, and pharmacies in cells 4-6 received a value outlier score of 0, suggesting that they have typical value. A t-test with the assumption of unequal variances was used to compare the mean and standard deviation of the high and low value outlier scores to a mean 0 and variance 0, which were the value score mean and distribution if no pharmacy was found to be an outlier. A finding that the means were significantly different at $p<0.05$ was sufficient to reject the null hypothesis of no value and state that there was observable variation in pharmacy value for a commercially insured population.

CHAPTER IV
RESULTS

4.a Data Preparation and Descriptive Analysis

This section describes the steps taken to prepare the dataset for evaluation of aims 1 and 2. The initial dataset contained 510,028 patients which, after applying demographic and coverage-based exclusion criteria, was reduced to 299,023 (Figure 7). This number was reduced further to 201,765 by the elimination of nearly 100,000 patients who filled no prescriptions in 2013. Only 2,942 patients failed to meet the 50% minimum fill percent threshold for pharmacy attribution, and an additional 6,918 met the threshold but were attributed to a pharmacy not located in Iowa or South Dakota. This left 191,905 patients considered for inclusion in the process metric denominators.

Pharmacies were also eliminated to create the set of pharmacies for which a process metric could be measured (Figure 8). Of the 4,101 unique pharmacies identified in the dataset, 3,124 were not located in Iowa or South Dakota. The remaining 977 were potentially eligible for process metric assessment. The number of pharmacies meeting the 15 patient minimum denominator for each of the four PDC metrics varied from 174 (17.8%) pharmacies for non-insulin diabetic agents (NIDA) to 678 (69.4%) for renin-angiotensin system antagonists (RASA) (Table 5). Eligible patients for each metric ranged from 3,714 for NIDA to 30,101 for RASA. After applying the exclusion criteria requiring eligible pharmacies to meet denominator requirements for all four process metrics, only 171 (17.5%) pharmacies remained. This criteria excluded an additional 117,324 patients, leaving 74,581 (38.9%) eligible for outcome and cost assessment. Sensitivity analysis including all 477 pharmacies that met statin, RASA and β-blocker PDC denominators and observing the relationship between process and outcome quality, and the resulting combined quality score found no material difference in model covariates or statistical results.

4.a.1 Assessment of Selection Effects

To assess for possible selection effects of the PDC metric eligibility requirement on the included population and pharmacy set, bivariate statistics were used to compare demographic variables by eligibility category (Table 6). Compared to patients attributed to a pharmacy failing to meet denominator metric for at least one PDC metric, the patients attributed to a PDC-eligible pharmacy were slightly older with greater frequency in higher age categories (X^2 $p < 0.0001$), a larger percent female (54.0% vs. 53.0%, X^2 $p < 0.0001$), and slightly sicker with rates of chronic Elixhauser conditions, prescription counts and cost all significantly larger. Pharmacy level comparisons find large and significant differences in observed weekly prescription volume and number of attributed patients (t-test $p<0.0001$ for both comparisons) and substantially fewer pharmacies observed as closed on Sundays (X^2 $p < 0.0001$) for pharmacies eligible for all PDC metrics.

4.a.2 Assessment of Differences between Iowa and South Dakota Pharmacies

Differences were also identified between pharmacies located in Iowa and South Dakota (Table 7). Patients attributed to Iowa pharmacies were slightly older (X^2 $p<0.0001$), more likely to be female (54.2% vs. 51.9%, $p=0.0004$), and slightly sicker with greater rates of chronic Elixhauser conditions, prescription fills, and healthcare cost in all three categories assessed. Pharmacies were not as significantly different, with mean attributed patients varying little (436.0 for IA vs. 438.1 for SD, t-test p-value=0.9656) and similar weekly prescription volumes (184.8 IA vs. 168.9 SD, t-test p-value=0.2690). There were significant differences, however, in Sunday filling categories with no marginally open pharmacies observed in SD (X^2 $p=0.01$).

4.a.3 Analysis of Sunday Filling Categories

The 171 pharmacies eligible for all PDC metrics included 11 pharmacies identified as non-Sunday filling pharmacies and 19 pharmacies as marginal Sunday filling pharmacies using the pre-established 0.1% weekly prescription volume cut-off for differentiating marginal and robust Sunday filling pharmacies (Table 8). The median number of Sundays with observed fills for marginal pharmacies was 2, compared to 52 with robust Sunday fillers. ANOVA was used to compare weekly prescription volume means across the three filling categories, and substantial but not significant variation was found (p=0.0633).

Figure 7. Eligible Patient Selection Flowchart

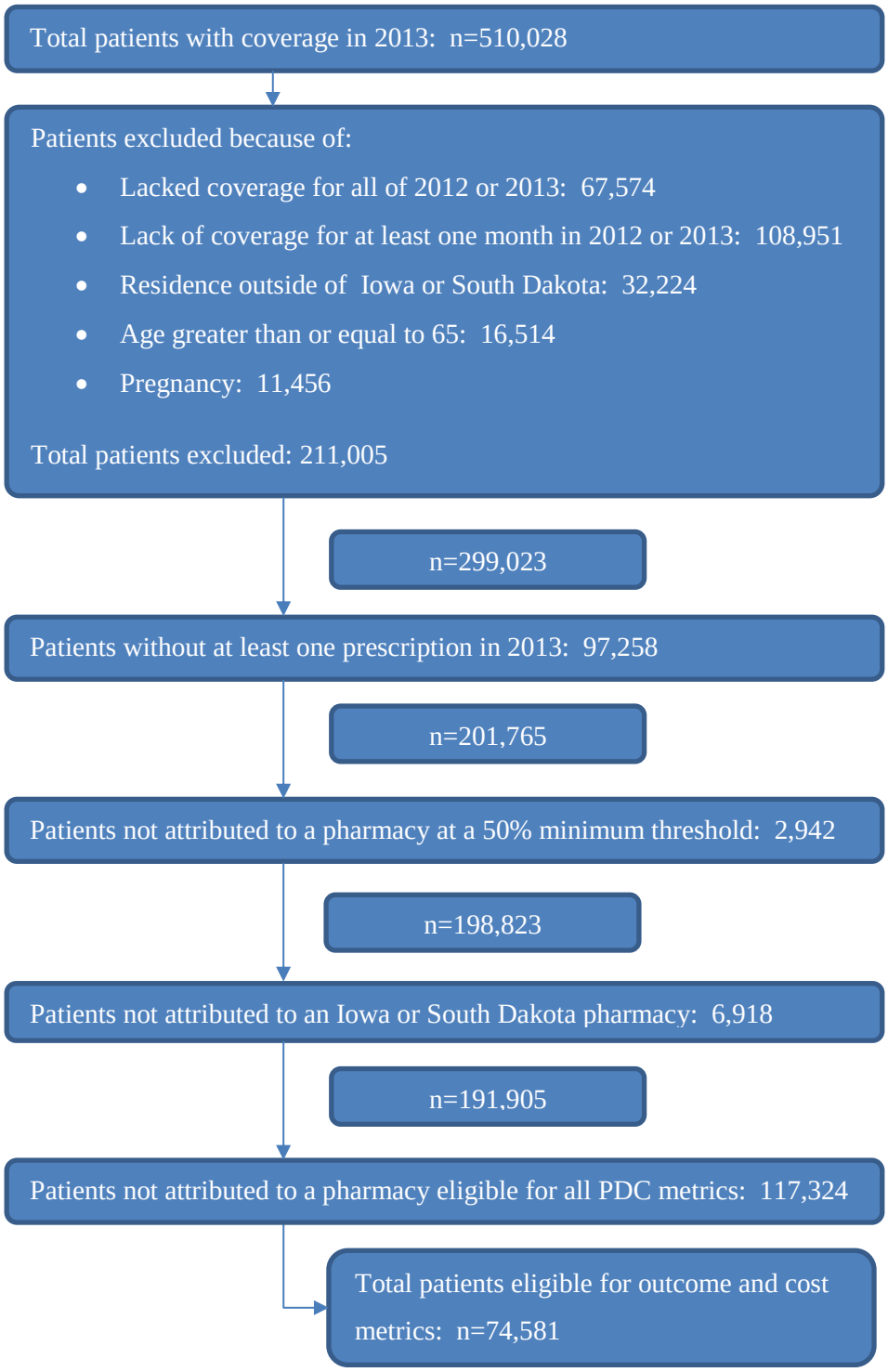


Figure 8. Eligible Pharmacy Selection Flowchart

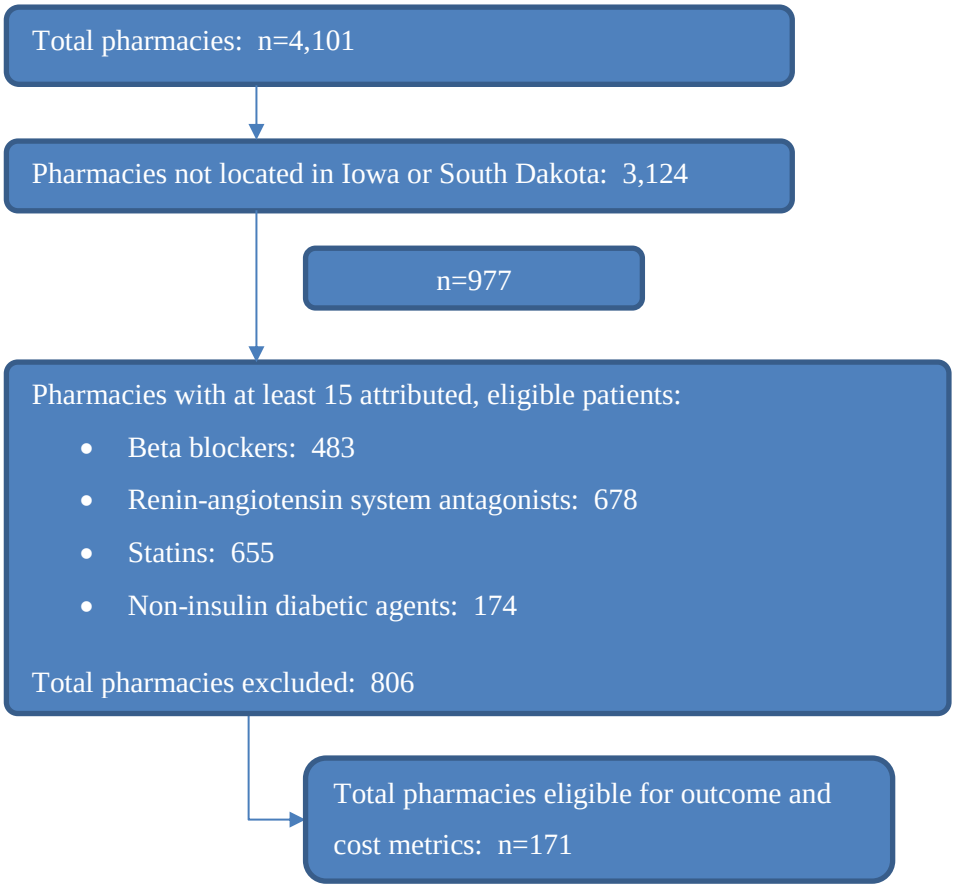


Table 5. Count of Eligible Patients and Pharmacies by PDC Metric

Percent of Days Covered Metric Category	**Eligible Patients**	**Eligible Pharmacies**
Statin	29,421	655
Renin-Angiotensin System Antagonists	30,101	678
Β-blockers	15,044	483
Non-insulin Diabetes Agents	3,714	174

Table 6. Comparison of Patients and Pharmacies by Eligibility Category According to Percent of Days Covered Metric Eligibility Requirement

Descriptive Variable	Ineligible Pharmacies	Eligible Pharmacies	Chi-square/ t-test p-value
Patient-level variables			
Total Patients (N)	117,318	74,581	
Age Category N (%)			<0.0001
18-24	9,907 (8.4%)	5,802 (7.8%)	
25-34	15,661 (13.3%)	9,919 (13.3%)	
35-44	21,581 (18.4%)	13,646 (18.3%)	
45-54	31,258 (26.6%)	20,053 (26.9%)	
55-64	38,911 (33.2%)	25,161 (33.7%)	
Female N (%)	62,198 (53.0%)	40,285 (54.0%)	<0.0001
Chronic Disease Count N (%)			<0.0001
0 Chronic Diseases	80,087 (68.3%)	49,581 (66.5%)	
1 Chronic Disease	26,729 (22.8%)	17,726 (23.8%)	
2+ Chronic Diseases	10,508 (9%)	7,274 (9.8%)	
Prescription Count Mean (SD)	15.8 (18.9)	16.6 (19.6)	<0.0001
Log(Annual Rx Cost) Mean (SD)	5.243 (1.84)	5.3 (1.84)	<0.0001
Log(Annual Medical Cost) Mean (SD)	7.14 (1.42)	7.18 (1.42)	<0.0001
Log(Annual TCOC) Mean (SD)	7.37 (1.56)	7.41 (1.55)	<0.0001
Pharmacy-level variables			
Total Pharmacies (N)	786	171	
Weekly Rx Volume Mean (SD)	63.7 (47.9)	183.5 (67.3)	<0.0001
Sunday Filling Categories N (%)			<0.0001
Marginal	68 (8.7%)	19 (11.1%)	
Non	263 (33.5%)	11 (6.4%)	
Robust	455 (57.9%)	141 (82.5%)	
Attributed Patients per Pharmacy Mean, (SD)	149.3 (120.7)	436.1 (173.8)	<0.0001

TCOC=Total Cost of Care

Table 7. Comparison of Patients and Pharmacies by Pharmacy Location

Descriptive Variable	Iowa Pharmacies	South Dakota Pharmacies	Chi-square/ t-test p-value
Patient-level variables			
Total Patients (N)	68,448	6,133	
Age Category N (%)			<0.0001
18-24	5,253 (7.7%)	549 (9%)	
25-34	9,050 (13.2%)	869 (14.2%)	
35-44	12,446 (18.2%)	1,200 (19.6%)	
45-54	18,345 (26.8%)	1,708 (27.8%)	
55-64	23,354 (34.1%)	1,807 (29.5%)	
Female N (%)	37,104 (54.2%)	3,181 (51.9%)	0.0004
Chronic Disease Count N (%)			0.0078
0 Chronic Diseases	45,417 (66.4%)	4,164 (67.9%)	
1 Chronic Disease	16,292 (23.8%)	1,434 (23.4%)	
2+ Chronic Diseases	6,739 (9.8%)	535 (8.7%)	
Prescription Count Mean (SD)	16.8 (19.8)	14.4 (17.1)	<0.0001
Log(Annual Rx Cost) Mean (SD)	5.31 (1.84)	5.12 (1.84)	<0.0001
Log(Annual Medical Cost) Mean (SD)	7.18 (1.42)	7.16 (1.42)	0.2778
Log(Annual TCOC) Mean (SD)	7.42 (1.55)	7.34 (1.58)	<0.0001
Pharmacy-level variables			
Total Pharmacies (N)	157	14	
Weekly Rx Volume Mean (SD)	184.8 (67)	168.9 (70.7)	0.2690
Sunday Filling Categories N (%)			0.0100
Marginal	19 (12.1%)	0 (0%)	
Non	8 (5.1%)	3 (21.4%)	
Robust	130 (82.8%)	11 (78.6%)	
Attributed Patients per Pharmacy Mean, (SD)	436 (169.8)	438.1 (221.1)	0.9656

Table 8. Comparison of Sunday Fills and Prescription Volume by Sunday Fill Category

Variable	Non-Sunday Filling Pharmacy	Marginal Sunday Filling Pharmacy	Robust Sunday Filling Pharmacy
N	11	19	141
Sundays with Prescription Fills Median (IQR)	0 (0-0)	2 (1-3)	52 (52-52)
Weekly Prescription Volume Mean (SD)*	138.4 (49.9)	179.9 (73.4)	187.5 (66.7)

*ANOVA for differences in weekly volume by fill category finds no significant differences (p=0.0633)

4.b. Aim 1 Results

Aim 1 was to design and test a conceptual model of pharmacy quality. The model was designed after a thorough review of the literature and is found in Section 2.d.3. The operationalized conceptual model (Section 3.d.4) was tested to evaluate hypothesis 1.1, that there was a relationship between structures and processes, and hypothesis 1.2, that there was a relationship between processes and outcomes.

4.b.1 Testing Hypothesis 1.1

The baseline mean PDC scores for included pharmacies for statins, RASA, β-blockers and NIDA were 0.699, 0.778, 0.750 and 0.732 respectively. Table 9 contains results from the hierarchical logistic model used to evaluate hypothesis 1.1. Variable testing found that there were strong correlations between the case-mix adjustment variables and odds of adherence, with many variables significant at $p<0.0001$. The state in which a pharmacy was located was correlated with odds of adherence at $p<0.05$ for statins and RASA. The strength of correlation was weaker for other metrics but the p-value remained less than the 0.2 cut-off threshold for excluding the variation from the equation.

Through variable testing, it was found that the natural log of weekly prescription volume was better correlated with odds of adherence than was raw weekly prescription volume or weekly prescription volume squared. Even with this transformation, there was no significant relationship between prescription volume and odds of adherence for any of the four medication categories assessed. Additionally, the sensitivity analysis replacing average weekly volume with average daily volume did not produce any change in the results.

There was a significant relationship between marginal and robust filling pharmacies as well as non-Sunday filling pharmacies and robust Sunday filling pharmacies, but this was only observed for statin adherence. For patients taking statins, the odds of adherence when attributed to a marginal Sunday filling pharmacy compared to a robust pharmacy were 1.138 (1.029-1.260, $p<0.05$). The reverse was true for patients attributed to pharmacies with no Sunday fills; the odds of adherence for patients attributed to a pharmacy appearing to be closed on Sundays compared to pharmacies that are clearly open was 0.869 (0.791-0.955, $p<0.01$). For other metrics, odds of adherence for patients attributed to marginal Sunday filling pharmacies are better than for patients attributed to pharmacies with no Sunday fills, but difference was not statistically significant. Models testing the significance of Sunday fills combining marginal and non-Sunday filling pharmacies together into one category found no significant relationships, with the smallest p-value for the Type III fixed effect across any medication class being only 0.155.

Results comparing prescription volume by Sunday fill category suggested that there may be an interaction between Sunday fill category and weekly prescription volume (Table 8). Therefore, an interaction between Sunday fill category and the natural logarithm of weekly prescription volume was tested for each of the four hierarchical logistic models predicting odds of adherence. The p-values of the interaction term for statins, β-blockers and NIDA were 0.8407, 0.7463 and 0.3401 respectively. Including the interaction term for these three models resulted in AIC values one to three points larger and no change to the associated c-statistic. Including the

interaction term in the RASA model, however, had an associated p-value of 0.0617 and a reduction in the p-values associated with F-statistics for weekly prescription volume and Sunday fill category (0.1270 vs. 0.2878 and 0.0851 vs. 0.3336). The AIC for the model was one point lower, but the c-statistic remained unchanged at 0.6669. Therefore, although there is evidence of an interaction between weekly prescription volume and Sunday fill category, the impact of including the term wasn't sufficient to justify the added complexity.

As there were no marginally open pharmacies identified in South Dakota, the interaction between Sunday fill category and pharmacy state was also evaluated. The interaction term for models predicting odds of adherence for statins, RASA and β-blockers was not significant, with p-values ranging from 0.1952 to 0.3138, AIC values for models with interaction terms 1-2 points greater than models without and c-statistics that were unchanged. For NIDA, the interaction term's p-value was 0.0775 and the model with the interaction term had an AIC value one point lower than the model without, and the c-statistic was nearly unchanged (0.7085 vs. 0.7099). In the same manner as the interaction term between weekly prescription volume and Sunday fill category, the interaction between state and fill category did not have a sufficiently strong impact on results to justify the added complexity.

Using a Wald test for the random intercept tem, there was found to be a significant effect of pharmacies on attributed patients' odds of adherence at $p<0.0001$ for all models. The residual intraclass correlation coefficient (RICC), which can be interpreted as the proportion of total variation explained by the level 2 effect, in this case pharmacy, ranged from 0.0231 to 0.046 across medication classes. A comparison was made to generalized linear models using the same modeling technique but lacking the random pharmacy intercept and differences varied by medication class. For statins, not including the random intercept term resulted in an AIC value 30 points higher and lower c-statistic (0.6339 vs. 0.6503). Likewise, the RASA model without the random intercept term had an AIC value 61 points larger and a c-statistic of 0.6406 compared to

0.6669. The effect of the random intercept on AIC for β-blockers was not as substantial, with the model lacking the intercept term only 2 points greater than the model with the intercept, but the c-statistic without the intercept was similarly diminished, 0.6281 vs. 0.6446. The NIDA model without the random intercept had a lower AIC by 2 points but still had a smaller c-statistic at 0.6976 compared to 0.7099. A model with only the random intercept and no other independent variables was created for each of the four process variables, and RICC values for each of the empty models were slightly lower than the fully specified model (Table 10).

4.b.2 Creating Process Quality Score

The model used to calculate risk adjusted pharmacy process scores and create the Process Quality Score used the same case-mix adjustment variables as the model used to test hypothesis 1.1 but did not include any structure variables (Table 10). Effect estimates and associated significance were similar across models with and without structure variables. AIC values when structure variables were removed were 3-5 points lower for RASA, β-blockers and NIDA. AIC was 11 points higher, however, with the removal of structural variables for statins, an effect of the significance of the Sunday fills variable. C-statistics and RICC values were essentially unchanged between the two models.

The risk adjusted pharmacy scores showed the effect of case-mix adjustment on explaining some of the variation in PDC scores across pharmacies (Figure 9). For every model, the distribution of risk adjusted scores was narrower than the distribution of observed PDC scores. When pharmacies were scored based on their outlier status, all metrics had some pharmacies identified as high quality or low quality outliers (Table 11). For each metric, pharmacies scored as low quality had risk adjusted PDC score means substantially below that of typical pharmacies and high quality pharmacies had risk adjusted PDC score-means substantially

above typical pharmacies. The range of scores for each category for each metric were found to overlap slightly, and this overlap was also found with non-risk adjusted scores.

When the set of pharmacies was reduced to those for which all PDC metrics could be measured, none of the eligible pharmacies were identified as high quality outliers for statins or RASA. Four pharmacies were identified as high quality for the β-blocker adherence metric and two high quality pharmacies were identified for the NIDA adherence metric. No pharmacies were identified as high quality for more than one adherence metric. There were eligible pharmacies identified as low quality outliers for each of the four quality metrics, with three low quality pharmacies for statins, one for RASA, three for β-blockers, and three for NIDA. One pharmacy was identified as a low quality outlier for statins, RASA and β-blockers. Also, no eligible pharmacy identified as high quality on a metric was identified as low quality on another metric.

When outlier status was identified using expected values from models without a random effect for pharmacy, the model's predictive statistics were similar but more pharmacies were identified as outliers. The range of percentages of low quality outliers for models without a random intercept was from 3.45% for NIDA to 6.78% for RASA. The percentage of high quality outliers ranged from 1.66% for β-blockers to 4.28% for RASA. A visual comparison between the distributions of risk adjusted scores for generalized linear models with and without the random pharmacy intercept found that models without the random intercept had wider distributions.

For reasons described in Section 3.e, scores resulting from the hierarchical models with the random intercept were used to create the Process Quality Score. When metric quality scores were summed and categorized to create the Process Quality Score, eight (4.7%) pharmacies were identified as low process quality outliers, six (3.5%) were identified as high quality outliers and the remainder (157) were identified as being of typical quality.

Table 9. Results from Hierarchical Logistic Models Testing the Relationship between Structural Variables and Odds of Adherence

	Odds Ratios and 95% Confidence Intervals for Effect Estimates			
Structural Variables	**Statin**	**RASA**	**β-Blocker**	**NIDA**
log (Weekly Rx Volume)	1.005 (0.945-1.07)	1.39 (0.968-1.115)	1.003 (0.911-1.104)	0.94 (0.741-1.192)
Marginal Sunday Filler	1.138 (1.029-1.26)*	1.082 (0.965-1.213)	1.118 (0.974-1.283)	1.133 (0.863-1.488)
Non-Sunday Filler	0.869 (0.791-0.955)**	1.047 (0.941-1.165)	1.016 (0.881-1.172)	0.856 (0.596-1.228)
Robust Sunday Filler	--	--	--	--
Case-Mix Adjustment Variables and Pharmacy State				
Log (Rx Count)	1.789 (1.722-1.858)****	1.766 (1.698-1.836)****	1.644 (1.557-1.737)****	2.431 (2.147-2.754)****
Age (10 year change)	1.393 (1.343-1.445)****	1.335 (1.291-1.381)****	1.333 (1.276-1.392)****	1.4 (1.276-1.536)****
Gender (female)	0.896 (0.85-0.945)****	0.953 (0.899-1.01)	0.946 (0.876-1.021)	0.797 (0.68-0.934)**
0 Elixhauser Conditions	--	--	--	--
1 Elixhauser Condition	0.936 (0.88-0.995)*	1.201 (1.121-1.287)****	1.197 (1.094-1.309)****	1.072 (0.841-1.365)
2 Elixhauser Conditions	0.809 (0.744-0.88)****	0.929 (0.851-1.014)	1.002 (0.89-1.128)	1.329 (1.036-1.706)*
3 Elixhauser Conditions	0.747 (0.648-0.861)****	0.741 (0.645-0.852)****	0.865 (0.715-1.046)	0.847 (0.608-1.179)
4+ Elixhauser Conditions	0.614 (0.492-0.766)****	0.483 (0.394-0.591)****	0.514 (0.403-0.657)****	0.890 (0.541-1.462)
Pharmacy State (IA)	1.095 (1.006-1.192)*	1.099 (1.002-1.205)*	1.043 (0.925-1.176)	1.268 (0.944-1.703)
Model Diagnostics				
C-statistic	0.6503	0.6669	0.6446	0.7099
R^2Dichotomous	0.0718	0.0802	0.065	0.148
RICC[†]	0.0231	0.0340	0.0302	0.0460
Significance of RE	p<0.0001	p<0.0001	p<0.0001	p<0.0001

*p<0.05 **p<0.01 ***p<0.001 ****p<0.0001

[†] RICC values for base model with only random pharmacy intercept: statin=0.0202, RASA=0.0325, β-Blocker=0.0291, NIDA=0.0431

Table 10. Results from Hierarchical Logistic Models Used to Create Process Quality Scores

	Odds Ratios and 95% Confidence Intervals for Effect Estimates			
Case-Mix Adjustment Variables and Pharmacy State	**Statin**	**RASA**	**β-Blockers**	**NIDA**
Log (Rx Count)	1.792 (1.725-1.861)****	1.767 (1.699-1.838)****	1.646 (1.559-1.739)****	2.431 (2.147-2.752)****
Age (10 year change)	1.395 (1.345-1.447)****	1.335 (1.291-1.381)****	1.333 (1.277-1.392)****	1.4 (1.276-1.536)****
Gender (female)	0.897 (0.851-0.946)****	0.952 (0.898-1.009)	0.944 (0.875-1.02)	0.796 (0.679-0.932)**
0 Elixhauser Conditions	--	--	--	--
1 Elixhauser Condition	0.936 (0.88-0.995)*	1.201 (1.121-1.287)****	1.196 (1.094-1.309)****	1.07 (0.84-1.363)
2 Elixhauser Conditions	0.808 (0.743-0.878)****	0.929 (0.851-1.014)	1 (0.889-1.126)	1.329 (1.035-1.705)*
3 Elixhauser Conditions	0.744 (0.646-0.857)****	0.741 (0.645-0.852)****	0.863 (0.713-1.044)	0.843 (0.605-1.173)
4+ Elixhauser Conditions	0.615 (0.493-0.768)****	0.483 (0.394-0.591)****	0.515 (0.403-0.658)****	0.889 (0.541-1.459)
Pharmacy State (IA)	1.096 (1.007-1.193)*	1.109 (1.013-1.214)*	1.04 (0.923-1.172)	1.291 (0.967-1.722)
Model Diagnostics				
C-statistic	0.6509	0.6671	0.6446	0.7106
R^2Dichotomous	0.0715	0.0802	0.0647	0.147
RICC†	0.0240	0.0345	0.0304	0.0475
Significance of RE	p<0.0001	p<0.0001	p<0.0001	p<0.0001

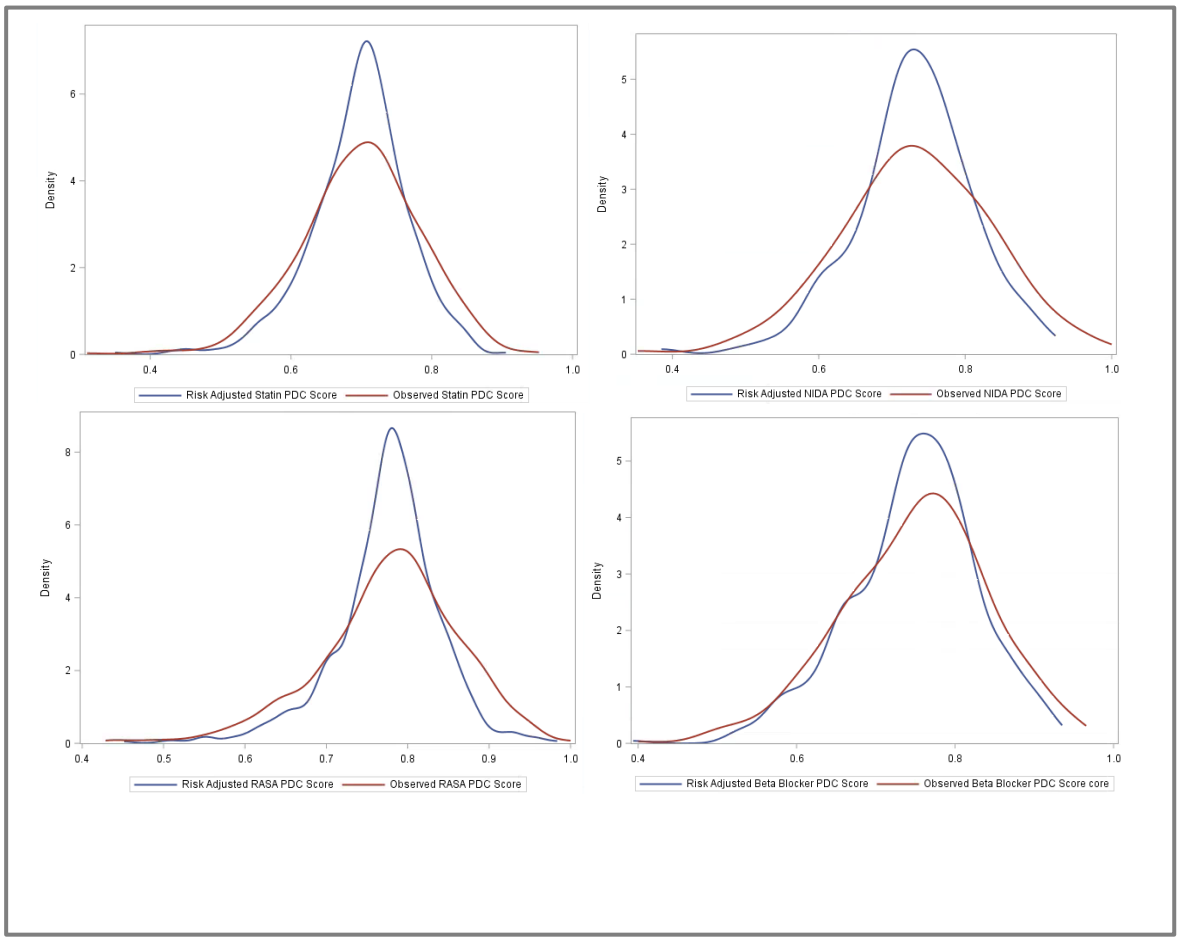
*p<0.05 **p<0.01 ***p<0.001 ****p<0.0001

† RICC values for base model with only random pharmacy intercept: statin=0.0202, RASA=0.0325, β-Blocker=0.0291, NIDA=0.0431

Table 11. Frequency of Pharmacies and Variation in Risk Adjusted PDC Scores by Process Quality Outlier Status

Process Quality Outlier Category	**Statin**		**RASA**		**β-Blockers**		**NIDA**	
	Frequency	PDC mean (min, max)	Frequency	PDC mean (min, max)	Frequency	PDC mean (min, max)	Frequency	PDC mean (min, max)
Low Quality Outlier (N)	12	0.496 (0.35 - 0.591)	9	0.548 (0.452 - 0.63)	10	0.555 (0.394 - 0.619)	4	0.504 (0.385 - 0.601)
Typical Quality (N)	642	0.701 (0.461 - 0.905)	665	0.777 (0.552 - 0.958)	466	0.750 (0.528 - 0.922)	168	0.733 (0.528 - 0.914)
High Quality Outlier (N)	1	0.822 (0.822 - 0.822)	4	0.937 (0.871 - 0.983)	7	0.907 (0.86 - 0.935)	2	0.906 (0.888 - 0.923)

Figure 9. Kernel Density Plots Comparing Distribution of Risk Adjusted PDC Scores to Observed PDC Scores



4.b.3 Testing Hypothesis 1.2

Table 12 contains results from the hierarchical logistic model used to evaluate hypothesis 1.2. Similar to variables used to case-mix adjust for predicting odds of adherence, case-mix adjustment variables for odds of hospitalizations and ED visits were found to be highly correlated, with many variables significant at $p<0.0001$. Pharmacy state was significantly correlated with odds of ED visits but not with hospitalizations. Using typical quality pharmacies as the reference, there was not found to be a significant relationship between low or high process quality status and the odds of a hospitalization or ED visit.

Using a Wald test for the random intercept term, there was found to be a significant effect of pharmacy attributed patients' odds of adherence at $p<0.0001$ for all models. The residual intraclass correlation coefficient (RICC) was 0.0249 for hospitalizations and 0.0178 for ED visits. A comparison was made to models lacking the random pharmacy intercept and differences varied by outcome. For hospitalizations, not including the random intercept term resulted in an AIC value 2 points higher and a slightly smaller c-statistic (0.7511 vs. 0.7577). The reduction in predictive ability for the ED visit model without the random intercept term was more substantial with an AIC value 111 points greater and a c-statistic of 0.6376 compared to 0.6526. Compared to models with random intercept only, RICC values for the fully specified model were slightly lower (Table 13).

4.b.4 Creating Outcome Quality Score and Combined Quality Score

The model used to test hypothesis 1.2, without the Process Quality Score, was used for evaluating pharmacies' outcome outlier status. Model coefficients were similar across the two

models, and diagnostic statistics were not different. AIC values were slightly higher for the model with the three tiered PQS, by 4 points for hospitalizations and 2 points for ED visits.

Baseline hospitalization rates were 0.021 and baseline ED visit rate was 0.089. In comparing the distributions of risk adjusted event rates with observed event rates, there was some difference in the hospital scores with fewer right side outliers in the risk adjusted distribution (Figure 10). ED visit risk adjusted scores demonstrated a greater difference compared to observed scores, with reductions in both positive and negative outliers. When pharmacies were scored on their outlier status, two pharmacies were identified as low quality outliers for hospitalizations and none were identified for ED visits (Table 14). Two pharmacies were identified as high quality outliers for hospitalizations and one was identified for ED visits. The ranges of risk adjusted and non-risk adjusted scores overlapped for both measures. These results were compared to a generalized linear model with the same specifications but lacking a random effect for pharmacy, and similar to process quality outliers, there was greater frequency of outliers for hospitalizations and ED visits and a wider distribution of risk adjusted scores.

When outlier scores derived from the hierarchical model with the random pharmacy intercept were summed, the resulting Outcome Quality Score identified two pharmacies as low quality outliers and three as high quality. A contingency table comparing outlier status across categories for PQS and OQS finds no association between the two quality scores (Table 15). The same lack of association was observed when PQS and OQS derived from generalized linear models without a random pharmacy intercept were compared. PQS and OQS were summed for each pharmacy to produce the combined quality score (CQS). A three-level version of CQs was created by splitting scores at 0, and there were ten pharmacies identified as low quality outliers and nine identified as high quality outliers.

Table 12. Results from Hierarchical Logistic Models Used Evaluating the Impact of Pharmacy Process Quality on Odds of Outcome Events

	Odds Ratios and 95% Confidence Intervals for Effect Estimates	
Process Quality Category Score	**Hospitalizations**	**Emergency Department Visits**
Low Quality Outlier	0.962 (0.729-1.268)	1.118 (0.92-1.359)
Typical Quality	--	--
High Quality Outlier	0.974 (0.709-1.338)	1.111 (0.891-1.389)
Case-Mix Adjustment Variables and Pharmacy State		
Log (Rx Count)	2.172 (2.04-2.312)****	1.512 (1.472-1.554)****
Age Cat 1	1.542 (1.227-1.937)***	2.245 (2.032-2.481)****
Age Cat 2	1.103 (0.905-1.345)	1.755 (1.609-1.914)****
Age Cat 3	1 (0.85-1.176)	1.501 (1.389-1.622)****
Age Cat 4	0.941 (0.827-1.069)	1.271 (1.188-1.361)****
Age Cat 5	--	--
Gender (Female)	0.63 (0.568-0.699)****	0.938 (0.89-0.988)*
0 Elixhauser Conditions	--	--
1 Elixhauser Condition	0.929 (0.813-1.061)	0.942 (0.882-1.007)
2 Elixhauser Conditions	1.135 (0.956-1.349)	1.12 (1.018-1.231)*
3 Elixhauser Conditions	2.163 (1.726-2.711)****	1.483 (1.27-1.731)****
4+ Elixhauser Conditions	3.62 (2.776-4.72)****	1.799 (1.448-2.235)****
Pharmacy State (IA)†	--	1.313 (1.12-1.539)***
Model Diagnostics		
C-statistic	0.7577	0.6526
R^2 Dichotomous	0.2214	0.0822
RICC††	0.0249	0.0178

*p<0.05 **p<0.01 ***p<0.001 ****p<0.0001

† Effect of state not significant at p<0.2 for hospitalization model

†† RICC values for base model with only random intercept: Hospital=0.0266, ED=0.0197

Table 13. Results from Hierarchical Logistic Models Used to Create Outcome Quality Scores

	Odds Ratios and 95% Confidence Intervals for Effect Estimates	
Case-Mix Adjustment Variables and Pharmacy State	**Hospitalizations**	**Emergency Department Visits**
Log (Rx Count)	2.171 (2.039-2.312)****	1.512 (1.472-1.554)****
Age Cat 1	1.542 (1.227-1.938)***	2.246 (2.033-2.482)****
Age Cat 2	1.104 (0.906-1.345)	1.752 (1.606-1.911)****
Age Cat 3	1.001 (0.851-1.177)	1.499 (1.387-1.62)****
Age Cat 4	0.941 (0.827-1.069)	1.272 (1.188-1.361)****
Age Cat 5	--	--
Gender (Female)	0.630 (0.568-0.699)****	0.938 (0.89-0.988)*
0 Elixhauser Conditions	--	--
1 Elixhauser Condition	0.929 (0.813-1.061)	0.943 (0.883-1.007)
2 Elixhauser Conditions	1.135 (0.956-1.348)	1.118 (1.017-1.23)*
3 Elixhauser Conditions	2.162 (1.726-2.71)****	1.484 (1.271-1.733)****
4+ Elixhauser Conditions	3.62 (2.776-4.721)****	1.8 (1.449-2.236)****
Pharmacy State (IA)†	--	1.308 (1.115-1.535)**
Model Diagnostics		
C-statistic	0.7577	0.6526
R^2 Dichotomous	0.2214	0.0822
RICC††	0.0249	0.0178

*p<0.05 **p<0.01 ***p<0.001 ****p<0.0001

† Effect of state not significant at p<0.2 for hospitalization model

†† RICC values for base model with only random intercept: Hospital=0.0266, ED=0.0197

Table 14. Frequency of Pharmacies by Outcome Quality Outlier Status

Outcome Quality Outlier Category	**Hospitalization**		**Emergency Dept. Visit**	
	Frequency	Event Rate mean (min, max)	Frequency	Event Rate mean (min, max)
Low Quality Outlier (N)	2	0.036 (0.035 - 0.037)	0	--
Typical Quality (N)	167	0.020 (0.004 - 0.032)	170	0.0883 (0.053 - 0.112)
High Quality Outlier (N)	2	0.006 (0.003 - 0.008)	1	0.047 (0.047 - 0.047)

Figure 10. Kernel Density Plots Comparing Distribution of Risk Adjusted Outcome Event Rates to Observed Outcome Event Rates

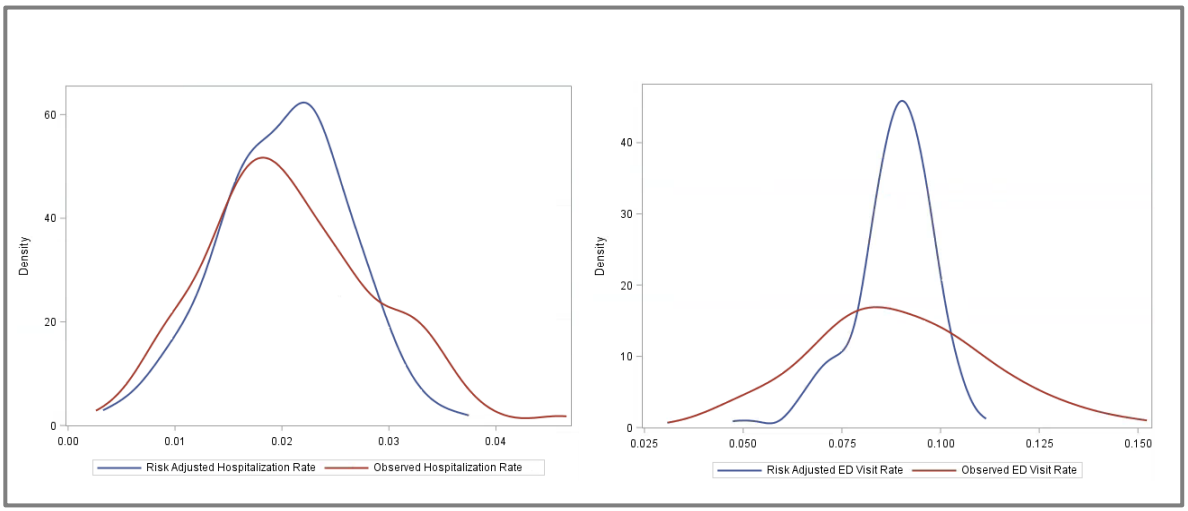


Table 15. Comparison of Process Quality Score and Outcome Quality Score Categories

Process Quality Score Category	**Outcome Quality Score Category**		
	Low Quality Outlier	Typical Quality	High Quality Outlier
Low Quality Outlier	0	8	0
Typical Quality	2	152	3
High Quality Outlier	0	6	0

4.c. Aim 2 Results

Aim 2 evaluated the relationship between cost and quality. Pharmacies' quality scores resulting from the conceptual model tested under Aim 1 were compared with pharmacies' impact on the cost of healthcare to create a measure of pharmacy value. Hypotheses 2.1 – 2.3 evaluated a constant quality score against pharmacies impact on pharmaceutical cost, medical cost and total cost of care. Baseline adjusted cost amounts for pharmaceutical cost, medical cost and total cost of care were $204.38, $1,312.91 and $1,669.03.

4.c.1 Calculating Cost Impact Scores

The model used to evaluate cost by attributed patient sets across pharmaceutical cost, medical cost and total cost of care included only age, Elixhauser conditions as a five category coding scheme, gender, and for pharmaceutical cost only, pharmacy state. There are strong correlations between these case-mix adjustment variables and cost in each of the three categories, but the RICC values only range from 0.0024 to 0.0068 (Table 16). This is slightly lower than RICC values from the base model with only a random intercept for pharmacy which ranged from 0.0038 to 0.0102. The Wald test found that the random effect for pharmacy in the fully specified model was significant. High cost and low cost pharmacies were identified for each of the three cost categories with some overlap in cost ranges across the three categories (Table 17). Risk adjustment was found to substantially decrease the range of cost estimates and resulted in a much more normal distribution of cost estimates compared to observed cost estimates (Figure 11).

4.c.2 Creating Value Matrices and Testing Hypotheses 2.1-2.3

In comparing pharmacies' cost-outlier scores to their combined quality scores, significant variation in value was observed for each of the three cost measures (Table 18, Table 19 and Table 20). There was variation in cell frequencies across all contingency tables evaluating pharmacy value, with the greatest number of high value pharmacies and low value pharmacies observed for the medical cost value matrix. Separate t-tests were analyzed for the comparison of high value to typical value and typical value to low value for each of the three cost models. The null hypothesis for each of the t-tests was there was no variation in value (all pharmacies' value score=0) and the alternative hypothesis was that there was significant presence of low value/high value pharmacies (value score=-1 and 1 respectively) with remaining pharmacies coded as a 0 value (not low value or not high value), For the comparison of low value pharmacies using the pharmaceutical cost measures, the p-value was 0.0004. For the five other comparisons, the p-value was <0.0001.

Table 16. Results from Hierarchical Linear Models Used to Create Cost Impact Scores

	Beta-values and Standard Errors for Effect Estimates		
Case-Mix Adjustment Variables, Pharmacy State	**Pharmaceutical Cost**	**Medical Cost**	**Total Cost of Care**
Intercept	3.65	5.88	5.94
0 Elixhauser Conditions	--	--	--
1 Elixhauser Condition	1.1646 (0.01468)****	0.3909 (0.01216)****	0.7023 (0.01275)****
2 Elixhauser Conditions	1.9219 (0.02374)****	0.7923 (0.01954)****	1.2239 (0.02061)****
3 Elixhauser Conditions	2.392 (0.04615)****	1.3081 (0.06789)****	1.7208 (0.04009)****
4+ Elixhauser Conditions	2.8308 (0.07184)****	1.8868 (0.05902)****	2.2921 (0.6242)****
Age	0.01788 (0.000496)****	0.01962 (0.000416)****	0.02058 (0.00043)****
Gender (Female)	0.4045 (0.01199)****	0.3177 (0.01044)****	0.376 (0.01041)****
Pharmacy State (IA)†	1.304 (0.04418)**	--	--
Model Diagnostics			
R^2_1	0.211	0.115	0.166
RICC††	0.0068	0.0028	0.0024

*p<0.05 **p<0.01 ***p<0.001 ****p<0.0001

† Effect of state not significant at p<0.2 for medical, total cost of care models

†† RICC values for base model with only random pharmacy intercept: pharmaceutical=0.0102, medical=0.0038, total cost of care=0.0047

Table 17. Frequency of Pharmacies by Cost Impact Score Outlier Status

Cost Impact Outlier Category	Pharmaceutical Cost		Medical Cost		Total Cost of Care	
	Frequency	Cost mean (min, max)	Frequency	Cost mean (min, max)	Frequency	Cost mean (min, max)
Low Cost Outlier	2	$183.43 (173.36 - 190.63)	21	$1,207.91 (1,082.88 – 1,261.9)	17	$1,522.23 (1403.49 - 1597.1)
Typical Cost	163	$204.91 (185.85 - 226.71)	125	$1,315.23 (1,235.87 – 1,397.39)	137	$1,665.81 (1,513.55 – 1,817.79)
High Cost Outlier	6	$222.67 (220.18 - 225.16)	25	$1,421.02 (1,364.62 – 1,551.65)	17	$1,827.04 (1,751.82 – 1,996.66)

Figure 11. Kernel Density Plots Comparing Distribution of Risk Adjusted log(Mean Cost) to Observed log(Mean Cost)

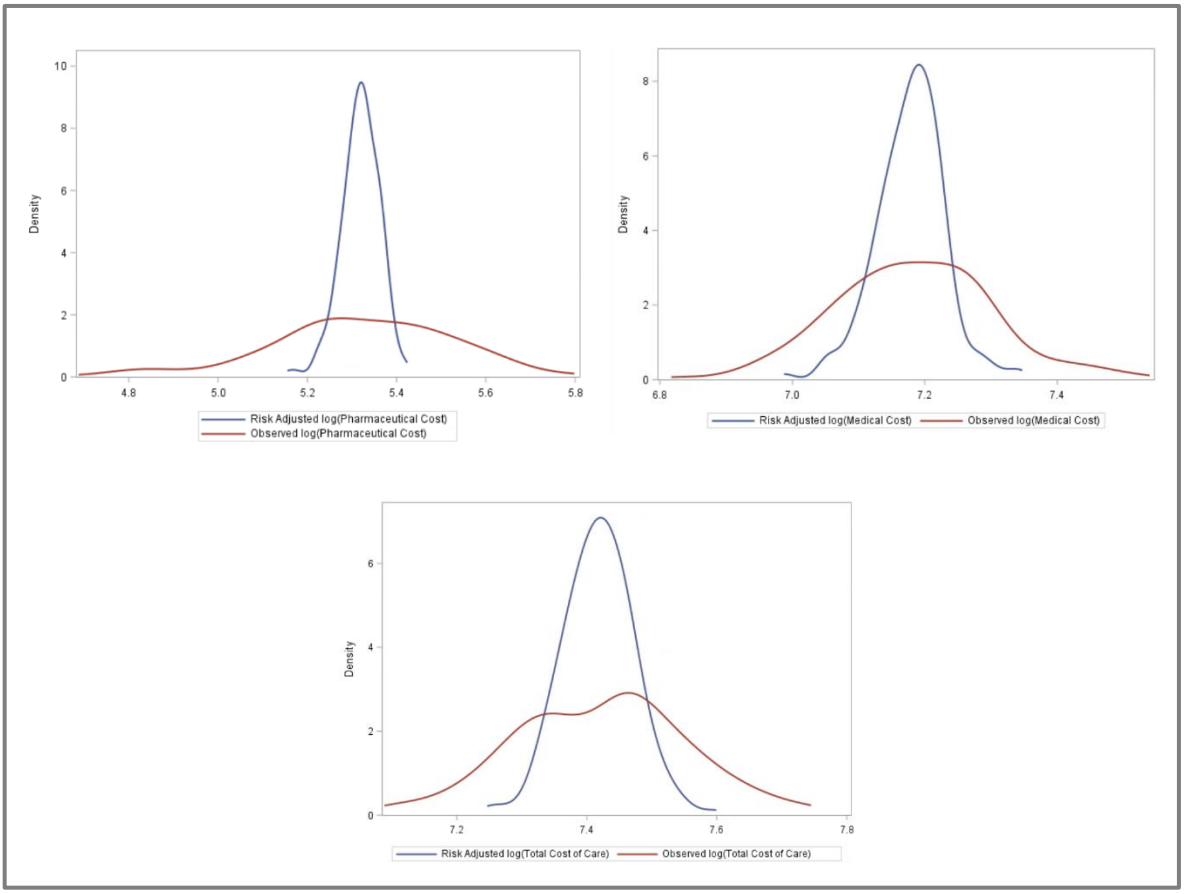


Table 18. Value Matrix for Pharmaceutical Cost

Pharmaceutical Cost Impact Score Category	**Combined Quality Score Category**		
	Low Quality Outlier	Typical Quality	High Quality Outlier
Low Cost Outlier	0	6	0
Typical Cost	10	144	9
High Cost Outlier	0	2	0

Table 19. Value Matrix for Medical Cost

Medical Cost Impact Score Category	**Combined Quality Score Category**		
	Low Quality Outlier	Typical Quality	High Quality Outlier
Low Cost Outlier	0	22	3
Typical Cost	8	112	5
High Cost Outlier	2	18	1

Table 20. Value Matrix for Total Cost of Care

Total Cost of Care Impact Score Category	**Combined Quality Score Category**		
	Low Quality Outlier	Typical Quality	High Quality Outlier
Low Cost Outlier	0	16	1
Typical Cost	9	121	7
High Cost Outlier	1	15	1

CHAPTER V
DISCUSSION

5.a. Aim 1. Evaluating Relationship between Structures and Processes, Processes and Outcomes

The first aim of this study was to design and test a model of pharmacy quality. The conceptual model was transformed into an operational model, and there were two hypotheses evaluated to test the operational model.

5.a.1 Hypothesis 1.1

Evidence for correlation between structure quality and process quality, as measured by this study, is very limited. No other known study has evaluated the relationship between Sunday filling category and process measures of quality. It was theorized that the Sunday filling category correlated with independent pharmacy ownership and a stronger orientation towards patient care by the pharmacy staff. Despite favorable arguments by organizations supporting independent pharmacy ownership (McKesson, 2016; National Community Pharmacists Association, 2016), little objective evidence supports the concept that independent pharmacies are clearly better than their chain counterparts in improving healthcare quality. Evidence from the National Pharmacist Workforce Study suggests that services delivered by pharmacists has increased in recent years across all settings and that few differences exist in service delivery between independent and chain pharmacies. Additionally, a study by Desai et al. (2016) found that independent pharmacies were more likely to perform worse on quality metrics than chain pharmacies.

Therefore, the expected effect of the Sunday filling variable was unclear. Interestingly, on the statin PDC metric, marginal Sunday filling pharmacies had larger observed odds of

adherence than both robust Sunday filling pharmacies and non-Sunday filling pharmacies. Non-Sunday filling pharmacies also had a significantly lower rate of adherence than robust filling pharmacies. This could be due to random statistical variation, poorer quality of care from non-Sunday filling pharmacies, or programs initiated by robust filling pharmacies and not initiated by non-Sunday filling pharmacies which focus on statin adherence improvement. The relationship between marginal and non-Sunday filling pharmacies was consistent across the other three medication classes, but the difference in adherence odds for these two categories and robust Sunday filling pharmacies was not significant.

One should be cautious in interpreting the significance of the association between Sunday filling category and statin adherence. Although it could be that targeted automated refill programs or some difference in the drug or disease for which the drug is taken could influence the relationship between Sunday filling category and adherence for the other three medication classes, it is perhaps more likely that the significant relationship between Sunday filling category and adherence for statins is due to random chance. If one evaluated the relationship for 100 medication classes, probability suggests that some of those medication classes would reveal a significant relationship between Sunday filling category and adherence.

Regarding the other structure quality variable, weekly prescription volume, no evidence exists to support a relationship between it and process quality. Theoretically, prescription volume (as a measure of busyness) and care quality are inversely related (Chui & Mott, 2012), and this is supported in a study assessing detection of drug-drug interactions, a care process quality measure (Malone et al., 2007). Counterbalancing evidence suggests, however, that larger prescription volumes may decrease rates of primary nonadherence (Jackson et al., 2014) and larger patient volumes may improve PDC scores (Desai et al., 2016). Therefore, the expected association was unclear and the lack of observed correlation does not surprise.

5.a.1.1 Process Metric Model Performance

Performance statistics found that regardless of the presence of structure quality variables, models predicting odds of adherence had suboptimal predictive ability. Statin, RASA and β-blockers all had c statistics less than 0.7, suggesting poor ability to discriminate between patients that were and were not adherent. NIDA performed better, with a c statistic of 0.71, just above the generally accepted threshold for good discrimination ability (c=0.7). This is similar to the c static of 0.73 reported for a for the two-level hierarchical model predicting odds of adherence for Medicare beneficiaries (Dharmarajan et al., 2014). The RICC values for all models in this study ranged from 0.0231 to 0.046, suggesting that between 2.3% and 4.6% of the patient-level variation in odds of adherence is due to the pharmacy to which the patient is attributed. Although small in absolute terms, these numbers are larger than the RICC of 0.013 for the similar model reported by Dharmarajan et al. (2014). Additionally, RICC values for the fully specified model are 0.001 to 0.004 greater than RICC values for the base model with only the random intercept term (Table 10), suggesting that the fully specified model controls for patient level factors that obscure the impact of pharmacy on attributed patients' adherence. Results from the RICC calculation and the significance of the Wald test suggest that there is an observable, but small, effect of pharmacy on adherence for commercially insured patients.

Including a random effect for pharmacy added only marginal statistical benefit, but resulted in substantially fewer pharmacies identified as outliers. A similar method employed by Li et al. calculating outlier status for nursing homes found that the frequency of nursing homes identified as high or low quality outliers was also smaller than models without a random intercept, even though the predictive statistics were not substantially different between the models. This suggests that although predictive ability may not differ greatly between fixed effects

and random effects models, there may be differences in the sensitivity and specificity with which high and low value pharmacies are identified. This makes models including a random intercept for pharmacy more conservative in predicting the presence of outliers and results in more conservative estimates of pharmacy value.

5.a.1.2 Identification of High and Low Process Quality Outliers

The number of outlier pharmacies identified using the Process Quality Score was quite small. Only 2.3% of pharmacies eligible for all process metrics were identified as low quality process outliers and 1.2% as high quality outliers. Interestingly, across each of the metrics, the range of risk adjusted PDC scores for typical quality pharmacies overlapped with the range of scores for low and high quality pharmacies (Table 11). This results from relying on the confidence interval around each pharmacy's risk adjusted scores to determine that pharmacy's outlier status. There were a small subset of pharmacies with extreme values that also had wide enough variation in their risk adjusted scores to preclude them from identification as an outlier. This is therefore a more conservative method of outlier identification than comparing each pharmacy's performance to a confidence interval around a mean score, or simply ranking pharmacies and declaring the top 10-20% high quality and the bottom 10-20% low quality. Pharmacies with smaller metric denominators are more sensitive to patient-level quality outliers and therefore more likely to have extreme values. Without considering the confidence with which the score was estimated, a typical quality pharmacy with a small denominator could be misidentified as high or low quality.

Theoretically, PDC measures correlate with underlying quality of pharmacists' care processes, therefore some consistency in process metric outlier identification should be observed. It is discovered from the results, however, that only one pharmacy was identified as a high or low

quality outlier on more than one metric once the set of pharmacies was reduced to only those that were eligible for all metrics. There are three possible conclusions from this finding: 1) The statistical method chosen to identify outliers is insufficiently sensitive to identify the pharmacies with high or low process quality (statistical problem), 2) PDC metrics are insufficient to consistently detect high and low process quality outliers (metric problem) or 3) There is, in reality, very little differentiation between pharmacies on process quality metrics when assessing healthcare quality for a commercially insured population (no problem).

Regarding the statistical method, a similar approach used by Dharmarajan et al. (2014) found greater differentiation between pharmacies in their impact on medication adherence for a Medicare population, with 12.6% identified as low quality outliers and 13.6% as high quality. Li et al. (2009) found that, using an identical method for quality differentiation, 19.4% of nursing homes were identified as low quality and 13.9% as high quality. This suggests that the low percent of outlier pharmacies identified in this study are not necessarily due to the statistical method.

Therefore, it could be the choice and design of metrics results in a system that poorly detects outliers, or it could be that little variation in pharmacy process quality exists. Entities constructing high performing pharmacy networks use scoring systems which find percentages of high value pharmacies in excess of 1.2%. Inland Empire Health Plan's (IEHP) scoring method, for example, identifies 12% of its pharmacies as 5/5 star performers (Inland Empire Health Plan, 2015a). Nearly all of IEHP's metrics are process metrics. Community Care of North Carolina had 255 pharmacies in its community pharmacy enhanced services network (CPESN) as of October of 2015 and the number has grown since then (Trygstad, 2015). The high performing pharmacy initiative in Iowa and the spreading of CPESNs across the country is further evidence that the pharmacy community believes that high value pharmacies comprise more than 1.2% of all

pharmacies. Why then, did this study's results find this small a number for the process metrics and method chosen?

It could be that this 1.2% are simply the best of the best, and the 2.3% of low quality pharmacies therefore the worst of the worst and the outlier detection method misses pharmacies with less exceptional quality. It could also be that the commercially insured population differs sufficiently from Medicare and Medicaid that there are fewer pharmacies of clearly better or worse quality. Additionally, it is possible that metrics chosen are insufficient to identify the variation in quality assumed to exist by the spread of high performing pharmacy networks and CPESNs. More investigation is needed to determine the underlying reason for low identification.

5.a.2 Hypothesis 1.2

According to Donabedian, there should be linkages between process and outcome quality in addition to linkages between structure and process quality. For this study, outcomes comprised a non-trauma, non-cancer, unplanned hospitalization metric and a non-trauma emergency department visit metric. No significant relationship was found between odds of these outcomes and the process quality score for the pharmacy to which a patient was attributed. Similar to the conclusion drawn from the lack of significance for the relationship between structures and processes, the lack of an observed relationship does not mean that a relationship does not exist for pharmacies. This would call into question a fundamental tenant of the SPO theory of healthcare quality. Rather, it is assumed that the design of analysis for process and outcome measures was insufficient to detect this latent correlation.

5.a.2.1 Outcome Metric Model Performance

Risk adjustment was also found to substantially improve model performance when evaluating outcome measures. At least some category of each of the case-mix adjustment variables were found to be significantly associated with odds of hospitalization and ED visits. There was greater difference in the coefficients for case-mix adjustment variables between the hospitalization and ED visit models than between PDCs for different medication classes, suggesting that the underlying variables that impact hospitalizations and ED visits differ in greater ways than variables impacting PDCs across medication classes. Females were both less likely to be hospitalized and experience an ED visit than males.

There was observed to be an effect of pharmacy on attributed patients' hospitalization and ED visit odds with RICC values at 0.0249 and 0.0178 respectively. These values are slightly lower than those for PDC process metric models and similar to those found by Dharmarajan et al. (2014). The slightly lower RICC values for the fully specified outcome models (Table 13) suggest that adding covariates into the model explains some of the correlation between patients within pharmacy. This is the opposite effect from the addition of covariates for PDC models. The changes are so slight that the difference is not very meaningful, but this reveals that the effect is inconsistent. The c-statistic for the hospitalization model (0.7577) showed that the case-mix adjustment variables performed reasonably well, but the c-statistic for the ED visit model (0.6526) was suboptimal. This suggests that a broader set of covariates should be explored for these models, and that improvement could be made if covariates were allowed to differ between the models. Differences between models including PQS and not including PQS were slight and fit was improved when PQS was removed. This adds further evidence to the lack of correlation between PQS and outcome event probability.

5.a.2.2 Identification of High and Low Outcome Quality Outliers and Combined Quality Score

High and low quality outcome outliers and combined quality outliers appeared at approximately the same frequency as process outliers. Two outliers were identified as low outcome quality outliers and three as high quality outliers. Literature evaluating the impact of community pharmacists on hospitalizations and ED visits is scare, therefore one cannot compare the frequency of high and low outcome quality pharmacies to other studies. As medication experts, pharmacists are in a position to optimize medication use, thereby reducing hospitalizations (IMS Institute, 2013). Evidence from adherence studies consistently finds that better adherence reduces hospitalization risk (Roebuck et al., 2015; Roebuck et al., 2011; Sokol et al., 2005). There is also evidence to suggest that using more medications offsets some of the risk of hospitalization (Stuart et al., 2009). To the extent that pharmacies can perform exceptionally well or poorly on improving medication use, it is reasonable that true variation in hospitalization and ED visit quality outliers exist. The effect is likely to be slight, however, and this matches with the outlier frequency observed.

Outliers identified using the combined quality score (CQS), 5.8% for low quality and 5.3% for high quality, appeared at a higher frequency than for PQS or OQS alone. This is still less than the percent differentiation observed for Medicare patients using process metrics only (Dharmarajan et al., 2014).

In the previous section, it was suggested that the pharmacies identified as quality outliers using the PQS could be the best of the best or the worst of the worst, but the complete lack of association between PQS and odds of adherence (Table 12 and Table 13) and PQS and OQS (Table 15) suggest that this hypothesis does not hold true. If the identified pharmacies were at the extreme ends of a wide distribution in pharmacy quality, it would be reasonable to think that

these exceptional pharmacies would have different rates of outcome events than other pharmacies. This is not observed, however. The complete lack of association calls into question the validity of the metrics chosen to assess quality. Despite this, there was observed to be a significant effect of pharmacy on attributed patients' healthcare quality for all process and outcome metrics chosen. Therefore, each metric likely measures an effect of pharmacy, but the measure set is incomplete and/or quality scoring should be modified.

5.b Aim 2. Detecting the Presence of High and Low Value Pharmacies

Evaluating the hypotheses under Aim 2 does not require the null hypotheses for the Aim to be rejected. As discussed in the previous section, there was no evidence of a link between structure quality and process quality and process quality and outcome quality. Nonetheless, the RICC and Wald test for the random intercept term find that there was an observable effect of pharmacy on attributed patients' process and outcome quality. Therefore, a summary measure of these effects, CQS, is a reasonable, if imperfect, measure of pharmacy quality. Additionally, CQS is similar to other scoring systems for pharmacy quality employed currently by other organizations (Mascardo, 2016; Trygstad, 2015). The low frequency of quality outliers may be insufficiently sensitive or may reflect the smaller differentiation in the impact of pharmacy quality on adherence and outcome event rates for a commercially insured population. Regardless, the chosen method is more conservative than other methods of quality identification that compare pharmacy scores to a confidence interval around a mean score or rank pharmacies and declare the top and bottom 10-20% to be high and low quality outliers. Therefore, even though expected quality linkages were not observed, sufficient reasons exist to expect that the identified high and low quality pharmacies can be used to explore the hypothesis that variation in pharmacy value exists.

5.b.1 Cost Model Performance

As measured by the RICC, the effect of pharmacy on cost was strikingly smaller than the effect on process and outcome measures. The RICC value was highest for the pharmaceutical cost model, which is expected given pharmacists' role as medication dispensers. Even so, the RICC from the fully specified pharmaceutical cost model was only 0.0068, and this was diminished from 0.0101 in the base model with only the random intercept. RICC values for medical cost and total cost of care were 0.0024 and 0.0028, and were similarly diminished compared to the base model. Diminished RICC values could suggest geographic clustering in cost that is observed as pharmacy-level correlations in cost, only to be explained in the fully specified model by variation in health status. These results suggest that quality scoring systems are less justified holding pharmacies to account for broad-based cost measures. The Wald test still found a significant effect of pharmacy, but this effect was very slight.

The R^2_1 values measure the improvement in predictive ability for the fully specified model compared to the model with only the random intercept for pharmacy (Snijders & Bosker, 2012). Small R^2_1 values suggest the model covariates perform poorly in controlling for variation in cost. Improvements in predictive ability may explain some of the variance across patients nested within pharmacies, thus improving RICC values, or it may explain more of the variance between patients nested within the same pharmacy (as would be the case with geographically clustered covariates) and this would lessen the already small RICC values. Therefore, one cannot say with certainty that lack of predictive ability is resulting in small RICC values.

5.b.2 Cost Impact Scores

Pharmacies were identified as outliers at a higher frequency for the Cost Impact Score (CIS) than the PQS, OQS and CQS. The lower RICC value and poor predictive ability for models used to calculate the CIS make less certain, however, that outlier pharmacies are true outliers. Evidence from the Pennsylvania Project (Pringle et al., 2014) supports the hypothesis that pharmacists can reduce healthcare cost even with brief, targeted interventions, therefore it is reasonable to believe that some of the savings outliers are providing these services and therefore reducing healthcare cost. Additionally, a wealth of evidence on adherence suggests that better adherence and greater use of medications reduces the cost of healthcare (Congressional Budget Office, 2012; IMS Institute, 2013; Nasseh et al., 2012; New England Healthcare Institute, 2009; Roebuck et al., 2015; Roebuck et al., 2011). As shown by the results from models used to calculate the PQS (Table 10) and evidence from other studies (Brennan et al., 2012; Fischer et al., 2014; D. Holdford & Saxena, 2015; D. A. Holdford & Inocencio, 2013; J. K. Lee et al., 2006; Nola et al., 2000; Perlroth et al., 2013; Pringle et al., 2014; Zillich et al., 2005), pharmacists can influence both of these care processes. Additionally, other opportunities for medication optimization, including primary medication nonadherence, underprescribing, dose adjustment, antibiotic stewardship and transitions of care, create avenues for care improvement which reduce the cost of healthcare (IMS Institute, 2013). Community pharmacy practice is transitioning towards greater delivery of clinical services, and it is highly likely that there are at least some community pharmacies with exceptional pharmacists that, through the aforementioned mechanisms, reduce the cost of their patients' healthcare. It is equally unlikely that there are not pharmacists who, either through inadequate environmental support, lack of education, or other means, fail to provide a basic level of patient care and therefore, in comparison to their peers, increase healthcare cost.

5.b.3 Hypotheses 2.1 – 2.3

The statistical tests found significant presence of high and low value pharmacies for each of the three cost categories. Because the chosen quality scoring method is more conservative than alternatives, this makes the hypothesis test for value more conservative as well. Using a confidence interval around a mean pharmacy-level score or declaring the top and bottom 10-20% of pharmacies to be high and low value, one is all but guaranteed to see significant variation in value. The only way not to see variation in value with those alternative scoring systems is if there was a perfect or near perfect direct correlation between quality and cost such that all or nearly all high quality pharmacies were also high cost and vice versa. One can state with some certainty variation in the value pharmacies provide a major commercial insurer in Iowa and South Dakota exists when using the chosen metrics and scoring system.

5.c. Reflection on Validity

In light of the previous discussions on the poor-to-nonexistent linkages between structure and processes and processes and outcomes, relatively weak c statistics and R^2_1 and low RICC values, one must question the validity of the significance of the value score. Can one be assured that significant variation in value exists if the measures creating the value measure are far from perfect? The answer is not a definitive yes or no.

5.c.1. Statistical Model Validity

Li et al. (2009) provides a framework for evaluating the validity of statistical models and quality measures that can be used to consider this study's results. Statistical model validity is assessed on five factors:

1. Face validity: The model includes variables that seem to be useful in adjusting for variation in case-mix across pharmacy.
2. Content validity: The risk-adjustment model incorporates all possible concepts affecting process, outcome and cost independent of effect of the pharmacy.
3. Construct validity: The effects of risk factors are estimated in the direction that would be expected.
4. Convergent validity: The effects of risk factors on the process, cost and outcome measures are consistent across alternative models.
5. Predictive validity: The model predicts the outcomes of interest well.

The exploration of literature and theory used to construct the conceptual model (Figure 4) adds face validity and content validity to the models used in quality and cost scoring pharmacies. It is acknowledged, however, that the operationalized model does not capture all quality related concepts. The operationalized model used to guide variable selection for statistical modeling (Figure 5) only approximates the complexity of pharmacy structures, leaves out explicit measures of patients' care processes, and fails to account for patients' care experiences. Therefore, although there is face validity for included measures, the inability to measure concepts contained in the conceptual model reduce the content validity of the statistical models.

In the assessment of construct and convergent validity, case-mix adjustment covariates were primarily designed to control for unobserved variation in health status. It was assumed that patients with more prescriptions, advanced age, and a greater number of Elixhauser comorbidities

would have worse health status, and therefore less adherence, more hospitalizations and ED visits, and higher cost of healthcare. The Elixhauser comorbidity count covariate followed this pattern across all models assessed. For age, older patients were found to have greater prescription adherence. This has been observed by other studies (Billups, Malone, & Carter, 2000; Ho et al., 2006), and is potentially the result of increasing care of one's health observed when comorbidity count is controlled for. Surprisingly, hospitalizations and ED visits decreased with increasing age. One explanation for the strikingly high rates of hospitalization and ED visits for those in age category 1, representing those patients aged 18-25, is that these could be sick children who stayed on their parents' health insurance. The Affordable Care Act allows children up to age 26 to remain on their parents' insurance, and there may be selection effects that make this cohort sicker than other age cohorts. Additionally, it could be that those with the worst health status drop out of the workforce or cannot find insurance in the small group and individual market, making higher age cohorts included in this study healthier than the average person of that age. Age performed as expected for cost measures.

Higher annual prescription counts were associated with greater odds of adherence and greater odds of an outcome event. Previous studies have found a relationship between increased prescription count and increased adherence (Billups et al., 2000; Ho et al., 2006), and higher adherence also mathematically increases annual prescription count. Greater odds of hospitalization and ED visit are logically linked via differences in health status not otherwise observed by age and comorbidity count. This analysis suggests that although there were some surprising covariate estimates, models generally do have acceptable construct and convergent validity. Variation in covariates can all be explained using empirical evidence or theory.

Assessment by gender found that women were both less likely to be adherent than males and less like to experience a hospitalization or ED visit. Female gender was also associated with greater cost, however. Supporting the adherence findings, Jackson et al. (2014) found that

females had higher rates of primary nonadherence. A study by Heaton, Tundia, and Luder (2013) found that women were slightly less likely to visit the ED for non-adherence related causes but slightly more likely to visit the ED overall. According to Osterberg and Blaschke (2005), gender has not been consistently associated with variation in adherence. Consistent with this finding, the effect of gender, although significant, only slightly impacts all the dependent variables except hospitalizations (OR=0.630). Assessment of other literature for gender effects doesn't uphold this study's findings, but it doesn't threaten its validity, either.

Using the construct and convergent validity framework to assess structure variables and PQS finds less validity for these variables. Structure measures had better convergent validity, with a consistent relationship between marginal and non-Sunday filling pharmacies for each of the four process metric models. Construct validity was less for these variables, though. There is little evidence to suggest a reason for differential performance between marginal and non-Sunday filling pharmacies. There was no significance associated with the weekly prescription volume covariate, but, as described in section 5.a.1, this is not surprising. The PQS performed poorly across both outcome models, not only lacking significance but also the point estimates found that both PQS outlier categories decrease hospitalizations and increase ED visits. Theory suggests that patients attributed to higher quality pharmacies should have lower hospitalization rates and ED visit rates.

Finally, these models have varying predictive validity. As previously discussed, some models do have c-statistics ≥ 0.7, but most are between 0.60 and 0.69. The cost models have relatively low R^2_1 values, suggesting that the predictive ability is only marginally enhanced by adding by fixed effects. This is an opportunity for improvement and development of novel covariates. Commercially available products, such as 3M's Clinical Risk Grouping Software (3M, 2016) and Johns Hopkins' Adjusted Clinical Groups® (Hopkins, 2016), are designed to capture variation in health status. This may improve predictive power beyond this study's simplistic

measure of age + comorbidities + prescription count and are used in HealthPartners' TCOC metric (Knudson & Heim, 2014). This presents an opportunity for future research.

Assessing evidence from all measures of model validity, the statistical models used in this study represent a reasonable attempt to estimate pharmacies' impact on healthcare quality and cost. The conceptual model building process was thorough, and the operationalized model was as complete as possible given the limitations of the data. Estimates from case-mix covariates were generally in the expected direction, and differences across the models could be explained using empirical evidence and theory. The lack of validity for the PQS measure is concerning, but models used to estimate the PQS were themselves valid. The predictive validity could be improved, but the case-mix covariates did improve predictive validity compared to a base model with only random intercept of pharmacy. Therefore, one can conclude that although far from perfect, the results of this study's models should not be dismissed as invalid.

5.c.2. Quality Metric Validity

In assessment of quality metric validity, Li et al. (2009) use a two factor framework:

1. Convergent validity: Pharmacy quality outliers are identified consistently across metrics.
2. Criterion validity: The quality measure reflects true quality of care delivered by the pharmacist.

This study's internal validity suffers most from the lack of convergence between process and outcome quality. Li et al. (2009) measure convergent validity with the same metric over multiple statistical methods. For this study, the definition of convergent validity is changed slightly to refer to identification as a consistent outlier on more than one quality metric. For the PQS, only one pharmacy was identified as a quality outlier on more than one metric. For OQS, no

pharmacy was identified as an outlier on more than one metric, and no pharmacy identified as a PQS outlier was also identified as an OQS outlier. When arrayed as a value matrix, there is some convergence between high quality outliers and low cost outliers and vice versa for medical cost and total cost of care, but not for pharmaceutical cost. The individual measures, however, are built on a foundation with reasonable validity and one should not completely discount the results from the value matrix simply because of lack of convergent validity.

The truest test of validity is comparing these pharmacies' quality, cost and value scores to actual variation in quality, cost and value. This is not possible with secondary datasets. Despite the popularity of collections of quality measurement like EQuIPP or systems of measurement like the Five Star Rating schemes used by Medicare, there is no evidence that for pharmacy, any of these tools correlate with true variation in pharmacy value. At the root of this inadequacy is a poor understanding of what differentiates a low quality pharmacy from a high quality pharmacy. To reexamine the definition from section 2.a.2, pharmacy quality can be defined as 1) achieving a degree of excellence 2) by providing pharmacy services 3) which maximize the probability of positive outcomes and minimize the probability of negative outcomes. The first part of this definition is the most difficult to observe. In relative terms, this means that a higher quality pharmacy achieves a higher degree of excellence than a low quality pharmacy. Scoring systems employed by this study, CCNC and IEHP estimate degrees of excellence with point-based schemes. The mechanism through which higher points are obtained, in theory, are through the provision of pharmacy services. With medical and prescription claims databases, there is almost never a record of pharmacist services because pharmacists cannot bill in the same way that physicians and other healthcare providers can. There is a possibility of linking claims databases from MTM vendors like OutcomesMTM to quality scoring systems, but research to this effect has not yet been published. Therefore, one can only assume that pharmacists are providing services and measure results through process metrics like adherence metrics. The final part of the

definition states that the provision of these services should maximize the probability of positive outcomes and minimize the probability of negative outcomes. This enforces the theoretical linkage between processes and outcomes, but it is exceedingly difficult to compare the effect of a pharmacist providing a specific service, for example adherence counseling, and a change in more broad based patient outcome, like a hospitalization. This linkage certainly cannot be directly observed through secondary claims databases.

To approach criterion validity, an assessment of variation in pharmacy quality derived through implicit measures of structure quality, observation of service delivery, and a measure of service volume is needed. This would create a training set of pharmacies that could be used to validate systems of quality measurement that assign degrees of excellence in the form of points to pharmacies based on metric performance. If a proposed system of quality measurement produces results that align with the more detailed, implicit assessment of quality, this system can claim to have criterion validity.

Until that time, the metric system used to create this study's measure of pharmacy value is as reasonable as any other. Far from perfect, the results of analyzing this study's metric system have many elements of validity and use a conservative method of quality scoring; therefore, the finding that significant variation in pharmacy value exists should not be considered invalid. This evidence is sufficient to add one more weight to side of the scale suggesting that variation in the value pharmacies provide to commercial insurers exists but should not be considered the final word on the subject.

IMPLICATIONS FOR THEORY, RESEARCH AND PRACTICE

5.d. Theory

This study's paradigm includes the idea that pharmacists make an impact on their patients' healthcare outcomes through medication optimization, yet linkages between structures and processes, processes and outcomes are not found. These results do not suggest that these linkages do not exist. Rather, one should observe this failure and wonder about the validity of the metrics chosen to measure the linkages. It is far more likely that a refined metric system and a more robust case-mix adjustment system are needed to reveal the underlying linkages. To state otherwise is to question SPO and the underlying premise of nearly all quality metric schema or suggest that care provided by pharmacists leads to outcomes in a completely different way than care from other healthcare providers.

The marginal significance in Sunday filling category is intriguing. For each PDC metric, marginal Sunday filling pharmacies outperformed non-Sunday filling pharmacies. This relationship was unexpected. It could be that the significance of the observation for statins was due to random chance, and that the consistent relationship over other metrics is again just two random points on overlapping distributions, but there may be a theoretical reason as to why marginal Sunday filling pharmacies perform better than non-fillers.

Donabedian liked to say that "The secret to quality is love" (Donabedian, 2001). In his words, healthcare providers have to love their patients, love their profession and love their God. In this way, the pharmacist who opens the pharmacy on the occasional Sunday goes out of their way to serve their patients and uphold their professional duties. In Donabedian's terminology, they loved more. It could be that this expression of love towards their patients spills over into other areas of patient care. These pharmacists could be driven to take the time to explain a medication, encourage adherence and make themselves available to address their patients'

concerns. This difference in underlying quality could be reflected through the process metrics chosen for this study. This theory could be too romantic to be realistic, but it nevertheless is a possible reason why marginal Sunday filling pharmacies slightly out-perform non-Sunday filling pharmacies.

5.e. Research

Substantial research is needed to evaluate the validity of pharmacy quality metric systems. The most pressing research need is the lack of a study which assesses criterion validity of any quality metric system used. To evaluate criterion validity, researchers would need to obtain access to a large enough set of pharmacies to assess variation in pharmacy quality using implicit metrics of care quality and the care delivery environment. SEIPS could be used to guide this inquiry. Pharmacies would be ranked or categorized based on observed quality as a way to quantify relative degrees of excellence. Then, a metric scoring system would be created using claims information for a group of pharmacies that includes the validation set, and this set would be used to evaluate the metric's assessment of relative degrees of excellence.

This study uses a risk adjustment method to evaluate pharmacies' performance on PDC metrics. Currently, no clear risk adjustment method is used by EQuIPP, IEHP or CCNC. Results from this study and the study by Dharmarajan et al. (2014) find that risk adjustment appears to improve identification of outliers. A study by the Pharmacy Quality Alliance also finds that potential case-mix adjustment variables have a significant impact on pharmacies' identification as high or low performers on process metrics (Desai et al., 2016). PQA has formed an advisory panel to evaluate the need for risk adjustment of process metrics (Fish, 2015). Results from this study suggest that failure to control for variation in case-mix could create an undue burden on pharmacies with riskier attributed populations. Research is needed in more diverse populations

and in Medicaid, and if evidence continues to mount which supports risk adjusting PDC measures this should become the standard method for research into pharmacies' process quality.

Additionally, more research is needed about details of quality measurement systems. Better understanding of the effect of attribution on evaluations of pharmacy quality is needed. As results from Appendix C show, stricter attribution criteria may inflate observed quality scores and select out patients who are most in need of pharmacists' care. Additionally, this study used a crude all-prescriptions measure to evaluate attribution. However, as suggested by the pharmaceutical care model from Hepler and Strand (1989) pharmacists make a difference through identification of drug therapy problems, and not all medications are equally prone to drug therapy problems. Therefore, work should be performed to narrow the set of prescriptions selected for determining attribution to better attribute patients to pharmacies that can have the greatest potential impact.

Also, research is needed on measuring structural variation in pharmacy practice that support high quality care processes. The SEIPS model is promising in this regard, and studies are needed which link variation in SEIPS-identified work system elements with process and outcome measures of care. Refinement of the Sunday prescription metric is needed to verify a valid cut-off for identifying pharmacies that are closed generally but open for special occasions. Research is also needed to correlate the idea of compassionate pharmacists opening the door on a Sunday with variation in pharmacists' perceptions of their role in patient care and professional identity.

Additionally, more work is needed to create valid, non-PDC process metrics that correlate with care quality by pharmacists and can be implemented in pharmacies with relatively low observed claims volume. Attempts were made in this study to include all of the relevant non-PDC metrics endorsed by PQA, but all of the metrics had either numerator or denominator counts too low to be reliably measured over a sufficient set of pharmacies. Possible alternatives include

patient surveys inquiring about pharmacists' prescription counseling and other observable care processes.

Outcome metrics also need refinement. Although efforts were made to limit hospitalizations and ED visits to those that a pharmacist can reasonably expect to impact, this still leaves a relatively broad set of possible admitting conditions, only a portion of which a pharmacist can actually affect. Possibilities for executing this study include series of focus groups with community pharmacy practice experts to identify conditions and admitting diagnoses to include and exclude. A challenge will be balancing hospital exclusion criteria with the need for a sufficient frequency of numerator flags to reliably measure the metric across the relatively healthy commercially insured population.

Furthermore, additional work is needed to link patients' pharmacy experiences with other processes and outcomes of care. Special consideration should be given to convergent validity with other metrics. Little research has been conducted which relates patients' assessments of pharmacy practice with patients' adherence or rates of hospitalization admissions and ED visits.

Similar to hospitalizations and ED visits, research is needed to create refined cost impact measures. The measure used for this study was capped to control for the effect of outliers, but this still exposes a pharmacy to nearly all of an attributed patients' annual cost of healthcare. Arguments can be made that pharmacists cannot influence most types of healthcare cost, and therefore a measure this broad may be inappropriate. Again, better measures could be created by convening stakeholders to evaluate sources of healthcare cost for exclusion from cost measures. Assessment can also be made for convergent validity with cost metrics and quality metrics.

Together, these research questions build towards the creation of a validated quality metric system that can be used to evaluate variation in pharmacy value. This system could also be used

to form the basis of a value-based payment model for pharmacies which would reward high value pharmacies and provide incentives for improvement among low performers.

5.f. Practice

If appropriate steps are taken to validate a system of quality measurement for community pharmacies, and this system were used to create a value-based payment model, community pharmacy practice could be profoundly affected. For decades, it has been said that community pharmacy practice is at a crossroads—moving from a focus on product to a focus on patients. A validated VBPM would align profit incentives around appropriate patient care without reliance on fee-for-service MTM consultations which are the current, dominant form of remuneration for clinical services. Pharmacists in this alternative system would not necessarily get paid for doing add-on services for patients but for incorporating high quality patient care into their practices.

The concern with all of this is that VBPMs are being implemented without regard to validity. The IEHP system, for example, shows little evidence of the necessary steps to ensure that the highest performers are providing patient care services which produce the observed outcomes. Without validation, implementation of VBPMs could lead to metric chasing instead of improvements in patient care. This would result in observations of higher quality care without changing the underlying truth of care quality and provide a false sense of satisfaction. There are many reasons to be enthusiastic about the future of VBPMs and pharmacy practice, but one must make sure that measurement systems are well designed and valid before implementation.

LIMITATIONS

The primary limitation of this study is the lack of criterion validity. Actual variation in pharmacy value for the included pharmacies is not known, therefore one cannot state with certainty that the variation observed is well matched to reality. This is an unavoidable drawback of cross sectional studies. Additionally, there is concern over the metric system used to determine value. Lack of convergent validity and low predictive validity suggests that pharmacies observed as high and low quality may be misidentified. This study represents a practical, reasonable attempt to measure variation in pharmacy value for a commercially insured population. To assume that this is the only or the best way to measure value would be inappropriate.

Additionally, the statistical methodology used estimates the effect of pharmacy on patients while accounting for heteroscedasticity caused by patients nested within pharmacies and some confounding due to variation in case-mix, but the models could be improved. Case-mix variables could be expanded or refined, and dependent quality variables may be subject to too much unobservable variation to reliably measure a true effect of pharmacists on healthcare quality. Furthermore, the use of a random intercept to control for the effect of pharmacy does not allow for estimation of correlation between patient characteristics and pharmacy choice. Patients are not randomly assigned to a pharmacy. It is entirely possible that pharmacies could select for a healthier patient population by actively discouraging sicker patients from frequenting their pharmacy. Additionally, and perhaps more likely, patients could select pharmacies based on their perceived healthcare needs. Patients with a stronger perceived need for healthcare services could select a pharmacy that they believe will provide a higher level of clinical service, whereas patients with a more casual attitude toward healthcare could choose to patronize a pharmacy with more convenient hours. This would result in differentiation in health status across pharmacies that may be difficult to control for using case-mix adjustment variables.

Also, the outcome models only detect pharmacists' influence on a patients' first hospitalization or ED visit. If a pharmacist did not reduce initial admissions, but had substantial impact on readmissions, this effect would not be detected by this study. This could partially explain the lack of correlation between structure and process measures of care, but the effect is somewhat mitigated by the health of the population. It is rare that a patient has one hospitalization or ED visit, and attempting the impact on a second may be too weak a signal to be reliably observed.

Additional limitations are related to the dataset itself. Per the data use agreement, no geographic information more specific than city name and 3-digit ZIP code could be used to identify pharmacy or patient. It would have been useful to attach more information, such as chain ownership, to a pharmacy or to have more detailed demographic information on patients. This was not possible with the data available, but variation in patient income is less of a concern in this study than in others with more diverse populations since all included patients were employed, married to an employed person, or had enough financial reserves to purchase insurance through the individual market. Also, variation in race/ethnicity is less of a concern because both Iowa and South Dakota are overwhelmingly white.

Furthermore, concern exists over the selection effects imposed on the population and pharmacies. Comparison between patients and pharmacies included and excluded finds that the populations are similar, with the exception that pharmacies included has substantially higher prescription volumes than pharmacies excluded. This could limit the generalizability of coefficients to pharmacies with small volumes, as these were likely not present in the final sample. This does not, however, hinder the exploration of the hypothesis that variation in value exists. One simply cannot comment on variation in value for smaller volume pharmacies.

Finally, these results are likely not generalizable to Medicare and Medicaid. Generalizability to other commercially insured populations would depend on the demographics of the pool. The insurer from which this project received its data is dominant in both Iowa and South Dakota small group and individual markets, therefore limiting churn and enhancing generalizability over populations of working adults, but this population is substantially different than Medicare or Medicaid. Health concerns of the aged and poor are different from those of the employed. Therefore, one cannot be sure that the results of pharmacy value extend to these populations.

CONCLUSIONS

Significant variation in the value pharmacies provide commercial insurers was found to exist. There are questions on the validity of metrics used to estimate pharmacies' impact on process and outcome quality, and neither of the structure quality variables tested were effective at explaining variation in process quality measures. The method chosen for quality outlier identification was quite conservative with only single digit percentages of pharmacies identified as high and low quality outliers for process, outcome and combined quality scores. No correlation was found between process and outcome quality scores, a concern for the validity of the quality metric system.

Pharmacies' impact on process and outcome quality was observed, but observable impact on cost measures was miniscule. This suggests that systems holding pharmacies to account for the cost of their patients' health may lack statistical justification to do so. Tests for the presence of high and low value outliers using a combined quality score and pharmaceutical cost, medical cost and total cost of care were all significant.

These results suggest that it may be reasonable to construct systems of quality measurement which support a value-based payment model for pharmacies in a commercial insurer's network. Systems need to be well designed, otherwise misidentification of pharmacies is possible. More research is needed to identify known high, typical and low quality pharmacies to ensure that systems of quality measurement are accurate. Additionally, further study is needed to examine attribution systems, develop and refine quality metrics and enhance case-mix adjustment methods.

APPENDIX A. VARIABLES FROM WELLMARK DATABASE USED FOR THIS PROJECT

Table A1. Variables Included from Membership Elements Table

Variable Name	Description	Purpose
Logical Person Key	Unique identifier for each person in the database.	Match member information to claims and claims across persons.
Birth Year	The year the person was born	Used to calculate age for case-mix adjustment
Gender	The gender of the person expressed as the conventional binary	Used for case-mix adjustment
Exposure Count	Indicates person enrollment during a given month and year	Assess person enrollment over entire 2 year period
Year	Year for the corresponding exposure count	Assess person enrollment over entire 2 year period
Month Number	Month for corresponding exposure count	Assess person enrollment over entire 2 year period

Table A2. Variables Included from Claims Files

Variable Name	Description	Purpose
Logical Person Key	Unique identifier for each person in the database.	Match member information to claims and claims across persons.
Admission Date	The date a person was admitted to a hospital	Identify hospitalizations and to exclude nonambulatory days from the PDC calculation
Discharge Date	The date a person was discharged to a hospital	Identify hospitalizations and to exclude nonambulatory days from the PDC calculation
Type of Service	Describes the general category of services rendered.	Identify prescription claims, hospitalizations.
Place of Service	Indicator for where the services paid were performed.	Identify prescription claims, hospitalizations.
Trend Line of Business Rollup	Differentiates between facility claims, practitioner claims, drug card claims, and comprehensive major medical claims.	Identify prescription claims, hospitalizations.
Drug Days Supply	Contains the number of days over which a prescription is expected consumed	Calculate percent of days covered metrics for estimating adherence.
National Drug Code	Contains 11-digit NDCs	Identifies specific drugs included in a claim.
Primary Valid Diagnosis Code	ICD-9-CM code most relevant to a person's hospital stay or care visit.	Identify a person's pregnancies and chronic conditions
Secondary Valid Diagnosis Code	ICD-9-CM code second most relevant to a person's hospital stay or care visit.	Identify a person's pregnancies and chronic conditions
Units of Services	Varies depending on type of service delivered. For inpatient stays, this is the number of days. For prescriptions, this is the units dispensed.	Identify number of days spent in hospital.
Allowed Amount	Amount used to determine copayment, coinsurance, and deductible amounts paid for a given claim.	Calculate healthcare cost.
Provider ID	Encrypted alphanumeric code specific to each provider.	Differentiate between pharmacies, hospitals.
Provider specialty code	Categorizes provider specialties	Used to confirm identification of a pharmacy
Provider type	Categorizes provider types	Used to confirm identification of a pharmacy

APPENDIX B. EVALUATION OF CRITERIA FOR DEFINING MARGINALLY OPEN PHARMACIES

Multiple reasonable criteria can exist for defining the cut-off for determining a pharmacy to be marginally open on Sundays. Theoretically, observations of care for marginal Sunday filling pharmacies are different than observations of care for robust filling pharmacies because of the differences in underlying care orientation and business model that correlate with the type of care provided and with the decision to be open on Sundays. Therefore, a threshold set too loose will result in marginal Sunday pharmacies appearing more similar to robust Sunday filling pharmacies than to pharmacies dispensing no prescriptions on Sundays.

The definition of a marginal filling pharmacy was based off of weekly prescription volume. Percent volumes of 0.05%, 0.1%, 0.25%, 0.5% and 1% were tested as criteria for defining the cut-off between marginal and robust Sunday filling pharmacies. Using each of these thresholds, regression models were constructed which assessed the relationship between the Sunday fill category and the four PDC metrics used for this study (Table 21). The decision on Sunday filling threshold was made using model F-statistics.

For β-blockers and RASA PDC metrics, the largest F-statistic for the regression model was for the Sunday fill categorization using the 0.05% cut-off, but for statins the largest F-statistic was for 0.1% and NIDA was a tie between 0.25% and 0.5%. The range of F-statistics for RASA and NIDA is small and therefore of little use for differentiating between thresholds. Results from the β-blocker PDC suggest using a 0.05% cut-off, but results for statins suggest using a 0.1% cut-off. The difference in F-statistics between 0.05% and 0.1% cut-off models is larger for statins, and a more generous threshold identifies a greater number of marginal pharmacies, thus increasing the power to detect differences by class.

Table B1. Testing Marginal Sunday Filling Pharmacy Cut-off Using OLS Regression with PDC Score as Dependent Variable and Robust Filling Pharmacies as Reference

	Percent Fills Cut-off	Marginal Pharm. Count	Non-Filling Pharm Count	Robust Filling Pharm. Count	Marginal Filling Point Estimate (p-value)	Non- Filling Point Estimate (p-value)	Overall F-statistic (p-value)
β-blockers	0.05%	35	66	382	3.79 (0.022)	1.00 (0.422)	2.79 (0.062)
	0.1	53	66	364	2.24 (0.1044)	0.967 (0.441)	1.47 (0.230)
	0.25	84	66	333	1.51 (0.189)	0.986 (0.436)	1.02 (0.362)
	0.5	93	66	324	1.74 (0.116)	1.07 (0.398)	1.39 (0.249)
	1	99	66	318	1.69 (0.117)	1.08 (0.393)	1.38 (0.251)
Statins	0.05%	44	118	492	2.57 (0.0530)	-1.96 (0.0236)	5.09 (0.006)
	0.1	73	118	463	2.96 (0.005)	-1.77 (0.042)	7.13 (0.001)
	0.25	122	118	414	1.58 (0.070)	-1.81 (0.040)	4.86 (0.008)
	0.5	141	118	395	0.73 (0.376)	-1.98 (0.026)	3.59 (0.028)
	1	156	118	380	0.66 (0.410)	-1.98 (0.027)	3.53 (0.030)
RASA	0.05%	48	132	497	0.98 (0.455)	1.471 (0.084)	1.63 (0.197)
	0.1	79	132	466	0.44 (0.675)	1.449 (0.092)	1.43 (0.239)
	0.25	124	132	421	0.58 (0.511)	1.517 (0.081)	1.56 (0.210)
	0.5	142	132	403	0.507 (0.550)	1.52 (0.082)	1.53 (0.218)
	1	157	132	388	0.141 (0.864)	1.43 (0.104)	1.36 (0.257)
NIDA	0.05%	15	12	147	3.15 (0.264)	-2.394 (0.4421)	1.00 (0.368)
	0.1	20	12	142	2.79 (0.261)	-2.34 (0.453)	1.01 (0.365)
	0.25	26	12	136	2.80 (0.208)	-2.24 (0.474)	1.18 (0.311)
	0.5	26	12	136	2.80 (0.208)	-2.24 (0.474)	1.18 (0.311)
	1	27	12	135	2.71 (0.215)	-2.23 (0.474)	1.15 (0.319)

APPENDIX C. SELECTING AN APPROPRIATE ATTRIBUTION THRESHOLD

There is no standard method for attributing patients to pharmacies for purposes of quality measurement. The method chosen for this study, the percent of total prescriptions, is a pragmatic method for attributing patients to the pharmacy that is most likely to employ pharmacists who have a therapeutic relationship with the patient. As a part of this method, a minimum attribution threshold must be set. Without this minimum threshold, it is possible for a patient to be attributed to a pharmacy that fills only a small percentage of their prescriptions. No standard for setting the minimum attribution threshold exists, therefore analysis was conducted to observe the impact of varying attribution threshold on the percent of total pharmacies eligible for the study, the percent of patients eligible for the study, the average number of patients attributed to a pharmacy, and process and outcome measures of care.

Figures C1-C3 contain decay curves illustrating the impact of attribution threshold on eligible pharmacies, patients, and average patients per pharmacy. The baseline for comparison is the total number of eligible patients and pharmacies if the minimum attribution threshold was 0%. These results show how nearly 100% of all potentially eligible patients and pharmacies are attributed at a minimum threshold of 50%, but less than 90% of pharmacies and less than 80% of patients are eligible at an attribution threshold of 90%. The number of patients attributed per eligible pharmacy also decreases by nearly 40 over the same change in thresholds.

Figures C4 and C5 illustrate the change in PDC scores and outcome event rates over the same change in thresholds. Tables C1 and C2 contain results from GEE models with a repeated measure for pharmacy that find that as the threshold increases, quality scores for eligible pharmacies improve.

These results suggest that choosing a high attribution threshold imposes selection effects on eligible patients and pharmacies. Pharmacies remaining at higher attribution thresholds have

greater observed quality than pharmacies eligible with lower thresholds. In considering the use of attribution thresholds in designing systems of quality measurement, eliminating patients with less stable prescription filling patterns may exclude the patients most in need of pharmacy services. Therefore, the minimum acceptable attribution threshold, 50%, was chosen for this study.

Figure C1. Decay Curve of Included Pharmacies as Minimum Attribution Threshold Increases

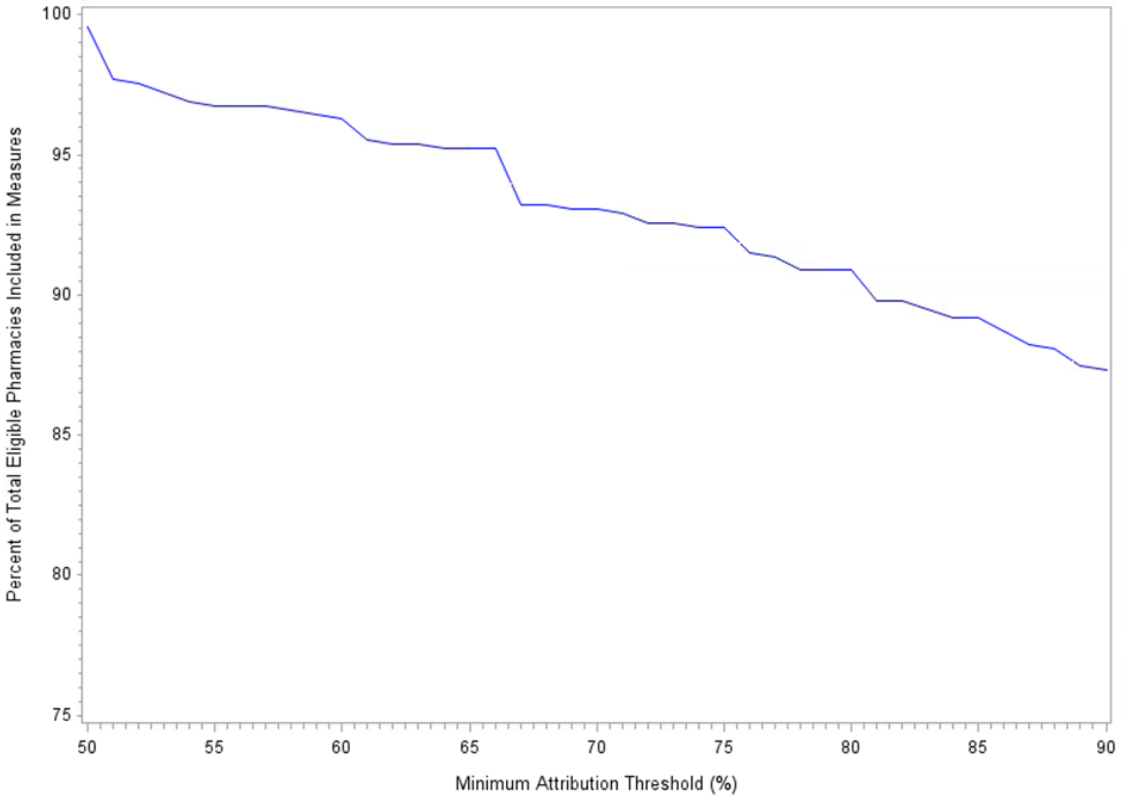


Figure C2. Decay Curve for Percent of Total Patients Attribution to a Pharmacy

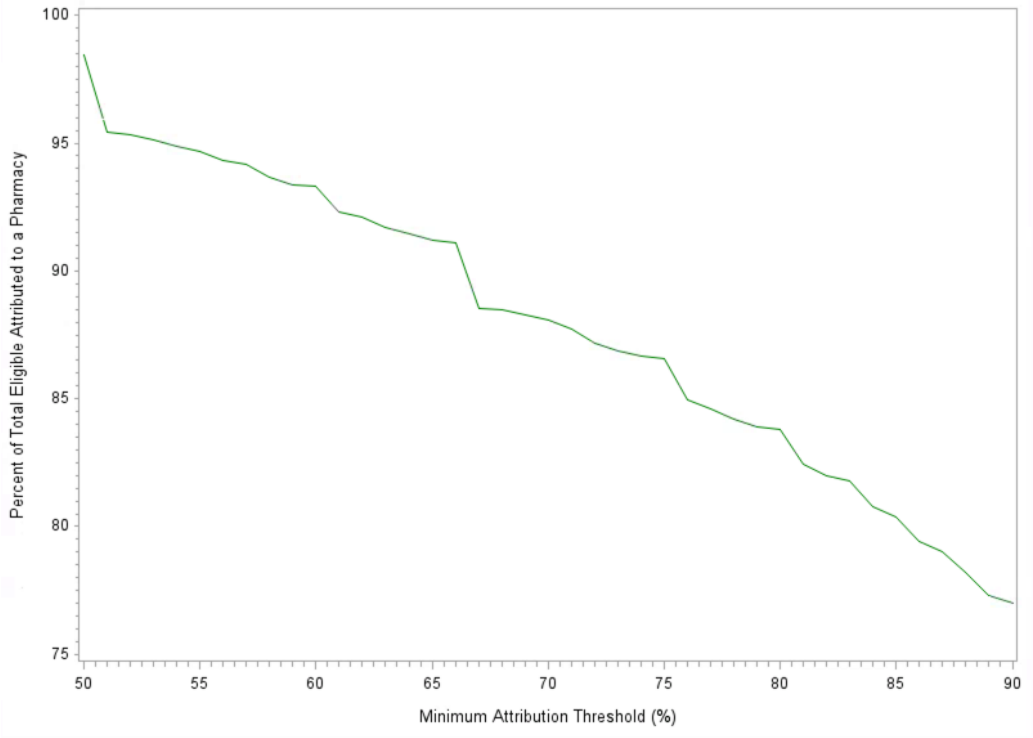


Figure C3. Trend in Total Attributed Patients as Minimum Attribution Threshold Increases

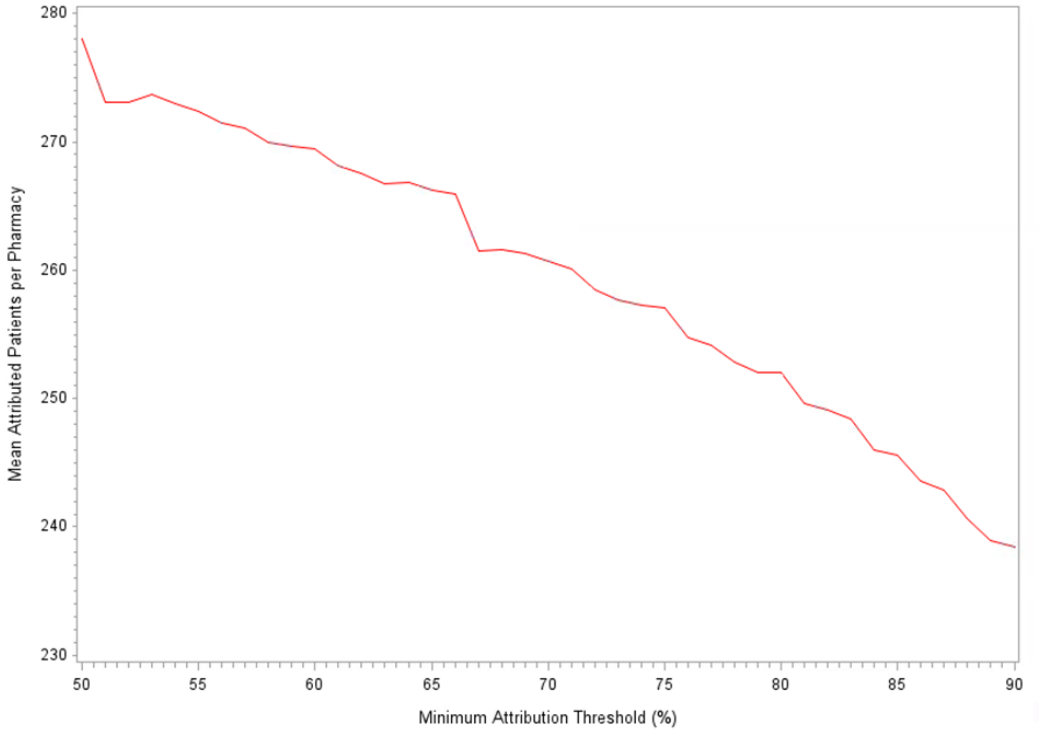


Figure C4. Comparison of Mean PDC Scores across Minimum Attribution Thresholds

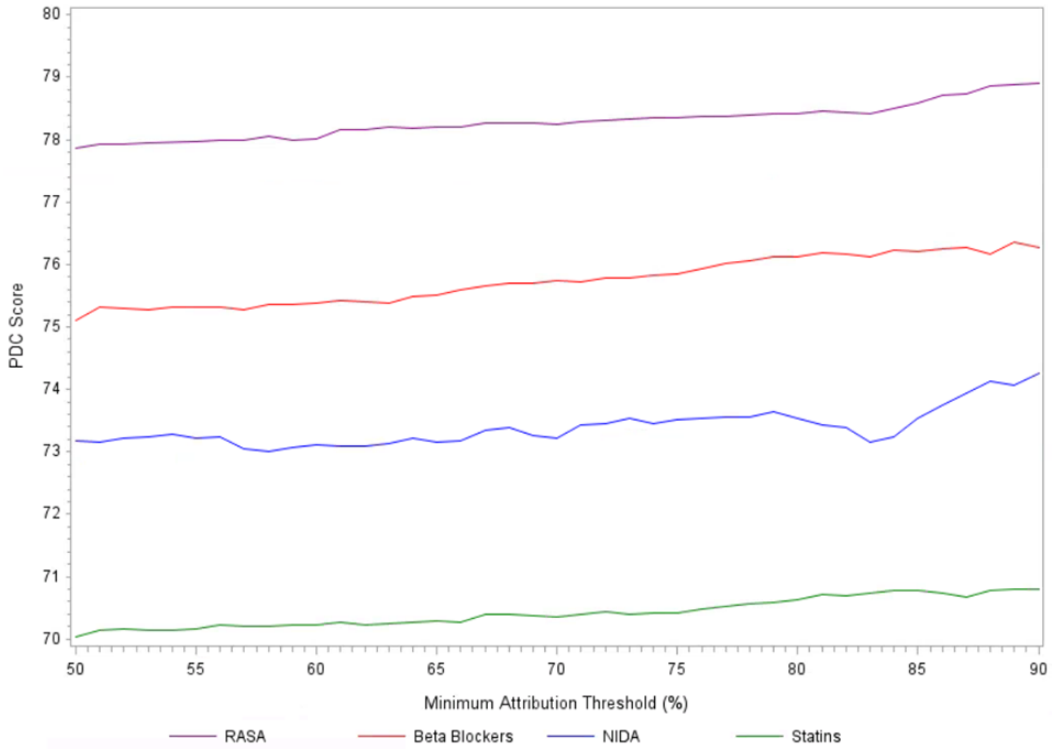


Figure C5. Comparison of Mean Outcome Rates across Minimum Attribution Thresholds

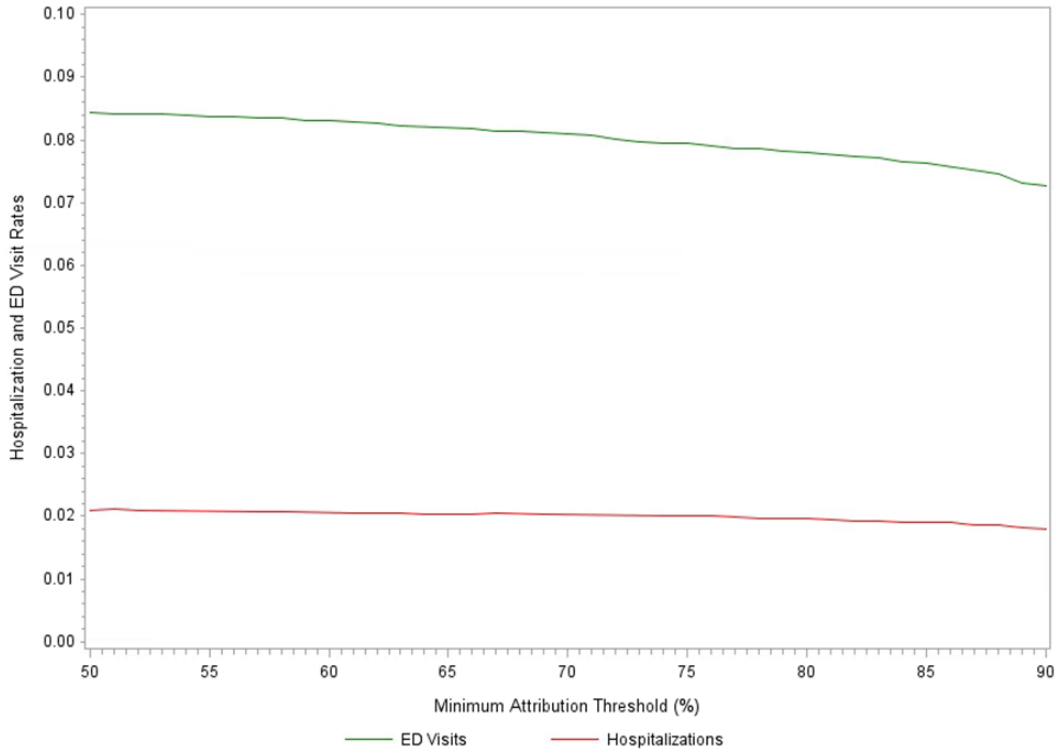


Table C1. Evaluation of Differences between PDC Scores at 5 Minimum Attribution Thresholds

PDC Medication Class	Metric-eligible Pharmacies	Model Intercept	GEE Estimate for Attribution Thresholds (%)				
			50	60	70	80	90
Beta Blockers	483	75.1	---	0.273*	0.638***	1.019***	1.164***
Statin	655	70	---	0.196*	0.329**	0.607***	0.778***
RASA	678	77.9	---	0.158*	0.376**	0.5499***	1.0362***
Noninsulin Diabetic Agents	174	73.2	---	-0.074	0.046	0.35	1.07
*p<0.05 **p<0.01 *** p<0.001 in comparison against reference minimum threshold of 50% with repeated measure for pharmacy							

Table C2. Evaluation of Differences between Outcome Rates at 5 Minimum Attribution Thresholds

Outcome Category	Metric-eligible Pharmacies	Model Intercept	GEE Estimate for Attribution Thresholds (%)				
			50	60	70	80	90
Hospitalizations	629	0.0209	---	-0.0002	-0.0005**	-0.0013***	-0.003***
ED Visits	644	0.0845	---	-0.0014**	-0.0035***	-0.0064***	-0.0117***
*p<0.05 **p<0.01 *** p<0.001 in comparison against reference minimum threshold of 50% with repeated measure for pharmacy							

APPENDIX D. EVALUATION OF PROCESS METRIC STABILITY AT VARYING DENOMINATORS

The Pharmacy Quality Alliance sets a 30 patient minimum standard for PDC metric reliability (Pharmacy Quality Alliance, 2014), but this denominator is designed to be used by CMS to measure Part D plan quality, and little evidence supports the use of a 30 patient minimum denominator in measuring quality for individual pharmacies (Kuhle, 2016).

If lower denominators can be used reliably, this increases study power by allowing more pharmacies to be included. To investigate this, a preliminary analysis was conducted with Iowa-only pharmacies (Table D1, Figures D1 and D2). The total number and percent of pharmacies achieving minimum denominator thresholds for each metric were compared at minimum denominators of 10, 15, 20 and 30. Measures of variance were also assessed, and it was found that the coefficient of variance was relatively stable until the denominator was reduced from 15 to 10. By using a denominator of 15 instead of 30, the number of included Iowa NIDA pharmacies increased from 18 to 156, and the number of β-blocker-eligible Iowa pharmacies increased from 185 to 406. There were substantially more pharmacies eligible at 10 compared to 15, but the coefficient of variance increased substantially when the denominator was moved to 10. Therefore, 15 was chosen as the minimum denominator that balanced reliability and power.

Table D1. Comparison of PDC Scores at Varying Minimum Denominator Thresholds

	Min. Denom.	Number of pharmacies included	Percent Included	Mean PDC Score	St. Dev.	CV	Median	1st Quartile	3rd Quartile
β-Blockers	30	185	45.8%	75.7	7.45	9.84	76.5	71	80
	20	321	63.1%	75.5	8	10.6	76.2	70	80.5
	15	406	73.8%	75.1	9.2	12.25	76.2	68.8	81.3
	10	498	82.5%	75.5	10.4	13.77	76.5	68.8	82.4
RASA	30	370	91.6%	78.2	7	8.95	78.4	74.4	83
	20	483	94.9%	78.2	7.8	9.97	78.6	73.9	83.3
	15	535	97.3%	78.2	8.2	10.49	78.6	73.7	83.3
	10	590	97.7%	78	8.8	11.28	78.6	73.3	83.9
Statin	30	380	94.1%	70.4	7.29	10.36	70.6	65.8	75
	20	482	94.7%	70.2	7.9	11.25	70.5	65.2	75
	15	527	95.8%	70.5	8.1	11.49	70.5	65.1	75
	10	583	96.5%	70.1	9.06	12.92	70.5	64.9	75.9
NIDA	30	18	4.5%	74.2	10.2	13.75	76.7	65.9	81.8
	20	65	12.8%	73.7	9.9	13.43	73.9	66.7	80
	15	156	28.4%	73.8	10.1	13.69	73.5	67.3	81.1
	10	272	45.0%	74.2	11.9	16.04	73.7	66.3	82.4

CV=Coefficient of Variance, calculated by St. Dev./Mean X 100

Figure D1. Chart of Coefficient of Variance as Denominator Decreases

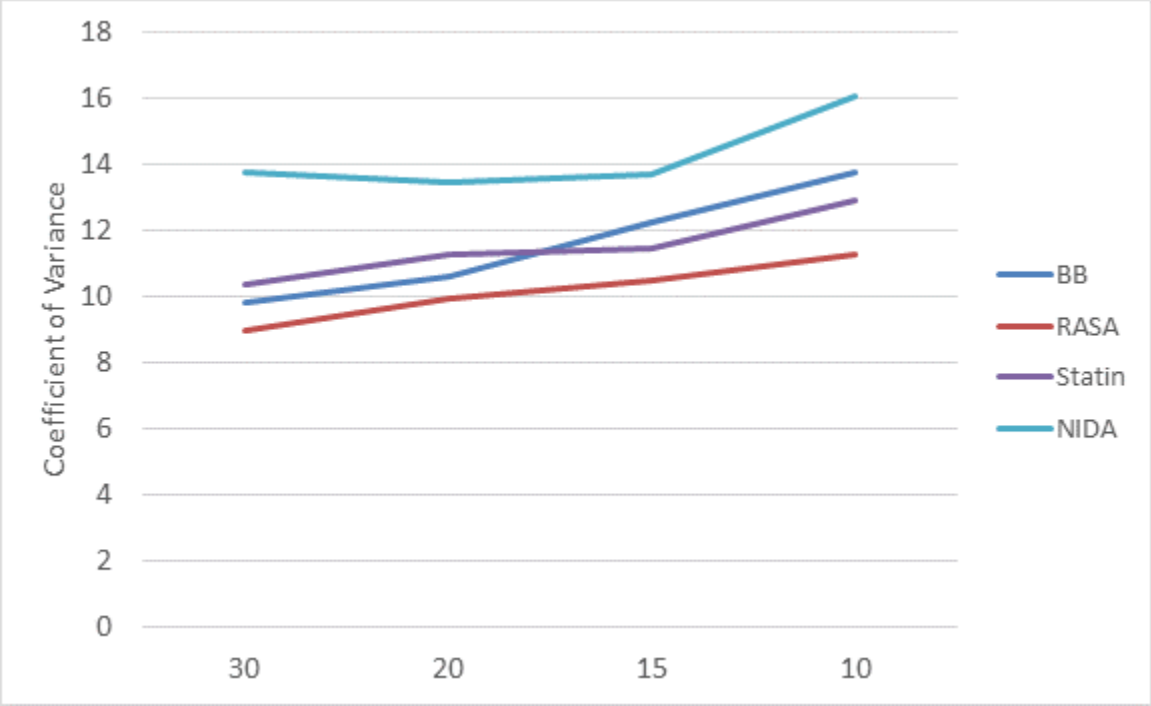
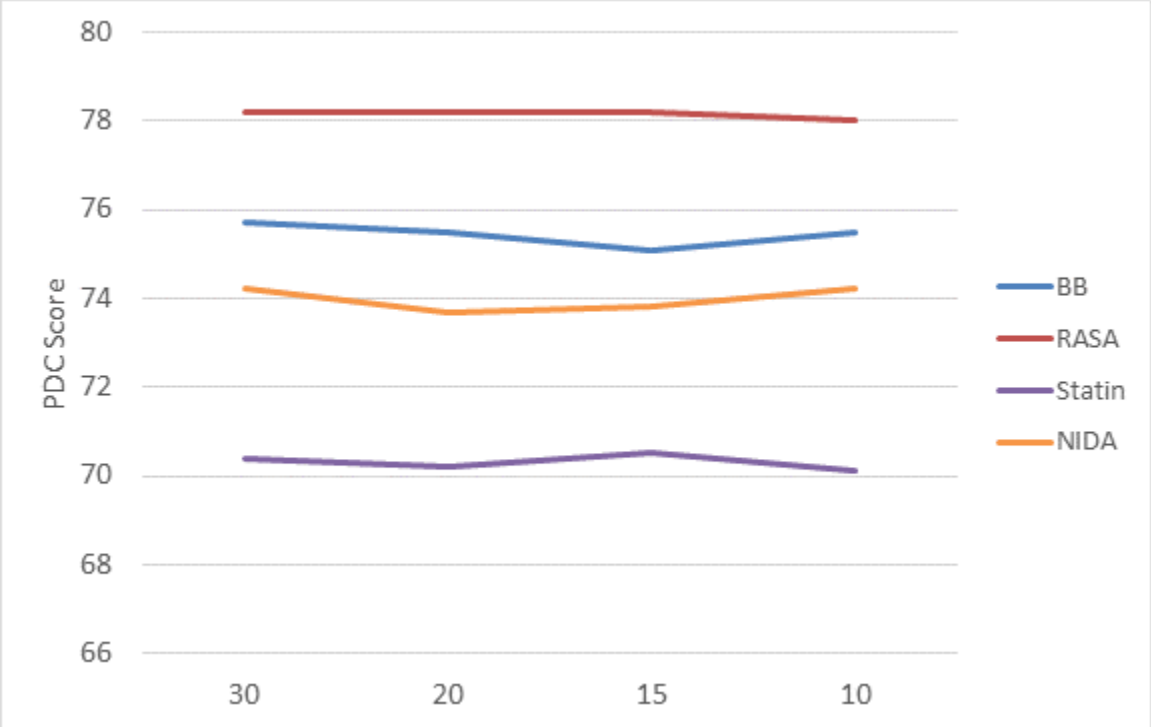


Figure D2. Chart of Mean PDC Scores as Denominator Decreases



APPENDIX E. ICD-9 CODES FOR CANCER, TRAUMA

Table E1. ICD-9-CM Codes Included in Hospitalization Metric Calculations and Exclusion Criteria

Disease State	CCS Classification Code	Corresponding ICD-9-CM
Diabetes mellitus without complications	49	24900 25000 25001 7902 79021 79022 79029 7915 7916 V4585 V5391 V6546
Diabetes mellitus with complications	50	24901 24910 24911 24920 24921 24930 24931 24940 24941 24950 24951 24960 24961 24970 24971 24980 24981 24990 24991 25002 25003 25010 25011 25012 25013 25020 25021 25022 25023 25030 25031 25032 25033 25040 25041 25042 25043 25050 25051 25052 25053 25060 25061 25062 25063 25070 25071 25072 25073 25080 25081 25082 25083 25090 25091 25092 25093
Essential hypertension	98	4011 4019
Hypertension with complications and secondary hypertension	99	4010 40200 40201 40210 40211 40290 40291 4030 40300 40301 4031 40310 40311 4039 40390 40391 4040 40400 40401 40402 40403 4041 40410 40411 40412 40413 4049 40490 40491 40492 40493 40501 40509 40511 40519 40591 40599 4372
Asthma	128	49300 49301 49302 49310 49311 49312 49320 49321 49322 49381 49382 49390 49391 49392

REFERENCES

3M. (2016). 3M(TM) Clinical Risk Grouping Software. Retrieved from http://solutions.3m.com/wps/portal/3M/en_US/Health-Information-Systems/HIS/Products-and-Services/Products-List-A-Z/Clinical-Risk-Grouping-Software/

Academy of Managed Care Pharmacy, & American Pharmacists Association. (2014). Medicare star ratings: stakeholder proceedings on community pharmacy and managed care partnerships in quality. *Journal of the American Pharmacists Association, 54*(3), 228-240. doi:10.1331/JAPhA.2014.13180

Agency for Healthcare Research and Quality. (2015, March). SAS Quality Indicators(R), Version 5.0. Retrieved from http://www.qualityindicators.ahrq.gov/Software/SAS.aspx

Agency for Healthcare Research and Quality. (2016a). Medical Expenditure Panel Survey Table 8: Total Expenses and Percent Distribution for Selected Conditions by Source of Payment: United States, Average Annual 2012-2013. Retrieved from http://meps.ahrq.gov/mepsweb/data_stats/tables_compendia_hh_interactive.jsp?File=HC2Y2013&Table=HC2Y2013_CNDXP_D&TCOPT1=&TCOPT2=&ModPopCheck=Yes&ModPop=Yes&_Debug=&DDAGELOW=18&DDAGEHIGH=64&DD=7&Action.x=150&Action.y=7

Agency for Healthcare Research and Quality. (2016b). National Quality Measures Clearinghouse: Measures by Domain. Retrieved from https://www.qualitymeasures.ahrq.gov/browse/by-domain.aspx?domain=1002&tab=0

AHRQ. AHRQ Patient Safety Network Glossary. Retrieved from http://psnet.ahrq.gov/glossary.aspx

Alston, G. L., & Blizzard, J. C. (2012). The value prescription: Relative value theorem as a call to action. *Research in Social & Administrative Pharmacy, 8*(4), 338-348. doi:10.1016/j.sapharm.2011.06.004

American Diabetes Association. (2015). Standards of Medical Care in Diabetes—2015. *Diabetes Care, 38*(Supplement 1), S1-S93.

American Medical Association. (2012). *Current Procedural Terminology, Standard Edition, 2013*. Chicago: American Medical Association.

American Pharmaceutical Association. (1986). APhA community pharmacy residency program: programmatic essentials. *American Pharmacy, NS26*(4), 34-43.

American Pharmacists Association. (2015). What Are Your Colleagues Doing? . Retrieved from http://www.pharmacist.com/what-are-your-colleagues-doing

American Pharmacists Association, & National Association of Chain Drug Stores Foundation. (2008). *Medication Therapy Management in Pharmacy Practice: Core Elements of an MTM Service Model, Version 2.0*. Retrieved from http://www.pharmacist.com/sites/default/files/files/core_elements_of_an_mtm_practice.pdf

American Society of Health-System Pharmacists. (2008, September). State Medicaid Programs Utilizing the Services of Pharmacists. Retrieved from https://www.ashp.org/DocLibrary/Advocacy/GAD/GetInvolved/MedicaidPrograms.aspx

Anderson, E. A., & Zwelling, L. A. (1996). Measuring service quality at the University of Texas M.D. Anderson Cancer Center. *International Journal of Health Care Quality Assurance, 9*(7), 9-22. doi:10.1108/09526869610150200

Ash, A. S., Shwartz, M., Pekoz, E. A., & Hanchate, A. D. (2013). Chapter 12. Comparing Outcomes Across Providers. In L. Iezzoni (Ed.), *Risk Adjustment for Measuring Health Care Outcomes* (4th ed.). Chicago: Health Administration Press.

Atlantic Information Services, I. (2016). How High-Performance Pharmacy Networks Can Improve Outcomes: A Case Study of SCAN Health Plan and Express Scripts. Retrieved from https://aishealth.com/marketplace/gc6p01-enlad

Berwick, D. M., Nolan, T. W., & Whittington, J. (2008). The triple aim: care, health, and cost. *Health Affairs, 27*(3), 759-769. doi:10.1377/hlthaff.27.3.759

Best, M., & Neuhauser, D. (2004). Avedis Donabedian: father of quality assurance and poet. *Qual Saf Health Care, 13*(6), 472-473. doi:10.1136/qhc.13.6.472

Billups, S. J., Malone, D. C., & Carter, B. L. (2000). The relationship between drug therapy noncompliance and patient characteristics, health-related quality of life, and health care costs. *Pharmacotherapy, 20*(8), 941-949.

Bitton, A., Choudhry, N. K., Matlin, O. S., Swanton, K., & Shrank, W. H. (2013). The Impact of Medication Adherence on Coronary Artery Disease Costs and Outcomes: A Systematic Review. *American Journal of Medicine, 126*(4). doi:10.1016/j.amjmed.2012.09.004

Blue Cross and Blue Shield Association. (2014, February). Blue Perspective: Value-Based Programs. Retrieved from http://www.bcbs.com/healthcare-news/press-center/BP-and-Quality-and-Plan-Innovations.pdf

Blue Cross and Blue Shield of Michigan. (2015a). Blue Cross Blue Shield of Michigan's Value Partnerships Program has Transformed the State's Health Care Landscape, Saved $1.4 Billion. Retrieved from http://www.mibluesperspectives.com/2015/08/26/blue-cross-blue-shield-of-michigans-value-partnerships-program-has-transformed-the-states-health-care-landscape-saved-1-4-billion/

Blue Cross and Blue Shield of Michigan. (2015b, September 14). Blue Cross Blue Shield of Michigan launches program that teams up pharmacists with primary care doctors to help patients with their medications. Retrieved from http://www.bcbsm.com/blue-cross-blue-shield-of-michigan-news/news-releases/2015/september-2015/blue-cross-launches-pharmacy-cqi.html

Blue Cross and Blue Shield of Michigan. (2015c). Rewarding value in health care: Physician Group Incentive Program. Retrieved from http://www.bcbsm.com/content/dam/public/Providers/Documents/physician-group-incentive-program-basics.pdf

Blue Cross and Blue Shield of Michigan. (2016, January 5). Physician Group Incentive Program: Clinical Quality Initiative. Retrieved from http://www.valuepartnerships.com/wp-content/uploads/2016/01/2016-CLQI-Fact-Sheet.pdf

Bluml, B. M., McKenney, J. M., & Cziraky, M. J. (2000). Pharmaceutical care services and results in project ImPACT: hyperlipidemia. *Journal of the American Pharmaceutical Association (Washington,D.C.: 1996), 40*(2), 157-165.

Brennan, T. A., Dollear, T. J., Hu, M., Matlin, O. S., Shrank, W. H., Choudhry, N. K., & Grambley, W. (2012). An integrated pharmacy-based program improved medication prescription and adherence rates in diabetes patients. *Health Affairs, 31*(1), 120-129. doi:10.1377/hlthaff.2011.0931

Bright, D. R., Lengel, A. J., & Powers, M. F. (2009). Pharmacists' Perceptions of Barriers to Implementing Medication Therapy Management and the Role of Pharmacy Technicians in Overcoming the Barriers. *Journal of Pharmacy Technology, 25*(6), 361-367. doi:10.1177/875512250902500603

Brilleman, S. L., Gravelle, H., Hollinghurst, S., Purdy, S., Salisbury, C., & Windmeijer, F. (2014). Keep it simple? Predicting primary health care costs with clinical morbidity measures. *Journal of Health Economics, 35*, 109-122. doi:10.1016/j.jhealeco.2014.02.005

Brookhart, M. A., Patrick, A. R., Dormuth, C., Avorn, J., Shrank, W., Cadarette, S. M., & Solomon, D. H. (2007). Adherence to lipid-lowering therapy and the use of preventive health services: an investigation of the healthy user effect. *American Journal of Epidemiology, 166*(3), 348-354. doi:10.1093/aje/kwm070

Brown, L. M. (2009). Measurement of pharmacy quality metrics at the pharmacy level should be our goal. *Journal of the American Pharmacists Association, 49*(2), 153. doi:10.1331/JAPhA.2009.09030

Bunting, B. A., & Cranor, C. W. (2006). The Asheville Project: long-term clinical, humanistic, and economic outcomes of a community-based medication therapy management program for asthma. *Journal of the American Pharmacists Association, 46*(2), 133-147.

Bunting, B. A., Smith, B. H., & Sutherland, S. E. (2008). The Asheville Project: clinical and economic outcomes of a community-based long-term medication therapy management program for hypertension and dyslipidemia. *Journal of the American Pharmacists Association, 48*(1), 23-31. doi:10.1331/JAPhA.2008.07140

Burwell, S. M. (2015). Setting value-based payment goals--HHS efforts to improve U.S. health care. *New England Journal of Medicine, 372*(10), 897-899. doi:10.1056/NEJMp1500445

Capanu, M., Gonen, M., & Begg, C. B. (2013). An assessment of estimation methods for generalized linear mixed models with binary outcomes. *Statistics in Medicine, 32*(26), 4550-4566. doi:10.1002/sim.5866

Carayon, P., Schoofs Hundt, A., Karsh, B. T., Gurses, A. P., Alvarado, C. J., Smith, M., & Flatley Brennan, P. (2006). Work system design for patient safety: the SEIPS model. *Qual Saf Health Care, 15 Suppl 1*, i50-58. doi:10.1136/qshc.2005.015842

Center for Pharmacy Practice Accreditation. (2013). *Community Pharmacy Practice Standards*. Retrieved from CPPA Web Site: https://pharmacypracticeaccredit.org/system/rich/rich_files/rich_files/107/original/cppa-20community-20pharmacy-20practice-20standards-20-26-20glossary-20final-20062515.pdf

Center for Pharmacy Practice Accreditation. (2016a). Community Pharmacy Practice Accreditations. Retrieved from https://pharmacypracticeaccredit.org/practices

Center for Pharmacy Practice Accreditation. (2016b). CPPA Accredited Pharmacies Receive Innovative Payments from Sunflower Health Plan. Retrieved from https://www.pharmacypracticeaccredit.org/news/2016/8/cppa-accredited-pharmacies-to-receive-innovative-payments-from-sunflower-health-plan

Center for Pharmacy Practice Accreditation. (2016c). The Kroger Co. Earns Community Pharmacy Accreditation from the Center for Pharmacy Practice Accreditation [Press release]. Retrieved from https://www.pharmacypracticeaccredit.org/system/rich/rich_files/rich_files/115/original/cppa-20press-20release-kroger-20receives-20cppa-20community-20pharmacy-20accreditation-20final-2003042016.pdf

Center for Public Health Statistics. (2016). About the Wellmark Data Repository. Retrieved from http://ph-cphs-web2.public-health.uiowa.edu/wellmark/home/about

Centers for Disease Control and Prevention. (2015a, May 7). Core Elements of Hospital Antibiotic Stewardship Programs. Retrieved from http://www.cdc.gov/getsmart/healthcare/implementation/core-elements.html

Centers for Disease Control and Prevention. (2015b, February 25). Nearly half a million Americans suffered from Clostridium difficile infections in a single year. Retrieved from http://www.cdc.gov/media/releases/2015/p0225-clostridium-difficile.html

Centers for Medicare and Medicaid Innovations. (2013, December). Health Care Innovation Awards Round One Project Profiles Retrieved from http://innovation.cms.gov/Files/x/HCIA-Project-Profiles.pdf

Centers for Medicare and Medicaid Innovations. (2014, July). Health Care Innovation Awards Round Two Project Profiles. Retrieved from http://innovation.cms.gov/Files/x/HCIATwoPrjProCombined.pdf

Centers for Medicare and Medicaid Services. (2003). *HCAHPS Three-State Pilot Study Analysis Results*. Retrieved from Centers for Medicare and Medicaid Services Web Site:

Centers for Medicare and Medicaid Services. (2014). *National Health Expenditures 2013 Highlights*. Retrieved from Baltimore, MD:

Centers for Medicare and Medicaid Services. (2015a). 2015 Medicare Part D MTM Programs. Retrieved from https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/CY2015-MTM-Fact-Sheet.pdf

Centers for Medicare and Medicaid Services. (2015b, November 20). 2015 Physician Quality Reporting System (PQRS): Implementation Guide. Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/PQRS/Downloads/2015_PQRS_ImplementationGuide.pdf

Centers for Medicare and Medicaid Services. (2015c, March 4). 2015 Value Modifier Results.

Centers for Medicare and Medicaid Services. (2015d, November 12). 2016 Physician Quality Reporting System (PQRS) List of Eligible Professionals. Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/PQRS/Downloads/2016_PQRS_List_of_EPs.pdf

Centers for Medicare and Medicaid Services. (2015e). *Accountable Care Organizations 2015 Program Analysis Quality Performance Standards Narrative Measure Specifications*. Retrieved from CMS Web Site: https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/Downloads/RY2015-Narrative-Specifications.pdf

Centers for Medicare and Medicaid Services. (2015f). Advance Notices of Methodological Changes for Calendar Year (CY) 2016 for Medicare Advantage Capitation Rates, Part C and Part D Payment Policies and 2016 Call Letter [Press release]. Retrieved from https://www.cms.gov/medicare/health-plans/medicareadvtgspecratestats/downloads/advance2016.pdf

Centers for Medicare and Medicaid Services. (2015g). The CMS Innovation Center. Retrieved from http://innovation.cms.gov/index.html

Centers for Medicare and Medicaid Services. (2015h). CMS Quality Strategy 2016. Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/QualityInitiativesGenInfo/Downloads/CMS-Quality-Strategy.pdf

Centers for Medicare and Medicaid Services. (2015i, September). Computation of the 2016 Value Modifier. Retrieved from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/Downloads/2016-VM-Fact-Sheet.pdf

Centers for Medicare and Medicaid Services. (2015j, April 7). CY 2016 Medication Therapy Management Program Guidance and Submission Instructions. Retrieved from https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Memo-Contract-Year-2016-Medication-Therapy-Management-MTM-Program-Submission-v-040715.pdf

Centers for Medicare and Medicaid Services. (2015k). Detailed Methodology for the 2016 Value Modifier and the 2014 Quality and Resource Use Report. Retrieved from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/Downloads/2014QRUR-2016VM-DetailedMethodology.pdf

Centers for Medicare and Medicaid Services. (2015l). Mediare Plan Finder. Retrieved from https://www.medicare.gov/find-a-plan/questions/home.aspx

Centers for Medicare and Medicaid Services. (2015m, June). Medicaid Covered Outpatient Prescription Drug Reimbursement Information by State: Quarter Ending June 2015. Retrieved from http://www.medicaid.gov/medicaid-chip-program-information/by-topics/benefits/prescription-drugs/downloads/xxxreimbursement-chart-current-qtr.pdf

Centers for Medicare and Medicaid Services. (2015n). *Medicare 2016 Part C & D Star Rating Technical Notes: First Plan Preview Draft*. Retrieved from https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovGenIn/Downloads/2016-Technical-Notes-Preview-1-v2015_08_05.pdf

Centers for Medicare and Medicaid Services. (2015o). Medicare ACOs Provide Improved Care While Slowing Cost Growth in 2014 [Press release]. Retrieved from https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2015-Fact-sheets-items/2015-08-25.html

Centers for Medicare and Medicaid Services. (2015p, August 5). Medicare Part C and D Star Ratings: Update for 2016. Retrieved from https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovGenIn/Downloads/2016-Star-Ratings-User-Call-Slides-v2015_08_05.pdf

Centers for Medicare and Medicaid Services. (2015q). *National Health Expenditures 2014 Highlights*. Retrieved from CMS Web Site: http://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/downloads/highlights.pdf

Centers for Medicare and Medicaid Services. (2015r, November 24). Physician Quality Reporting System Payment Adjustment Information. Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/PQRS/Payment-Adjustment-Information.html

Centers for Medicare and Medicaid Services. (2015s). Remarks of CMS Acting Administrator Andy Slavitt at the HHS Pharmaceutical Forum: Innovation, Access, Affordability and Better Health. Retrieved from http://blog.cms.gov/2015/11/20/remarks-of-cms-acting-administrator-andy-slavitt-at-the-hhs-pharmaceutical-forum-innovation-access-affordability-and-better-health/

Centers for Medicare and Medicaid Services. (2015t). Value Based Payment Modifier Program: Risk Adjustment. Retrieved from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeedbackProgram/Downloads/Risk-Adjustment-Fact-Sheet.pdf

Centers for Medicare and Medicaid Services. (2016a). *2015 Measure Information Form: ACO #8 Hospital Wide Readmissions*. Retrieved from CMS Web Site:

Centers for Medicare and Medicaid Services. (2016b, January 7). 2016 PQRS Individual Claims Registry Measure Specifications. Retrieved from http://www.cms.gov/apps/ama/license.asp?file=/PQRS/Downloads/2016_PQRS_IndMeasuresSpecs_ClaimsRegistry_121815.zip

Centers for Medicare and Medicaid Services. (2016c). Part D Enhanced Medication Therapy Management Model. Retrieved from https://innovation.cms.gov/initiatives/enhancedmtm/

Change to Win. (2013). *Behind the Desk: Risks to Public Health, Patient Privacy and Drug Security under Walgreens' New Pharmacy Model*. Retrieved from

Cheetham, T. C., Niu, F., Green, K., Scott, R. D., Derose, S. F., Vansomphone, S. S., . . . Reynolds, K. (2013). Primary Nonadherence to Statin Medications in a Managed Care Organization. *Journal of Managed Care Pharmacy, 19*(5), 367-373.

Choudhry, N. K., Glynn, R. J., Avorn, J., Lee, J. L., Brennan, T. A., Reisman, L., . . . Shrank, W. H. (2014). Untangling the relationship between medication adherence and post-myocardial infarction outcomes: Medication adherence and clinical outcomes. *American Heart Journal, 167*(1), 51-+. doi:10.1016/j.ahj.2013.09.014

Chrischilles, E. A., Carter, B. L., Lund, B. C., Rubenstein, L. M., Chen-Hardee, S. S., Voelker, M. D., . . . Kuehl, A. K. (2004). Evaluation of the Iowa Medicaid pharmaceutical case management program. *Journal of the American Pharmacists Association, 44*(3), 337-349.

Chrischilles, E. A., Doucette, W., Farris, K., Lindgren, S., Gryzlak, B., Rubenstein, L., . . . Wallace, R. B. (2014). Medication therapy management and complex patients with disability: a randomized controlled trial. *Annals of Pharmacotherapy, 48*(2), 158-167. doi:10.1177/1060028013512472

Chu, Y. T., Ng, Y. Y., & Wu, S. C. (2010). Comparison of different comorbidity measures for use with administrative data in predicting short- and long-term mortality. *BMC Health Services Research, 10*, 140. doi:10.1186/1472-6963-10-140

Chui, M. A., & Mott, D. A. (2012). Community pharmacists' subjective workload and perceived task performance: A human factors approach. *Journal of the American Pharmacists Association, 52*(6), E153-+. doi:10.1331/JAPhA.2012.11135

Chui, M. A., Mott, D. A., & Maxwell, L. (2012). A qualitative assessment of a community pharmacy cognitive pharmaceutical services program, using a work system approach. *Research in Social & Administrative Pharmacy, 8*(3), 206-216. doi:10.1016/j.sapharm.2011.06.001

CMS Innovations Center. (2016). North Carolina Communty Care Networks, Inc. Retrieved from https://innovation.cms.gov/initiatives/participant/health-care-innovation-awards-round-two/north-carolina-community-care-networks-inc.html

Congressional Budget Office. (2012). *Offsetting Effects of Prescription Drug Use on Medicare's Spending for Medical Services*. Retrieved from https://www.cbo.gov/sites/default/files/112th-congress-2011-2012/reports/43741-MedicalOffsets-11-29-12.pdf

Cramer, J. A. (2004). A systematic review of adherence with medications for diabetes. *Diabetes Care, 27*(5), 1218-1224.

Cranor, C. W., Bunting, B. A., & Christensen, D. B. (2003). The Asheville Project: long-term clinical and economic outcomes of a community pharmacy diabetes care program. *Journal of the American Pharmaceutical Association (Washington,D.C.: 1996), 43*(2), 173-184.

Cranor, C. W., & Christensen, D. B. (2003). The Asheville Project: short-term outcomes of a community pharmacy diabetes care program. *Journal of the American Pharmaceutical Association (Washington,D.C.: 1996), 43*(2), 149-159.

Cronin, J. J., Jr., & Taylor, S. A. (1992). Measuring Service Quality: A Reexamination and Extension. *Journal of Marketing, 56*(3), 55-68. doi:10.2307/1252296

Cutrona, S. L., Choudhry, N. K., Fischer, M. A., Servi, A., Liberman, J. N., Brennan, T. A., & Shrank, W. H. (2010). Modes of delivery for interventions to improve cardiovascular medication adherence. *American Journal of Managed Care, 16*(12), 929-942.

Dade, S. (2015). *Learning from State-Based Initiatives: How the Washington Health Alliance is Using Performance MEasurement to Drive Improved Value in Health Care*. Retrieved from Washington Health Alliance:

Davis, K., Stremikis, K., Squires, D., & Schoen, C. (2014). *Mirror, Mirror on the Wall: How the Performance of the U.S. Health Care System Compares Internationally*. Retrieved from

Deninger, M. (2015, May 7). The Rewards of Performance. Retrieved from http://www.thethrivingpharmacist.com/2015/05/07/the-rewards-of-performance/

Department of Health and Human Services. (2011). National Strategy for Quality Improvement in Health Care. Retrieved from http://www.ahrq.gov/workingforquality/nqs/nqs2011annlrpt.pdf

Des Moines Register. (2015, September 3). New care organizations save $17 million, Wellmark says. Retrieved from http://www.desmoinesregister.com/story/news/health/2015/09/02/accountable-care-organizations-save-17-million-wellmark-says/71609858/

Desai, V., Nau, D., Conklin, M., & Heaton, P. C. (2016). Impact of Environmental Factors on Differences in Quality of Medication Use: An Insight for the Medicare Star Rating System. *J Manag Care Spec Pharm, 22*(7), 779-786. doi:10.18553/jmcp.2016.22.7.779

Dharmarajan, S., Bentley, J. P., Banahan III, B. F., & West-Strum, D. S. (2014). Measuring pharmacy performance in the area of medication adherence: addressing the issue of risk adjustment. *J Manag Care Spec Pharm, 20*(10), 1057-1068.

DiMatteo, M. R., Giordani, P. J., Lepper, H. S., & Croghan, T. W. (2002). Patient adherence and medical treatment outcomes - A meta-analysis. *Medical Care, 40*(9), 794-811.

Donabedian, A. (1988). The quality of care. How can it be assessed? *JAMA, 260*(12), 1743-1748.

Donabedian, A. (2001). A founder of quality assessment encounters a troubled system firsthand. Interview by Fitzhugh Mullan. *Health Affairs, 20*(1), 137-141.

Donabedian, A. (2005). Evaluating the quality of medical care. 1966. *Milbank Quarterly, 83*(4), 691-729. doi:10.1111/j.1468-0009.2005.00397.x

Dorich, N. (2016, February 5). [RE: EQuIPP Question].

Doucette WR, G. C., Kreling DH, Mott DA, Schommer JC. (2014). *Final Report of the 2014 National Sample Survey of the Pharmacist Workforce to Determine Contemporary Demographic Practice Characteristics and Quality or Work-Life*. Retrieved from Minneapolis, MN: http://www.aacp.org/resources/research/pharmacyworkforcecenter/Documents/FinalReportOfTheNationalPharmacistWorkforceStudy2014.pdf

Doucette, W. R., McDonough, R. P., Klepser, D., & McCarthy, R. (2005). Comprehensive medication therapy management: identifying and resolving drug-related issues in a community pharmacy. *Clinical Therapeutics, 27*(7), 1104-1111.

Dubner, S. (2016, January 7). The True Story of the Gender Pay Gap. Retrieved from http://freakonomics.com/podcast/the-true-story-of-the-gender-pay-gap-a-new-freakonomics-radio-podcast/

Duffy, J. A., Duffy, M., & Kilbourne, W. E. (2001). A comparative study of resident, family, and administrator expectations for service quality in nursing homes. *Health Care Management Review, 26*(3), 75-85.

EQuIPP. (2015a). News. Retrieved from https://www.equipp.org/

EQuIPP. (2015b). Pharmacy Quality Solutions Surpasses Milestone for EQuIPP [Press release]. Retrieved from http://www.pharmacyquality.com/Documents/PQS_press_release_on_milestone_October_26_2015_FINAL.pdf

EQuIPP. (2016). Welcome to the Quality Improvement Platform for Plans and Pharmacies. Retrieved from https://www.equipp.org/default.aspx

Evans, S. M., Lowinger, J. S., Sprivulis, P. C., Copnell, B., & Cameron, P. A. (2009). Prioritizing quality indicator development across the healthcare system: identifying what to measure. *Internal Medicine Journal, 39*(10), 648-654. doi:10.1111/j.1445-5994.2008.01733.x

Express Scripts. (2012, February 23). Express Scripts' CEO Discusses Q4 2011 Results -- Earnings Call Transcript. Retrieved from http://seekingalpha.com/article/387101-express-scripts-ceo-discusses-q4-2011-results-earnings-call-transcript?part=single

Express Scripts. (2015, May 5). Quality Network Solution Improves Medicare Beneficiary Health. Retrieved from http://lab.express-scripts.com/lab/insights/government-programs/quality-network-solution-improves-medicare-beneficiary-health

Fera, T., Bluml, B. M., & Ellis, W. M. (2009). Diabetes Ten City Challenge: final economic and clinical results. *Journal of the American Pharmacists Association, 49*(3), 383-391. doi:10.1331/JAPhA.2009.09015

Finley, P. R., Bluml, B. M., Bunting, B. A., & Kiser, S. N. (2011). Clinical and economic outcomes of a pilot project examining pharmacist-focused collaborative care treatment for depression. *Journal of the American Pharmacists Association, 51*(1), 40-49. doi:10.1331/JAPhA.2011.09147

Fischer, M. A., Choudhry, N. K., Brill, G., Avorn, J., Schneeweiss, S., Hutchins, D., . . . Shrank, W. H. (2011). Trouble Getting Started: Predictors of Primary Medication Nonadherence. *American Journal of Medicine, 124*(11). doi:10.1016/j.amjmed.2011.05.028

Fischer, M. A., Choudhry, N. K., Bykov, K., Brill, G., Bopp, G., Wurst, A. M., & Shrank, W. H. (2014). Pharmacy-based Interventions to Reduce Primary Medication Nonadherence to Cardiovascular Medications. *Medical Care, 52*(12), 1050-1054.

Fischer, M. A., Jones, J. B., Wright, E., Van Loan, R. P., Xie, J., Gallagher, L., . . . Shrank, W. H. (2015). A Randomized Telephone Intervention Trial to Reduce Primary Medication Nonadherence. *Journal of Managed Care Pharmacy, 21*(2), 124-131.

Fish, H. (2015, November 16). [Invitation to PQA Risk Adjustment Advisory Panel].

Galt, K. A. (2000). The need to define "care" in pharmaceutical care: An examination across research, practice and education. *American Journal of Pharmaceutical Education, 64*(3), 223-233.

Garrett, D. G., & Bluml, B. M. (2005). Patient self-management program for diabetes: first-year clinical, humanistic, and economic outcomes. *Journal of the American Pharmacists Association, 45*(2), 130-137.

Goldin, C. (2015). How to Achieve Gender Equality in Pay. *The Milken Institute Review*(Third Quarter), 10.

Goode, J. V., Swiger, K., & Bluml, B. M. (2004). Regional osteoporosis screening, referral, and monitoring program in community pharmacies: findings from Project ImPACT: Osteoporosis. *Journal of the American Pharmacists Association, 44*(2), 152-160.

Halsall, D., Noyce, P. R., & Ashcroft, D. M. (2012). Characterizing healthcare quality in the community pharmacy setting: Insights from a focus group study. *Research in Social & Administrative Pharmacy, 8*(5), 360-370. doi:10.1016/j.sapharm.2011.09.001

Hanlon, J. T., & Schmader, K. E. (2013). The medication appropriateness index at 20: where it started, where it has been, and where it may be going. *Drugs and Aging, 30*(11), 893-900. doi:10.1007/s40266-013-0118-4

Harris, Y., Hu, D. J., Lee, C., Mistry, M., York, A., & Johnson, T. K. (2015). Advancing Medication Safety: Establishing a National Action Plan for Adverse Drug Event Prevention. *Jt Comm J Qual Patient Saf, 41*(8), 351-360.

Headley, D. E., & Miller, S. J. (1993). Measuring service quality and its relationship to future consumer behavior. *Journal of Health Care Marketing, 13*(4), 32-41.

Healthcare Cost and Utilization Project (HCUP). (2015, October 23). Comorbidity Software, Version 3.7. Retrieved from https://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp

HealthPartners. (2016, August 9). Consideration for TCOC: Medicaid and Medicare products. Retrieved from https://www.healthpartners.com/ucm/groups/public/@hp/@public/documents/documents/entry_180261.pdf

Heaton, P. C., Tundia, N. L., & Luder, H. R. (2013). U.S. emergency departments visits resulting from poor medication adherence: 2005-07. *Journal of the American Pharmacists Association, 53*(5), 513-519. doi:10.1331/JAPhA.2013.12213

Hepler, C. D. (2010). A dream deferred. *American Journal of Health-System Pharmacy, 67*(16), 1319-1325. doi:10.2146/ajhp100329

Hepler, C. D., & Strand, L. M. (1989). Opportunities and Responsibilities in Pharmaceutical Care. *American Journal of Pharmaceutical Education, 53*, S7-S15.

Ho, P. M., Rumsfeld, J. S., Masoudi, F. A., McClure, D. L., Plomondon, M. E., Steiner, J. F., & Magid, D. J. (2006). Effect of medication nonadherence on hospitalization and mortality among patients with diabetes mellitus. *Archives of Internal Medicine, 166*(17), 1836-1841.

Hochberg, M. C., Altman, R. D., April, K. T., Benkhalti, M., Guyatt, G., McGowan, J., . . . American College of, R. (2012). American College of Rheumatology 2012 recommendations for the use of nonpharmacologic and pharmacologic therapies in osteoarthritis of the hand, hip, and knee. *Arthritis Care & Research, 64*(4), 465-474.

Holden, R. J., Carayon, P., Gurses, A. P., Hoonakker, P., Hundt, A. S., Ozok, A. A., & Rivera-Rodriguez, A. J. (2013). SEIPS 2.0: a human factors framework for studying and improving the work of healthcare professionals and patients. *Ergonomics, 56*(11), 1669-1686. doi:10.1080/00140139.2013.838643

Holdford, D., & Saxena, K. (2015). Impact of Appointment-Based Medication Synchronization on Existing Users of Chronic Medications. *J Manag Care Spec Pharm, 21*(8), 662-669. doi:10.18553/jmcp.2015.21.8.662

Holdford, D. A., & Inocencio, T. J. (2013). Adherence and persistence associated with an appointment-based medication synchronization program. *Journal of the American Pharmacists Association, 53*(6), 576-583. doi:10.1331/JAPhA.2013.13082

Hopkins, J. (2016). About the ACG System. Retrieved from http://acg.jhsph.org/index.php/the-acg-system-advantage

Hosford, M. (2015, April 10). [Pharmacy Quality Advisory Council (Email Communication)].

Hsiao, C. J., & Boult, C. (2008). Effects of quality on outcomes in primary care: A review of the literature. *American Journal of Medical Quality, 23*(4), 302-310. doi:10.1177/1062860608315643

IMS Institute. (2013). *Avoidable Costs in U.S Healthcare: The $200 Billion Opportunity from Using Medicines More Responsibly*. Retrieved from Parsippany, NJ:

Inland Empire Health Plan. (2014). Pharmacy P4P Program. Retrieved from https://ww3.iehp.org/en/providers/pharmaceutical-services/pharmacy-p4p-program

Inland Empire Health Plan. (2015a). *IEHP P4P Summary*. Retrieved from Inland Empire Health Plan Web Site: https://ww3.iehp.org/~/media/Pharmacy/Clinical/P4P/P4P-PerformanceSummary-062415.pdf?la=en

Inland Empire Health Plan. (2015b). *IEHP Recognizes Top Performing Pharmacies for 2014/2015*. Retrieved from https://ww3.iehp.org/~/media/Pharmacy/Clinical/P4P/Top-Pharmacies.pdf?la=en

Institute for Healthcare Improvement. (2015a). IHI Triple Aim Initiative. Retrieved from http://www.ihi.org/engage/initiatives/tripleaim/Pages/default.aspx

Institute for Healthcare Improvement. (2015b). IHI Triple Aim Measures. Retrieved from http://www.ihi.org/Engage/Initiatives/TripleAim/Pages/MeasuresResults.aspx

Institute of Medicine. (2001). *Crossing the Quality Chasm: A New Health System for the 21st Century*. Retrieved from

Iowa Department of Human Services. (2015). Accountable Care organizations and the Value Index Score. Retrieved from http://dhs.iowa.gov/ime/about/iowa-health-and-wellness-plan/ACO-VIS

Iowa Pharmacy Association. (2015). Performance Based Networks -- Activity Underfoot in Iowa. *Journal of the Iowa Pharmacy Association,* 1.

Jackson, T. H., Bentley, J. P., McCaffrey, D. J., 3rd, Pace, P., Holmes, E., & West-Strum, D. (2014). Store and prescription characteristics associated with primary medication nonadherence. *J Manag Care Spec Pharm, 20*(8), 824-832.

Johnson, J. (2013). Achieving Wisconsin Pharmacy Quality Collaborative (WPQC) Certification. Retrieved from http://pophealth.wisc.edu/PopHealth/files/Jessica%20Johnson.pdf

Kaiser Family Foundation. (2015). Health Costs. Retrieved from http://kff.org/health-costs/

Kaldenberg, D., Becker, B. W., Browne, B. A., & Browne, W. G. (1997). Identifying service quality strengths and weaknesses using SERVQUAL: a study of dental services. *Health Marketing Quarterly, 15*(2), 69-86.

Kaskie, B., Obrizan, M., Cook, E. A., Jones, M. P., Liu, L., Bentler, S., . . . Wolinsky, F. D. (2010). Defining emergency department episodes by severity and intensity: A 15-year study of Medicare beneficiaries. *BMC Health Services Research, 10*, 173. doi:10.1186/1472-6963-10-173

Keehan, S. P., Poisal, J. A., Cuckler, G. A., Sisko, A. M., Smith, S. D., Madison, A. J., . . . Lizonitz, J. M. (2016). National Health Expenditure Projections, 2015-25: Economy, Prices, And Aging Expected To Shape Spending And Enrollment. *Health Affairs, 35*(8), 1522-1531. doi:10.1377/hlthaff.2016.0459

Keshishian, F. (2010). Factors influencing pharmacy students' choice of major and its relationship to anticipatory socialization. *American Journal of Pharmaceutical Education, 74*(4), 75.

Kessell, E., Pegany, V., Keolanui, B., Fulton, B. D., Scheffler, R. M., & Shortell, S. M. (2015). Review of Medicare, Medicaid, and Commercial Quality of Care Measures: Considerations for Assessing Accountable Care Organizations. *Journal of Health Politics Policy and Law, 40*(4), 761-796. doi:10.1215/03616878-3150050

Kincaid, C. (2005, March 9). Guidelines for Selecting the Covariance Structure in Mixed Model Analysis. Retrieved from http://www2.sas.com/proceedings/sugi30/198-30.pdf

Knudson, S., & Heim, C. (2014, June 19). Total Cost of Care (TCOC) and Total Resource Use. Retrieved from https://www.healthpartners.com/ucm/groups/public/@hp/@public/documents/documents/dev_057649.pdf

Knudson, S., & Heim, C. (2016, March 3). HealthPartner's Attribution Technical Paper: Assigning Accountability to Health Care Costs. Retrieved from https://www.healthpartners.com/hp/about/tcoc/index.html

Kuhle, J. (2016, October 3). [RE: pharmacy data].

Kulik, A., Singh, J. P., Levin, R., Avorn, J., & Choudhry, N. K. (2010). Association between statin use and the incidence of atrial fibrillation following hospitalization for coronary artery disease. *American Journal of Cardiology, 105*(12), 1655-1660. doi:10.1016/j.amjcard.2010.01.341

Kuntz, J. L., Chrischilles, E. A., Pendergast, J. F., Herwaldt, L. A., & Polgreen, P. M. (2011). Incidence of and risk factors for community-associated Clostridium difficile infection: a nested case-control study. *BMC Infectious Diseases, 11*, 194. doi:10.1186/1471-2334-11-194

Law, A. V., Okamoto, M. P., & Brock, K. (2009). Ready, willing, and able to provide MTM services?: A survey of community pharmacists in the USA. *Research in Social & Administrative Pharmacy, 5*(4), 376-381. doi:10.1016/j.sapharm.2009.01.001

Lee, J. K., Grace, K. A., & Taylor, A. J. (2006). Effect of a pharmacy care program on medication adherence and persistence, blood pressure, and low-density lipoprotein cholesterol: a randomized controlled trial. *JAMA, 296*(21), 2563-2571. doi:10.1001/jama.296.21.joc60162

Lee, J. L., Maciejewski, M., Raju, S., Shrank, W. H., & Choudhry, N. K. (2013). Value-based insurance design: quality improvement but no cost savings. *Health Affairs, 32*(7), 1251-1257. doi:10.1377/hlthaff.2012.0902

Li, Y., Cai, X., Glance, L. G., Spector, W. D., & Mukamel, D. B. (2009). National release of the nursing home quality report cards: implications of statistical methodology for risk adjustment. *Health Services Research, 44*(1), 79-102. doi:10.1111/j.1475-6773.2008.00910.x

Lounsbery, J. L., Green, C. G., Bennett, M. S., & Pedersen, C. A. (2009). Evaluation of pharmacists' barriers to the implementation of medication therapy management services. *Journal of the American Pharmacists Association, 49*(1), 51-58. doi:10.1331/JAPhA.2009.017158

Luder, H. R., Frede, S. M., Kirby, J. A., Epplen, K., Cavanaugh, T., Martin-Boone, J. E., . . . Heaton, P. C. (2015). TransitionRx: Impact of community pharmacy postdischarge medication therapy management on hospital readmission rate. *Journal of the American Pharmacists Association, 55*(3), 246-254. doi:10.1331/JAPhA.2015.14060

Malone, D. C., Abarca, J., Skrepnek, G. H., Murphy, J. E., Armstrong, E. P., Grizzle, A. J., . . . Woosley, R. L. (2007). Pharmacist workload and pharmacy characteristics associated with the dispensing of potentially clinically important drug-drug interactions. *Medical Care, 45*(5), 456-462. doi:10.1097/01.mlr.0000257839.83765.07

Mascardo, L. (2016). *High Performance Pharmacy Network*. PowerPoint Presentation. University of Iowa Department of Pharmaceutical Care.

McKesson. (2016). Plan an Independent Pharmacy Career. Retrieved from http://rxownership.com/students/

Menges, J., Batt, J., Mouna, A., Pantaleo, N., & Singh, P. (2015). *Comparison of Medicaid Pharmacy Costs and Usage in Carve-In Versus Carve-Out States*. Retrieved from America's Health Insurance Plans Web Site: http://www.ahip.org/Report/CompMedicaidPharmCosts/

Munro, D. (2015, January 4). U.S. Healthcare Spending on Track to Hit $10,000 Per Person This Year. Retrieved from http://www.forbes.com/sites/danmunro/2015/01/04/u-s-healthcare-spending-on-track-to-hit-10000-per-person-this-year/

Nasseh, K., Frazee, S., Visaria, J., & Vilahiotis, A. (2012). Cost of Medication Nonadherence Associated with Diabetes, Hypertension and Dyslipidemia. *American Journal of Pharmacy Benefits, 4*(2), e41-e47.

National Association of Chain Drug Stores. (2012). NACDS Responds to Express Scripts CEO Comments that Disparage Pharmacists, Show Disregard for Pharmacy Patient Care. Retrieved from http://www.nacds.org/Home/98/2012-02-24/nacds-responds-to-express-scripts-ceo-comments-that-disparage-pharmacists,-show-disregard-for-pharmacy-patient-care

National Association of Chain Drug Stores Foundation. (2015). Research. Retrieved from http://nacdsfoundation.org/research_priorities.html

National Community Pharmacists Association. (2011). Medco Chief Slights Community Pharmacists after Brief Embrace Retrieved from https://ncpanet.wordpress.com/2011/10/25/medco-chief-slights-community-pharmacists-after-brief-embrace/#comments

National Community Pharmacists Association. (2012a). *2012 NCPA Digest*. Retrieved from Alexandria, VA:

National Community Pharmacists Association. (2012b). Express Scripts Continues Its Assault on Community Pharmacy Retrieved from https://ncpanet.wordpress.com/2012/02/28/express-scripts-continues-its-assault-on-community-pharmacy/

National Community Pharmacists Association. (2013). *Simplify My Meds: Pharmacy Operations Manual v1.2*. Retrieved from Alexandria, VA:

National Community Pharmacists Association. (2015). NCPA's Blog - The Dose.

National Community Pharmacists Association. (2016). Independent Pharmacy Today. Retrieved from http://www.ncpanet.org/home/independent-pharmacy-today

National Quality Measures Clearinghouse. (2015, June 18). Desirable Attributes of a Quality Measure. Retrieved from https://www.qualitymeasures.ahrq.gov/tutorial/attributes.aspx

Nau, D. (2012). Proportion of Days Covered as a Preferred Method of Measuring Medicaiton Adherence. Retrieved from http://www.pqaalliance.org/images/uploads/files/PQA%20PDC%20vs%20%20MPR.pdf

Nau, D. (2015). *Quality Improvement: Opportunities beyond Medicare*. Retrieved from NACDS Web SIte: http://tse.nacds.org/presentations/2015/sunday/QUALITY_IMPROVEMENT_BUSINESS_OPPORTUNITIES_BEYOND_MEDICARE.pdf

New England Healthcare Institute. (2009). Thinking Outside the Pillbox: A System-wide Approach to Improving Patient Medication Adherence for Chronic Disease. Retrieved from http://www.nehi.net/writable/publication_files/file/pa_issue_brief_final.pdf

Nola, K. M., Gourley, D. R., Portner, T. S., Gourley, G. K., Solomon, D. K., Elam, M., & Regel, B. (2000). Clinical and humanistic outcomes of a lipid management program in the community pharmacy setting. *Journal of the American Pharmaceutical Association (Washington,D.C.: 1996), 40*(2), 166-173.

Odukoya, O. K., Stone, J. A., & Chui, M. A. (2015). Barriers and facilitators to recovering from e-prescribing errors in community pharmacies. *Journal of the American Pharmacists Association, 55*(1), 52-58. doi:10.1331/JAPhA.2015.13239

OECD. (2013). *Health at a Glance 2013: OECD Indicators*. Retrieved from http://dx.doi.org/10.1787/health_glance-2013-en

Office of Disease Prevention and Health Promotion. (2014). *National Action Plan for Adverse Drug Event Prevention*. Retrieved from U.S. Department of Health and Human Services Web Site: http://health.gov/hcq/pdfs/ade-action-plan-508c.pdf

Osterberg, L., & Blaschke, T. (2005). Adherence to medication. *New England Journal of Medicine, 353*(5), 487-497. doi:10.1056/NEJMra050100

OutcomesMTM. (2015). *2015 MTM Trends Report*. Retrieved from West Des Moines, IA: http://www.outcomesmtm.com/documents/2015MTMTrendsReport.pdf

OutcomesMTM. (2016). *MTM Trends Report*. Retrieved from West Des Moines, IA:

Pantely, S. E. (2011). *Whose patient is it? Patient attribution in ACOs*. Retrieved from Milliman:

Parasuraman, A., Zeithaml, V., & Berry, L. (1994). Alternative scales for measuring service quality: A comparative assessment based on psychometric and diagnostic criteria. *Journal of Retailing, 70*(3), 193-194. doi:http://dx.doi.org/10.1016/0022-4359(94)90032-9

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A Conceptual Model of Service Quality and Its Implications for Future Research. *Journal of Marketing, 49*(4), 41-50.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing, 64*(1), 12-40.

Patient Access to Pharmacists' Care Coalition. (2016). About PAPCC. Retrieved from http://pharmacistscare.org/about-papcc/

Perlroth, D., Marrufo, G., Montesinos, A., Lewis, C., Dixit, A., Li, B., . . . Stratos, S. (2013). *Medication Therapy Management in Chronically Ill Populations: Final Report* Retrieved from https://innovation.cms.gov/files/reports/mtm_final_report.pdf

Pharmacy Quality Alliance. (2013, November 8th). Primary Medication Non-adherence. Retrieved from http://www.pqaalliance.org/images/uploads/files/Primary%20Medication%20NonAdherence_Nov2013vote.pdf

Pharmacy Quality Alliance. (2014). *Technical Specifications for PQA Approved Measures*. Retrieved from Springfield, VA:

Pharmacy Quality Alliance. (2015). PQA Performance Measures. Retrieved from http://pqaalliance.org/images/uploads/files/PQA%20measuresJuly2015.pdf

Pharmacy Quality Alliance. (2016). *Technical Specifications for PQA Approved Measures*. Retrieved from Springfield, VA:

Pillittere-Dugan, D., Nau, D. P., McDonough, K., & Pierre, Z. (2009). Development and testing of performance measures for pharmacy services. *Journal of the American Pharmacists Association, 49*(2), 212-219. doi:10.1331/JAPhA.2009.09012

Planas, L. G., Crosby, K. M., Farmer, K. C., & Harrison, D. L. (2012). Evaluation of a diabetes management program using selected HEDIS measures. *Journal of the American Pharmacists Association, 52*(6), e130-138. doi:10.1331/JAPhA.2012.11148

Porter, M. E. (2010a). What is value in health care? *New England Journal of Medicine, 363*(26), 2477-2481. doi:10.1056/NEJMp1011024

Porter, M. E. (2010b). What is value in health care? Supplementary Appendix 2. *New England Journal of Medicine, 363*, 5.

Pringle, J. L., Boyer, A., Conklin, M. H., McCullough, J. W., & Aldridge, A. (2014). The Pennsylvania Project: pharmacist intervention improved medication adherence and reduced health care costs. *Health Affairs, 33*(8), 1444-1452. doi:10.1377/hlthaff.2013.1398

Raebel, M. A., Ellis, J. L., Carroll, N. M., Bayliss, E. A., McGinnis, B., Schroeder, E. B., . . . Steiner, J. F. (2012). Characteristics of patients with primary non-adherence to medications for hypertension, diabetes, and lipid disorders. *Journal of General Internal Medicine, 27*(1), 57-64. doi:10.1007/s11606-011-1829-z

Research Data Assistance Center. (2012). *How to Identify Emergency Room Services in the Medicare Claims Data*. Retrieved from Minneapolis, MN:

Roberto, P. N., & Onukwugha, E. (2015). Binary Measures for Associating Medication Adherence and Healthcare Spending. *American Journal of Managed Care, 21*(4), E271-U239.

Roebuck, M. C. (2014). Medical Cost Offsets from Prescription Drug Utilization Among Medicare Beneficiaries. *Journal of Managed Care Pharmacy, 20*(10), 994-995.

Roebuck, M. C., Dougherty, J. S., Kaestner, R., & Miller, L. M. (2015). Increased Use Of Prescription Drugs Reduces Medical Costs In Medicaid Populations. *Health Affairs, 34*(9), 1586-1593. doi:10.1377/hlthaff.2015.0335

Roebuck, M. C., Liberman, J. N., Gemmill-Toyama, M., & Brennan, T. A. (2011). Medication adherence leads to lower health care use and costs despite increased drug spending. *Health Affairs, 30*(1), 91-99. doi:10.1377/hlthaff.2009.1087

San Diego County Office of the District Attorney. (2015). *Walgresns Pharmacy to Pay $502,200 to Resolve Consumer Protection Case*. Retrieved from San Diego County District Attorney's Web Site: http://www.sdcda.org/files/Walgreens%20to%20Pay%20Half%20Million%20Dollar%20Settlement%2008-17-15.pdf

Santschi, V., Chiolero, A., Burnand, B., Colosimo, A. L., & Paradis, G. (2011). Impact of pharmacist care in the management of cardiovascular disease risk factors: a systematic review and meta-analysis of randomized trials. *Archives of Internal Medicine, 171*(16), 1441-1453. doi:10.1001/archinternmed.2011.399

SAS Institute Inc. (2015, July). The KDE Procedure. Retrieved from http://support.sas.com/documentation/cdl/en/statug/68162/HTML/default/viewer.htm#statug_kde_toc.htm

Saseen, J. J., Grady, S. E., Hansen, L. B., Hodges, B. M., Kovacs, S. J., Martinez, L. D., . . . Taylor, C. T. (2006). Future clinical pharmacy practitioners should be board-certified specialists. *Pharmacotherapy, 26*(12), 1816-1825. doi:10.1592/phco.26.12.1816

Sasich, L. D. (1983). A proposal for a community pharmacy practice residency program. *American Pharmacy, NS23*(5), 25-28.

Schroeder, M. C., Robinson, J. G., Chapman, C. G., & Brooks, J. M. (2015). Use of statins by medicare beneficiaries post myocardial infarction: poor physician quality or patient-centered care? *Inquiry, 52*. doi:10.1177/0046958015571131

Shaw Phillips, M., & Chisholm-Burns, M. (2014). Quality Improvement. In M. Chisholm-Burns, A. Vaillancourt, & M. Shepherd (Eds.), *Pharmacy Management, Leadership, Marketing and Finance* (2 ed.). Burlington, MA: Jones & Bartlett.

Shin, J., McCombs, J. S., Sanchez, R. J., Udall, M., Deminski, M. C., & Cheetham, T. C. (2012). Primary Nonadherence to Medications in an Integrated Healthcare Setting. *American Journal of Managed Care, 18*(8), 426-434.

Shrank, W. H., Sussman, A., & Brennan, T. A. (2014). The Role of Retail Pharmacies in CVD Prevention After the Release of the ATP IV Guidelines. *American Journal of Managed Care, 20*(11), E487-E489.

Sidorenkov, G., Haaijer-Ruskamp, F. M., de Zeeuw, D., Bilo, H., & Denig, P. (2011). Relation Between Quality-of-Care Indicators for Diabetes and Patient Outcomes: A Systematic Literature Review. *Medical Care Research and Review, 68*(3), 263-289. doi:10.1177/1077558710394200

Smith, M., Bates, D. W., Bodenheimer, T., & Cleary, P. D. (2010). Why pharmacists belong in the medical home. *Health Affairs, 29*(5), 906-913. doi:10.1377/hlthaff.2010.0209

Smith, S. C., Jr., Benjamin, E. J., Bonow, R. O., Braun, L. T., Creager, M. A., Franklin, B. A., . . . the Preventive Cardiovascular Nurses, A. (2011). AHA/ACCF Secondary Prevention and Risk Reduction Therapy for Patients with Coronary and other Atherosclerotic Vascular Disease: 2011 update: a guideline from the American Heart Association and American College of Cardiology Foundation. *Circulation, 124*(22), 2458-2473. doi:10.1161/CIR.0b013e318235eb4d

Snijders, T., & Bosker, R. (2012). How Much Does the Model Explain? In T. Snijders & R. Bosker (Eds.), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (2 ed., pp. 109-118). Thousand Oaks, CA: SAGE Publications.

Sokol, M. C., McGuigan, K. A., Verbrugge, R. R., & Epstein, R. S. (2005). Impact of medication adherence on hospitalization risk and healthcare cost. *Medical Care, 43*(6), 521-530.

Spinewine, A., Schmader, K. E., Barber, N., Hughes, C., Lapane, K. L., Swine, C., & Hanlon, J. T. (2007). Prescribing in elderly people 1 - Appropriate prescribing in elderly people: how well can it be measured and optimised? *Lancet, 370*(9582), 173-184. doi:10.1016/s0140-6736(07)61091-5

Stuart, B. C., Dai, M. L., Xu, J., Loh, F. H. E., & Dougherty, J. S. (2015). Does Good Medication Adherence Really Save Payers Money? *Medical Care, 53*(6), 517-523.

Stuart, B. C., Doshi, J. A., & Terza, J. V. (2009). Assessing the Impact of Drug Use on Hospital Costs. *Health Services Research, 44*(1), 128-144.

Stulberg, J. (2008). The physician quality reporting initiative--a gateway to pay for performance: what every health care professional should know. *Quality Management in Health Care, 17*(1), 2-8. doi:10.1097/01.QMH.0000308632.74355.93

Sunflower Health Plan. (2016). CPPA Accreditation: Sunflower Health Plan CPPA Accreditation How To Guide.

Swenson, T. (2016). *Overview of Quality Metrics*. Paper presented at the Pharmacy Quality Summit, Des Moines, Iowa

Ta, J. T., Erickson, S. C., Qiu, W. A., & Patel, B. V. (2016). Is There a Relationship Between Part D Medication Adherence and Part C Intermediate Outcomes Star Ratings Measures? *J Manag Care Spec Pharm, 22*(7), 787-795. doi:10.18553/jmcp.2016.22.7.787

The Asheville Project Web Site. Frequently Asked Questions. Retrieved from http://www.theashevilleproject.net/frequently_asked_questions

The Dartmouth Institute. (2013). *The Dartmouth Atlas of Medicare Prescription Drug Use*. Retrieved from Lebanon, NH: http://www.dartmouthatlas.org/downloads/reports/Prescription_Drug_Atlas_101513.pdf

The National Quality Forum. (2010). *The ABCs of Measurement*. Retrieved from National Quality Forum Web Site: http://www.qualityforum.org/WorkArea/linkit.aspx?LinkIdentifier=id&ItemID=44311

The National Quality Forum. (2015). Find Measures. Retrieved from http://www.qualityforum.org/Measuring_Performance/ABCs_of_Measurement.aspx

The World Bank. (2015). *Gross Domestic Product, 2014*. Retrieved from: http://data.worldbank.org/data-catalog/GDP-ranking-table

Trapskin, K., Johnson, C., Cory, P., Sorum, S., & Decker, C. (2009). Forging a novel provider and payer partnership in Wisconsin to compensate pharmacists for quality-driven pharmacy and medication therapy management services. *Journal of the American Pharmacists Association, 49*(5), 642-651. doi:10.1331/JAPhA.2009.08158

Truven Health Analytics. (2013). *Avoidable Emergency Department Usage Analysis*. Retrieved from Truven Health Analytics Web Site: http://truvenhealth.com/news-and-events/press-releases/detail/prid/113/Study-Finds-Most-Emergency-Room-Visits-Made-by-Privately-Insured-Patients-Avoidable

Trygstad, T. (2015, November 4). *The North Carolina Experiment: Weaving Community Pharmacy into the Medical Neighborhood.* Paper presented at the Wellmark Project Kick-off, Urbandale, IA.

Uberoi, N., & Yeh, S. (2012, September). Statistical Brief #387: Expenditures for Trauma-Related Disorders, 2009: Estimates for the U.S. Civilian Noninstitutionalized Population. Retrieved from http://meps.ahrq.gov/mepsweb/data_files/publications/st387/stat387.shtml

United States Department of Agriculture Economic Research Service. (2014). Table 13--Per Capita Food Expenditures. Retrieved from http://www.ers.usda.gov/datafiles/Food_Expenditures/Food_Expenditures/table13.xls

Urick, B. Y., & Urmie, J. M. (2016a, August 18). Evaluation of Thresholds for Attributing Patients to Pharmacies Using Prescription Claims. Retrieved from www.pqaalliance.org/images/uploads/files/Aug%202016%20Quality%20Forum_Brenda%20Barnes%20and%20Ben%20Urick.pdf

Urick, B. Y., & Urmie, J. M. (2016b). *Evaluation of Thresholds for Attributing Patietns to Pharmacies Using Prescription Claims*. Paper presented at the Pharmacy Quality Alliance Annual Meeting, Alexandria, VA.

Viswanathan, M., Kahwati, L. C., Golin, C. E., Blalock, S. J., Coker-Schwimmer, E., Posey, R., & Lohr, K. N. (2015). Medication therapy management interventions in outpatient settings: a systematic review and meta-analysis. *JAMA Intern Med, 175*(1), 76-87. doi:10.1001/jamainternmed.2014.5841

Wang, Y., Yeo, Q. Q., & Ko, Y. (2015). Economic evaluations of pharmacist-managed services in people with diabetes mellitus: a systematic review. *Diabetic Medicine*. doi:10.1111/dme.12976

Warholak, T. L. (2012). Ensuring Quality in Pharmacy Operations. In S. P. Desselle, D. P. Zgarrick, & G. L. Alston (Eds.), *Pharmacy Management* (3 ed.). Chicago: McGraw-Hill.

Wellmark Blue Cross and Blue Shield. (2016). Physician Quality Measurement Program. Retrieved from http://www.wellmark.com/Provider/QualityAndTransparency/PQM.aspx

Wenzloff, N. J. (1987). Community pharmacy residency. 10 steps toward implementing your own program. *American Pharmacy, NS27*(12), 34-38.

White, E. V. (1965). Behind the scenes of the pharmaceutical center. *Journal of the American Pharmaceutical Association, 5*(10), 532-535 passim.

Wier, L. M., Barrett, M., Steiner, C., & Jiang, J. (2011). *All-Cause Readmissions by Payer and Age, 2008*. Retrieved from Rockville, MD: http://www.hcup-us.ahrq.gov/reports/statbriefs/sb115.pdf

Witry, M. J., Doucette, W. R., & Gainer, K. L. (2011). Evaluation of the pharmaceutical case management program implemented in a private sector health plan. *Journal of the American Pharmacists Association, 51*(5), 631-635. doi:10.1331/JAPhA.2011.09137

World Health Organization. (2000). *Health Systems: Improving Performance*. Retrieved from Geneva:

World Health Organization. (2003). *Adherence to Long-Term Therapies: Evidence for Action*. Retrieved from Geneva: http://www.who.int/chp/knowledge/publications/adherence_full_report.pdf

WPQC. (2016). About WPQC. Retrieved from http://www.pswi.org/WPQC/About-WPQC/About-WPQC

Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value - a Means-End Model and Synthesis of Evidence. *Journal of Marketing, 52*(3), 2-22. doi:Doi 10.2307/1251446

Zillich, A. J., Sutherland, J. M., Kumbera, P. A., & Carter, B. L. (2005). Hypertension outcomes through blood pressure monitoring and evaluation by pharmacists (HOME study). *Journal of General Internal Medicine, 20*(12), 1091-1096. doi:10.1111/j.1525-1497.2005.0226.x