2021

The Strategic Orientation of Skilled Nursing Facilities

Jennifer R. Palazzolo
Virginia Commonwealth University

The Strategic Orientation of Skilled Nursing Facilities

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

Jennifer R. Palazzolo
M.P.H., Virginia Commonwealth University, 2011
B.S., Commerce, University of Virginia, 1988

Director: Jan P. Clement, Ph.D.
Cardwell Professor
Department of Health Administration

Virginia Commonwealth University
Richmond, Virginia
July, 2021

Acknowledgements

I am truly thankful for the continuing support of the Health Administration Department, fellow students, colleagues, and my friends and family. I begin by expressing the deepest appreciation to my Dissertation Chair, Dr. Jan Clement. Dr. Clement has been pivotal in sparking my interest in my dissertation topic and has provided guidance, insight, and encouragement throughout this journey. A special thanks also to my committee members: Dr. Gloria Bazzoli, Dr. Patrick Shay, Dr. David Harless, and Dr. Shoou-Yih Lee. I am grateful for your insightful comments, time, enthusiasm, and words of support. I would also like to acknowledge the generosity of David Muhlestein at Leavitt Partners in sharing the Torch Insight dataset with me for this research.

I have enjoyed working with and learning from the professors, students, and staff in the department. I appreciate having had the opportunity to work with Dr. Michael McCue, and to learn along with my fellow doctoral students including Drs. Jaya Khushalani, Hillary Linhart, Sandra Lamm, Priya Chandan, Matt DePuccio, Marisa Roczen, Tina Highfill, and Jennifer Early. Their collegiality, intelligence, and passion for the field continue to inspire me.

I am grateful for the support of my colleagues at the Virginia Department of Medical Assistance Services and Virginia Health Information, especially Michael Lundberg who helped me take the first steps of this journey.

I appreciate my dear friends and family, including Mary Catherine Ruskan, Kim Oliver, and Teri Ashby, who have supplied encouragement throughout the program and never once questioned my return to the classroom at a later stage in life.

Finally, I could not have completed this degree without the loving support of my husband, Dan Palazzolo. Dan has graciously participated in discussions of organizational theory and health services research, provided me with time, meals, and all manner of support. My daughters, Sarah and Elena Palazzolo, have likewise provided encouragement and unwavering confidence in my abilities, and I dedicate the completion of the requirements of this degree to them. I remain thankful for God’s love and mercy.

Table of Content

List of Tables

List of Figures

List of Abbreviations

ACA	Affordable Care Act of 2010
ACO	Accountable Care Organization
AHRF	Area Health Resource Files
ALF	Assisted Living Facilities
ARI_{HA}	Hubert-Arabie Adjusted Rand Index
BBA	Balanced Budget Act of 1997
BBRA	Balanced Budget Refinement Actof 1999
BIPA	Benefits Improvement and Protection Act of 2000
BPCI	Bundled Payments for Care Improvement Initiative
CMI	Case Mix Index
CMS	Centers for Medicare and Medicaid Services
DID	Difference in Differences
FFS	Fee for Service
HHA	Home Health Agencies
HCRIS	Healthcare Cost Report Information System
HRRP	Hospital Readmissions Reduction Program
IMPACT	Improving Medicare Post-Acute Care Transformation Act of 2014

IRF	Inpatient Rehabilitation Facility
LOS	Lengths of Stay
LTACH	Long-Term Acute Care Hospital
LTCF	Long-Term Care Focus Database
MANOVA	Multivariate Analysis of Variance
MCCA	Medicare Catastrophic Coverage Act of 1988
MDA	Multiple Discriminant Analysis
MDS	Medicare’s Minimum Data Set
MedPAC	Medicare Payment Advisory Commission
NHC	Nursing Home Compare
PAMA	Protecting Access to Medicare Act of 2014
PDPM	Patient Driven Payment Model
PPS	Prospective Payment System
RN	Registered Nurse
RUG	Resource Utilization Groups
SD	Standard Deviation
SMT	Strategic Management Theory
SNF	Skilled Nursing Facility
SNF VBP	Skilled Nursing Facility Value-Based Purchasing Program
UTI	Urinary Tract Infection

Abstract

THE STRATEGIC ORIENTATION OF SKILLED NURSING FACILITIES

By Jennifer Palazzolo, Ph.D., MPH

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

Virginia Commonwealth University, 2021

Director: Jan P. Clement, Ph.D.
Cardwell Professor, Department of Health Administration

Since the early 2000s, skilled nursing facilities (SNFs) have operated in an environment made uncertain by changes in health care policy, growth in substitutes for nursing care, and increasing demand for services. To better understand how SNFs are strategically positioning themselves to survive and thrive, this study develops a taxonomy of strategic groups of SNFs.

A conceptual framework is based in Strategic Management Theory and classification of SNFs is based on scope of business decisions including length of stay, complexity of patients, and referral networks with hospitals. Two-step, hierarchical cluster analysis finds six strategy groups of SNFs: Post-Acute Care Focus – Wide Network, Private Pay Focus – Narrow Network, High Acuity Care Focus – Wide Network, Intermediate Care Focus – Wide Network, Long-Stay Care Focus – Narrow Network, and Long-Stay Complex Care Focus – Narrow Network.

Support is found for a structure-performance link between membership in a particular strategy group and financial and quality performance. A longitudinal analysis finds stability in the structure of the groups, but fluidity of movement from one strategy group to another. A comparison of strategy groups with those in prior studies suggests changes in reimbursement policies and industry trends align with shifts in strategy.

This study contributes to the understanding of how SNFs adjust strategically to environmental uncertainty and provides a unique assessment of the relational dynamics of referrals to SNFs from hospitals. A better understanding of the industry structure can benefit managers as they make strategic decisions and help policymakers better target funding and policy changes to improve patient outcomes.

Chapter 1: Introduction

This study explores the strategic orientation of skilled nursing facilities (SNFs) during a time of environmental uncertainty. The first section of this chapter discusses the uncertainties faced by the industry in the last few decades through the present. The second section identifies the study's objectives and aims. An overview of the conceptual framework and scope and analytic approach to the study are provided in the third and fourth sections, respectively. Finally, the study's contribution and organization of the remaining chapters are presented.

The Study Problem

Nursing homes serve patients along the continuum of care by providing long-term custodial care for individuals who are not able to care for themselves and short-term post-acute care to individuals rehabilitating after a stay in the hospital. In 2015, over 15,000 skilled nursing facilities provided care for approximately 1.3 million individuals. It is estimated that 60% of nursing home patients were long-stay residents staying 100 days or more in a facility, while the remaining 40% were short-stay residents staying less than 100 days (Harris-Kojetin et al., 2019). Medicaid, usually the payer for long-term care, spent $45 billion while Medicare, usually the payer for short-term care, spent $30 billion on nursing home care in 2015 (Medicare Payment Advisory Commission, 2017). These estimated expenditures do not include private payments or managed care. The California Health Care Foundation estimates that $158 billion was spent on nursing care facilities in the US in 2015, or approximately 6.5% of U.S. health care expenditures (California Health Care Foundation, 2020).

Nursing homes have been operating in an environment of uncertainty since the early 2000s because of multiple factors. The restructuring of payment systems, national health care policy changes, growth of enrollment in managed care, increasing use of substitutes for nursing home care, and changing demographics have contributed to environmental changes and greater competition for preferred patients. Perhaps the greatest shock to nursing homes came in 2020 with the COVID-19 pandemic's disproportionately high toll of morbidity and mortality on nursing home residents and staff (Barnett & Grabowski, 2020; Ouslander & Grabowski, 2020). This study focuses on understanding how SNFs are strategically positioning themselves to survive and thrive in response to changes in the nursing home industry and the overall health care system. A discussion of the turbulence in the environment of SNFs follows.

Major restructuring of payment systems in the U.S. health care system occurred in 1983 when Medicare introduced a prospective payment system for reimbursement of hospital care. Hospitals, facing pressure to reduce the length of hospital stays, began discharging more acute patients to SNFs than they had previously. Consequently, SNFs began to provide a greater amount of short-stay care. SNFs were reimbursed with higher rates by Medicare for short-stay post-acute care compared to per-diem rates paid by Medicaid for long-stay custodial care. Medicare costs for post-acute care in SNFs rose accordingly, increasing at an average annual rate of 25% between 1988 and 1997 (Buntin, Colla, & Escarce, 2009). The percentage of nursing home costs paid by Medicare grew from 2% in 1988 to 15% in 1997 (California Health Care Foundation, 2020). In an attempt to control growth in volume of care provided by SNFs to

Medicare beneficiaries, the Balanced Budget Act (BBA) of 1997 introduced a prospective payment system incorporating case-mix reimbursement for SNFs. Initial financial pressures negatively impacted the industry and led to adjustments to enhance Medicare payment rates through the Balanced Budget Refinement Act (BBRA) of 1999 and the Benefits Improvement and Protection Act (BIPA) of 2000. Subsequently, the intensity of services provided to SNF patients increased, effectively extending the growth in SNF expenditures (Grabowski, Afendulis, & McGuire, 2011). However, Medicare nursing home patients continue to provide more profitable reimbursements than Medicaid nursing home patients. For 2015, the Medicare Payment Advisory Commission (MedPAC) estimates that the average total profit margin of stand-alone nursing facilities was 1.6%, but the average non-Medicare margin, excluding Medicare fee-for-service (FFS), was -2.0%, while the average Medicare margin was 12.6% (Medicare Payment Advisory Commission, 2017). Further, there is wide variation in Medicare margins with the lowest quartile at 2.4% and the highest quartile at 21.0%. Overall, Medicare FFS accounted for a median of 11% of facility days in 2015, but 21% of revenue, whereas, the median Medicaid share of facility days was 61% (Medicare Payment Advisory Commission, 2017). For SNFs, profits on Medicare and private pay patients can offset low reimbursements by Medicaid. MedPAC has recommended changes in the SNF prospective payment system (PPS) to better align payments with costs incurred by SNFs (Medicare Payment Advisory Commission, 2018b). Most recently, changes to the SNF PPS include a Patient Driven Payment Model (PDPM) implemented in October 2019 with the goal of reducing the delivery of inappropriate services (Navathe & Grabowski, 2020).

Since 2010, several national health care policy changes have included provisions that affect the nursing home industry. The Affordable Care Act (ACA) of 2010 creates Accountable Care Organizations (ACOs), the Hospital Readmissions Reduction Program (HRRP), and the Bundled Payments for Care Improvement Initiative (BPCI), all providing incentives for better hospital-SNF patient coordination and reducing the length of patient stays in hospitals and in SNFs. The Protecting Access to Medicare Act (PAMA) of 2014 implements hospital readmission penalties for SNFs through the SNF Value-Based Purchasing Program (SNFVBP) beginning in 2018. Additionally, SNFs are required to comply with the Improving Medicare Post-Acute Care Transformation (IMPACT) Act of 2014 to standardize assessments and reporting measures across post-acute care settings. The overall goal of these programs is to reduce the cost of care while maintaining, or improving, standards of quality, and most incentivize better coordination across providers.

While contending with changes in payment systems and policies, SNFs have faced a number of market changes that contribute to environmental pressures. Enrollment in Medicare Advantage, Medicare's managed care program, grew 50% between 2010 and 2015, to include almost one-third of all Medicare beneficiaries (Jacobson, Damico, Neuman, & Gold, 2015). Medicare Advantage plans can control post-acute care costs by limiting patient selection to a specified network of providers and by reducing utilization of skilled nursing facilities (Gadbois et al., 2018). State Medicaid agencies are also implementing managed care for long-term care services (Lewis, Eiken, Amos, & Saucier, 2018). Additionally, nursing homes face growing competition from substitutes for nursing home care. Substitutes for short-stay care include home health services and inpatient rehabilitation facilities, and substitutes for long-stay care include home health services, assisted living facilities, adult day health care, and long-term care hospitals (Denham, 2018).

Simultaneously, demographics in the US are changing as the population ages, increasing the demand for health care. The number of Americans ages 65 and older is expected to represent over 20% of the population by 2030. Demand for post-acute care will likely also increase based on demographic trends, and individual need for some form of long-term care is expected to double by 2030 (Spetz, Trupin, Bates, & Coffman, 2015).

The confluence of these factors has created an environment of uncertainty for SNFs. On one hand, there is pressure to admit patients of greater acuity from hospitals requiring provision of more intense services by SNFs, and the number of patients is expected to increase. On the other hand, SNFs face pressures on profit margins from growth in managed care and value-based programs, pressures on Medicare utilization and Medicaid reimbursement, and competitive pressures from alternative sources of care. Although an aging population and extended lifespan strengthen the demand for short-stay post-acute care and long-stay custodial care, ongoing efforts to reform Medicare and Medicaid payments threaten the stability of revenues for nursing homes (IBISWorld Industry Report, 2017). The progression to value-based and alternative payment models with implementation of the ACA in 2010 and the growth in Medicare Advantage beneficiaries have put increasing pressure on SNFs to more effectively coordinate with hospitals the transfer of patients to SNFs (McHugh et al., 2017; Mor, Intrator, Feng, & Grabowski, 2010) and to reduce lengths of stay (LOS) for post-acute care patients. At the same time, incentives tied to SNFVBP to reduce readmissions from SNFs to hospitals may serve to discourage premature discharges from hospitals (Mechanic, 2014).

It is unclear how SNFs will seek to offset reduced LOS among Medicare patients. SNFs may seek to increase the volume of patients by securing a preferred status with hospitals for Medicare referrals, or they may seek more complex cases to increase utilization. Evidence suggests there is increasing competition among SNFs for preferred patients, raising concerns about access to care for less-preferred patients (Lawrence et al., 2018; Shield, Winblad, McHugh, Gadbois, & Tyler, 2018). Given this context, the objective of this study is to address the question: how are SNFs strategically positioning themselves to survive and thrive in response to changes in the nursing home industry and the overall health care system?

Study Objective and Aims

This study explores the strategic orientation of SNFs to better understand their organizational responses during a time of environmental uncertainty. For managers grappling with how to address uncertainty resulting from environmental changes, strategic group modeling provides a method for identification of strategic approaches within an industry and evaluation of the success of the approaches (Marlin, Huonker, & Sun, 2002). Organizations are grouped based on the commonality of their strategic approaches to competing within an industry. Strategy refers to decisions made by organizations about which markets to serve, how they will compete in these markets, and specific tactics for implementing these decisions (Scott & Davis, 2003). For researchers and policymakers, identifying strategic groups can enhance analysis by focusing on comparisons within and between relevant groups (Luke, Walston, & Plummer, 2004).

Additionally, identifying strategic groups provides an intermediate frame of reference between individual firms and an entire industry that allows for analysis of how an industry is structured that goes beyond organizational size or type of proprietorship. To the best of this researcher’s knowledge, only four studies have conducted strategic group modeling of SNFs. The first study to identify strategic groups of nursing homes was Zinn, Aaronson, and Rosko (1994). Marlin, Sun, and Huonker (1999) followed, adding their own improvements to the modeling of strategic groups. Castle (2003) and Zinn, Spector, Weimer, and Mukamel (2008) also modeled strategic groups of SNFs but used a different methodology. These studies are discussed in depth in the next chapter. Findings in the existing literature do not consistently identify strategic groups of SNFs, nor do they address the stability of strategic groups over time. The current study provides an updated analysis of the strategic orientation of groups of SNFs in the post-ACA reform time period and examines the structure of the industry across a time span of three years.

This study has three aims. First, to better understand the behavior of SNFs by classifying SNFs into groups based on their strategic orientation. Second, to examine whether financial and quality outcomes are associated with strategic orientation. And, finally, to evaluate whether SNFs change their strategic orientation during a time of environmental uncertainty indicating a change in the structure of the nursing home industry. The following research questions are examined to explore the strategic orientation of SNFs during environmental turbulence:

1) What taxonomies of strategic groups exist among SNFs?

2) Do strategic groups of SNFs differ in financial and quality outcomes?

3) How has the strategic orientation of SNFs changed over time?

Conceptual Framework

The study is based on a conceptual framework informed by Strategic Management Theory (SMT). SMT helps explain strategic adaptation through managerial choices to identify and align external opportunities and threats with internal strengths and weaknesses. Organizations adapt *strategically* to their environments to assure survival (Shortell & Zajac, 1990a). Moreover, strategic decisions are primarily responsible for an organization's fit within an environment and determine organizational performance (Kimberly & Zajac, 1985; Shay, 2014). Propositions and corresponding hypotheses addressing the study's aims are derived from the conceptual framework.

Scope and Approach

This study uses data from the Long-Term Care Focus database (LTCF) maintained by Brown University, Healthcare Cost Report Information System (HCRIS) reports for SNFs from the Centers for Medicare and Medicaid Services (CMS), Leavitt Partners' Torch Insight database, CMS's Nursing Home Compare (NHC), and the Area Health Resource Files (AHRF). The level of analysis for this study is at the facility level and the study sample is limited to Medicare-certified SNFs reporting Medicare Cost Reports from 2012 to 2015. Hospital-based facilities are excluded as they have different cost structures than freestanding SNFs.

To address the first aim of this study, a descriptive analysis employing strategic group modeling is undertaken to classify SNFs into groups based on dimensions of strategic orientation identified in the conceptual framework. A cluster analysis is performed using cross-sectional data from 2015, the most recent study year, to test the hypothesis for research question one.

The study's second aim, to see if performance outcomes are associated with strategic orientation, is first tested by assessing differences in performance measures between groups. Then, multivariate models are estimated to test the two hypotheses for research question two. Both tests use cross-sectional data for 2015.

For the study's third aim, to evaluate whether the strategic orientations of SNFs have changed over time, two methods are used to test the two hypotheses for research question three. First, discriminant analysis is applied to a longitudinal panel study design to examine the differences in the composition of strategic groups from 2012 to 2015. Then, performance differences between SNFs that have changed strategic groups compared to those that have not changed strategic groups are assessed with a difference-in-differences model.

Study Contributions

The study provides an updated assessment of SNF strategic groups after a time of industry-wide environmental and organizational changes and utilizes a data source for quantification of referral patterns that, to the best of this researcher's knowledge, has not previously been used in the classification of SNFs. Identifying the differences in strategy groups may facilitate more focused research (Bazzoli, Shortell, Dubbs, Chan, & Kralovec, 1999; Shay & Mick, 2017) and provide managers and policy makers with a more informed view of the local or regional market. Assessing differences in the strategic orientation of SNFs and their associated success in financial and quality outcomes may be beneficial as reforms in the health care system are evaluated and disseminated. For managers, strategic group analysis can provide a framework for strategic decision making (Cool & Schendel, 1988; Porter, 1980).

A better understanding of structural changes in the nursing home industry over time can provide insight into how SNFs are adapting to confront environmental challenges posed by changes in policy, demographics, and competition from substitutes. SNFs play an important role in the provision of care across the continuum, and reforms that facilitate reduced costs may have unintended consequences such as reduced access to more lucrative referrals for SNFs in some markets or restricted access to higher quality care for patients (Huckfeldt, Sood, Romley, Malchiodi, & Escarce, 2013; Shield et al., 2018).

This research is being completed during the COVID-19 pandemic, requiring acknowledgement of one of the greatest environmental shocks SNFs and entire health care systems have ever experienced. The volume of COVID-19 cases and deaths of patients residing in nursing facilities and staff caring for them, as well as the measures required to attempt to prevent the spread of disease have been devastating for residents and staff (Barnett & Grabowski, 2020; Ouslander & Grabowski, 2020). Medicare and state Medicaid agencies have implemented policies and additional funding streams to try to provide guidelines and resources to nursing homes during the pandemic (Chen, Ryskina, & Jung, 2020). It remains to be seen what the longer-term consequences of the pandemic are for SNFs, but changes are certain (Sinsky & Linzer, 2020; Young, Quinn, Brassard, Gualtieri, & Reinhard, 2020). The current study does not include the timespan of the pandemic, but it is the author's hope that the study may provide some insights to help inform future nursing home policies through a better understanding of the strategic orientation and strategic adaption of SNFs.

Organization of Remaining Chapters

The study is presented in six chapters. This chapter introduced the study's focus on the strategic orientation of SNFs during a time of environmental uncertainty, aims of the study, its significance, and an overview of the study's conceptual framework and research design. Chapter 2 discusses the literature relevant to the aims of this study. The study's conceptual framework and theoretical basis are presented in Chapter 3, along with the propositions and corresponding hypotheses derived from the framework. Chapter 4 provides the study's research design, data sources, the study sample, variable measurement, and analytical methodologies. The study's results are included in Chapter 5. Finally, the results of the study are summarized in Chapter 6, and policy and theoretical implications, study limitations, and areas for future research are discussed.

Chapter 2: Literature Review

The first section of this chapter looks at strategic group modeling as a means for explaining variation in strategic behaviors and in performance among organizations within the same industry. The focus in the second section turns to strategic modeling studies specific to SNFs. The third section reviews recent qualitative literature exploring strategic behaviors of SNFs to obtain market share. The fourth section summarizes the existing studies and identifies gaps in the literature. Finally, the last section discusses the potential contributions of the current study to the understanding of the strategic orientation of SNFs.

Strategic Group Modeling

Managers, policymakers, and health services researchers desire a better understanding of strategic behavior and why some organizations outperform others. Classifying firms into groups based on similar management strategies provides a tool for identifying and explaining varying levels of performance among firms within a single industry (Porter, 1980). The concept of classifying organizations into strategic groups grew from the field of industrial organization. Differences in performance were initially thought to be due solely to differences in profitability at the *industry* level. Over time, examination of variation in performance of organizations at the *group* level within an industry evolved into strategic group modeling.

In the study of industrial organization during the 1950s, the primary paradigm for explaining differences in performance among organizations was the structure-conduct-performance (SCP) approach (Bain, 1956). SCP originated out of Harvard and posits a chain of causation in which an industry's structure (S) determines conduct (C) and, in turn, performance (P). Structural barriers to entry into an industry, such as the necessity for large capital investment to operate, serve to protect firms by making entrance difficult for organizations outside of the industry (Bain 1956), thus preserving the level of profitability within an industry. Moreover, industry profitability was thought to dictate the profitability of individual firms, with variation of profitability among firms within an industry attributed to greater efficiency or to randomness (Porter, 1979). During the 1960s and 1970s SCP was challenged, particularly by the Chicago school of industrial organization, and greater emphasis was placed on the role of individual managers in maximizing profit instead of an industry's structure dictating profitability (Bogner & Mahoney, 1998; Demsetz, 1973; Dobbin & Baum, 2014).

In response, Harvard industrial organization economists "attempted to rescue the SCP view" (Bogner & Mahoney, 1998, p. 65). Michael Hunt (1972) provided evidence of heterogeneity of competitive strategies and profitability *within* the home appliance industry in his Harvard dissertation. Hunt was the first to use the term "strategic groups" to help explain differences in performance between groups of firms within the same industry. Later, Caves and Porter (1977), also at Harvard, and Porter (1979) built the foundation for what came to be known as the strategic management perspective to explain differences in profitability among firms within an industry. They argued that not only are there structural barriers to entry *into* an industry, but there are also barriers to mobility *within* an industry limiting change from one strategy group to another. In this perspective, mobility barriers are the basis for explaining differences in profitability among firms within an industry (McGee & Thomas, 1986; Porter, 1979). Higher mobility barriers combined with other factors such as less competition, greater bargaining power with customers and suppliers, less exposure to substitute products or services, and managers' ability to execute strategy result in higher profit potential within some strategy groups (Porter, 1979). Limited organizational resources or environmental constraints restrict movement across mobility barriers. The costs of moving from one group to another group reflect mobility barriers that discourage entry from rival organizations into a group (Caves & Porter, 1977; Marlin, Sun, & Huonker, 1999). This stream of work has evolved to bridge empirical structural analysis of an industry and applications in strategic management (Porter, 1980). Examining industries at a more refined level can provide insights into the structure of the industry and performance differences among organizations. Identifying strategic groups within an industry provides researchers and managers "an intermediate frame of reference between looking at an industry as a whole and considering each firm separately" (Porter, 1980, pg. 132).

Regardless of industry, researchers make four key decisions when modeling strategic groups. First, researchers determine their *approach to defining strategic groups* in an industry. Second, researchers identify *strategic dimensions* for classifying organizational configurations within an industry. Third, the *method for classifying* members into groups is selected. Fourth, researchers may choose to test the *structure-performance link* between strategy groups and performance outcomes. These distinguishing characteristics of strategic group modeling are discussed in the following sections and help guide the review of the quantitative studies presented in this chapter.

Approach to defining strategic groups.

There are two approaches researchers can take to defining strategic groups within an industry. Ketchen, Thomas, and Snow (1993) delineate approaches to modeling groups as either a deductive method or an inductive method. Choosing a *deductive approach* to defining strategic groups relies upon *a priori* expectations of typologies of strategic groups. This approach is rooted in the strategic choice perspective and allows for testing of predictions based on theory. In the deductive approach, a limited number of strategic configurations of organizations are believed to exist and organizational behavior can be predicted and tested (Ketchen Jr, Thomas, & Snow, 1993). A deductive approach assumes most organizations fall within one of the chosen strategic typologies.

In contrast to a deductive approach, in an *inductive approach* to defining strategic groups the researcher allows the number of strategic groups to emerge organically from the analyses. This approach is exploratory and conducted without *a priori* expectations as to the number of strategic groups or typology of groups (Ketchen & Shook, 1996). The assumption in the inductive approach is that the number of strategy groups and the typology depend on the number of unique strategies within an industry (Marlin et al., 1999). Selection of one approach over the other depends on *a priori* expectations of the researcher (Short, Ketchen Jr, Palmer, & Hult, 2007).

Strategic dimensions.

Researchers select strategic dimensions as the basis for classification of organizations whether the study takes a deductive or an inductive approach. A study using the deductive approach to defining strategic groups uses strategic dimensions consistent with the generic typology being applied to the industry. Porter (1980), for instance, offers thirteen possible strategic dimensions: specialization, brand identification, push versus pull, channel selection, product quality, technological leadership, vertical integration, cost position, service, price policy, leverage, relationship with parent company, and relationship to home and host government. These strategic dimensions are used to classify organizations into strategic groups of *low-cost leaders*, *differentiators* of product or service, or *focused* on a market segment or product line. Miles and Snow (1978) identify three general dimensions of strategy as entrepreneurial, administrative, and technical (Miles, Snow, Meyer, & Coleman Jr, 1978; Shortell & Zajac, 1990b). Classification of organizations based on the Miles and Snow (1978) typology usually use these dimensions to identify firms as *prospectors*, *defenders*, *analyzers*, or *reactors*.

In a study using an inductive approach to defining strategic groups, selection of strategic dimensions should likewise have a theoretical basis (Aldenderfer & Blashfield, 1984). There is consistency in the literature that strategic groups should be classified using dimensions that are relevant to an industry (Cool & Schendel, 1988; Porter, 1980). Strategic theorists have used various strategic dimensions for classifying organizations. For example, McGee and Thomas (1986) contest that dimensions pertaining to mobility barriers provide the best differentiation of strategy among groups and broadly consist of: market-related strategies, industry supply characteristics, and characteristics of firms. Luke and Begun (1988) identify growth and action orientations as two general dimensions of strategy. Cool and Schendel (1988) use two broad categories of strategic actions, *business scope* and *resource commitments*, to capture decisions involving market segments, range of products or services offered, and geographic reach. The selection of dimensions for classification of groups should align with the purpose of the study (Ketchen & Shook, 1996).

Methods for classifying members.

Both inductive and deductive approaches to strategic modeling necessitate a method for classifying observations. Cluster analysis has been the commonly used method for identifying strategic groups in the literature. Other methods include classification based on the size of a firm such as in Porter's (1973) early work, applying indices of differentiation measures (Marlin, Lamont, & Hoffman, 1994), and factor analysis. Surveys of firms have been used to allow firms to 'self-type' into generic typologies of strategic groups (Castle, 2003; Zinn, Spector, Weimer, & Mukamel, 2008). However, cluster analysis better captures the multidimensional aspects of the dimensions than these other methods of classification by maximizing between-group variance and minimizing with-in group variance (Ketchen & Shook, 1996). Cluster analysis methods can accommodate both an inductive approach to group modeling using hierarchical clustering techniques, and a deductive approach to group modeling using non-hierarchical techniques that include *a priori* expectations of the number of strategic groups. Some researchers have argued there are drawbacks and limitations to using cluster analysis including the *a priori* assumption of the existence of any clusters and a lack of a test of significance that discrete groups exist. Methodologists are working to address these limitations, but cluster analysis remains the dominant method for classifying strategy groups (Carroll & Thomas, 2019). Once a taxonomy of strategic groups is identified, the researcher typically applies a typology to the groups and profiles the groups based on characteristics relevant to an industry. Selection of the method for classifying group members depends on the approach taken to define strategic groups and data used to define strategic dimensions (Hair, Black, Babin, Anderson, & Tatham, 2006).

Structure – Performance link.

The genesis of strategic modeling was to explain differences in performance among organizations. Porter (1980) explains that mobility barriers not only define strategic groups but are a major reason “why some firms in an industry will be persistently more profitable than others” (pg. 134). Higher mobility barriers are usually associated with greater profit potential and serve to protect strategic groups, otherwise all competitors would attempt to implement the most profitable strategies (Porter, 1980). Consequently, most studies that model strategic groups test the structure-performance link between membership in a specific strategy group and associated performance outcomes. Performance measures may include financial performance, quality performance, or other measures such as efficiency. Further, association between performance and the strategic group structure can help strengthen validity of the study (Hair et al., 2006).

Strategic Group Modeling of Skilled Nursing Facilities

There are four previous studies that have conducted strategic group modeling of skilled nursing facilities based upon SNFs’ strategic orientation. The first study was published in 1994 by Zinn, Aaronson, and Rosko (1994) examining data from 1987 and 1989, and the most recent study was published more than a decade ago in 2008 using data from 2004 (Zinn et al., 2008). The first two studies, Zinn et al. (1994) and Marlin, Sun and Huonker (1999), take an inductive approach to identifying groups, and both are based on secondary data using measures of strategic dimensions of scope of business and resource deployment. The later studies by Castle (2003) and Zinn et al. (2008) employ a deductive approach to classifying SNFs, and survey nursing home administrators to 'self-type' their organization into one of the four strategic groups in the Miles and Snow (1978) typology. The researchers later combine administrative data with the survey data to test whether performance measures are associated with strategic types. All of the studies investigate the relationship of strategic groups to quality performance while one study includes an efficiency measure, and one study explores efficiency and financial performance. Two studies examine SNFs in a single state to control for differences in state regulations; one study uses data for SNFs in five states; and one study uses a national dataset. Table 1 summarizes the studies. These four studies are reviewed in more detail in the following discussion to provide a foundation for the current study. Of primary interest are each study's approach to strategic group modeling, the strategic dimensions selected for modeling groups, the method used for defining strategic groups and resulting typology, and whether groups are associated with performance.

Table 1. *Studies classifying SNFs by strategy*

Study	**Sample, Timeframe**	**Approach to Taxonomy**	**Strategic Dimensions**	**Method and Taxonomic Results**
Zinn, Aaronson & Rosko (1994)	PA, 1987 and 1989	Inductive	Scope of business & resource deployment	Cluster Analysis: 7 groups
Marlin, Sun & Huonker (1999)	FL, 1995	Inductive	Scope of business & resource deployment	Cluster Analysis: 7 groups
Castle (2003)	KS, ME, MS, TX, SD, 1999	Deductive	Miles & Snow	Survey :4 groups
Zinn, Spector Weimber & Mukamel (2008)	National, 2004	Deductive	Miles & Snow	Survey: 4 groups

Approach, strategic dimensions, method, and results.

Zinn et al. (1994) take an inductive approach and limit their study to SNFs in Pennsylvania to control for differences in state regulations. Cross-sectional data from 1987 is used for classification of SNFs and change in strategic behavior is assessed using 1989 data.

Their selection of dimensions for defining group membership draws upon earlier works identifying scope of business and resource deployment as key dimensions for determining strategic groups within an industry (Caves & Porter, 1977; Cool & Schendel, 1988; Newman, 1978).

An organization's scope of business encompasses market segments in which the organization competes and services it offers within these market segments (Cool & Schendel, 1988). Zinn et al. (1994) distinguish source of payment to nursing homes as the most important basis of market segmentation in the nursing home industry. At the time of their study, Zinn et al. (1994) cite private or self-pay patients as comprising the majority (51%) of nursing home revenue, Medicare accounting for only 2% of revenue, and the remaining care paid for by Medicaid (47%). By 2015, private pay patients comprised a smaller proportion of revenue (35% versus 51%), while Medicare revenues had grown to 23% from 2% of revenues, and payments from Medicaid fell to 31% of nursing home revenues, with the remaining revenues coming from other payers (California Health Care Foundation, 2020). The following variables are included as measures of scope of business decisions in their analysis: percent of Medicaid recipients, percent of Medicare recipients, percent of capacity for independently paying patients, case mix index, average length of stay, and percent of residents over age 85. Longer lengths of stay and higher percentages of residents over age 85 characterize nursing homes more likely to have a greater number of patients with longer-term care needs. The second key dimension, resource deployment, measures resources committed to the targeted market segments. For nursing homes, Zinn and colleagues (1994) identify labor, price, and capacity key resources as using the following measures: registered nurses per resident, staff per resident, private pay rate, number of staffed beds, and facility occupancy rate.

A cluster analysis results in seven different strategic groups of SNFs. Table 2 summarizes the strategic groups found in the Zinn et al. (1994) and in the Marlin et al. (1999) studies and selected variables used in each of their cluster analyses. For Zinn et al. (1994), Group 1 "Medicare Skilled Nursing Care Focus Strategy" (19% of SNFs) has a significantly higher Medicare census and lower percentage of Medicaid residents than the other groups. SNFs in Group 2 "Differentiated Focus Strategy: Care Continuum" (5% of SNFs) focus on a care continuum including independent living services and have the lowest percentage of Medicaid residents. Group 3 "Generic Skilled Nursing Care Strategy" (18% of SNFs) is labeled generic since it has both a high Medicare and Medicaid census and the highest average case mix index. Group 4 "Low-Cost Intermediate Care Strategy" (23% of SNFs) has a low-cost intermediate care strategy with high Medicaid census, but lower staffing and case mix compared to other groups. Group 5 "Low-Cost Skilled and Intermediate Care Strategy" (13% of SNFs) has a low-cost intermediate care strategy like that of Group 4 but has a shorter average length of stay and fewer residents over age 85. Group 6 "Low-Cost Focus Strategy: Care Continuum" (19% of SNFs) similarly focuses on a care continuum as does Group 2 but has more Medicaid residents than Group 2. Finally, Group 7 "Large Municipal Facilities" (3% of SNFs) has the largest average number of beds, length of stay, and Medicaid census.

Marlin et al. (1999) conduct a study of SNFs in response to Zinn, Aaronson, and Rosko's (1994) call for comparative studies, but make some changes to correct what they consider to be "pitfalls" of the prior study. Like Zinn et al. (1994), Marlin et al. (1999) use an inductive approach to identifying strategic groups and the same dimensions of strategy as the prior study. However, they classify nursing homes in a different state, Florida, using more recent 1995 cross-sectional data, and they enhance cluster dimension and performance measures. Marlin et al. (1999) examine the process of formation of strategic groups specific to the nursing home industry in more detail than Zinn et al. (1994), and they discuss the significance of the application of strategic group modeling to nursing home administrators instead of focusing on implications for policymakers, as do Zinn, Aaronson and Rosko (1994).

Marlin et al. (1999) retain the same dimensions of strategic grouping, scope of business and resource deployment, but add utilization measures of health maintenance organizations (HMOs), the Veterans Administration and private payers. The percent of residents aged 85 and older is replaced by the average patient age. Two measures, percentage of nursing costs and percentage of ancillary costs, are added to the measures of resource deployment. While there are many similarities in these early studies, there are differences. Zinn et al. (1994) include hospital-based SNFs, but Marlin et al. (1999) are not clear as to whether hospital-based SNFs are included in their sample. Importantly, the samples vary in markets and point in time which may account for differences in some characteristics of the samples. The average percentage of revenues from Medicare in the Zinn et al. (1994) study is 3%, while in the Marlin et al. (1999) study the average percentage of revenue from Medicare is almost 12%. In the Zinn et al. (1994) study in Pennsylvania in 1987, the percent of non-profit ownership of SNFs is lower with an average of 43% among the strategic groups compared to an average of 88% among the strategic groups in the Marlin et al. (1999) study.

Like Zinn et al. (1994), Marlin et al. (1999) find seven distinct strategic groups of SNFs. Some of the seven groups identified by each of the studies are very similar and the characteristics of the rest are roughly aligned. Table 2 pairs the strategic groups identified in the Marlin study with those found in the Zinn et al. (1994) study on selected attributes for comparison in this review. Paired groups are labeled in this study with letters as Groups A through G. For ease of discussion, we refer to the Group letters in the first column to compare strategic groups from the two studies.

Table 2. *Comparison of strategy groups in Zinn et al. (1994) and Marlin et al. (1999)*

Group	Study	Study Group #	Description of Group	% of Sample	Case Mix	% Medicaid	% Medicare	% Private Pay	ALOS	% For-Profit	% Chain
Group A	Zinn	Group 1	Medicare Skilled Nursing Care Focus	19%	HIGH	LOW	HIGH	LOW	LOW	79%	NA
	Marlin	Group 3	Medicare Skilled Nursing Care Focus	17%	MID	MID	HIGH	MID	LOW	97%	97%
Group B	Zinn	Group 2	Differentiated Focus - Care Continuum	5%	LOW	LOW	LOW	HIGH	MID	5%	NA
	Marlin	Group 7	Private Pay and Medicare Focus	6%	MID	LOW	MID	HIGH	LOW	91%	74%
Group C	Zinn	Group 3	Generic Skilled Nursing Care	18%	HIGH	MID	MID	LOW	MID	59%	NA
	Marlin	Group 5	Low-Cost Intermediate Nursing Care	9%	HIGH	MID	MID	MID	LOW	83%	78%
Group D	Zinn	Group 4	Low-cost Intermediate	23%	LOW	MID	LOW	LOW	MID	25%	NA
	Marlin	Group 6	Intermediate Nursing Care	11%	LOW	HIGH	MID	LOW	MID	86%	72%
Group E	Zinn	Group 5	Low-cost Skilled & Intermediate care	13%	MID	HIGH	MID	LOW	MID	63%	NA
	Marlin	Group 2	Short-term Skilled Nursing Care	20%	MID	MID	MID	MID	LOW	96%	91%
Group F	Zinn	Group 6	Low-cost Focus -Care Continuum	19%	LOW	MID	LOW	MID	HIGH	17%	NA
	Marlin	Group 1	Low-Cost Skilled Nursing Care	18%	LOW	MID	MID	MID	MID	92%	93%
Group G	Zinn	Group 7	Large Municipal Facilities	3%	MID	HIGH	MID	MID	HIGH	0%	NA
	Marlin	Group 4	Long-term Intermediate Nursing Care	19%	MID	HIGH	LOW	MID	HIGH	72%	66%

Group A includes strategy groups found in both studies focused on Medicare skilled nursing care providing short-term rehabilitative care with the highest Medicare census, mid-range and low percentages of Medicaid, shortest lengths of stay, and mid-range and high case mix. The proportion of SNFs in Group A is similar in both studies, with the Zinn et al. (1994) study having 19% of SNFs in this group compared to 17% in the Marlin et al. (1999) study. Likewise, Group B includes strategy groups found in both studies focused on private pay patients that account for the highest average percentage of private pay patients, have low and mid-range Medicare census, the lowest Medicaid census, low and mid-range lengths of stay, and low and mid-range case mix. The proportions of SNFs in Group B are similar with 5% in the Zinn et al. (1994) study compared to 6% in the Marlin et al. (1999) study. The paired groups in Group C that Zinn et al. (1994) call "Generic Skilled Nursing Care" have the highest average case mix, mid-range levels of Medicare and Medicaid census, low and mid-range rates of private pay, and low and mid-range lengths of stay. The proportions of SNFs in Group C differ with the Zinn et al. (1994) study finding 18% of SNFs in this group compared to 9% in the Marlin et al. (1999) study. The Zinn et al. (1994) study notes that this group has the highest percentage of hospital-based facilities (12%) which may help explain the proportional difference as it is not clear if the Marlin et al. (1999) study includes hospital-based facilities. The paired groups in Group D described as "Low-cost Intermediate" in the Zinn et al. (1994) study have low and mid-range rates of revenues from Medicare, mid-range and high rates from Medicaid, low rates from private pay, mid-ranges of length of stay, and low case mixes. Though these groups appear similar, the proportion of SNFs in Group D in the Zinn et al. (1994) study is 23% versus 11% in the Marlin et al. (1999) study.

The paired groups in Group E described as “Low-cost Skilled and Intermediate Care” in the Zinn et al. (1994) study and “Short-term Skilled Nursing Care” in the Marlin et al. (1999) study have the least in common, but do not align well with any other groups. Both have mid-range case mix and Medicare census, but the Zinn et al. (1994) group has a high percentage of Medicaid, and low percentage of private pay residents and mid-range lengths of stay, while the Marlin et al. (1999) group has mid-range levels of Medicaid residents, and private pay residents, shorter lengths of stay. The proportions of SNFs in Group E differs, with 13% in the Zinn et al. (1994) study compared to 20% in the Marlin et al. (1999) study.

The paired groups in Group F described as “Low-cost Focus – Care Continuum” in the Zinn et al. (1994) study are alike with low case mixes, mid-range proportions of Medicaid patients, and mid-range levels of private pay residents. They differ in mid-range and high levels of lengths of stay and low and mid-range Medicare census. The proportions of SNFs in Group F is similar in both studies, with 19% in the Zinn et al. (1994) study compared to 18% in the Marlin et al. (1999) study.

The paired groups in Group G are alike with mid-range case mixes, high Medicaid censuses, mid-range rates of private pay, and long lengths of stay. They differ in the level of Medicare patients being at mid-range and low levels. and. However, in the Zinn et al. (1994) study, this group represents large municipal facilities with an average bed-size of 539 beds. In contrast, the largest average bed-size in the Marlin study is 151 beds (Marlin study Group 6). Consequently, the proportion of SNFs in Group G in the Zinn et al. (1994) study is only 3%, while the most similar group in the Marlin et al. (1999) study accounts for 19% of SNFs.

The two later studies, Castle (2003) and Zinn et al. (2008), use a deductive approach to identify strategic groups of SNFs by applying the Miles and Snow (1978) typology. Castle

(2003) and Zinn et al. (2008) survey nursing home administrators and then classify SNFs based on self-typing as having a Prospector, Defender, Analyzer, or Reactor strategy. Castle (2003) and Zinn et al. (2008) adapt their surveys from a survey of key informants in hospitals (Shortell & Zajac, 1990a; Zajac & Shortell, 1989) to identify an organization's strategic orientation. Castle (2003) surveys 470 nursing facilities in 1999 in five states: Kansas, Maine, Mississippi, Texas, and South Dakota. Zinn et al. (2008) survey a random sample of 10% of all facilities in the nation included in the Nursing Home Compare report conducted May through June 2004.

The makeup of the industry structure differs between the two studies taking a deductive approach. Castle (2003) finds: 32% Analyzers, 27% Reactors, 25% Defenders, and 17% Prospectors, whereas Zinn et al. (2008) find their sample includes approximately: 43% Defenders, 33% Analyzers, 19% Prospectors, and 7% Reactors. The number of Analyzers (32% and 33%) and Prospectors (17% and 19%) in both studies are similar, but Defenders (25% and 43%) and Reactors (27% and 7%) differ by wide margins. The surveys are conducted at different times using different samples which may explain the variation in the structure of the industry. Castle (2003) surveys a sample of nursing homes in 1999 located in five states to determine strategic orientation. Zinn et al. (2008) surveys a national sample of SNFs for classification in the Miles and Snow (1978) typology. Using a survey to self-type strategic orientation may better capture the strategic intent of management, compared to using secondary data, but respondents are subject to response bias by perhaps making themselves look more desirable or strategically adept than the management decisions that have been implemented (Zinn et al, 2008). Surveying also requires a larger amount of resources than using secondary data. The Miles and Snow (1978) typology has been used in a number of health care studies (Shortell & Zajac, 1990b), but it may not fully capture the structure of the nursing home industry.

Performance.

Each of the four studies finds support for the association of strategic groups with measures of performance. Reasoning that maximizing profit may not be the only or most important objective of all nursing homes since many SNFs operate as non-profits, Zinn et al. (1994) choose performance indicators of quality and an efficiency measure in lieu of financial performance measures. Rates of patients with pressure ulcers, catheterization, and restraint use measure quality, and an efficiency score is derived using data envelopment analysis. Change in Medicare census from 1987 to 1989 is assessed to determine whether SNFs changed their behavior in response to the 1988 Medicare Catastrophic Coverage Act (MCCA) by increasing Medicare participation.

In addition to finding distinct groups based on strategic dimensions among nursing homes, Zinn et al. (1994) find support for their hypotheses that performance and strategic behavior are associated with strategic group membership. Multiple analysis of variance (MANOVA) is used to test the significance of group membership on group means for clustering and performance variables, and Tukey's honestly significant differences (HSD) tests are used to compare group means for each variable. Significant differences in performance measures among the groups are found. The highest performing groups on quality measures are Groups 2 and 6 with a focus on a continuum of care, while the poorest performing groups are Groups 4 and 5, focused on low-cost intermediate care. The most efficient group is Group 1 with a high Medicare census, and the groups with the least efficiency scores are those with a care continuum focus, Groups 2 and 6, in contrast to their high performance on quality measures. All groups increase Medicare participation as a result of "the MCCA effectively lower[ing] mobility barriers to participation in the lucrative Medicare market" (Zinn, Aaronson, & Rosko, 1994, p. 202). Group

1, however, already having the highest Medicare census, has the largest increase. Groups 2 and 6 have the lowest increase in Medicare participation over the study time period.

Marlin and colleagues (1999) include operating margin and average profit per patient day as indicators that would be useful to nursing home administrators in order to measure financial performance. An efficiency score is calculated using similar inputs and outputs as Zinn et al. (1994). For quality performance measures, however, Marlin et al. (1999) add total number of health deficiencies and the total number of life and safety deficiencies to address overall nursing home quality. The same three quality measures used by Zinn et al. (1994) (prevalence of patients with pressure ulcers, catheterization, and physical restraint) are included, but the number of admitted patients having the condition is subtracted to exclude counting conditions present on admission. An additional quality measure, unplanned weight change, is included.

Like Zinn et al. (1994), Marlin and colleagues find significant differences in performance measures among strategic groups using MANOVA to test for significance of difference between groups on the clustering and performance variables and Tukey's HSD test to compare group means for each variable. However, strategic groups do not perform in the same ways across the two studies. Marlin et al. (1999) find that their Group 7, SNFs with high private pay and Medicare census, perform the best financially and at a high level of quality and efficiency. The high level of quality is similar for the comparable group in the Zinn study (Group 2), but the Marlin study finds a high level of efficiency in this group, in contrast with Zinn's finding. Other comparisons in performance measures between the two studies have mixed results. Sampling differences and local competition and regulations are offered as explanations by Marlin et al. (1999) along with a call for further research to address differences in the findings of the two studies.

Castle (2003) assesses quality across strategic groups by examining rates of patients with catheterization, restraint use, contractures, pressure ulcers, and psychoactive medication use. Logistic regression is used to test the association of strategic groups with high or low scored measures. Castle (2003) finds support for association of each the quality measures with strategic orientation. SNFs classified as Prospectors demonstrate the best outcomes followed by Defenders, Analyzers, and Reactors in each of the quality measures as hypothesized. Differences in measures between the four groups are significant with the exception of the rate of use of psychoactive medications, which trended in the same manner as the other quality measures with Prospectors having the lowest rate of usage and Reactors having the highest.

The last study, Zinn et al. (2008), assesses whether a SNF's response to a change in policy for publicly reporting quality measures is associated with its strategic group designation. Measures of quality include seven actions SNFs may take in response to public release of the Nursing Home Compare (NHC) website. Logistic regression is used to assess whether the response of SNFs is associated with their Miles and Snow (1978) strategic orientation. Overall, SNFs classified as Prospectors and Analyzers are more likely to respond and Reactors are less likely to respond compared to Defenders. Specifically, Prospectors and Analyzers are most likely to have an immediate response, investigate reasons for poor scores, and change priorities of programs compared to Defenders; Prospectors are most likely to revise job descriptions based on quality measure publications; Analyzers are most likely to invest in new technology as a response compared to Defenders; Reactors are least likely to make an immediate response, and Defenders are most likely to have no response to the publication compared to Prospectors. Zinn and colleagues (2008) conclude that SNFs' responses to the change in their environment follows the competitive actions expected by their strategic types: Prospectors use change to their advantage, Analyzers tend to follow Prospectors, Defenders resist change, and Reactors respond when forced.

Qualitative Studies Informing SNFs' Strategic Management of Scope of Business

Qualitative studies are reviewed to gain a better understanding of strategies managers of SNFs are currently pursuing in their scope of business in the context of industry changes. These lines of research have much to add to identifying strategic dimensions of SNFs and mobility barriers within the industry. Recent work has been undertaken by scholars to better understand the hospital to SNF referral process in light of pressures experienced by hospitals and SNFs from value-based purchasing programs. In particular, the qualitative work of Shield and colleagues (2018) and Lawrence and colleagues (2018) elucidate the processes and strategies that some SNFs use to obtain patient admissions. Drawing upon exploratory qualitative research is intended to provide insights that can help inform the development of the conceptual framework for quantitative analyses of SNFs (Creswell, Klassen, Plano Clark, & Smith, 2011).

Shield, Winblad, McHugh, Gadbois, and Tyler (2018) conduct qualitative research to explore perspectives of hospitals discharging patients to SNFs and of SNFs admitting patients from hospitals in a post-ACA environment. The research team conducted interviews with 138 administrative personnel in 16 hospitals and 25 SNFs across eight sites. They find that some hospitals are creating formal and informal preferred networks of SNFs in hopes of reducing readmissions from SNFs and readmission penalties. For some SNFs, having a strong source of hospital referrals allows the SNF to be more selective about accepting patients with complex care needs. However, SNFs that do not have a reliable source of hospital referrals may be more likely to accept less-desirable patients (more complex patients requiring a greater level of care without generating a higher level of revenue) to increase occupancy. SNFs screening patients by expected source of payment and complexity, with a preference for short-stay and less complex patients, are strong themes throughout the study. Shield et al. (2018) conclude with a concern that SNFs with higher referral rates may have greater access to post-acute care patients with higher reimbursement rates, while SNFs with lower referral rates will be left with more complex and long-term care patients with lower reimbursement rates. Moreover, as SNFs shift more of their beds to short-stay from long-stay, there is even greater competition for short-stay patients.

Though smaller in scale than the Shield et al. (2018) study, a qualitative study by Lawrence and colleagues (2018) similarly find some hospitals creating narrow networks of SNFs for their post-acute patients and the potential for preferred SNFs to respond with greater screening of patients. Eighteen clinicians at three different SNFs were interviewed using semi-structured interviews. They find that screening and admissions processes vary at the SNFs, and external pressures driving variation in process are identified as: lack of consistent medical documentation, lack of familiarity of hospital staff with a SNF's capabilities, and payment models encouraging rapid discharge from hospitals to SNFs. SNFs' screening of patients by payer, complexity, and expected length of stay are overarching themes. Lawrence et al. (2018) suggest that SNFs increase their agency in the hospital referral process by better screening patients to match a patient's needs with a facility's capabilities.

Summary and Gaps in the Literature

There are only four studies that model the strategic orientation of SNFs and the relationship between SNF strategic groups and performance outcomes. The studies find evidence that groups of SNFs have similar strategies and that strategic orientation is related to performance. Two studies identify their own typologies using an inductive approach and two studies use a deductive approach by applying the Miles and Snow (1978) typology.

The Zinn et al. (1994) and Marlin et al. (1999) studies use an inductive approach to define strategic groups based on dimensions of scope of business and resource commitments and apply the cluster analysis method to identify the number of groups that exist within the industry. Both studies rely upon cross-sectional secondary data to operationalize strategic dimensions, both find a typology consisting of seven strategic groups of SNFs, and both test the association between groups and performance measures. Marlin et al. (1999) conclude that the consistency in strategic groups in the two studies “suggests an underlying stability in the segmentation of the industry” (pg. 171). However, Marlin and his colleagues note differences in performance measures between the groups found in their study compared to performance of the groups found in the Zinn et al. (1994) study and indicate the need for further study to explain the differences.

The Castle (2003) and Zinn et al. (2008) studies take a deductive approach to defining strategic groups using the Miles and Snow (1978) typology based on surveys of nursing home administrators. Both studies find associations between group membership and performance measures. However, the proportion of SNFs in each of the four Miles and Snow groups differ, indicating a difference in the underlying structure of the industry in the two studies.

The qualitative studies (Lawrence et al., 2018; Shield et al., 2018) provide a glimpse into the competitive trends in a post-ACA environment among SNFs for patient referrals from hospitals that helps inform the current study. Themes of market related strategies are consistent between the two qualitative studies, providing some convergence of strategic dimensions in the current environment and indication of mobility barriers within the industry. Some SNF administrators may be limited in their ability to acquire the most desired referrals due to capacity constraints for short-stay patients or complex patients, or weak relationships with referring hospitals. SNFs that have strong relationships with referring hospitals and excess capacity for short-stay patients may seek out less complex, more profitable patients. The proportion of short-stay and long-stay residents that a SNF can accommodate has implications for revenues. However, there are capacity restraints and accommodations with referral partners that create mobility barriers within the industry.

There are several gaps in the literature focusing on strategic orientation of SNFs. First, there is some inconsistency in the existing literature as to the industry structure. The structure of groups that emerged from the earlier studies by Zinn et al. (1994) and Marlin et al. (1999) demonstrated a similar structure of strategy groups, and hence mobility barriers, in their samples of the nursing home industry. However, the strategic groups are not entirely aligned and the structure – performance link, while significant in each study, is not consistent across similar groups of SNFs. Variation in outcomes of the studies applying the Miles and Snow (1978) typology suggest that the industry structure either is not stable altogether or is at least not stable using the Miles and Snow (1978) typology of strategy groups. Second, there is an absence of studies using more recent data to classify SNFs by strategic orientation despite strategic modeling being applied to other services within the healthcare sector (Bazzoli et al., 2017; Shay and Mick, 2017; Kirby, 2012; Evans et al., 2019). This is important because the gap covers a time of changes in the industry and increasing environmental uncertainty. Policy changes affecting SNFs include the SNF prospective payment system in 1998, Balanced Budget Refinement Act (BBRA) of 1999, Benefits Improvement and Protection Act (BIPA) of 2000, Affordable Care Act (ACA) of 2010, Hospital Readmissions Reduction Program (HRRP) in 2012, Bundled Payment for Care Improvement (BPCI) in 2013, the SNF Value Based Purchasing Program (SNFVBP) in 2018, and the Patient Driven Payment Model (PDPM) in 2019. Simultaneously, there has been growth in managed care (Emily A Gadbois et al., 2018) and nursing home substitutes which may decrease demand for nursing home care (Geng, Mansouri, Stevenson, & Grabowski, 2020; Silver, Grabowski, Gozalo, Dosa, & Thomas, 2018), while a shift in demographics towards an older population may increase demand (Spetz et al., 2015). Third, the generalizability of results of Zinn et al. (1994), Martin et al. (1999), and Castle (2003) is limited as samples are restricted to one or a few states. An analysis using nationwide data provides greater generalizability of results. Fourth, each of the studies reviewed uses cross-sectional data to classify SNFs into groups. A longitudinal analysis of classification provides a better perspective of changes occurring over time. Finally, the exploratory, qualitative studies of strategies used by SNFs in the admissions process provided by Shield et al. (2018) and Lawrence et al. (2018) are limited in generalizability. Quantitative analysis can serve to support their qualitative findings.

Summary and Study Contribution

Strategic group modeling provides a means for researchers, policymakers and managers to identify strategic approaches within an industry and evaluate the success of varying approaches (Marlin et al., 1999). The method has been applied in multiple industries including the healthcare sector since it was first developed in the early 1970s. This study provides an updated and expanded analysis of the strategic orientation of SNFs and whether their strategic orientation is associated with performance measures. Building upon studies by Zinn et al. (1994) and Marlin et al. (1999), this study examines SNFs during a time of environmental change occurring during the last ten years. Earlier works were limited to one state and used cross-sectional data to identify groups at one point in time. This study provides greater generalizability by including SNFs across the United States and provides a more robust perspective of changes occurring over time by utilizing a longitudinal analysis to examine the composition of strategic groups of SNFs in different time periods. Finally, this study is informed by recent qualitative studies exploring strategic priorities of some SNFs competing for business in a changing environment. These priorities, maximizing payer mix of short-stay patients, screening for complexity of care, and strengthening referral relationships, align with Cool and Schendel's (1988) definition of scope of business, and are the dimensions used to classify SNFs in this study. These strategic dimensions are discussed fully as part of the conceptual framework in Chapter 3.

Chapter 3: Conceptual Framework

This chapter develops a conceptual framework to address the aims of the study. Strategic Management Theory (SMT) provides theoretical underpinnings to the framework to help explain the expectation of strategic groups within the nursing home industry and variation in financial and quality performance associated with membership in a group. The first section of this chapter provides an overview of SMT, the second section presents the conceptual framework and how it is informed by SMT, and the third section of the chapter develops the propositions and hypotheses derived from the conceptual framework to address each of the study's research questions.

Strategic Management Theory

Chandler's (1962) *Strategy and Structure* is credited as the genesis of SMT with works by Ansoff (1965), Andrews (1971), Child (1972), Schendel and Hoffer (1979), Miles and Snow (1978), and Porter (1980, 1985) shaping and expanding its theoretical concepts. SMT emerged in the context of conceptualizing organizations as open system models operating within an environmental context (Shortell & Zajac, 1990a). Lawrence and Lorsch's (1967) and Thompson's (1967) works focused on the contingent relationship between an organization's environment and the *structure* of an organization leading to contingency theory, whereas, theorists such as Chandler (1962) and Ansoff (1965) focused on the contingent relationship between an organization's environment and the *strategy* chosen by an organization to manage the environment that, in turn, leads to changes in structure (Boyd, Takacs Haynes, Hitt, Bergh, & Ketchen, 2012; Hoskisson, Wan, Yiu, & Hitt, 1999). This difference in the interplay between the environment and strategy is the foundational assumption of SMT: organizations adapt *strategically* to their environments to assure survival (Shortell & Zajac, 1990a).

SMT recognizes the influence of organizational and environmental factors in organizational performance, however managerial strategic choices are believed to be the primary factor determining the structure and performance of an organization. Child (1972) identifies management and strategic choice as the mechanism by which structures are adapted to environmental and organizational dimensions. Choices such as "where the organization's operations shall be located, the clientele it shall serve, or the types of employees it shall recruit" (Child, 1972, p. 10) provide organizations with the ability to enact strategic choice to reduce dependence upon environmental factors and achieve better performance. SMT conceives of "fit" between the environment and organizational *strategy*, differing from contingency theory's conception of "fit" occurring between the environment and organizational *structure* (Zajac, Kraatz, & Bresser, 2000). SMT emphasizes the agency of managers to make strategic decisions regarding how to handle environmental factors and changes for the advantage of the organization (Scott & Davis, 2007). Just as contingency theorists recognize there is no one best way to organize, strategic management theorists recognize there is no one best strategy for an organization to undertake and that some strategies work better than others in certain environments.

The study of strategic management assumes a continual process of strategic adaptation by organizations to changes in the environment. Managers are expected to "anticipate or react to environmental changes by formulating specific strategies, taking into account environmental conditions, organizational variables, and past performance" (Shay, 2014, p. 111). Implementation of chosen strategies may require structural adaptation. Moreover, it is anticipated that strategic adaptations and structural changes affect performance outcomes (Kimberly & Zajac, 1985; Shortell & Zajac, 1990a; Zajac & Shortell, 1989). Managers' abilities to adapt strategically by aligning organizational factors with environmental demands ultimately determine performance and whether the organization survives (Kimberly & Zajac, 1985; Shay, 2014).

Porter (1979, 1980, 1991) applies tools from industrial organizational economics to the concepts of SMT by emphasizing the identification and alignment of internal strengths and weaknesses with external opportunities and threats in analysis for strategic management (Luke et al., 2004). Porter's work focuses on the strategic positioning of organizations within an industry by aligning internal structures with the external environment to gain competitive advantage. For Porter, "the key aspect of the firm's environment is the industry or industries in which it competes" (Porter, 1980, p. 3). Understanding the industry structure helps organizations identify mobility barriers within the industry that may limit the strategic opportunities available to an organization, while allowing it to use competitive advantages in pursuit of better outcomes. Hunt (1972) and Porter's (1979) work is the foundation of strategic group modeling to explain differences in organizational performance within an industry. Porter (1980) and Miles and Snow (1978) developed generic typologies of strategic orientation that they argue apply to all industries.

SMT draws from multiple theories and perspectives to explain why some organizations succeed and others fail. Some scholars think a wide range of perspectives gives SMT flexibility and allows for greater insights into the complexities of strategic management (Boyd et al., 2012;

Shay, 2014). However, a recurring criticism of SMT is that it lacks a clear theoretical foundation and is difficult to define (Shay, 2014; Linhart, 2020).

Kimberly and Zajac (1985) attribute an increasing use of SMT in health care studies to the changing environment of the mid-1970s that necessitated strategic adaptation for health care organizations facing resource constraints not previously encountered. Scholars have used SMT as the theoretical basis for many health care studies. A number have been focused on hospitals (Linhart, 2020; Luke & Begun, 1988; Mick, Morlock, Salkever, & de Lissovoy, 1993; Shay, 2014; Trinh & O'Connor, 2000, 2002; Zajac & Shortell, 1989), and the nursing home studies reviewed in Chapter 2 are also based on SMT (Castle, 2003; Marlin, Huonker, & Sun, 2002; Zinn, Aaronson, & Rosko, 1994).

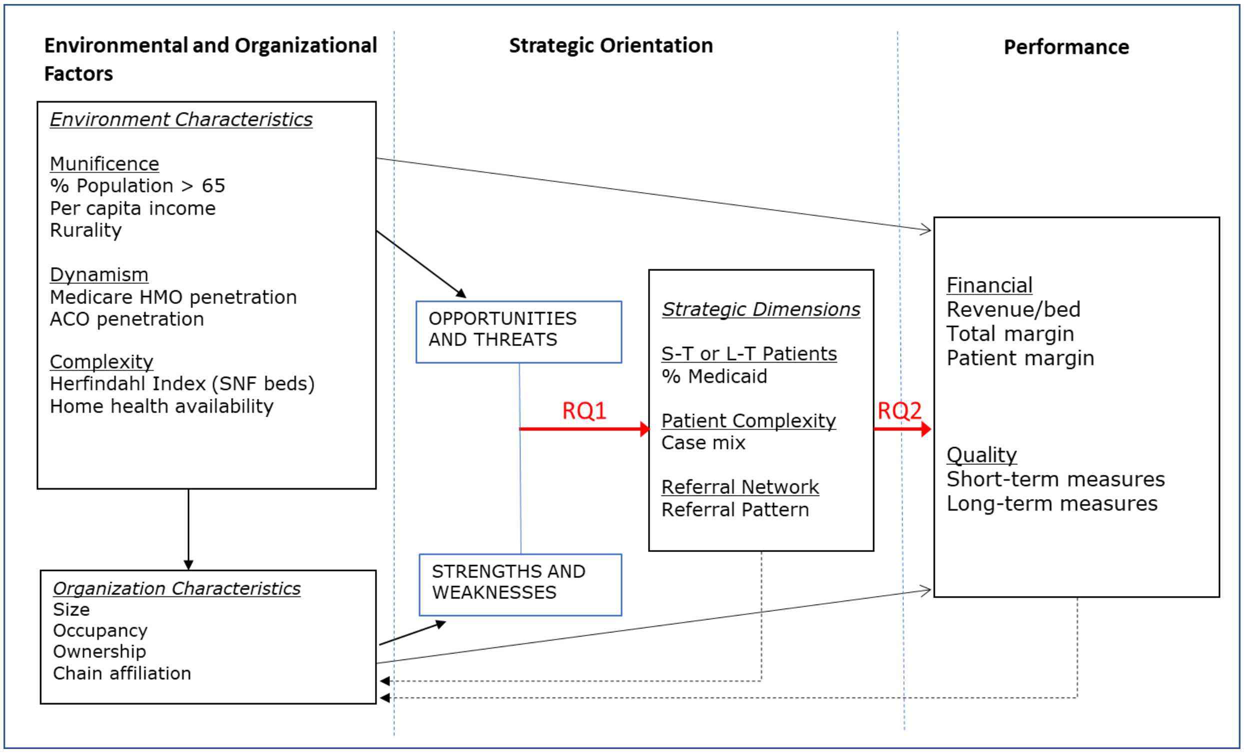
Conceptual Framework

The purpose of this study is to better understand the strategic behavior of SNFs facing environmental uncertainty by: 1) identifying groups of SNFs using similar strategies, 2) testing whether performance is associated with membership in a particular strategy group, and 3) assessing how the composition of strategic groups changes over time.

The conceptual framework proposed for the current study closely follows the process of strategic adaptation assumed in SMT. Examples of a conceptual framework based on strategic adaptation are present in multiple studies. Zajac, Kraatz, and Bresser (2000) provide a model of strategic adaptation of US Savings and Loan institutions. In their study of dynamic strategic fit and performance, they find support for hypotheses that variation in environmental and organizational contingencies leads to variation in strategic change, resulting in strategic fit or misfit and influencing organizational performance. Trinh and O'Connor's (2000; 2002) studies of rural and urban hospitals examining whether strategic change influences financial performance employ a similar conceptual framework. Their research questions address the influence of environmental and organizational characteristics on hospitals' strategic behavior and performance and whether specific strategies are related to changes in performance. The authors attribute their conceptual framework to SMT, and the framework models the process depicted in Zajac et al. (2000): namely, that managers react to environmental changes with specific strategies that lead to performance changes. Whether change in performance is better or worse depends on whether the strategic changes increase fit with external pressures imposed on the organization or the strategic changes result in misfit.

Figure 1 presents a visual representation of this study's conceptual framework. The overarching flow of the framework follows the pattern of strategic adaptation: environmental and organizational factors lead to the development of the strategic orientation of an organization and both strategy and structure exert influence on organizational performance. However, there are some additions to the framework for this study and the earlier studies just described. First, managers identifying external opportunities and threats, as well as internal strengths and weaknesses, is explicitly acknowledged as part of the strategic process. Second, strategies are conceptualized as dimensions of strategic orientation. The focus on strategic dimensions facilitates modeling of strategic groups. These additions, including opportunities, threats, strengths, and weakness, and dimensions of strategic orientation, support developing propositions and hypotheses to address this study's research questions. Starting on the left side of the conceptual framework in Figure 1, a description of the theoretical foundation of the conceptual flow of strategic adaptation in the nursing home industry follows.

Figure 1. *Conceptual framework of SNF strategic orientation and performance*



Environmental and Organizational Factors.

Environmental factors influence all aspects of strategic adaptation: the development of strategies, the structure of the organization, and performance. The influence of external environmental factors is represented by direct paths from environmental factors to organizational characteristics, opportunities and threats informing strategic behaviors, and performance.

As discussed in Chapter 1 of this study, SNFs have faced environmental uncertainty stemming from changes in reimbursement and health care policies, market forces, and demographics. Most legislative changes have applied to all SNFs equally, however local environmental factors are likely to vary with geographic and market location. The environment is conceptualized in terms of munificence, dynamism, and complexity (Pfeffer & Salancik, 2003). For SNFs, the munificence of the environment is characterized by the percentage of the population that may need its services, the wealth of the population, and the rurality of its location. Changing demographics with an increase in the population over sixty-five years of age points toward an increase in demand for services. Per capita income of a locality is an indication of the availability of patients anticipated to be low or high margin patients. The level of rurality of the location of a SNF is an indicator of the density of potential patients in the area and the ability to find staff to provide complex care. Dynamism in the market is characterized by the change in penetration of managed care in the form of Medicare HMOs. The level of penetration of Medicare ACOs, newer models of care for nursing homes, is used due to data limitations. Greater levels of managed care may create pressure to reduce lengths of stay for Medicare patients. Complexity in the environment is characterized by competition in the area among SNFs and for substitute care provided by home health services. Environmental factors represent opportunities and threats managers must recognize and assess when making strategic decisions.

A direct link between environmental characteristics and organization characteristics acknowledges that organizations may choose to organize differently under different environmental conditions to ensure their success. In the US, there are almost 15,000 SNFs and their organizational forms vary widely. SNFs are often characterized by form of ownership, chain affiliation, and size in terms of number of beds. Rate of occupancy provides an indicator of the ability of a facility to respond to market demands (Marlin, Sun, & Huonker, 1999; Zinn et al., 1994). Organizational characteristics represent strengths and weaknesses managers must assess when making strategic decisions.

Strategic Orientation.

SMT, while recognizing the importance of environmental factors, emphasizes that it is the ability of managers to align opportunities and threats in the environment with strengths and weaknesses of the organization with sound strategies that lead to performance outcomes.

Managerial actions and reactions to opportunities and threats taking into consideration their organizational strengths and weaknesses lead directly to the formulation of strategies. SMT provides an important prediction about strategic orientation in the conceptual framework. SMT predicts there is variation in strategic orientation contingent on differences in environmental and organizational factors, tasks, and managerial decision making in terms of key decision variables (Porter, 1979). This prediction of variation of strategies facilitates the importance of strategic group modeling of SNFs to better understand strategic behavior within the industry. The implication is that there is variation in strategic adaptation, but some SNFs may face environmental constraints or industry mobility barriers that limit strategies available to them. Research question one (RQ1) seeks to identify the existence of distinct strategy groups of SNFs, and dimensions for classifying SNFs are discussed in detail in a later section of this chapter. The process of strategic adaption may require or result in changes in organizational structures. This is depicted in the conceptual model as a feedback loop from SNF strategic dimensions to organizational characteristics reflecting “that major changes in strategy will be accompanied by changes in structure” (Kimberly & Zajac, 1985, p 284).

Performance.

A premise of strategic group modeling is the link between the structure of an industry and profits within an industry. While there are some industrywide structural traits, such as market growth or regulations, that affect profitability across firms in an industry, “profitability of the individual firm will depend on the structure with the industry” (Porter, 1979, p.215). The structure of the industry depends on the number of strategies firms take to address key decision variables. For nursing homes, patient care is their primary business and patients are a key resource. Obtaining and maintaining a source of patient referrals for nursing home care is crucial to the survival of SNFs. Qualitative studies reviewed in Chapter 2 suggest that the greatest opportunities for SNFs to improve financial performance is to maximize the number of short-term patient referrals having less complex care needs (Lawrence et al., 2018; Shield et al., 2018).

SMT bridges environmental factors and performance by emphasizing that managerial decisions affect performance as “managers have discretion in choosing and implementing strategies to match environmental demands in ways that enhance organizational performance” (Zinn et al., 2007, p. 1202). SMT expects that there will be variation in organizational structures and strategies adopted by managers in response to external pressures to ensure survival and strive for better strategic fit. A feedback loop from performance to organizational characteristics represents the ongoing strategic adaptation process. When the fit between strategy and performance deteriorates, managers make adaptations to structures and strategies to regain fit and better performance.

There is evidence of SNFs adapting strategically to environmental changes. Zinn and colleagues (2007) find support for strategic adaptation by SNFs to diversify services in response to environmental changes increasing the acuity of patients. Their research indicates that SNFs adjusted strategy and structure and achieved a better fit with environmental pressures, leading to improved performance. Park, Konetzka, and Warner (2011) likewise find that nursing homes responding strategically to public reporting of quality of care is associated with better financial performance outcomes. Research question two (RQ2) addresses whether strategic groups of SNFs differ in financial and quality performance measures.

The conceptual framework for this study is designed to follow the flow of strategic adaptation with theoretical underpinning informed by SMT. Environmental and organizational factors recognized by organizational leaders as external opportunities or threats and internal strengths or weaknesses facilitate strategic decision making that affect organizational performance. Moreover, this is an ongoing process as changes in the environment occur. This section of the chapter discussed the logical flow of the conceptual framework. In the next section of the chapter, propositions and hypotheses derived from the framework are presented.

Propositions and Hypotheses

RQ1: Strategic Dimensions for Classification of SNFs.

The conceptual framework is used to derive a single proposition and hypothesis concerning the typology of strategic groups among SNFs. SMT prioritizes managerial choices in determining the strategies organizations employ to adapt to environmental forces. Organizations operating in the same industry can strategically choose to pursue different markets depending upon where managers identify opportunities in the environment and how they choose to position their organization's strengths (Porter, 1980). Therefore, SNFs adapt strategies to align their internal strengths and weaknesses with environmental opportunities and threats to gain competitive advantage. However, mobility barriers may restrict strategic adaptation within the industry due to organizational characteristics and environmental constraints resulting in a finite number of strategies available to SNFs. For example, SNFs that desire to increase the number of post-acute care Medicare patients may be restricted by the number of short-term beds available in their facility. An investment of resources and time would be needed to have access to more highly trained staff (Wagner et al., 2020), adapt physical space to short-stay patients, and develop referral relationships to increase the number of short-stay beds. Moreover, SNFs in rural areas are likely constrained in the number of hospital referral relationships that can be cultivated and access to highly trained staff. The result is that although there is variation in the strategies that SNFs pursue as predicted by SMT, there may be a limited number of strategies available to SNFs given environmental and organizational constraints that constitute mobility barriers.

As discussed in Chapter 2, classifying organizations into groups of similar strategic orientation provides a more refined view of an industry than looking at the entire industry. When performing strategic group modeling, strategy groups should be classified using dimensions that are relevant to a particular industry (Cool & Schendel, 1988), and the number of strategy groups depends on the number of unique strategies within an industry (Marlin et al., 1999). Using this logic, this study takes an inductive approach, allowing the number of strategic groups to emerge from the analysis, like the approach taken by Zinn et al. (1994) and by Marlin et al. (1999).

Zinn et al. (1994) and Marlin et al. (1999) classify SNFs along dimensions of scope of business and resource deployment. Both studies base their selection of dimensions on Cool and Schendel's (1988) use of scope of business and resource deployment in classifying strategy groups in the US pharmaceutical industry. However, this study uses only dimensions of scope of business to classify SNFs. Marlin et el. (1999) make the point that "scope and resource deployment decisions…are more or less consistent with one another" (p. 158). Following that reasoning, this study assumes that resources are used to support scope of business strategies and resource commitments are not considered separately in this analysis.

Moreover, the dimensions of scope of business as defined by Cool and Schendel (1988) align with the strategies some SNFs are using to obtain a key resource for nursing homes: patient admissions. The qualitative work of Shield and colleagues (2018) and Lawrence and colleagues (2018) identify the strategic priorities of SNFs when seeking admissions as: 1) expected length of stay, 2) patient complexity, and 3) strength of referral networks. These strategies align with Cool and Schendel's (1988) description of scope of business decisions: 1) range of market segments targeted (short-stay care versus long-stay care), 2) types of services offered in the selected market segment (complexity of care), and 3) the geographic reach or scope of product-market strategy (strength of relationships with referring hospitals), respectively. The rationale for using scope of business dimensions as strategic dimensions for classification of SNFs is summarized in Table 3.

Table 3. *Strategic dimensions for classification of SNFs*

Scope of Business (Cool and Schendel, 1987)	**Dimension for classification of SNFs**	**Rationale**
1. Range of market segments targeted	Short-Stay Care versus Long-Stay Care	Short-stay care is usually post-acute care and more profitable than long-stay custodial care. SNFs may decide to seek admissions from either segment of patients. **Mobility barriers:** greater resources for short-stay care; higher quality rankings to attract short-stay care referrals
2. Types of products and/or services offered in the market segments selected	Patient Complexity	The complexity of patients varies along with comorbidities, cognitive ability, and psychosocial challenges. SNFs may seek patients that maximize revenue but not costs. **Mobility barriers:** greater resources for more complex patients
3. Geographic reach or scope of product-market strategy	Referral Network	Concentration of referrals indicates scope of market. Patient choice of SNFs is usually based on location. SNFs may benefit by gaining admissions through a stronger hospital relationship, or through relationships with a greater number of hospitals. **Mobility barriers:** geographic restrictions; resources for hospital relationship; quality rankings may limit partnerships

The first dimension, proportion of short-stay care versus long-stay care patients, is indicative of the payer mix within a SNF. Short-stay and long-stay care are the primary market segments in nursing home care. Short-stay care is usually post-acute care paid for by Medicare and is more profitable than providing long-stay custodial care which is most often paid for by Medicaid (Mor, Zinn, Angelelli, Teno, & Miller, 2004). However, caring for post-acute patients requires more resources and structural adaptation in terms of staffing and equipment than caring for long-stay patients, which may create mobility barriers for SNFs seeking to acquire more post-acute patients (Tyler et al., 2013; Wagner et al., 2020). Zinn et al. (1994) consider the ratio of source of payment (from Medicaid, Medicare, or private payers) to be the most important differentiator of market segments among nursing homes. Quality rankings may also affect the ability of SNFs to attract patient referrals (McHugh et al., 2017).

The second dimension, patient complexity, varies with comorbidities, cognitive ability, and psychosocial challenges. More complex patients can increase revenues, but may consume more resources resulting in lower profits (Goldfeld, Stevenson, Hamel, & Mitchell, 2011; Hurd, Martorell, Delavande, Mullen, & Langa, 2013; Kelley, McGarry, Gorges, & Skinner, 2015). Services provided by nursing homes can differ in complexity for both short-stay and long-stay patients. Some SNFs offer specialized care for complex patients such as memory care units, while others may actively screen to avoid complex patients. Resources, such as increased staffing or secured units, required to provide care to more complex patients (Eskildsen & Price, 2009) may present mobility barriers to SNFs seeking to offer these types of services in the market.

The third dimension, strength of relationships with referring hospitals, indicates the scope of the market that SNFs are capturing. Referrals concentrated from one or two hospitals indicate a different scope and geographic concentration than SNFs receiving referrals from multiple hospitals. SNFs may receive more preferred referrals from hospitals with which they have a strong relationship (McHugh, Rapp, Mor, & Rahman, 2021), or they may be able to be more selective in their admissions if they are not dependent on one hospital, but instead receive referrals from multiple hospitals (Shield et al., 2018). SNFs may face different kinds of mobility barriers in the geographic scope of their market. SNFs seeking to expand referral relationships with hospitals may face limitations to the number of hospitals in their geographic area, whereas SNFs seeking to strengthen referral relationships may face having to achieve a level of quality required by hospitals for preferred referral partners.

Therefore, it is proposed:

<u>Proposition 1</u>: Classification of strategic groups of SNFs is based on dimensions of scope of business.

<u>Hypothesis 1</u>: There are differences among subsets of SNFs based on: 1) the proportion of long-stay care patients, 2) complexity of admitted patients, and 3) the strength of referral relationships with hospitals.

RQ2: Performance of Strategic Groups of SNFs.

The conceptual framework is used to derive one proposition and two hypotheses to explain variation in financial and quality performance measures. SMT posits that strategic management choices to align internal strengths and weaknesses with external opportunities and threats lead to better performance. Strategic group modeling of SNFs helps to distinguish strategies SNFs are using and may help explain different levels of performance among facilities. In accordance with the structure – performance link of strategic modeling, membership in a particular strategy group is expected to be associated with performance. Porter (1980) contends that firms operating in a segment of an industry with "high mobility barriers will have greater profit potential than those in groups with lower mobility barriers" (Porter, 1980, p. 134). Higher mobility barriers serve to limit competition, thus helping firms remain profitable in desirable market segments. For SNFs, membership in strategic groups based on the dimensions of length of stay of patient populations, patient complexity, and referral networks is expected to be associated with performance measures. Therefore,

Proposition 2: Membership in a specific strategic group of SNFs is associated with a SNF's performance.

As shown in the third section of the conceptual framework, performance, in this study, has two dimensions: financial and quality outcomes. Profitability is used as an indicator of financial performance. Patient outcomes are used as indicators of quality performance. A brief discussion of for-profit and non-profit organizations and the relationship of outcomes with form of ownership, along with the interplay of financial and quality performance follows. Then, each strategic dimension is considered in terms of its association with performance.

The expectations of financial and quality performance under different forms of ownership in health care settings vary. For-profit organizations are expected to seek to maximize their profitability, including for-profit health care providers (J. Clement, 2016). Traditional views of differences between for-profit and non-profit ownership status contributed to widely held assumptions that while for-profit firms seek to increase quantity until profits are maximized, non-profit firms may seek to increase quality for the intangible value of prestige in providing a service of high quality. However, non-profit firms may forsake quality and profits in order to provide services where there is unmet need for the public good (Newhouse, 1970).

Approximately 30% of nursing homes have non-profit ownership status. Research examining the relationship of financial performance and quality outcomes in nursing homes has found that generally non-profit nursing homes deliver higher quality than for-profit nursing homes (Comondore et al., 2009; Grabowski, Feng, Hirth, Rahman, & Mor, 2013; Hillmer, Wodchis, Gill, Anderson, & Rochon, 2005). However, some scholars suggest that profit and quality maximization is more nuanced in both for-profit and non-profit organizations. Werner, Konetzka, and Polsky (2016) find that demonstrating high quality scores on Nursing Home Compare was associated with nursing homes experiencing greater demand for their services than facilities with low quality scores. The implication is that for-profit organizations may focus on better quality in order to build referrals and increase revenue. This complements evidence that providing high quality care is associated with better financial performance (Park, Konetzka, & Werner, 2011; Weech-Maldonado, Pradhan, Dayama, Lord, & Gupta, 2019). Other scholars have explored the influence of spillover effects in the markets in which nursing homes operate. Grabowski and Hirth (2003) find evidence of better overall nursing home quality when there is an increase in the market share of non-profit nursing homes in a market. On the other hand, Bowblis, Brunt, and Grabowski (2016) find competitive spillovers in the form of upcoding patients into higher reimbursement categories by non-profit nursing homes when there is an increase in the market share of for-profit nursing homes in a market. The regulatory exploitation of reimbursement systems through upcoding results in greater revenue, an action consistent with maximizing profitability.

In sum, predicting the performance of for-profit and non-profit nursing homes may be more complex than assuming that for-profit firms seek to maximize profit and non-profit firms do not. Market and regulatory forces may apply pressures on for-profit nursing homes to increase quality in expectation of increased profit, or non-profit nursing homes may take profit-maximizing actions or, alternatively, may accommodate patients while forsaking quality. This study controls for ownership status, with an aim to explore the association of performance with membership in a particular strategic group, rather than for-profit status.

Strategic dimensions and financial performance.

The market segment served by SNFs reflects a difference that has a strong impact on revenues. Short stays in a SNF are usually for post-acute care that is reimbursed by Medicare or private payers. Long stays are most often funded by Medicaid and are reimbursed at a lower rate than Medicare or private payers reimburse. One source estimates that the overall average for Medicare per diem rate of $503 is more than double that of Medicaid (Weech-Maldonado, Pradhan, et al., 2019). SNFs that provide a higher proportion of care to short-stay Medicare patients are likely to have greater levels of revenues and profit than SNFs that have higher proportions of Medicaid residents (Weech-Maldonado, Lord, et al., 2019).

The types of services provided by SNFs are likely to vary in level of profitability. The relationship of providing more complex care to profitability is unclear. After the introduction of SNF PPS with case mix reimbursement in 1997, the proportion of intensive therapy days as a proportion of total days increased from 29% to 82% between 2002 and 2015 (Medicare Payment Advisory Commission, 2017). The utilization of inpatient rehabilitation facilities (IRFs) and long-term acute care hospitals (LTACHs) also increased during this time (Buntin et al., 2009). However, the qualitative studies reviewed in Chapter 2 indicate that most SNFs prefer patients with less complex needs to maximize profitability (Lawrence et al., 2018; Shield et al., 2018). Patient complexity may be a function of a need for more acute medical care or behavioral health care. For those SNFs that handle more complex patients, revenues may be higher, but profit margins may not necessarily be greater as complex patients have higher costs and staffing needs. On the other hand, the structural adaptation required to accommodate complex patients may serve to protect a lucrative segment of the market, providing a competitive advantage to SNFs with the necessary resources while preventing competitors from entering this market.

The scope of market for SNFs is defined geographically and by referral relationships with hospitals. For SNFs, obtaining referrals from hospitals is a means of controlling resources in a less restrictive manner than vertical integration with a hospital would require (Scott & Davis, 2007). SNFs may actively develop referral relationships with multiple area hospitals to obtain a greater number of referrals, if multiple hospitals are within their geographic proximity. Alternatively, SNFs may focus on referral relationships with one or a few hospitals. SNFs that have close ties with one or a few hospitals may have a steady stream of patient referrals, better access to information when screening patients from those hospitals, and may have access to better transition planning (Konetzka, Stuart, & Werner, 2018; Rahman, Gadbois, Tyler, & Mor, 2018). Shay and Mick (2013) propose that post-acute care providers with strong relationships with hospitals will be less likely to integrate vertically with hospitals post-ACA, relying instead on trusted relationships to navigate policy changes successfully. The qualitative literature reviewed in Chapter 2 corroborates the findings of studies that SNFs can demonstrate agency through their referral relationships with hospitals without vertical integration. Shield et al. (2018) find that "depending on the strength of their relationships, such as the volume of referrals SNFs have with area hospitals, SNFs use different strategies both for screening *out* potential admissions considered less preferable" if there is a strong relationship, or for "casting a wide net to *attract* as many admissions as possible" (p.490) if there are not strong relationships with hospitals.

Given the variation that different levels of strategic dimensions of lengths of stay, patient complexity, and strength of referral networks may have on financial performance, it is hypothesized:

Hypothesis 2a: Membership in a specific strategic group of SNFs is associated with a SNF's *financial* performance.

Strategic dimensions and quality performance.

NHC reports separate quality indicators for short-stay and long-stay patients, reflecting the different focus of care for short-stay and long-stay segments of the market (Saliba, Weimer, Shi, & Mukamel, 2018). SNFs with lower rates of hospital readmission, a short-stay quality measure, may be more attractive referral partners for post-acute patients for hospitals, thus creating an incentive for SNFs to provide higher quality of care to obtain better fit with the new policies. Those SNFs that have higher quality performance have a competitive advantage in competing for short-stay patients. The growing proportion of short-stay post-acute patients in SNFs and the greater profitability of these patients raises the question of whether quality of care is being maintained among long-stay care patients. Findings in the literature are mixed. There is evidence that increasing the proportion of Medicare days in nursing homes, and thus revenues, improves quality of care for long-stay care patients in the same facility (Lepore & Leland, 2015). Another study finds that most long-stay quality measures are not improved with an increase in Medicare post-acute patients, but neither does quality decline (Gaudet Hefele, Wang, Bishop, & Barooah, 2019). Recent research suggests quality improvements that spill-over from short-stay to long-stay care patients may be limited to domains that span the two populations such as rates of influenza and pneumococcal vaccination (Wang & Hefele, 2021).

The relationship between quality outcomes and the types of services provided in terms of level of acuity of admitted patients is unclear. SNFs are likely to benefit from having high levels of quality measures by having a competitive advantage when seeking referrals. Shield et al. (2018) found that lower rated SNFs were often those accepting more complex patients as a way to compete for patient referrals. However, SNFs that admit a greater proportion of complex patients require more specialized staffing and greater differentiation of tasks. The resources required to care for complex patients may reduce resources used for quality improvement activities, serving to reinforce a lower level of quality.

The relationship between high quality performance and concentration of referral networks is expected to be positively related. Although SNFs can demonstrate agency in their SNF-hospital referral relationships, hospitals have incentives to create referral partnerships with SNFs offering high quality of care to short-stay post-acute care patients. Thirty-day hospital readmissions is a key quality indicator of short-stay care. As many as one in four Medicare beneficiaries discharged to a SNF in 2006 was readmitted to a hospital within thirty days (Mor et al., 2010). As hospitals began to prepare for HRRP, many started developing or expanding preferred networks of SNFs. Hospital readmission rates have been falling with the initiation of the HRRP program, and hospitals with formal networks of SNFs have experienced greater reductions in thirty-day readmissions rates than hospitals without preferred relationships with SNFs (McHugh et al., 2017). Some ACOs have also established networks of SNFs to broaden their continuum of care. The preferred networks are looking for SNFs that can help achieve better outcomes for short-stay and long-stay patients and have high overall quality ratings (Chang, Mainor, Colla, & Bynum, 2021; Huckfeldt, Weissblum, Escarce, Karaca-Mandic, & Sood, 2018). In contrast, there are indications that SNFs with lower quality ratings may take almost all types of referrals from hospitals in order to increase occupancy, suggesting that SNFs with lower quality rankings may have a less centralized referral network in order to maximize the number of patient admissions (Shield et al., 2018).

Given the variation that different levels of strategic dimensions of length of stay, patient complexity, and strength of referral networks may have on quality outcomes, it is hypothesized:

Hypothesis 2b: Membership in a specific strategic group of SNFs is associated with a SNF's *quality* performance.

RQ3: Changes in Strategic Groups of SNFs over Time

For research question three (RQ3), the conceptual framework is used to derive one proposition and two hypotheses to explain longitudinal differences in the composition of strategic groups. The current study is based upon a conceptual framework that closely follows the process of strategic adaptation. Organizational strategy is contingent on decisions made by management to address opportunities and threats in the environment. During times of environmental changes resulting in uncertainty, managers may change their strategies to obtain a better fit for the organization within the new environment. Strategic adaptation presumes organizations are continually making efforts to adapt to changes in the environment to achieve better fit between the organization structure and its environment helping to explain organizational change (Kimberly & Zajac, 1985). This ongoing process is illustrated in the conceptual framework as a feedback look from performance outcomes to strategy. This question does not assess the fit of SNFs within their specific environments, but rather attempts to better understand the association of strategy and outcomes (Drazin & Van de Ven, 1985).

Zajac and Shortell (1989) found evidence that health care organizations change their strategic orientation over time when faced with turbulent environmental conditions. They examined shifts among hospitals classified using the Miles and Snow (1978) typology from one group to another in response to the implementation of Medicare Prospective Payment over a two-year period. Bazzoli et al.'s (1999) classification of multi-hospital arrangements has been used to assess changes in structural dimensions in hospital-led health networks and systems from one time period to another (Bazzoli et al., 1999; Dubbs, Bazzoli, Shortell, & Kralovec, 2004; Shortell, Gottlieb, Martinez Camblor, & O'Malley, 2021).

As strategic adaption occurs, change in organizational structures "signals a change in the concentration mix in the industry and therefore represents a change in the structure of the industry as well as in the structure of individual corporate entities" (Kimberly & Zajac, 1985, p. 285). Though there have been studies that classify SNFs into strategic groups, there has not been a study of longitudinal changes in strategy groups of SNFs. Marlin et al. (1999) suggest structural changes in the nursing home industry may account for differences in their study and the Zinn et al. (1994) study and they call for research on the stability of strategy groups over time to gain a better understanding of unexplained differences.

SNFs have faced uncertainty since 2010 in the form of policy changes, growth of enrollment in managed care, increasing use of nursing home substitutes, and changing demographics. SNF managers may make strategic changes to achieve a better fit with a changing environment. Specifically, evidence suggests they may seek to admit preferred patients that are expected to be short-stay care, less medically complex, and develop a narrower referral network as discussed in the development of prior hypotheses. In turn, the structure of the nursing home industry may change. Therefore, it is proposed:

<u>Proposition 3</u>: The composition of the strategic groups changes over time.

<u>Hypothesis 3a:</u> The composition of the strategic groups changes over time.

The process of strategic adaptation occurs to gain better strategic fit between an organization and its environment. A better fit between an organizational strategy and structure with the environment is expected to result in better performance (Donaldson, 2001, 2006; Zajac et al., 2000). Mobility barriers within an industry are believed to restrict movement from one strategy group to another, but if an organization is able to overcome mobility barriers, it may achieve better financial performance if changes result in a better strategic fit with its environment (Porter, 1979, 1980). Although there may be limited strategic choices in the nursing home industry, SNFs are likely to attempt to adapt their strategies to compete in a more profitable part of the industry for better performance, and for viability (Marlin et al., 1999). Thus, it is proposed:

Hypothesis 3b: Shifting from one strategy group to another strategy group is associated with a subsequent positive change in performance.

Summary

A conceptual framework was developed using SMT to explain the existence of strategic groups and their association with performance outcomes. The conceptual framework was used to derive three propositions and five corresponding hypotheses to address the three research questions with the objective of better understanding the strategic orientation of SNFs during environmental changes. The next chapter presents the research methods used to operationalize the conceptual framework and test the hypotheses developed in this chapter.

Chapter 4: Methods

This chapter presents the research methods used to address the study's aims and research questions of better understanding the strategic behavior of SNFs, assessing whether membership in a particular strategy group is associated with performance outcomes, and evaluating whether the structure of the industry changes over time. The first section describes the research design of the study. Subsequent sections discuss data sources, the study sample, variable measurement, and the analytical methodologies used to address the study's research questions. The final sections describe sensitivity analyses and provide a summary.

Research Design

The study is retrospective and observational in nature. To address the study's first aim of classifying SNFs into groups based on strategic orientation, a descriptive study design is deployed. The proposition and hypothesis derived from the conceptual framework for RQ1 is tested using cross-sectional data for one year (2015), applying cluster analysis methods and validation techniques, and profiling a taxonomy of SNFs.

The study's second aim of examining whether performance outcomes are associated with strategic orientation is tested in two ways. First, a descriptive analysis is conducted using ANOVA and post-hoc tests for differences in performance measures between groups. Then, multivariate models are estimated to test the proposition and two hypotheses previously presented for RQ2 using cross-sectional data for one year (2015).

The study's third aim is to evaluate whether SNFs changed strategic orientation during a time of environmental uncertainty. A longitudinal analysis of differences in the composition of strategic groups is used to test the proposition and two hypotheses previously presented for RQ3. First, discriminant analysis results from the classification of strategic group clusters addressing RQ1 is applied to 2012 to identify any shifts in the composition of strategic groups over time. Then, differences in performance from 2012 to 2015 are compared for any SNFs that changed strategic groups to those that did not change strategic groups. The most recent year, 2015, is chosen as the base year for comparison of strategic group membership as 2015 is the cross-sectional year of study for RQ1 and RQ2.

The unit of measure for the study is at the SNF level. A balanced panel is used to compare the same facilities over time and to control for omitted variables that include time-invariant effects. Analyses are conducted in Stata version 14.2 and SPSS version 27.

Data Sources

Administrative data are merged from multiple sources to obtain measures of SNFs' organizational characteristics, financial and quality performance, and environmental factors. The three primary data sources are the Long-Term Care Focus database (LTCF) maintained by Brown University, Healthcare Cost Report Information System (HCRIS) reports for SNFs and Nursing Home Compare (NHC) data from CMS, and Leavitt Partners' Torch Insight database.

The first primary data source, the LTCF database, is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health. The dataset is provided upon request to researchers and intended to facilitate understanding of how the long-term care system is organized, financed, and delivered. The LTCF dataset contains data on resident and facility characteristics aggregated from multiple sources including the MDS (Medicare's Minimum Data Set) and OSCAR/CASPER (Online Survey Certification and Reporting/Certification and Survey Provider Enhanced Reporting systems), Medicare claims files, CMS's NHC, and the Area Health Resource Files (AHRF). A brief overview of the data sources used to compile the LTCF dataset follows.

The MDS is based on clinical assessments of nursing home residents at admission, and then quarterly, annually, when there is a significant change in patient status, and at discharge. The assessment helps nursing home staff identify health problems by documenting comorbidities, physical, psychological, and psychosocial functioning along with any treatments or therapies the patient is receiving. Medicare or Medicaid certified nursing homes are required to conduct the assessment for all residents, and CMS maintains the national MDS database (CMS, 2012). The LTCF dataset contains selected resident level measures from the MDS aggregated at the facility level.

CMS requires surveys of Medicare or Medicaid certified nursing facilities at least once every 15 months through the OSCAR/CASPER system. The CASPER system replaced OSCAR in 2012. On behalf of CMS, states conduct inspections of laboratories, acute and continuing care providers, including hospitals, nursing homes, home health agencies (HHAs), end-stage renal disease (ESRD) facilities, hospices, and other facilities serving Medicare and Medicaid beneficiaries (CMS, 2018). For nursing homes, data is collected on organizational characteristics, staffing, any quality deficiencies found during the inspection, and aggregate resident characteristics ("Long-term Care: Facts on Care in the US," 2017).

In addition to the MDS and CASPER datasets, the LTCF project uses Medicare enrollment and Medicare claims data to track individual residents for calculating re-hospitalization rates. Rates of readmissions are based upon an entire year's worth of claims data, whereas most other variables are based on data collected at a particular point in time. Some of the other quality measures included in LTCF come from NHC. The LTCF project uses AHRF data for providing county level measures of health professionals and facilities, and state policy indicators are available at the state level.

The second primary data source for this study are cost reports submitted to CMS and maintained in the Healthcare Cost Report Information System (HCRIS). CMS requires institutional providers certified by Medicare to submit an annual cost report including facility characteristics, utilization data, cost and charges by cost center, and financial statement data (CMS, 2019). HCRIS reports for SNFs by fiscal year are available from CMS as public use files.

The third primary data source is data from NHC for selected quality measures. CMS compiles and publicly reports on quality measures and deficiency citations for Medicare and Medicaid certified nursing homes. Public use files of NHC data are available from CMS. Data representing a snapshot from the second quarter of each year is used as it most closely coincides with some of LTCF prevalence measures from the first Thursday of each April.

The fourth primary data source for this study is Leavitt Partners' Torch Insight database. Torch Insight is a proprietary database that integrates over 2,000 data elements from multiple proprietary and public data sources to provide information about the context of local healthcare markets. Data metrics include ACO and value-based payments, claims, payers, health systems, hospitals, provider groups, physicians, health insurance marketplaces, healthcare facilities, and key market and demographic information (Leavitt Partners, n.d.). Two data elements from Torch Insight were provided upon request by Leavitt Partners: 1) referrals between hospitals and other healthcare facilities based on Medicare claims data aggregated to the facility level, and 2) the rate of ACO penetration at the county level. The referral data from Torch Insight provides a novel way of measuring a SNF's referral network. Referral data from hospitals to SNFs is used to construct a measure of referral concentration from hospitals to SNFs that is used as a dimension for classifying SNFs. There are limitations to the referral data. The Torch Insight data only includes Medicare fee-for-service beneficiaries, and if the number of referrals from a hospital to a SNF is less than eleven in a year, the relationship is excluded to conform with CMS reporting requirements. ACO penetration also includes only Medicare fee-for-service beneficiaries.

Additional data sources used in the study provide measures of environmental factors. The Area Health Resource Files (AHRF) available from the Health Resources and Services Administration (HRSA) are an aggregation of over 50 data sources and provide many data elements at the county level including information about health care professions, health facilities, population characteristics, and hospital utilization. The study uses Rural-Urban Commuting Area Codes (RUCA) maintained by the United States Department of Agriculture for a more refined measure of rurality. These codes use measures of population density, urbanization, and daily commuting to classify census tracts into ten primary levels of metropolitan, micropolitan, small town, and rural areas. The RUCA data is provided at the zip code level and rolled up to four levels of rurality: urban, suburban, large rural town, and rural.

The dataset is created by merging annual data from LTCF with annual HCRIS files for each of four years from 2012 until 2015 by the SNF's Medicare Provider Identification number. HCRIS records with fiscal years not corresponding with a calendar year are assigned to a year based on the year containing the majority days of the fiscal year. Using this method, approximately 2% of HCRIS records are assigned to a calendar year differing from their fiscal year. Linked records are merged with Torch Insight data and NHC data by the SNF's Medicare

Provider Identification number. AHRF data are merged by the SNF's County Federal Information Processing Standard (FIPS) code, and RUCA data is merged by a SNF's zip code.

Study Sample

The study sample is limited to freestanding, Medicare-certified SNFs reporting Medicare Cost Reports from 2012 to 2015 (n=56,617). This sample does not include hospital-based SNFs, which have different cost structures than freestanding SNFs and are not required to submit SNF HCRIS reports. Consequently, 3,483 observations for 950 hospital-based SNFs were removed from the LTCF data prior to merging with HCRIS data.

Table 4 describes the stepwise process of removal of observations across all study years resulting from the merging of data sources and application of exclusion criteria. HCRIS and LTCF observations are merged by the SNF's Medicare Provider Identification number and calendar year. SNFs report financial data to HCRIS for their fiscal year. Approximately 98.4% of the HCRIS observations were successfully matched with corresponding LTCF data.

The sample is then merged with data from Torch Insight, RUCA, AHRF, and NHC. The measure of referral concentration (centrality) from Torch Insight's referral data is constructed prior to merging with the data sample of SNFs. The next section contains details of how the referral concentration (centrality) variable is constructed. Medicare Provider Identification numbers are used to merge the Torch Insight referral measure with the sample, and approximately 70% of the observations are successfully merged. AHRF data are merged with the sample by FIPS code and RUCA data are merged by zip code with only 89 unmatched observations. NHC data are merged by Medicare Provider Identification number with only 18 unmatched observations.

The single largest loss of observations, approximately 30%, result from merging the Torch Insight referral concentration variable into the sample. Although using Torch Insight referral data results in a significant reduction of observations, this measure is crucial to operationalizing a classification dimension of the cluster analysis. SNF observations unmatched to Torch Insight referral data are examined separately to identify differences in this group of SNFs and the final sample of SNFs.

After merging the datasets, additional steps are taken to increase the homogeneity of the study sample including applying exclusion criteria and reviewing variables for missing or invalid values. SNFs identified as government-owned facilities, specialty centers, and facilities with less than ten beds are excluded because forces shaping their market behaviors are likely to differ from other SNFs. The validity of the remaining observations is then evaluated. Facilities with fewer than 360 days of financial data reported on the HCRIS reports are excluded. Observations with missing variables are excluded, and those with an average case mix index greater than 3.0. Finally, financial measures are calculated, and observations with the lowest and highest one percent values of the measures of financial performance are trimmed as a step to remove outliers (Coomer, Ingber, Coots, & Morley, 2017). Overall, 10,604 observations are excluded from the sample due to sample criteria or missing or inconsistent values. The sample was then balanced across the four years resulting in a final sample of 18,156 observations representing 4,539 SNFs per year. Tests of RQ1 and RQ2 are conducted using 2015 data. RQ3 tests utilize data from 2012 and 2015.

Table 4. *Stepwise removal process of study observations across all study years*

	2012	2013	2014	2015	Total
Merging of data sources					
HCRIS by assigned year	14,117	14,163	14,202	14,135	56,617
LTCF Unmatched	115	150	265	381	911
Torch Insight Unmatched	4,164	4,271	4,340	4,405	17,180
RUCA Unmatched	25	23	22	19	89
AHRF Unmatched	0	0	0	0	0
NHC Unmatched	6	6	4	2	18
Successfully merged	9,807	9,713	9,571	9,328	38,419
Exclusions					
Sample criteria					
Govt - Owned	401	378	372	397	1,548
Specialty	4	4	6	6	20
Less than 10 beds	10	9	6	9	34
Missing/inconsistent values					
Fewer than 360 days of data	355	359	423	509	1,646
Missing/Inconsistent Values	59	76	123	103	361
Missing Adjusted Readmissions	158	128	95	78	459
Missing % Pressure Ulcers	603	559	528	542	2,232
Missing % UTIs	606	685	626	653	2,570
Trim patient margin	157	149	146	138	590
Trim total margin	163	164	124	127	578
Trim Net Patient Revenue per Bed	166	134	131	135	566
Observations excluded	2,682	2,645	2,580	2,697	10,604
Sample prior to balancing	7,125	7,068	6,991	6,631	27,815
Unbalanced observations	2,586	2,529	2,452	2,092	9,659
Final Sample	4,539	4,539	4,539	4,539	18,156

Variable Measurement

This section presents how the hypotheses developed in Chapter 3 are operationalized into variable measures for conducting descriptive analyses and inferential testing.

RQ1 and RQ3: cluster dimensions.

RQ1 examines whether a taxonomy of groups exists among SNFs based on their strategic orientation, corresponding to Hypothesis 1. The conceptual framework of the study predicts that clusters of SNFs exist based upon dimensions of their scope of business. Informed through qualitative studies, dimensions of scope of business are identified as: 1) short-stay care versus long-stay care, 2) complexity of care, and 3) strength of relationships with referring hospitals. Dimension variables are summarized in Table 5 and operationalized as follows.

Table 5. *Description of variables*

Construct	**Variable**	**Measurement**	**Source**
RQ1 and RQ3			
Cluster Dimensions			
Short-stay versus Long-stay Care	% Medicaid	Continuous variable; Proportion of facility residents whose primary support is Medicaid.	LTCF
Patient Complexity	Case Mix Index for New Admissions	Continuous variable; The average Resource Utilization Group Nursing Case Mix Index (a measure of the relative intensity of care of different nursing home populations) for new admissions.	LTCF
Referral Network	Referral Concentration	Continuous variable; An HHI calculation of referral concentration. A low ratio indicates a wider referral network, whereas a higher value indicates a narrower network. See discussion below for more details.	Constructed from Torch Insight data
RQ2			
Environmental Characteristics			
	% Population > 65	Continuous variable; Population > 65 divided by Total Population in the county.	AHRF
	Per capita income (000s)	Continuous variable; Per capita income in the county.	AHRF
	Rurality	Categorical variable to indicate Urban, Suburban, Large Rural Town, or Rural. Rural Urban Commuting Area (RUCA) Code assigned based on the zip code in which the SNF is located.	RUCA
	% Change in Medicare HMO Penetration	Continuous variable; Percent change in Medicare Advantage penetration in county	AHRF
	ACO Penetration	Continuous variable; Percent of population covered by an ACO. Only available for 2015.	Torch Insight
	Herfindahl-Hirschman Index	Continuous variable; Constructed by summing the squared market share	LTCF

Construct	Variable	Measurement	Source
		of beds of each SNF in the county. Ranges between 0 (perfect competition) and 1 (no competition).	
	Home health availability / Population > 65 per 100,000	Continuous variable; Number of home health agencies in a county divided by Population > 65 multiplied by 100,000.	AHRF
Organizational Characteristics			
	Size	Continuous variable; Number of beds as reported on the annual OSCAR (imputed from previous year if missing or implausible).	LTCF
	Occupancy	Continuous variable; Number of occupied beds in facility divided by the total number of beds.	LTCF
	Ownership	Binary variable; Indicates whether or not the facility is for-profit.	LTCF
	Chain Affiliation	Binary variable; Indicates whether or not facility is part of a chain.	LTCF
Outcomes			
	Revenue/Bed	Continuous variable; Net patient revenue divided by total number of beds.	HCRIS/LTCF
	Total margin	Continuous variable; measured as ratio of net income to total revenue (net patient revenue plus total other income).	HCRIS
	Operating margin	Continuous variable; measured as ratio of net income from services to patients to net patient revenue.	HCRIS
	Hospital readmission rate	Continuous variable; All payer risk-adjusted readmission rates.	LTCF
	Prevalence of pressure ulcers	Continuous variable; Proportion of low-risk long-stay residents in the facility with pressure ulcers.	NHC
	Prevalence of urinary tract infections (UTIs)	Continuous variable; Proportion of facility residents with UTIs.	NHC

The first strategic dimension, short-stay care versus long-stay care, reflects the focus of a SNF's market segment. In nursing home care, market segments are generally delimited as short-stay care or long-stay care. Medicaid is typically the payer for long-term custodial residents, while short-term stays are the responsibility of Medicare and private payers. A measure of the proportion of residents whose primary support is Medicaid serves to approximate a SNF's pursuit of short-stay versus long-stay residents. This variable comes from the LTCF dataset and represents the proportion of facility residents whose primary support is Medicaid at the time of the annual CASPER survey. In this study, the proportion of Medicaid residents serves as a proxy estimate of the proportion of long-term custodial residents, indicating the inverse of Medicare and private payers.

The second strategic dimension, complexity of care, differentiates the types of services offered in the selected market segments. Nursing home care varies by level of complexity. A measure of the average CMI of patients at admission serves to approximate a SNF's pursuit of patients with lesser or greater health care needs. CMS approximates the complexity of care required by nursing home patients by applying a classification of Resource Utilization Groups (RUGs) to each patient as part of the MDS assessment upon admission. CMS uses the RUG classification for adjusting Medicare payments to reflect patient acuity. The RUG classification is converted into a Nursing Case Mix Index (NCMI) following CMS guidelines. LTCF provides the average NCMI for all residents admitted to a facility during the calendar year. Higher scores indicate a greater level of resident acuity, and thus the need for greater complexity of care.

The third strategic dimension, strength of relationships with referring hospitals, indicates the relational dynamics of the product-market strategy. A measure of referral concentration is constructed to approximate the flow of referrals from hospitals to a particular SNF. Leavitt Partners' Torch Insight database includes aggregated referrals from individual hospitals to individual SNFs. Referral patterns from hospitals to SNFs are measured as a concentration of discharges using a calculation similar to that of a Herfindahl-Hirschman Index (HHI) (Liao, Konetzka, & Werner, 2018). The variable of referral concentration is calculated by squaring the proportion of each hospital's referrals to a SNF and summing the shares across hospitals that have generated referrals for a SNF. The variable measures whether a SNF receives referrals from a wider network of hospitals or from a single hospital. For example, a value of 0.30 indicates that referrals are less concentrated and received from multiple hospitals, whereas a value of 1.00 indicates that all referrals of patients come from a single hospital.

This calculated measure of referral patterns has limitations. The data only includes Medicare fee-for-service beneficiaries, and if the number of referrals from a hospital to a SNF is less than eleven in a year, the relationship is excluded from reporting to conform with CMS reporting requirements. This restriction likely accounts for the unmatched records when merging Torch Insight referral data during the data sampling process. However, despite limitations in the underlying referral data, the construct of referral concentration provides a measure of geographic business scope that managers may strategically control through building relationships with hospitals.

The same measures of cluster dimensions are applied longitudinally to determine if the structure of the groups changed over time. RQ3 explores whether the strategic orientation of SNFs changed over time, corresponding to Hypotheses 3a and 3b.

RQ2: dependent and key independent variables.

RQ2 investigates whether strategic groups of SNFs differ in financial and quality outcomes, corresponding to Hypotheses 2a and 2b. This study uses three dependent variables to measure the construct of financial performance and three dependent variables to measure the construct of quality performance. Dependent variables are summarized in Table 5 and discussed in the next sections.

SNF Financial Performance. To test the association between strategic groups and performance outcomes, three different financial performance measures are used as dependent variables. The first dependent variable of financial performance is revenue per bed. Revenue per bed is measured as net patient revenue divided by the total number of beds in a facility. This measure provides an indication of whether there is sufficient revenue to meet the organization's mission and financial goals. The measure is calculated using HCRIS data for net patient revenue and LTCF data for total number of beds and adjusted to 2015 values using the annual consumer price index from the U.S. Bureau of Labor Statistics. The second dependent variable of financial performance is total margin. Total margin provides an indication of overall profitability (Weech-Maldonado et al., 2012). Total margin is measured as the ratio of net income to total revenue. Total revenue is net patient revenue plus total other income. The measure is calculated using HCRIS data. The third dependent variable of financial performance is operating margin. Operating margin removes non-operating revenue and provides a measure of the core business function (Weech-Maldonado et al., 2012). Operating margin is measured as the ratio of net income from services to patients to net patient revenue. The measure is calculated using HCRIS data. Each of these measures allows comparisons across facilities of different size.

SNF Quality Performance. To test the association between strategic groups and quality outcomes, three different quality measures are used as dependent variables. Because of the hypothesized differences in the proportions of short-stay and long-stay patients among strategic groups, one measure is an indicator of short-stay care and two are indicators of long-stay care.

Important considerations when choosing quality measures for study are salience, validity, and if using more than one measure, lack of correlation (Grabowski, Angelelli, & Mor, 2004). Since this study examines differences in outcomes associated with strategic group membership, variance across SNFs is a consideration. An additional aspect to consider when choosing performance measures is the dimension of quality being assessed. Donabedian's Quality of Care Model provides a framework for differentiating quality measures of health care in terms of structures (S), processes (P), and outcomes (O). Measures of structural quality refer to organizational attributes of the setting where the care occurs. Structure can include the physical structure as well as level of staffing. Process measures attempt to capture the process of care provided to a patient. Measures of outcomes assess the effects of care provision on a patient's health (Donabedian, 1966). Development and validation of nursing home quality indicators rely upon the SPO framework (Zimmerman et al., 1995), and researchers often use Donabedian's approach to quality measures to distinguish dimensions of quality in the nursing home setting (Castle & Ferguson, 2010; Wagner, McDonald, & Castle, 2012; Weech-Maldonado, Pradhan, et al., 2019). For this study, Donabedian's framework helps to guide selection of quality measures that reflect outcomes of care to align with RQ2 concerning the association between quality of care and membership in a strategic group. Based on these considerations, a measure of 30-day hospital readmission rates provides an indicator of the quality outcomes for short-stay care patients, while measures of prevalence of pressure ulcers and urinary tract infections (UTIs) provide measures of quality outcomes in long-stay residents.

The first dependent variable measuring quality performance is 30-day hospital readmission rates. Thirty-day readmission rates are considered a measure of quality for short-stay patients (McHugh et al., 2017). Thirty-day hospital readmission rates are currently the only measure used to evaluate the performance of SNFs in the VBP-SNF program. CMS reports considerable variation among 30-day readmission rates of SNFs with the best performing quartile of rates at or below 7.7% and the worst quartile of rates at or above 13.5% in 2016 (Medicare Payment Advisory Commission, 2018a). The readmission measure used in this study comes from the LTCF dataset and is the proportion of patients admitted to a SNF who were readmitted to a hospital directly from the SNF within 30 days of a hospital discharge. The measure is risk-adjusted and includes unplanned readmissions of all causes.

The second dependent variable measuring quality performance is the prevalence of pressure ulcers among low-risk, long-stay residents. The prevalence of pressure ulcers among nursing home residents has dropped since the early 2000s, however, there are concerns that there is racial disparity in the prevalence of pressure ulcers (Li, Yin, Cai, Temkin-Greener, & Mukamel, 2011). Additionally, an increasing rate of obesity among nursing home residents may increase the risk of pressure ulcers among residents (Cai, Rahman, & Intrator, 2013). Pressure ulcers contribute to increased morbidity, mortality, and costs of care for patients (Jaul, Barron, Rosenzweig, & Menczel, 2018; Li et al., 2011), but they are often preventable with appropriate interventions that require the coordination of care providers (Berlowitz, Bezerra, Brandeis, Kader, & Anderson, 2000). Some studies have found an improvement in the prevalence of pressure ulcers among long-stay patients associated with an increase in Medicare census (Gaudet Hefele et al., 2019; Lepore & Leland, 2015). These findings suggest that increasing focus on short-stay care, thus greater financial resources, may lead to gains in some measures of quality for long-stay patients. Grabowski, Angelelli, and Mor (2004) find improvement in prevalence of pressure ulcers to be associated with higher Medicaid reimbursements. These findings suggest there may be variation in the quality measures depending on profitability differences among strategic groups. More profitable strategy groups, or those with higher revenues, may have greater resources to dedicate to quality improvement activities (Lepore & Leland, 2015). The measure for the prevalence of pressure ulcers comes from CMS's NHC data reported for the second quarter of the year.

The third dependent variable measuring quality performance is the prevalence of UTIs as a measure of quality outcomes for long-stay patients. UTIs are an adverse outcome that can likely be prevented with specific assessment and surveillance activities by care providers. In addition to increased morbidity and costs of care, treatment of UTIs with antibiotics may contribute to colonization of multi-drug resistant bacteria (Nelson & Flynn, 2015). Prevention of UTIs is included as part of the quality domain of infection control in nursing homes. The measure for prevalence of UTIs in this study comes from CMS's NHC data reported for the second quarter of the year. Each quality measure is salient, validated, and there is minimal correlation between the three measures. The key independent variable of interest in RQ2 is the strategy group derived from RQ1.

RQ2: control variables.

In addition to the key explanatory variable of membership in a strategy group, performance of SNFs may be influenced by environmental and organizational factors. To control for confounding in the regression models in RQ2, seven control variables for environmental characteristics and four control variables for organizational characteristics are included in the model. Table 5 lists the variables for analyses, their measure descriptions, and data source.

Environmental factors are chosen to measure munificence, dynamism, and complexity in a SNF's environment. Munificence variables capture the demand for services and availability of resources. The percentage of the population over 65 years of age and per capita income at the county level from AHRF are included as continuous variables. An area with a greater proportion of individuals over 65 years of age is likely to have greater demand for SNF services than an area with a smaller proportion. Higher levels of per capita income are more likely to have Medicare or private pay patients than areas with lower levels of per capita income. Rurality is estimated as a categorical variable using the Rural Urban Commuting Area (RUCA) Code assigned based on the zip code in which the SNF is located. More urban areas are expected to be munificent in terms of patients and availability of staffing than are more rural areas (Yeager et al., 2014).

Dynamism in the environment is measured as an indication of change in the nursing home industry. A change in the level of managed care in the community provides an indication of fluctuation in payer requirements that may reduce utilization of SNF services or require participation in a preferred network for patient referrals. Dynamism is measured in two ways: the annual change in the proportion of Medicare beneficiaries participating in a Medicare HMO, and the level of Medicare ACO penetration in 2015. Medicare HMO penetration is from AHRF. ACO penetration is from Torch Insight and only available for 2015. Both are continuous variables measured at the county level.

Complexity in the environment represents environmental information required for managers to make strategic decisions (Menachemi, Mazurenko, Kazley, Diana, & Ford, 2012), and is often conceptualized as competition (Yeager et al., 2014). Complexity is operationalized in this study as two measures of competition. First, a Herfindahl-Hirschman Index (HHI) is constructed based on the number of SNF beds in the county using LTCF bed counts. An HHI is frequently used to measure competition in health care studies (Yeager et al., 2014), and is often based on the number of beds in a facility in the nursing home literature (Hirth et al., 2017). A continuous measure is calculated by summing the squared market share of beds of each SNF in the county, with a range from 0 indicating perfect competition and 1 indicating no competition. Second, the availability of home health is calculated as the number of home health agencies per 1000 of the population over 65 years of age. The number of home health agencies in a county and population over 65 years of age are continuous variables from AHRF.

Organizational characteristics included in the model are: size as measured by number of beds, occupancy rate, for-profit or non-profit ownership, and chain affiliation. Bed size and occupancy are continuous variables, and ownership and chain affiliation are binary. The organizational characteristic measures are from LTCF.

Analytic Approach

Descriptive/preliminary analysis.

Univariate profiles of individual variables and bivariate relationships are used to assess the quality of the data. The count, mean, standard deviation, minimum and maximum values of individual variables are examined to identify missing or outlying values. For nominal variables, the frequency of values is examined. Box plots and histograms are used to help identify extreme values and assess distributive properties of variables. Bivariate relationships of selected variables are examined through scatterplots and correlation to assess multicollinearity. Variables demonstrating skewed distribution are assessed for transformation to a normal distribution. The panel is rebalanced if observations with missing or outlying values are excluded, and excluded observations are profiled on selected characteristics.

RQ1: empirical model.

A taxonomic analysis is conducted to address whether a typology of groups exists among SNFs based on their strategic orientation. Cluster analysis is the method most commonly applied to classify strategic groups (Hair et al., 2006; Shay, 2014; Short, Payne, & Ketchen Jr, 2008). It is also the method used by Zinn, Aaronson, and Rosko (1994) and Marlin, Sun and Huonker (1999) to classify SNFs by strategic orientation. The objective of cluster analysis is to classify members into groups that maximize between-group differences while minimizing within-group differences.

Cluster analysis is a descriptive technique, and a test statistic does not exist for testing hypotheses. Critics have raised concerns that stem from “the extensive reliance on researcher judgment that is inherent in cluster analysis" (Ketchen & Shook, 1996, pg. 442). Aldenderfer and Blashfield (1984), Ketchen and Shook (1996), and Hair and colleagues (2006) identify critical issues faced by researchers conducting cluster analysis and offer suggestions for addressing the issues. The areas of concern and methods for addressing them in this study are discussed in the following sections.

Preparing variables for cluster analysis.

Selection of variables. There is wide agreement that the selection of clustering variables by researchers is fundamental to the analysis. Many scholars agree that basing the choice of variables in theory provides the best foundation to an analysis (Aldenderfer & Blashfield, 1984; Bazzoli et al., 1999; Shay, 2014). The selection of clustering dimensions and variables in this study are guided by the conceptual framework developed in Chapter 3.

Detecting Outliers. Identifying and eliminating outliers is important to a cluster analysis because of the sensitivity of most clustering algorithms to outliers. Univariate and bivariate procedures are used to detect outliers in the descriptive analysis. A multivariate assessment of outliers is conducted using a Mahalanobis D^2 calculation to measure each observation's distance from the mean of all observations. Observations with a D^2/df greater than 4 are reviewed as outliers as recommended by Hair et al (2006).

Standardization. Because cluster analysis seeks to maximize the distance between groups, variables with greater magnitudes of scale can have more impact on the final solution than variables measured in smaller scales. Standardizing variables in the cluster analysis gives each variable equal weight. Aldenderfer and Balshfield (1984) suggest the decision to standardize variables be made on a case-by-case basis. Ketchen and Shook (1996) propose conducting the analyses with and without standardized variables and comparing the results.

Each method can then be assessed to determine if there is inconsistency in the resulting clusters. This study is conducted with standardized variables and then a second analysis using non-standardized variables is conducted and assessed for reliability and validity. Z-scores are commonly used for standardizing variables and are applied to the clustering variables in this study.

Multicollinearity. In cluster analysis, multicollinearity effectively increases the weight of a particular construct represented by more than one variable. Multicollinearity must first be identified and then steps can be taken for correction. A correlation matrix can help identify high correlation between two variables. Some scholars conducting cluster analysis adhere to detecting multicollinearity between two or more variables using a variance inflation factor (VIF) (Hair et al., 2006; Shay, 2014). A VIF score is the inverse of variability not explained by the other independent variables. A VIF score above 10 is generally considered to indicate multicollinearity. Should multicollinearity exist, it can be corrected by removing a variable, using the Mahalanobis distance measure that standardizes and compensates for correlation, or conducting factor analysis (Ketchen & Shook, 1996). This study evaluates cluster variables for multicollinearity using VIF scores.

Clustering algorithm.

The clustering algorithm prescribes how observations are partitioned into clusters. Clustering algorithms are either hierarchical or nonhierarchical. Hierarchical algorithms create clusters of observations in a tree-like or hierarchical form by either agglomerating or dividing clusters. In contrast, nonhierarchical algorithms divide observations into an initial set of specified number of clusters and then allocate observations to clusters based on the nearest centroid (or center point).

An agglomerative hierarchical algorithm begins with assuming each observation is a separate cluster and then aggregates similar observations into larger clusters until there is only one group. There are five commonly used agglomerative hierarchical methods for distinguishing similar observations: single linkage, complete linkage, average linkage, centroid method, and Ward's method. Single linkage measures the closest pair of members; complete linkage measures the furthest pair of members; whereas average linkage compares the average of members in a cluster to determine dissimilarity with other clusters. The centroid method uses the central member of groups to determine distance. Ward's method combines clusters by minimizing the variance within clusters. In Ward's method "at each step, the two clusters combined are those that minimize the increase in the total sum of squares across all variables in all clusters" (Hair et al., 2006, p. 588; Ketchen & Shook, 1996; Shay, 2014).

A method for measuring distance, referred to as a similarity measure in a hierarchical cluster analysis, is required for comparison of clusters. The common measure of distance is Euclidean or straight-line distance. A squared Euclidean distance is derived as the sum of the squared distances and is recommended for Ward's method.

Each method has its own biases, and the choice of method depends upon the researchers' goals and knowledge of the dataset (Aldenderfer & Blashfield, 1984). Some known biases of cluster algorithms follow. The single linkage method is likely to result in less compact clusters that are not well delineated. The complete linkage method is biased towards outliers since it depends on the outer-most observations. The average linkage and centroid methods are less biased by outliers than the other methods. The centroid method requires interval or ratio scales and is often used in the physical sciences; it is not used in this study. Ward's method tends to produce clusters of the same size and can be unduly influenced by outliers (Hair et al., 2006; Ketchen & Shook, 1996; Shay, 2014).

Nonhierarchical algorithms are used for classification when the number of clusters is predetermined and is also referred to as *K*-means clustering. Nonhierarchical methods are less biased by outliers and effectively optimize homogeneity within clusters and heterogeneity between clusters. One option for conducting cluster analysis is to take a two-step combination of approaches by first conducting a hierarchical algorithm to determine the number of clusters and cluster centroids, and then conducting a nonhierarchical analysis using those centroids as starting points (Hair et al., 2006; Ketchen & Shook, 1996; Shay, 2014).

Ward's method and squared Euclidean distance are used as the primary clustering method in this study for identifying the number of clusters. Selecting an algorithm requires assessing known systemic tendencies and addressing possible drawbacks. Researchers have found Ward's method to be the most effective method for determining clusters that are unknown *a priori* (Alexander & Morrisey, 1989; Alexander et al., 1996; Shay, 2014; Short et al., 2008). Ward's method is popular among social science scholars and has been used in many studies classifying health care organizations (Bazzoli, Harless, & Chukmaitov, 2017; Bazzoli et al., 1999; Shay & Mick, 2017; Short et al., 2008), including the classification of SNFs (Marlin et al., 1999; Zinn et al., 1994). Following Shay's (2014) methods for comparing algorithms, simple classification agreement rates and Hubert-Arabie Adjusted Rand Index (ARI_{HA}) scores are used to help identify an optimal cluster solution. ARI_{HA} scores provide a way of comparing agreement among cluster solutions through an algorithm that counts pairs of observations similarly classified. Comparisons are scored between 0 and 1, with 1 indicating perfect agreement.

Determining number of clusters.

Determining the number of clusters in an analysis is a subjective process. Hair and colleagues (2006) provide several methods, known as *stopping rules*, for selecting the optimal solution and general rules of thumb for consideration. Stopping rules either measure change in heterogeneity between successive clusters, or directly measure heterogeneity between clusters. A change in heterogeneity between successive clusters can be detected by looking at the percentage increase in distance of cluster solutions, increases in change in variance across clusters, or statistical measures of heterogeneity change for comparison among solutions. An agglomeration coefficient provides a measure of the distances used to determine when a new cluster is formed. A commonly used method for identifying increased distance in cluster solutions is to look for sizable changes in the agglomeration coefficient. Large rates of change in agglomeration coefficients indicate new clusters. As the change in the agglomeration coefficient declines, the differences in clusters becomes smaller (Hair et al., 2006).

Generally, optimal cluster solutions eliminate extremely small clusters, and clusters are significantly different from one another. A dendrogram is a visual representation of the hierarchical tree of clusters and provides a means of visually assessing the solutions. Ketchen and Shook (1996) recommend using multiple methods to determine the number of clusters and assessing the convergence of the solutions, and this study implements that approach through examination of dendrograms, changes in agglomeration coefficients, and inspection of agglomeration plots (Aldenderfer & Blashfield, 1984; Shay, 2014).

Nonhierarchical cluster analysis.

Once the optimal cluster solution is determined, nonhierarchical cluster analysis is used for classifying SNFs into clusters. There is agreement that while hierarchical clustering methods are best suited for determining the structure of the cluster groups, a nonhierarchical method "optimizes within-cluster homogeneity and between-cluster heterogeneity" (Ketchen & Shook, 1996, p. 446). The respective final cluster centers of the optimal solution are used as seeds for conducting a *K*-means nonhierarchical cluster analysis.

Reliability and validity of clusters.

The reliability of the optimal cluster solution is established in two ways. First, the results of multiple methods of cluster analysis are compared. Additional methods of hierarchical analysis are conducted including single-linkage, complete-linkage, average-linkage, and centroid method. Analyses are conducted using standardized and non-standardized variables. Nonhierarchical clustering is conducted using centroids from the chosen hierarchical analysis and by using random initial seeds. Results are evaluated for their consistency using the level of agreement of classification of across clusters and Hubert-Arabie Adjusted Rand Index (ARI_{HA}) scores. ARI_{HA} scores account for chance classifications and provide a more robust means of determining the alignment between classifications (Hubert & Arabie, 1985; Shay, 2014).

Second, the sample is randomly split in half to create a training sample and a testing sample. After a preferred solution of the number of clusters is found for the training sample, a separate cluster analysis is performed on the testing sample as an additional means of testing the reliability of the cluster solution (Hair et al., 2006; Ketchen & Shook, 1996; Shay, 2014). Multiple discriminant analysis is commonly used to assess internal validity of the cluster solution, allowing "the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously" (Klecka, 1980, pg. 7). This technique provides indication of whether the groups in the optimal cluster solution can be statistically discriminated from one another. The groups identified in the cluster analysis serve as a categorical dependent variable and the clustering variables serve as independent variables. The centroid of each variable for each group is compared for statistical significance. Discriminant analysis can be used for evaluating differences among groups for validation, or for classifying new observations into groups as used in RQ3.

Assumptions for conducting multiple discriminant analysis are assessed for validation of the optimal solution. Sample sizes are expected to have a minimum of 20 observations per group and per independent variable., Independent variables are assumed to have a normal distribution, and the dependent variable is assumed to have equal covariance among the defined groups. Box's M test is used to evaluate the equality of covariance among the groups (Hair et al., 2006).

In this study, the cluster dimension variable, referral centrality, is expected to have nonparametric distributions. Some facilities only receive referrals from one hospital. This results in a high number of observations with values of one. To accommodate the underlying data, a nonparametric discriminant analysis using the *K*th-nearest-neighbor method is conducted (Hair et al., 2006). The statistical significance of the overall discriminant model is determined by the Wilks' lambda measure, and the predictive accuracy of the model is assessed by the number of observations correctly classified, known as the hit ratio (Hair et al., 2006).

Proportional chance criterion is used to evaluate the hit ratios as recommended by Hair et al., (2006). This calculation results in the average probability of classification taking into account all group sizes. Applying this criterion helps to account for observations that could be classified correctly simply due to chance. Proportional chance criterion is calculated as $C_{PRO} = p_1^2 + p_2^2 + \ldots p_n^2$ where p is the proportion of observations in the respective groups. Levels of classification are considered acceptable when the hit ratio is at least 25% greater than the proportional chance criterion calculation (Hair et al., 2006; Shay, 2014).

Cluster Profiles.

The chosen optimal cluster solution is profiled in two ways. First, the classification groups are described in terms of the clustering dimensions. Analysis of variance (ANOVA) is conducted to identify differences in the clustering dimensions across the groups.

MANOVA is the preferred method for identifying differences across group means, but in the absence of equal variance, ANOVA is used to test for differences across the group means of each variable (Hair et al., 2006). The Welch and the Brown-Forsythe tests are conducted as alternative tests of significance equality of means among groups when there is variance heterogeneity (Lix, Keselman, & Keselman, 1996), and Games-Howell tests are used for post-hoc pairwise comparisons since there is unequal variance among the groups (Lee & Lee, 2018; Shay, 2014). This analysis of variance of clustering dimensions, along with multiple discriminant analysis, contributes to establishing internal validity of the cluster solution.

Second, the classification groups are described in terms of external descriptive variables. Clusters are profiled in terms of descriptive variables not used to measure cluster dimensions to better understand the external characteristics of each cluster. Profiles of clusters are assessed based on theoretical expectations and practical experience (Hair et al., 2006; Ketchen & Shook, 1996). The analysis of external variables, along with performance measures tested in RQ2 contribute to establishing external validity of the cluster solution. Hypothesis 1 is tested by establishing the existence of an optimal cluster solution.

RQ2: Regression analyses empirical model.

Association of the optimal cluster solution identified in RQ1 is associated with performance differences is assessed using two methods. First, ANOVA and Games-Howell tests are used to test for significance of performance differences between groups identified using cluster dimensions derived from 2015 data. Second, a multivariate analysis using ordinary least squares (OLS) regression is conducted to determine if the strategic group is a significant predictor of outcomes when controlling for other factors. Separate regression models are estimated for each of the six performance outcomes. The model is:

$$Outcome_i = \beta_0 + \beta_1 Strategy\ Group_{\mathrm{i}} + \beta_2 \mathrm{ENV}_i + \beta_3 \mathrm{ORG}_i + \varepsilon_i$$

where *i* indexes the SNF, $Outcome_i$ is the financial or quality performance variable, $Strategy\ Group_i$ indicates strategic group membership in 2015, ENV_i is a vector of covariates of environmental factors, ORG_i is a vector of covariates of organizational characteristics, and ε_i is the error term. All models assess 2015 performance measures and use standard errors robust to heteroskedasticity. The significance of strategic group membership associated with outcomes is assessed to address Hypotheses 2a and 2b.

RQ3: Empirical models.

Classification of 2012 strategy groups.

To test hypotheses in RQ3, the temporal stability of groups is assessed by first classifying the 2012 observations into the taxonomy of strategy groups developed in RQ1. Discriminant analysis is used in the cluster analysis to validate the solution. In this part of the study, discriminant analysis is used for classifying new observations into groups, also known as predictive classification. Discriminant coefficients from the final cluster solution for 2015 are used to classify SNFs based on 2012 observations. Simple classification agreement rates and Hubert-Arabie Adjusted Rand Index ($\mathrm{ARI}_{\mathrm{HA}}$) scores are used to estimate how similar strategy groups are in 2015 and in 2012 to address Hypothesis 3a.

Characterization of Shifters and Non-Shifters.

SNFs that have shifted from one strategy group to another are identified. Characteristics of SNFs that are classified in a different strategy group in 2012 versus 2015 (Shifters) are compared to SNFs consistently classified in the same group (Non-Shifters) using t-tests.

Performance differences.

Performance differences between Shifters and Non-Shifters are compared to assess whether moving from one strategy group to another strategy group is associated with a subsequent change in performance to address Hypothesis 3b. First, t-tests are used to test for differences from 2012 to 2015 performance measures between Shifters and Non-Shifters within each strategy group.

Then, a more robust test of changes in performance among SNFs shifting strategy is conducted with a difference-in-differences (DID) analysis. A DID helps to control for confounding factors while assessing the significance of differences in performance between Shifters and non-Shifters between 2012 and 2015. DID assumptions include OLS assumptions, that common shocks occur to treated and untreated groups, and that parallel trends of outcomes would continue without treatment (Ryan, Burgess, & Dimick, 2015). Common shocks to SNFs within a strategy group can be assumed. The assumption of parallel trends of outcomes in the sample of Shifters and Non-Shifters is a considerably stronger assumption. The sample limits tracking performance prior to 2012. A limitation of this analysis is that the parallel trends assumption cannot be assessed.

The OLS model, extended from the model in RQ2 to include DID estimation and fixed effects is:

$$Outcome_{it} = \beta_0 + \beta_1 \text{ENV}_{it} + \beta_2 \text{ORG}_{it} + \beta_3 \text{SHIFT}_i + \beta_4 \text{POST}_{it} + \beta_5 (\text{SHIFT x POST})_{it} + \mu_i + \varepsilon_{it}$$

where SHIFT_i represents SNFs classified as changing strategy sometime between 2012 and 2015 representing the treatment group, and POST_{it} indicates observations in 2015 after shifting strategy groups (post-treatment). The interaction between SHIFT_i and POST_{it} serves as the DID estimator. Fixed-effects for SNFs allowing for within-facility comparisons while controlling for time invariant factors is represented by μ_i. Observations from 2012 are considered pre-treatment. Each strategy group is modeled separately based upon SNF classifications in 2015, and a model is run for each performance measure to test whether SNFs that changed strategy groups had significant differences in performance compared to those that did not. In total, 36 regressions are run, one for each strategy group for each of six outcome measures. Robust standard errors are used to account for heteroskedasticity, and the model is clustered at the facility level.

Sensitivity Analyses

This study conducts sensitivity analysis using an alternative measure for patient complexity as a dimension for classifying SNFs. SNFs with more complex patients require higher staffing levels (Bostick, Rantz, Flesner, & Riggs, 2006), and staffing levels may represent the resources required to care for different levels of patient complexity. Cluster analysis is conducted substituting average direct-care staff hours per resident day for the average CMI of admitted patients.

Sensitivity analysis is also conducted by using a process measure of quality in addition to outcome measures of quality. Prevalence of residents with a catheter is a process measure. Use of catheters elevates the risk of UTIs and functional decline (Weech-Maldonado, Neff, & Mor, 2003). Zinn et al., (1994) and Marlin et al., (1999) found the prevalence of residents with a catheter to be associated with a SNF's membership in a strategic group in their studies.

Summary

This chapter discusses the research design, data sources, study sample, variables, and analytic approaches used to address the aims of this study. RQ1 and RQ2 are investigated using cross-sectional data, and RQ3 employs a balanced panel of SNFs over a period of four years. Cluster analysis is used to identify a taxonomy of SNFs, and regression models are used to test associations between group membership and performance outcomes. Discriminant analysis is used to assess the temporal stability of strategic groups, and differences in performance of SNFs that shifted strategies groups over time is tested. Chapter 5 presents the results of the analyses.

Chapter 5: Results

This chapter provides the results of the analysis using the data and methodologies described in Chapter 4. The first section presents descriptive analysis of the study sample. The second section presents the cluster analysis and a preferred cluster solution for RQ1.
The third section provides the regression results for RQ2. The fourth section presents the analysis to address RQ3. Sensitivity analyses are provided in the fifth section, followed by a summary of the chapter.

Results of Descriptive Analysis

Descriptive statistics.

Table 5.1 provides descriptive statistics for all variables used for the study years of 2012 and 2015. The three variables selected to operationalize strategic dimensions for classifying SNFs are examined first. Most patients are supported by Medicaid, with an average of 61.60% in 2012 (SD = 15.22%) and a significantly lower average of 60.79% in 2015 (SD = 15.84%). The average case mix index (CMI) of patients admitted to a SNF is 1.332 (SD = 0.104) in 2012 and significantly higher at 1.343 (SD = 0.100) in 2015. The average calculated measure of referral centrality is 0.780 (SD = 0.251) in 2012 and 0.783 (SD = 0.250) in 2015, but not significantly different between 2012 and 2015. Referral centrality is measured on a scale from 0 to 1, with a higher value indicating greater centrality of patient referrals from hospitals. Means and standard deviations for control variables, performance measures, and additional descriptive variables that are used to profile strategic groups are included in Table 6. Significant differences in means between 2012 and 2015 are indicated.

Table 6 *Descriptive statistics of study sample for 2012 and 2015*

		Variable	2012 Mean (n=4,539)	SD	2015 Mean (n=4,539)	SD	
Classification Variables:							
		Medicaid %	61.60	15.22	60.79	15.84	***
		Avg CMI Admitted Patients	1.332	0.104	1.343	0.100	***
		Referral Centrality	0.780	0.251	0.783	0.250	
Control Variables:							
Environmental Characteristics							
	Munificence	Population > 65 %	14.84	3.77	16.02	3.95	***
		Per capita income ($)	43,013	10,890	46,840	13,454	***
		Rurality (RUCA)					
		Urban (0,1)	73.25	44.27	73.21	44.29	
		Suburban (0,1)	4.96	21.71	5.00	21.80	
		Large Rural Town (0,1)	14.36	35.08	14.36	35.07	
		Rural (0,1)	7.43	26.22	7.43	26.22	
	Dynamism	ACO Penetration %	NA	NA	9.86	9.61	
		Medicare HMO Penetration %	24.77	13.43	29.52	13.85	***
	Complexity	HHI (SNF Beds)	0.175	0.216	0.180	0.220	
		Home Health Availability / Population > 65 per 100,000	24.64	28.20	22.86	25.05	***
Organizational Characteristics							
		Size (# Beds)	138	56	137	56	
		Occupancy %	87.24	9.59	85.79	10.20	***
		Ownership (FP 0,1)	80.80	39.40	79.80	40.10	
		Chain Affiliation (0,1)	62.70	48.40	64.30	47.90	
Performance Measures:							
	Financial	Revenue/Bed ($)	87,786	23,364	88,177	25,465	
		Total Margin %	2.53	6.31	1.09	6.83	***
		Patient Margin %	0.64	9.13	-0.84	9.85	***
	Short-stay	Adj. Hospital Readmissions %	18.87	4.71	17.55	4.39	***

	Variable	2012 Mean (n=4,539)	SD	2015 Mean (n=4,539)	SD	
Long-stay	Prevalence of Pressure Ulcers %	6.57	4.26	5.83	3.98	***
	Prevalence of Urinary Tract Infections %	7.43	5.09	4.97	4.16	***
Additional Descriptive Variables:						
	Medicare %	16.91	9.13	16.18	9.04	***
	Observed Median Length of Stay (Days)	31.96	13.39	31.09	12.60	***

Significance level of * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Outliers and distributions of values.

All variables are assessed for outlying values and distributive qualities. The assessment shows that the sampling process was robust enough to negate the need to remove any outlying values. Distributive properties are examined and the measures of per capita income, the number of beds in a SNF, and revenue per bed are transformed to logarithmic scales to achieve a more normal distribution of data and reduce skewness.

The measure of referral concentration demonstrates a non-normal distribution due to a large proportion of SNFs receiving referrals from a single hospital (54% in 2015). Having a referral concentration equal to one may be caused by the geographic location of a SNF in a rural area where there is only one hospital within a reasonable distance for referrals, limiting the number of referral partnerships. Alternatively, highly concentrated referrals may reflect a strategic decision made by a SNF to focus on a single referral relationship, or an inability of a SNF to develop stronger referral relationships (Lawrence et al., 2018; McHugh et al., 2021; Shield et al., 2018). To explore the relationship between geographic location and relational dynamics, levels of referral centrality of one and less than one are stratified by level of rurality in Table 7. A larger proportion of SNFs with a single referral relationship are in a rural area or large rural town compared to SNFs with lower levels of referral centrality (10% vs. 4% and 20% vs. 8%, respectively). However, approximately 70% of SNFs that have a single referral relationship are in urban or suburban areas, suggesting that geographic location is not the underlying reason for having a single referral relationship for all SNFs and that relational dynamics may better explain referral centrality for some SNFs.

Table 7. *Referral centrality by level of rurality in 2015*

RUCA Designation	Total Sample		Referral Centrality < 1		Referral Centrality = 1	
Urban	3,323	73%	1,733	83%	1,590	65%
Suburban	227	5%	95	5%	132	5%
Large Rural Town	652	14%	160	8%	492	20%
Rural	337	7%	93	4%	244	10%
Total	4,539	100%	2,081	100%	2,458	100%

Excluded observations.

SNFs that were excluded from the sampling process differ from the final sample. The means of selected variables from the final study sample were compared with mean values from the observations that were excluded during the sampling process. For 2015, excluded observations on average have a lower Medicaid census (45.66% vs. 60.79%), lower average CMI of admitted patients (1.291 vs. 1.343), are smaller (102 beds vs.137 beds), less likely to be for profit (64.10% vs. 79.80%), and have lower levels of occupancy (79.24% vs. 85.79%). A smaller proportion of excluded observations are in urban areas (67.84% vs. 73.21%) and approximately the same proportion are in suburban areas (5.88% vs. 5.00%) and large rural towns (15.19% vs. 14.36%) compared to observations included in the sample. However, a greater proportion of excluded SNFs are in rural areas (12.09% vs. 7.43%) compared to the sample. More specifically, observations that were dropped during the merge with the Torch Insight dataset (approximately 4,405 SNFs in 2015) have a higher Medicaid census (65.92% vs. 60.79%), lower average CMI of admitted patients (1.244 vs. 1.343), are smaller (84 beds vs. 137 beds), less likely to be for-profit (71.49% vs. 79.80%), have lower levels of occupancy (78.94% vs. 85.79%), and more are in rural areas (42.87% vs. 21.79%) compared to urban areas.

This comparison suggests that a large proportion of SNFs excluded from the sample are smaller in size, serve more short-stay and less complex patients, and are in rural areas. It is likely that the Torch Insight dataset did not have matching observations for many of these SNFs due to CMS's exclusion of small size cell counts of less than eleven if a SNF had less than eleven patients referred from a particular hospital in a one-year time period. Exclusion of observations appears to be systematic rather than random, limiting the generalizability of the study.

RQ1: Empirical Analysis

Identifying strategic groups requires first preparing the variables and then conducting the cluster analysis. Variables selected for classification are assessed for outliers, the need for standardization, and whether multicollinearity exists. Then, to conduct the cluster analysis, clustering algorithms are executed, the number of clusters is determined, a nonhierarchical cluster analysis is run, the reliability and validity of the cluster solution is assessed, and clusters are profiled.

Preparing variables for cluster analysis.

Selection of variables. The clustering dimensions are guided by the conceptual framework discussed in Chapter 3. Three scope of business dimensions – market segments, types of services, and geographic reach – are operationalized as three classification variables – percent Medicaid, average CMI of admitted patients, and referral centrality.

Detecting Outliers. Most clustering algorithms are sensitive to outliers, making this assessment an important part of preparation. Univariate analyses used in the descriptive analyses do not reveal outlying values reflecting the robust sampling process. An additional step often used in preparing variables for cluster analysis is to calculate Mahalanobis D^2 distance measures for each observation to detect observations with outlying values. The Mahalanobis distance is the distance between multiple variables of an observation and the centroid (or mean) of the sample. Observations with Mahalanobis distances significantly different from the sample mean are identified as outliers. This measure provides a way of looking at multiple variables simultaneously to detect outliers while taking into account correlation among variables. The Mahalanobis measure for each observation is calculated using the three classification variables: percent Medicaid, average CMI at admission, and referral centrality. The Mahalanobis measure is squared and then divided by the degrees of freedom. Observations with D^2 / df greater than four are reviewed as outliers (Hair et al., 2006). The analysis indicated there are no outliers across the observations based on the classification variables.

Standardization. Standardizing variables used in cluster analysis gives each variable equal weight, preventing variables of greater magnitudes of scale from having a greater impact than those with measures of smaller scale. Classification variables are standardized using z-scores for the main cluster analysis, and an additional analysis is conducted with non-standardized classification variables as part of the cluster reliability and validation process.

Multicollinearity. Multicollinearity among classification variables would increase the weight of a particular construct and should be avoided in cluster analysis. A correlation matrix of the three classification variables is presented in Table 8. The highest level of correlation is between the average percentage of patients supported by Medicaid and the level of referral centrality at 0.2172. Though statistically significant, this level of correlation is acceptable for performing cluster analysis. Variable inflation factor (VIF) scores of cluster variables and control variables are well below 10, indicating that multicollinearity is not a concern (Hair et al., 2006; Shay, 2014).

Table 8. *Classification variable correlation matrix*

	% Medicaid	**CMI for New Admissions**	**Referral Centrality**
% Medicaid	1.0000		
CMI for New Admissions	(0.0078)	1.0000	
Referral Centrality	0.2172*	-0.1185*	1.0000

* Correlations significant at <0.001 level

Cluster analysis.

Clustering algorithm.

The sample for 2015 is randomly split into halves to provide a subset of data for validation of the results from the training set. In the first stage of the two-stage cluster analysis, hierarchical cluster analysis is used to determine the optimal number of clusters. Hierarchical cluster analysis is conducted on the training set using Ward's method, single linkage, complete linkage, and average linkage algorithms. Squared Euclidian distance is used in each of the cluster analyses as a measure of similarity, and all classification variables are standardized using z-scores. Results of cluster analysis using split-half data sets and different algorithms are used to confirm reliability and validity of the chosen cluster solution.

Determining the number of clusters.

Multiple stopping rules are deployed to identify the optimal cluster solution. Stopping rules provide a way of identifying solutions that maximize heterogeneity between groups and homogeneity within groups. In agglomerative hierarchical analysis the intent is to stop the agglomeration of clusters at a point where a parsimonious cluster solution is balanced with one that provides groups that are granular enough to inform the analysis (Hair et al., 2006).

Dendrograms, agglomeration coefficients, and agglomeration plots are assessed to help determine a final cluster solution.

An examination of the dendrograms in Appendix 1 reveals that the Ward's method dendrogram appears to have natural breaks of two, five, and six clusters. The complete linkage dendrogram appears to have natural breaks at two, four, and five clusters. The average linkage dendrogram appears to have natural breaks at two and three clusters. Average linkage, however, shows that there are some observations that are not joined until later in the agglomerative process, potentially resulting in a small cluster size (n=5). The single linkage algorithm displays a chaining effect that is not informative to the analysis (Hair et al., 2006; Shay, 2014).

Next, incremental changes in the agglomeration coefficients are reviewed to identify where the largest increases in heterogeneity occur in the agglomeration process. When dissimilar clusters are merged, the agglomeration coefficient reflects a relatively large change, indicating "the number of clusters prior to the merger is most appropriate" (Ketchen & Shook, 1996, pg. 446). The visual breaks in the dendrograms of the four hierarchical analyses are evident in the agglomeration coefficients shown in Table 9. The largest percentage increases in agglomeration coefficients resulting from the Ward's method are prior to combining the last two (215%), five (65%), and six (74%) clusters. A seven-cluster solution also demonstrates a relatively large percentage increase of 21%, but this solution is not readily visible on the dendrogram. Agglomeration coefficients from the complete linkage algorithm have the largest percentage increases prior to combining the last two (71%), four (44%), and five (26%) clusters. Average linkage has the largest percentage increases in coefficients prior to combining the last two (26%), three (81%), and six (23%) clusters. The chaining effect is evident in the largest percentage increases in coefficients occurring only in the last three agglomerations of two (80%), three (58%), and four (175%) clusters.

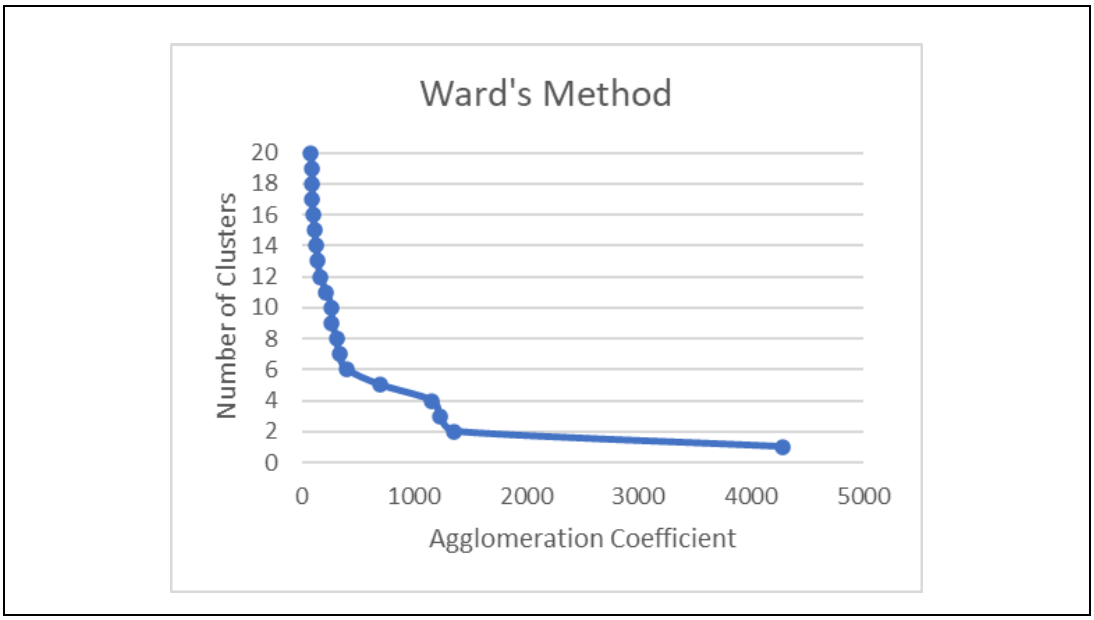
Table 9. *Percent change in agglomeration coefficients in hierarchical cluster analyses*

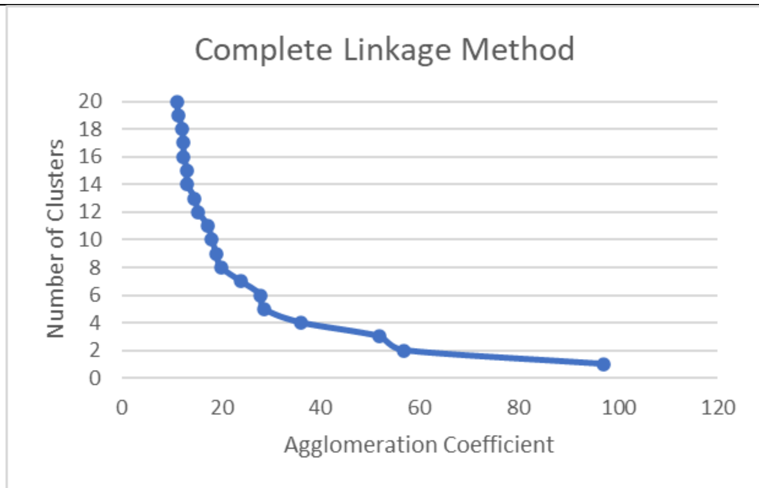
Clusters Com-bined	# Clusters Appro-priate	**Ward's Method**		**Complete-Linkage**		**Average-Linkage**		**Single-Linkage**	
		Agglom-eration Coef.	%Δ	Agglom-eration Coef.	%Δ	Agglom-eration Coef.	%Δ	Agglom-eration Coef.	%Δ
10 to 9	10	271.5	2%	18.96	5%	7.8	18%	0.7	3%
9 to 8	9	310.3	14%	19.93	5%	7.9	1%	0.7	4%
8 to 7	8	333.8	8%	23.86	20%	9.3	17%	0.7	4%
7 to 6	7	403.8	**21%**	27.94	17%	9.8	5%	0.8	3%
6 to 5	6	703.8	**74%**	28.62	2%	12.1	**23%**	0.8	1%
5 to 4	5	1,158.7	**65%**	36.00	**26%**	12.8	6%	0.8	5%
4 to 3	4	1,231.5	6%	51.86	**44%**	14.0	9%	2.2	**175%**
3 to 2	3	1,360.6	10%	56.71	9%	25.3	**81%**	3.5	**58%**
2 to 1	2	4,285.6	**215%**	96.94	**71%**	31.8	**26%**	6.3	**80%**

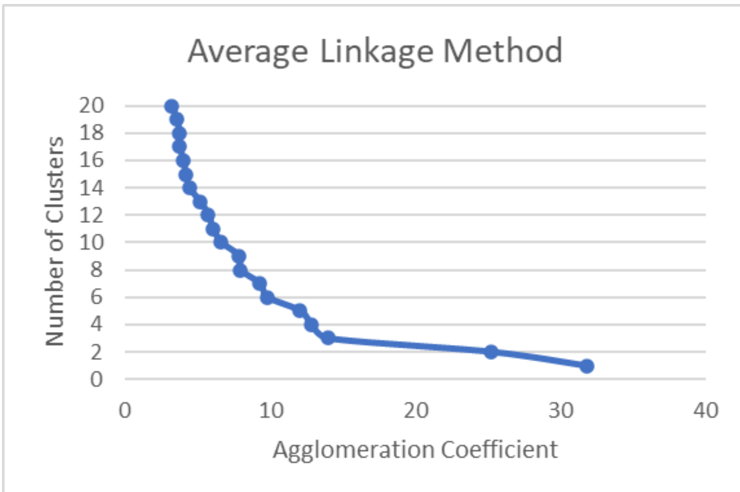
Note: Bold values indicate larger percentage increases from one step to the next.

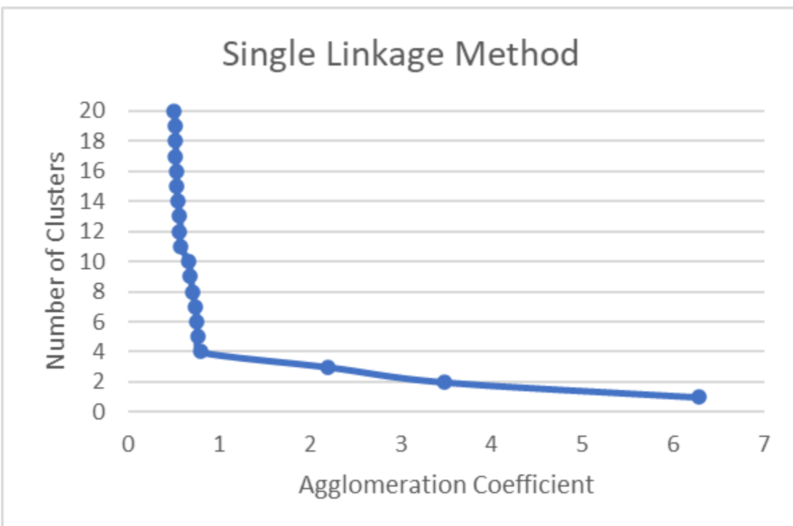
Additionally, agglomeration plots are evaluated for each of the hierarchical methods. The agglomeration plot is another way of examining changes in agglomeration coefficients (on the x-axis) and the number of clusters at a particular level of the coefficient (on the y-axis). A flattening of the agglomeration curve indicates greater dissimilarity between the clusters being combined as the distance between coefficients is greater. An “elbow” in the chart results where the flattening occurs. There can be multiple “elbows” on a chart if there is more than one natural set of clusters (Ketchen & Shook, 1996). The agglomeration plots shown in Figure 2 are consistent with the assessments of changes in the agglomeration coefficients and the dendrograms. All methods demonstrate a flattening of the agglomeration curve at the two-cluster solution. Additionally, the plot for Ward's method displays a flattening of the agglomeration curve at the five- and six-cluster solutions. A seven-cluster solution is barely perceptible. The plot for complete linkage demonstrates a flattening of the curve at the four- and five-cluster solutions. The plot for average linkage displays flattening of the curve at the three- and six-cluster solutions, and the chaining effect is again evident in the single linkage plot with a flattened curve between two-, three-, and four-cluster solutions.

Figure 2. *Agglomeration plots of hierarchical analyses*




Complete Linkage Method
Number of Clusters
20
18
16
14
12
10
8
6
4
2
0
0
20
40
60
80
100
120
Agglomeration Coefficient


Average Linkage Method
Number of Clusters
20
18
16
14
12
10
8
6
4
2
0
0
10
20
30
40
Agglomeration Coefficient


Single Linkage Method
Number of Clusters
20
18
16
14
12
10
8
6
4
2
0
0
1
2
3
4
5
6
7
Agglomeration Coefficient

Evaluating the dendrograms, percentage of change in agglomeration coefficients, and agglomeration plots of the different hierarchical cluster analyses indicates support for a two-cluster solution. Three-, four-, and seven- cluster solutions are suggested by the single linkage, average linkage, complete linkage, and Ward's method, respectively. Five- and six-cluster solutions are each indicated by two algorithms – five-cluster by Ward's method and complete linkage, and six-cluster by Ward's method and average linkage.

A two-cluster solution is rejected in favor of a solution that can identify heterogeneity among clusters more granularly. The five- and six-cluster solutions are compared across the hierarchical algorithms to help determine the validity and reliability of an optimal cluster solution. The number of cluster members in each cluster for the five- and six-cluster solutions are shown in Table 10 for each of the hierarchical algorithms. Neither the five- nor six-cluster solutions demonstrate high levels of agreement between the clustering algorithms as to the number of members in a particular cluster. The average linkage and single linkage methods result in most observations being classified into one cluster. However, with most observations in one cluster in the average linkage and single linkage results, neither solution is informative.

Ward's method and complete linkage demonstrate 20% agreement in the five-cluster solution, but only 1% agreement in the six-cluster solution. Likewise, the Hubert-Arabie Adjusted Rand Index (ARI_{HA}) scores indicate low levels of agreement of classification among the hierarchical algorithms. The Ward's method and complete linkage five-cluster solution ARI_{HA} score is 0.1297 and the six-cluster solution ARI_{HA} score is 0.1719, both low on a range of 0 to 1, with 1 indicating perfect agreement. Further, in the five-cluster solution, the size of cluster 3 in the complete linkage method is considerably larger than any of the clusters in the Ward's method and the size of cluster 5 is considerably smaller. Similarly, in the six-cluster solution, the size of cluster 4 in the complete linkage method is considerably larger than any of the clusters in the Ward's method and the size of cluster 6 is considerably smaller. The difference in sizes of clusters between the two methods may be explained by the tendency of Ward's method to classify observations into more evenly sized clusters.

Table 10. *Comparisons of five- and six-cluster solutions*

	Five-Cluster Solution				**Six-Cluster Solution**			
Comparison	Ward's Method	Complete Linkage	Average Linkage	Single Linkage	Ward's Method	Complete Linkage	Average Linkage	Single Linkage
Number of Cluster Members								
Cluster 1	386	603	2196	1	386	308	2196	1
Cluster 2	459	237	55	2	459	295	55	2
Cluster 3	405	1234	2	2	405	237	2	2
Cluster 4	276	164	3	1	276	1234	2	1
Cluster 5	732	20	2	2252	318	164	1	2
Cluster 6	--	--	--	--	414	20	2	2250
Total	2258	2258	2258	2258	2258	2258	2258	2258
Cluster Solution Agreement (%)								
Ward's Method	--	20%	17%	32%	--	1%	17%	18%
Complete Linkage	20%	--	27%	1%	1%	--	14%	1%
Average Linkage	17%	27%	--	0%	17%	14%	--	0%
Single Linkage	32%	1%	0%	--	18%	1%	0%	--
Hubert-Arabie Adjusted Rand Index								
Ward's Method	--	0.1297	0.0031	0.0008	--	0.1719	0.0004	0.0001
Complete Linkage	0.1297	--	0.0163	0.0057	0.1719	--	0.1373	0.0062
Average Linkage	0.0031	0.0163	--	0.1427	0.0004	0.1373	--	0.1373
Single Linkage	0.0008	0.0057	0.1427	--	0.0001	0.0062	0.1373	--

The convergence of a cluster solution when examining multiple hierarchical methods is unclear. Five- and six-cluster solutions appear to have the most agreement across hierarchical methods, but agreement is limited for these solutions. Ward's method and the complete linkage method present solutions that have some distribution of members across groups, unlike the average and single linkage methods. Ward's method is favored for conducting hierarchical cluster analysis when clusters are unknown *a priori* and has been used in the prior classification of SNFs (Marlin et al., 1999; Shay, 2014; Zinn et al., 1994), therefore, the cluster solutions are limited to the five- and six-cluster solutions identified in the Ward's method.

Hair and colleagues (2006) recommend profiling clusters using the clustering variables to identify the most appropriate cluster solution once a limited number of possible solutions have been identified. Table 11 summarizes the means of the three classification variables for the five- and six- cluster solutions found using Ward's method on the training sample. The only difference between the two possible solutions is that in the five-cluster solution, cluster 5 contains the observations that are separated into clusters 5 and 6 in the six-cluster solution. The main difference in clusters 5 and 6 in the six-cluster solution is the average CMI of admitted patients (1.41 vs. 1.27). This suggests that cluster 6 represents a strategy group with higher average complexity of patients. For reference, in 2015, the average case-mix index of SNFs in the top quartile of Medicare earnings was 1.40 compared to an average case-mix index of 1.31 for SNFs in the bottom quartile of Medicare earnings (Medicare Payment Advisory Commission, 2017). The six-cluster solution likely represents a segment of the underlying industry structure that is important to the analysis and understanding strategies related to case-mix reimbursement policies. Therefore, the six-cluster solution using the Ward's method algorithm is the favored solution from the hierarchical analysis.

Table 11. *Means of classification variables of potential cluster solutions in the training sample*

Five-Cluster Solution					**Six-Cluster Solution**				
	# Cluster Members	% Medicaid	Avg CMI Admitted	Referral Centrality		# Cluster Members	% Medicaid	Avg CMI Admitted	Referral Centrality
Cluster 1	386	46.77	1.34	1.00	Cluster 1	386	46.77	1.34	1.00
Cluster 2	459	72.06	1.25	1.00	Cluster 2	459	72.06	1.25	1.00
Cluster 3	405	70.85	1.42	1.00	Cluster 3	405	70.85	1.42	1.00
Cluster 4	276	37.33	1.37	0.51	Cluster 4	276	37.33	1.37	0.51

Five-Cluster Solution					Six-Cluster Solution				
	# Cluster Members	% Medicaid	Avg CMI Admitted	Referral Centrality		# Cluster Members	% Medicaid	Avg CMI Admitted	Referral Centrality
Cluster 5	732	64.35	1.35	0.53	Cluster 5	318	66.62	1.27	0.52
					Cluster 6	414	62.60	1.41	0.53
Total	2258	60.77	1.34	0.79	Total	2258	60.77	1.34	0.79

Nonhierarchical cluster analysis.

The second stage of the two-stage approach to cluster analysis is conducted using nonhierarchical clustering methods. The preferred hierarchical solution is used as the basis for classifying the observations in the training set into clusters using the *K-means* method. Cluster centroids from the six-cluster solution identified with the Ward's method algorithm are used to seed the *K-means* nonhierarchical cluster analysis, resulting in high cluster solution agreement of 80.12% and ARI_{HA} = 0.6160.

Reliability and validity of clusters.

Multiple clustering algorithms. Several analyses are conducted to assess the validity of the clusters in the preferred solution. Table 12 compares some possible cluster solutions with the final cluster solution identified by applying the two-step cluster analysis method. The final cluster solution using the *K-means* nonhierarchical method has a high degree of agreement with the solution found using the hierarchical Ward's method on the training sample. The other solutions, however, demonstrate poor agreement.

Table 12. *Comparison of cluster solutions*

Comparison Solution	ARIHA	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Total	Cluster Solution Agreement
Ward's Method Training Sample		338	492	444	257	411	316	2258	

Comparison Solution	ARIHA	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Total	Cluster Solution Agreement
Nonhierarchical *K*-Means on Training Sample	0.6160	386	459	405	276	318	414	2258	80%
Complete Linkage	0.1911	308	295	237	1234	164	20	2258	1%
Average Linkage	0.0008	2196	55	2	2	1	2	2258	15%
Ward's Method – Non-standardized variables	0.1293	504	487	325	186	594	162	2258	19%
Final Cluster Solution (*K*-means)		676	970	891	529	850	623	4539	
K-Means 1 - random seeds	0.5732	1013	87	729	645	1196	859	4539	26%
K-Means 2 - random seeds	0.5623	1196	715	642	882	1017	87	4539	7%
K-Means 3 - random seeds	0.5605	1019	87	712	884	639	1198	4539	8%

Other than the comparison of the Ward's method and *K-means* nonhierarchical analysis, the other six-cluster solutions do not demonstrate a high level of agreement with the final solution. The complete linkage and average linkage methods have low levels of agreement with the final *K-means* solution just as they did with the Ward's method hierarchical solution. A six-cluster solution resulting from Ward's method using non-standardized classification variables also has a low level of agreement with the *K-means* solution, reflecting the unequal magnitude of the classification variables. Finally, random solutions are generated to see if the final solution is better fitted than random classifications of observations. The full sample of the final solution is compared to non-hierarchical solutions using randomly generated centroids to seed a six-cluster solution. This is repeated three times because the order of the observations can affect the solution (Hair et al., 2006; Shay, 2014). Randomly seeded classifications reflect mid-level agreement with the final solution, suggesting that a similar cluster solution emerges even when starting with randomly seeded centroids.

Discriminant analysis. Multiple discriminant analysis (MDA) is often conducted to determine if the groups in the chosen solution can be statistically discriminated from one another using the classification variables. The variable defining the cluster solution is the dependent variable and the classification variables are the independent variables. However, two assumptions are required: first, a minimum sample size with at least 20 cases per group and 20 cases per independent variable; second, equality of the covariance matrixes of the groups. The sample size exceeds the minimum requirements for MDA, but equality of covariance matrixes is unlikely with the non-normal distribution of the referral centrality variable. Box's M test is performed to test for equality of covariance among the cluster groups and found to be significant ($p < 0.001$), indicating within-group covariance matrixes are unequal and may demonstrate heteroscedasticity. As the Box's M test is sensitive to non-normally distributed variables, the referral centrality variable is the likely cause of the unequal covariance matrixes (Hair et al., 2006).

A quadratic rather than a linear function of MDA is an alternative method for conducting MDA that provides more reliability in discriminating groups when there are unequal variances. Quadratic discriminant analysis (QDA) relies upon quadratic rather than linear functions. QDA is applied to the test sample of observations classifying clusters using the *K-means* method seeded with the centroids from the training sample. The test sample shows a high level of agreement with the training sample (87.9%) indicating high internal reliability of the solution between the two samples ($ARI_{HA} = 0.7494$). Wilk's lambda indicates significance of the discriminant model and for each of the classification variables' discriminant function ($p < 0.001$). Finally, the hit ratio of 87.9% is more than 25% greater than the proportional chance criterion of 13.5%, indicating that the discriminant classification achieved accuracy beyond a level attributed to chance.

Cluster profiles.

The cluster solution is first tested to determine if the classification variables of groups of SNFs demonstrate significant differences across groups. Then, groups are profiled by classification variables and descriptive study variables that are external to the two-stage cluster analysis to better understand the characteristics of each cluster.

MANOVA is the preferred method for comparing the means of the cluster variables, but in the absence of equal variance, ANOVA is used to test for differences across the group means of each classification variable. The Welch and the Brown-Forsythe tests are conducted as alternative tests of equality of means among groups when there is variance heterogeneity (Lix et al., 1996). Both the Welch and the Brown-Forsythe tests indicate significant differences among the groups for each of the three classification variables ($p < 0.001$).

The Games-Howell test is used for post-hoc pairwise comparisons since there is unequal variance among the groups (Lee & Lee, 2018; Shay, 2014). Table 13 summarizes the means of the classification variables and selected descriptive variables, and with how many groups each cluster significantly differs. The post-hoc pairwise comparisons indicate that all groups differ significantly on the means of the percent of Medicaid patients and the average CMI of admitted patients. The mean referral centrality of groups is differentiated by high and low levels. Groups 1, 2, and 3 have similarly high levels of average referral centrality between 0.99 and 1.00, with groups 2 and 3 demonstrating equivalency, but both differing significantly from group 1. In contrast, groups 4, 5, and 6 have low levels of referral centrality between 0.50 and 0.53, but do not differ significantly from one another. In sum, significant differences across groups suggest that the cluster analysis identified groups that differ by market segment served, complexity of admitted patients, and scope of referral networks. Appendix 2 includes charts of trends of the classification variables for each strategy group from 2012 to 2015.

Table 13. *Cluster solution group mean values for classification variables and selected descriptive variables*

Variable	**Group 1 n=676**	**Group 2 n=970**	**Group 3 n=891**	**Group 4 n=529**	**Group 5 n=850**	**Group 6 n=623**
Classification Variables						
% Medicaid*	44.93 [all]	72.96 [all]	67.75 [all]	36.38 [all]	66.16 [all]	62.51 [all]
Avg CMI Adm. Patients*	1.31 [all]	1.27 [all]	1.43 [all]	1.34 [all]	1.30 [all]	1.45 [all]
Referral Centrality*	0.99 [all]	1.00 [1,4,5,6]	0.99 [1,4,5,6]	0.50 [1,2,3,5]	0.53 [1,2,3,4]	0.51 [1,2,3]
Descriptive Variables						
% Medicare*	17.57 [2,3,4,5]	10.95 [all]	14.98 [1,2,4,6]	25.57 [all]	14.43 [1,2,4,6]	18.92 [2,3,4,5]
Median Length of Stay*	28.62 [2,3,4]	33.06 [1,4,5,6]	32.78 [1,4,5,6]	25.99 [all]	27.93 [2,3,4,6]	29.62 [2,3,4,5]
Size (# beds) *	120 [all]	132 [1,5,6]	131 [1,5,6]	132 [1,5,6]	152 [1,2,3,4]	158 [1,2,3,4]
% Occupancy*	85.10 [4,6]	84.26 [3,4,5,6]	85.71 [2,6]	87.12 [1,2]	86.11 [2]	87.45 [1,2,3]
% For-profit Ownership*	0.62 [2,3,5,6]	0.87 [1,4,5]	0.87 [1,4,5]	0.68 [2,3,5,6]	0.79 [all]	0.89 [1,4,5]
% Chain Affiliation*	0.61 [5]	0.66 [--]	0.64 [--]	0.61 [5]	0.69 [1,4,6]	0.62 [5]
% Suburban	0.05 [--]	0.06 [--]	0.05 [--]	0.03 [--]	0.05 [--]	0.05 [--]
% Rural*	0.09 [4,6]	0.11 [4,5,6]	0.09 [4,6]	0.03 [1,2,3]	0.06 [2]	0.05 [1,2,3]
% Urban*	0.64 [4,5,6]	0.65 [4,5,6]	0.67 [4,5,6]	0.90 [all]	0.79 [1,2,3,4]	0.83 [1,2,3,4]
% Large Rural Town*	0.22 [4,5,6]	0.19 [4,5,6]	0.19 [4,5,6]	0.04 [1,2,3,5]	0.10 [1,2,3,4]	0.08 [1,2,3]

* The mean difference is significant at the 0.05 level.
Superscripts denote which clusters are significantly different; all = significantly different from all 5 other groups;
-- = not significantly different from any other group

A profile for each group is developed to describe the strategic scope of business that is captured in dimensions used to classify SNFs as part of strategic modeling. Groups are characterized based on the means of variables in the analysis. The selection of variables for characterizing strategic groups is informed by the taxonomies of SNFs developed in prior studies and review of qualitative literature summarized in Chapter 2. To assist in profiling the final cluster solution, the group means of selected study variables are classified as Low, Mid, or High relative to other groups as presented in Table 14. Groups classified as Low or High are statistically different from those classified as Mid-range. There was no difference in the percentage of SNFs located in suburban areas among the groups. The strategic groups are profiled as follows and described in greater detail subsequently:

Group 1: Private Pay Care Focus – Narrow Network

Group 2: Long-stay Care Focus – Narrow Network

Group 3: Long-stay Complex Care Focus – Narrow Network

Group 4: Post-Acute Care Focus – Wide Network

Group 5: Intermediate Care Focus – Wide Network

Group 6: High Acuity Care Focus – Wide Network

Table 14. *Study variables for profiling strategy groups*

	Group 1	**Group 2**	**Group 3**	**Group 4**	**Group 5**	**Group 6**
% Sample	15%	21%	20%	12%	19%	14%
Classification Variables						
% Medicaid	MID	HIGH	MID	LOW	MID	MID
Avg CMI Adm. Patients	MID	LOW	MID	MID	MID	HIGH
Referral Centrality	MID	HIGH	HIGH	LOW	LOW	LOW
Descriptive Variables						
% Medicare	MID	LOW	MID	HIGH	MID	MID
Median Length of Stay	MID	HIGH	HIGH	LOW	MID	MID
Size (# beds)	LOW	MID	MID	MID	HIGH	HIGH
% Occupancy	LOW	LOW	MID	HIGH	HIGH	HIGH
% For-profit Ownership	LOW	HIGH	HIGH	LOW	MID	HIGH
% Chain Affiliation	LOW	MID	MID	LOW	HIGH	LOW
% Suburban	--	--	--	--	--	--
% Rural	HIGH	HIGH	HIGH	LOW	LOW	LOW

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
% Urban	LOW	LOW	LOW	HIGH	MID	MID
% Large Rural Town	HIGH	HIGH	HIGH	LOW	MID	LOW

Group 1: Private Pay Care Focus – Narrow Network: This group is distinguished by a low total proportion of average Medicaid and Medicare patients (63%), suggesting a higher proportion of private pay patients than other groups, except the Post-Acute Care Focus group. Complexity of admitted patients and average length of stay are mid-range compared to the other groups, indicating provision of an intermediate level of care on average. Although the average referral centrality of this group is statistically different from the most highly concentrated groups, it is high at 0.99, indicating that most SNFs in this group receive referrals from a single hospital. On average, these are the smallest facilities based on number of beds and have low levels of occupancy relative to the other groups. Although a majority of SNFs are for-profit and chain affiliated, this group has a low proportion of for-profit and chain affiliated SNFs compared to the other groups. The exceptions are the Post-Acute Care Focus group in the level of for-profit ownership and the Post-acute Care and High Acuity Care groups in level of chain affiliation. While the majority of SNFs in this group are in urban areas (64%), this group has a high level of SNFs located in rural areas and large rural towns (31% in total).

Group 2: Long-stay Care Focus – Narrow Network: This group has the highest proportion of Medicaid patients, the lowest proportion of Medicare patients, admits the least complex patients, and has the longest average length of stay – all indicating low acuity custodial care. On average, SNFs in this group have highly concentrated referral relationships, receiving most referrals from a single hospital. The size of facilities based on number of beds are mid-range and levels of occupancy are low compared to other groups. There are higher levels of for-profit and chain affiliated SNFs in this group. Like the Private Pay Care Focus group, this group has a majority of SNFs located in urban areas (65%), and a high level of SNFs located in rural areas and large rural towns (30% in total). The long-stay care focus group represents the largest cluster of SNFs.

Group 3: Long-stay Complex Care Focus – Narrow Network: On average, this group has mid-level ranges of the proportion of Medicaid and Medicare patients, and referrals come from a single hospital. This group has the second highest average CMI for admitted patients and high lengths of stay indicating long-stay care for more complex patients. The size of the facility and rates of occupancy are neither high nor low compared to the other groups. Like the Long-stay Care Focus group, the rates of for-profit and chain affiliated SNFs are high in the group. And, like the Long-stay Care Focus and Private Pay Care Focus groups, there are high levels of SNFs located in rural areas and large rural towns (28%) compared to the other groups.

Group 4: Post-Acute Care Focus – Wide Network: This group has the highest average Medicare census and lowest average Medicaid census indicating that SNFs in this group serve a high level of short-stay post-acute care patients relative to the other groups. The total of the average of Medicaid and Medicare is the lowest of any group (62%), suggesting a higher proportion of private pay patients than the other groups, with the exception of the Private Pay Care Focus group (63%). Admitted patients are in a mid-range of complexity based on average CMI and have the shortest median length of stay, also in accordance with a high level of post-acute care patients. On average, this group has a wide referral network, receiving patient referrals from multiple hospitals. While this group is in the mid-range of size based on number of beds, they have the highest level of occupancy indicating high demand for services. Although a majority of SNFs are for-profit and chain affiliated, this group has a low proportion of each compared to the other groups, except the Private Pay Care Focus group in the level of for-profit ownership and the Private Pay and High Acuity Care Focus groups in level of chain affiliation. Similarly, a majority of SNFs in each group are located in urban areas, but this group has the highest proportion of urban SNFs (90%). The Post-Acute Care Focus group represents the smallest cluster of SNFs.

Group 5: Intermediate Care Focus – Wide network: This group has mid-range levels of the proportion of Medicaid and Medicare patients compared to the other groups. The average CMI of admitted patients is also mid-range and referral concentration for this group is low, indicating relationships with multiple hospitals. Lengths of stay are mid-range. This group is not distinguished by any one metric and thus is characterized as having an Intermediate Care Focus. Patients with an intermediate level of care generally require more than custodial care, but not the same level of care required for the most complex patients. On average, SNFs in this group are larger and have higher levels of occupancy. The level of for-profit ownership is mid-range compared to other groups, but the level of chain affiliation is high. Like the other groups, a majority of SNFs are in urban areas, but this group is also in the mid-range of locations in large rural towns.

Group 6: High Acuity Care Focus – Wide Network: Average levels of Medicaid and Medicare patients are mid-range for this group; however, this group admits more complex patients than any other group. On average, SNFs in this group receive referrals from multiple hospitals, are large facilities, and have high levels of occupancy. Lengths of stay are mid-range. There is a high level of for-profit ownership, but low levels of chain affiliation compared to the other groups. This group is second only to the Post-Acute Care Focus group in urban locality.

The profiles presented validate the six-cluster solution of the two-stage cluster analysis. The taxonomy confirms Hypothesis 1: there are differences among subsets of SNFs based on the average proportion of long-stay care patients, complexity of admitted patients, and the strength of referral relationships with hospitals. Profiles based on strategic dimensions operationalized as classification variables and descriptive variables relevant to the industry identify a taxonomy of strategic groups of SNFs. A comparison of the strategic groups of SNFs found in this study and strategic groups found in the Zinn et al. (1994) and Marlin et al. (1999) studies is presented in Chapter 6. For ease, strategy groups are referred to without the full description of their network centrality in the following analyses, or simply with (N) for narrow or (W) for wide.

RQ2: Empirical Analysis

First, differences in performance between strategy groups are tested with ANOVA and Games-Howell post-hoc tests and results are presented in Table 15. The greatest differences between strategy groups are in the financial performance measures. Average revenue per bed differs significantly among each of the strategy groups, with the Post-Acute Care group having the highest revenue per bed ($110,000), followed by High Acuity ($98,095), Private Pay ($91,654), Intermediate Care ($86,193), Long-stay Complex ($85,818), and the Long-stay Care group has the lowest revenue per bed ($75,066). Patient margins are highest in the High Acuity (1.34%) and Long-stay Complex (0.75%) groups and lowest in the Private Pay (-2.42%), Post-Acute (-2.17%), Long-stay (-1.61%), and Intermediate (-1.13%) groups. Total margins are highest in the High Acuity (2.55%) and Long-stay Complex (1.87%) groups, at mid-range in the Post-Acute (1.35%), Private Pay (1.14%), and Intermediate (0.49%) groups, and lowest in the Long-stay (-0.20%) group.

There are some differences among strategy groups in quality measures. The short-stay measure of adjusted 30-day readmissions is highest in the Long-stay (17.99%), Intermediate (17.97%), High Acuity (17.61%), and Long-stay Complex (17.59%) groups, and lowest in the

Post-Acute (17.14%) and Private Pay (16.58%) groups. The prevalence of pressure ulcers is lowest in the Private Pay (5.03%) and Post-Acute (5.64%) groups, and highest in the High Acuity (6.34%), Long-stay Complex (6.03%), Long-stay (5.94%), and Intermediate (5.89%) groups. Variation in the prevalence of UTIs is not wide. The highest rate is in the Private Pay (5.43%) group, and lowest in the High Acuity (4.70%) group with equivalent rates in the Long-stay (4.87%), Long-stay Complex (4.92%), Post-Acute (5.26%), and Intermediate (4.79%) groups.

Table 15. *Cluster solution group mean values for performance measures*

Variable	**Group 1 n=676**	**Group 2 n=970**	**Group 3 n=891**	**Group 4 n=529**	**Group 5 n=850**	**Group 6 n=623**
Net Patient Revenue/Bed*	$91,654 [all]	$75,066 [all]	$85,818 [all]	$110,000 [all]	$86,193 [all]	$98,095 [all]
Patient Margin*	-2.42 [3,6]	-1.61 [3,6]	0.75 [1,2,4,5]	-2.17 [3,6]	-1.13 [3,6]	1.34 [1,2,4,5]
Total Margin*	1.14 [2,6]	-0.20 [1,3,4,6]	1.87 [2,5]	1.35 [2,6]	0.49 [3,6]	2.55 [1,2,4,5]
Adj 30-day Readmissions*	16.58 [2,3,5,6]	17.99 [1,4]	17.59 [1]	17.14 [2,5]	17.97 [1,4]	17.61 [1]
% Pressure Ulcers*	5.03 [2,3,5,6]	5.94 [1]	6.03 [1]	5.64 [6]	5.89 [1]	6.34 [1,4]
% UTIs*	5.43 [5,6]	4.87 [--]	4.92 [--]	5.26 [--]	4.79 [1]	4.70 [1]

* The mean difference is significant at the 0.05 level.
Superscripts denote which clusters are significantly different; all = significantly different from all 5 other groups;
-- = not significantly different from any other group
Group 1: Private Pay Care Focus – Narrow Network
Group 2: Long-stay Care Focus – Narrow Network
Group 3: Long-stay Complex Care Focus – Narrow Network
Group 4: Post-Acute Care Focus – Wide Network
Group 5: Intermediate Care Focus – Wide Network
Group 6: High Acuity Care Focus – Wide Network

Ordinary Least Squares (OLS) regression is performed to assess whether measures of financial and quality performance are associated with membership in a particular strategic group while controlling for other factors. The OLS model is estimated for each of the outcome measures with the outcome as the dependent variable and membership in a strategic group as the key independent variable of interest. Variables representing environmental and organizational characteristics are included to control for possible confounding factors, and standard errors are robust to heteroskedasticity.

Table 16 shows the main results from the OLS regressions for financial outcomes, and Table 18 includes results for quality outcomes. Membership in a strategic group is coded as a dummy variable to allow for each strategic group to vary in level in relationship to the dependent variable. Differences of membership in a strategic group are interpreted relative to the base reference group of Private Pay Care Focus. The Private Pay Care Focus group serves as the reference group as it may be less directly impacted by policy changes made by Medicare or Medicaid (Grabowski et al., 2011).

Table 16. *OLS Regression results for financial performance*

Variable	**Natural log of Revenue per Bed**			**Patient Margin**			**Total Margin**		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Group 1: Private Pay Care Focus (N)	ref			ref			ref		
Group 2: Long-stay Care Focus (N)	-0.138	***	0.010	-1.099	*	0.532	-1.980	***	0.360
Group 3: Long-stay Complex Care Focus (N)	-0.026	*	0.011	1.265	*	0.520	0.053		0.359
Group 4: Post-Acute Care Focus (W)	0.133	***	0.014	-0.608		0.724	-0.204		0.394
Group 5: Intermediate Care Focus (W)	-0.041	***	0.011	-0.265		0.573	-1.236	**	0.376
Group 6: High Acuity Care Focus (W)	0.070	***	0.011	1.533	*	0.535	0.505		0.383
% Population > 65	0.003	***	0.001	0.063		0.037	0.021		0.024
Per Capita Income (log)	0.193	***	0.013	-1.111		0.637	-1.257	*	0.464
Urban	0.068	***	0.014	0.272		0.645	0.066		0.525
Suburban	0.011		0.019	-1.408		0.939	-0.417		0.661
Large Rural Town	-0.003		0.013	-0.133		0.663	-0.098		0.527
Rural	ref			ref			ref		
%Δ Medicare HMO Penetration	-0.002	***	0.000	0.016		0.022	0.010		0.016
ACO Penetration	0.001		0.000	-0.004		0.015	-0.010		0.011
HHI (SNF beds)	-0.080	***	0.019	2.325	*	0.920	1.823	*	0.735
Home Health Availability / Pop > 65 (per 100,000) (log)	-0.041	***	0.003	-0.142		0.165	-0.041		0.117
# Beds (log)	-0.075	***	0.010	0.749		0.476	0.389		0.311
% Occupancy	0.012	***	0.000	0.127	***	0.014	0.137	***	0.011

Variable	Natural log of Revenue per Bed			Patient Margin			Total Margin		
For-profit	-0.068	***	0.009	6.972	***	0.522	1.920	***	0.264
Chain Affiliated	-0.016	*	0.006	-0.567		0.313	-0.876	***	0.208

Significance at $p < 0.05$= *, $p < 0.01$ = **, $p < 0.001$ = ***

Revenue per bed. Net patient revenue per bed was associated with membership in each of the strategy groups. Net patient revenues per bed, the dependent variable, is a natural log requiring the regression coefficients to be transformed to their exponential value and then the value of one is subtracted to find the percentage difference estimated for each of the group variables. The formula is *exponent (natural log) – 1*. Using this method, the Long-stay, Long-stay Complex, and Intermediate groups generate less in net patient revenues per bed relative to the Private Pay group (-12.91%, -2.54%, and -4.04%, respectively), whereas net patient revenues per bed are 14.20% higher in the Post-Acute Group and 7.20% higher in the High Acuity Group compared to the Private Pay Care group, other things constant.

Patient margins. On average, the Long-stay Care group has patient margins 1.099% lower than the Private Pay Care Group. In contrast, patient margins are 1.265% higher for the Long-stay Complex Care group and 1.533% higher for the High Acuity group when compared to the Private Pay Care group, other things constant.

Total margins. Membership in the Long-stay Care group was associated with a total margin 1.980% lower, and the Intermediate Care had a total margin 1.236% lower than the Private Pay Care Group, other things constant.

Table 17. *Summary of group membership and association with financial performance*

Group	Patient Revenue per Bed	Patient Margin	Total Margin
Group 1: Private Pay Care Focus (N)	--	--	--
Group 2: Long-stay Care Focus (N)	Negative	Negative	Negative
Group 3: Long-stay Complex Care Focus (N)	Negative	Positive	--
Group 4: Post-Acute Care Focus (W)	Positive	--	--
Group 5: Intermediate Care Focus (W)	Negative	--	Negative
Group 6: High Acuity Care Focus (W)	Positive	Positive	--

Measures of financial performance are significantly associated with membership in each strategic group, demonstrating a relationship between strategies and the selected measures of financial performance. The results from the OLS models, summarized in Table 17, provide some support for Hypothesis 2a, that membership in a particular strategic group is associated with financial performance. Compared to the Private Pay Care group, membership in the Long-stay Care group is negatively associated with each of the financial performance measures. The Long-stay Complex Care group is negatively associated with patient revenue per bed, but positively associated with patient margin. The Post-Acute Care group is positively associated with revenue per bed, but not with either measure of margins. The Intermediate Care group is negatively associated with revenue per bed and total margin. Finally, the High Acuity Care Group is positively associated with revenue per bed and with patient margin. The rate of occupancy was positively associated with each of the financial measures. Interestingly, for-profit ownership status was associated negatively with net patient revenue per bed, but positively associated with patient margin and total margin.

Table 18. *OLS Regression results for quality performance*

Variable	Adj. 30-day Readmissions			Prevalence of Pressure Ulcers			Prevalence of UTIs		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Group 1: Private Pay Care (N)	ref			ref			ref		
Group 2: Long-stay Care (N)	1.138	***	0.239	0.584	**	0.198	-0.419		0.228
Group 3: Long-stay Complex Care (N)	0.686	**	0.237	0.639	**	0.207	-0.359		0.239
Group 4: Post-Acute Care (W)	0.234		0.246	0.397		0.238	0.152		0.270
Group 5: Intermediate Care (W)	1.094	***	0.241	0.580	**	0.207	-0.203		0.232
Group 6: High Acuity Care (W)	0.496	*	0.245	0.774	**	0.226	-0.396		0.248
% Population > 65	-0.035	*	0.016	-0.093	***	0.015	-0.017		0.016
Per Capita Income (log)	-0.910	**	0.298	-1.007	***	0.287	-0.711	*	0.280
Urban	0.707		0.381	-0.031		0.346	-0.721		0.385
Suburban	0.021		0.453	-0.60		0.418	-0.698		0.446
Large Rural Town	0.083		0.376	-0.763	*	0.330	-0.253		0.375
Rural	ref			ref			ref		
%Δ Medicare HMO Penetration	0.023	*	0.010	0.012		0.010	-0.015		0.010
ACO Penetration	-0.033	***	0.007	-0.024	***	0.006	0.009		0.006
HHI (SNF beds)	-1.430	**	0.529	-0.149		0.438	0.508		0.495
Home Health Availability / Pop > 65 (per 100,000) (log)	0.555	***	0.073	-0.162	*	0.075	-0.030		0.071
# Beds (log)	0.538	*	0.209	0.567	*	0.194	-0.891	***	0.185
% Occupancy	-0.011		0.007	-0.010		0.006	-0.002		0.006
For-profit	1.352	***	0.180	0.773	***	0.145	-0.362	*	0.164
Chain Affiliated	-0.363	*	0.146	-0.377	*	0.129	-0.536	***	0.137

Significance at $p < 0.05$= *, $p < 0.01$ = **, $p < 0.001$ = ***

Adjusted 30-day readmissions. Adjusted 30-day readmissions are positively associated with the Long-stay Care, Long-stay Complex Care, Intermediate Care, and High Acuity Care groups, indicating worse performance. On average, these groups have higher rates of 30-day hospital readmissions of 1.138%, 0.686%, 1.094%, and 0.496%, respectively, compared to the Private Pay Care group, other things constant.

Prevalence of Pressure Ulcers. All groups, except the Post-Acute Care group, demonstrate positive association with the prevalence of pressure ulcers among long-stay patients. Thus, relative to the Private Pay Care group, four of the five strategy groups show worse performance on pressure ulcers. The Long-stay Care, Long-stay Complex Care, Intermediate Care, and High Acuity Care groups are associated with higher rates of prevalence of pressure ulcers of 0.584%, 0.639%, 0.580%, and 0.774%, respectively, compared to the Private Pay Care group, other things held constant.

Prevalence of UTIs. None of the strategy groups were associated with the prevalence of UTIs compared to the Private Pay Care group, other things constant at a significance level of $p < 0.05$. The Long-stay Care group demonstrated a negative association of 0.419% with the prevalence of UTIs at $p = 0.067$.

Table 19. *Summary of group membership and association with quality performance*

Group	**Adj. 30-day Readmissions**	**Prevalence of Pressure Ulcers**	**Prevalence of UTIs**
Group 1: Private Pay Care (N)	--	--	--
Group 2: Long-stay Care (N)	Positive	Positive	--
Group 3: Long-stay Complex Care (N)	Positive	Positive	--
Group 4: Post-Acute Care (W)	--	--	--
Group 5: Intermediate Care (W)	Positive	Positive	--
Group 6: High Acuity Care (W)	Positive	Positive	--

Measures of quality performance are significantly associated with membership in each strategic group, except for the Post-Acute Care group, demonstrating a relationship between strategies and the selected measures of quality performance. The results from the OLS models, summarized in Table 19, provide some support for Hypothesis 2b, that membership in a particular strategic group is associated with quality performance. The significant associations are all positive, indicating worse performance outcomes. Compared to the Private Pay Care group, membership in the Long-stay Care group, Long-stay Complex Care, Intermediate Care, and High Acuity Care groups is associated with higher levels of adjusted 30-day readmissions, and prevalence of pressure ulcers. None of the groups demonstrated a significant association with the prevalence of UTIs above the threshold of $p < 0.05$.

RQ3: Empirical Analysis

To assess RQ3, strategy groups for 2012 are classified. Then, SNFs that changed strategy groups between 2012 and 2015 are compared to SNFs that did not change. Descriptive differences are presented, followed by an analysis of change in performance over time between SNFs changing strategy groups and those that did not change strategy groups.

Classification of 2012 strategy groups.

Quadratic discriminant analysis (QDA) provides more reliability in discriminating groups where there are unequal variances than multiple discriminant analysis and was used in RQ1 to assess the reliability of the cluster solution. In this part of the study QDA was used to predict the composition of strategy groups in 2012 based upon the discriminant coefficients from 2015 strategic groups. The level of agreement between the 2012 and 2015 strategic groups is relatively low. Only 53.3% of SNFs were classified into the same strategic group in 2012 as in 2015 and the Adjusted Rand Index is low at 0.2016. Table 20 displays a crosstab of the counts and percentages of SNFs defined in 2015 and identified as belonging to the same groups in 2012.

By examining the percentages of SNFs classified in each group in 2015 compared to 2012, the shifts from one group to another can be discerned. Many of the shifts from one group to another group are among groups with some resemblance to one another. Generally, Private Pay, Long-stay, and Long-stay Complex Groups tended to shift from one to another. Similarly, Post-Acute, Intermediate, and High Acuity tended to shift from one to another. Some of the groups may have more in common (organizational resources or environmental pressures) than others resulting in lower mobility barriers between some groups and movement from one strategy to another. The Long-stay groups are likely more similar to one another than to the groups that provide more short-stay care (Post-Acute, Intermediate, and High Acuity Care groups). Likewise, groups that have a wide referral network (Post-Acute, Intermediate, and High Acuity Care) may have greater fluidity in strategic decisions regarding preferred markets than groups with narrow networks. Environmental uncertainty may also facilitate shifting to a different strategy. These results provide some support for Hypothesis 3a that the composition of the strategic groups changes over time and will be discussed in more detail in Chapter 6. Of note is that even though there is evidence of a high proportion of fluidity of SNFs between strategy groups within the sample, the industry structure of the strategy groups between 2012 and 2015 is relatively stable: Private Pay Care, 14% vs. 15%; Long-stay Care, 23% vs. 21%; Long-stay Complex Care, 18% vs. 20%; Post-Acute Care, 11% vs. 12%; Intermediate Care, 21% vs. 19%; and, High Acuity Care, 13% vs 14%.

Table 20. *Crosstab of SNFs in 2015 groups and 2012 groups*

	2015 Groups						
2012 Groups	**1**	**2**	**3**	**4**	**5**	**6**	**Total 2012**
Group 1: Private Pay Care (N)	355	96	68	72	47	20	658
Group 2: Long-stay Care (N)	108	576	203	8	127	25	1047
Group 3: Long-stay Complex Care (N)	79	136	438	16	39	93	801
Group 4: Post-Acute Care (W)	55	5	12	291	71	57	491
Group 5: Intermediate Care (W)	64	147	86	78	463	121	959
Group 6: High Acuity Care (W)	15	10	84	64	103	307	583
Total 2015	676	970	891	529	850	623	4539
Percentages							
	2015 Groups						
2012 Groups	1	2	3	4	5	6	Total 2012 %
Group 1: Private Pay Care (N)	53%	10%	8%	14%	6%	3%	14%

2012 Groups	2015 Groups 1	2	3	4	5	6	Total 2012
Group 2: Long-stay Care (N)	16%	59%	23%	2%	15%	4%	23%
Group 3: Long-stay Complex Care (N)	12%	14%	49%	3%	5%	15%	18%
Group 4: Post-Acute Care (W)	8%	1%	1%	55%	8%	9%	11%
Group 5: Intermediate Care (W)	9%	15%	10%	15%	54%	19%	21%
Group 6: High Acuity Care (W)	2%	1%	9%	12%	12%	49%	13%
Total 2015 %	15%	21%	20%	12%	19%	14%	100%

Characterization of Shifters and Non-Shifters.

Next, differences from 2012 to 2015 in classification variables, financial measures, and quality measures are examined by strategy group. Differences are discussed in absolute percentage points. Means and differences of classification variables across time for the full strategy group, Shifters, and Non-Shifters are presented in Table 21. T-tests are used to test for significance of differences from 2012 to 2015 for each group.

Percentage of Medicaid. Overall, there is a decline of 0.81% in Medicaid census among SNFs from 2012 to 2015, but strategy groups demonstrate different levels of change. In total, Private Pay and Post-Acute Care groups have a decline of 6.2% and 6.4%, respectively, in their average percent of Medicaid patients. The reduction in average Medicaid for SNFs that shifted to Private Pay and Post-Acute Care groups was about twice that amount at 12.0% and 14.1%, respectively. Overall, Long-stay Care and Intermediate Care groups increased their average Medicaid census from 2012 to 2015 by 2.3% and 1.6%, respectively, while Shifters had 5.6% and 3.6% increases, respectively. Shifters into High Acuity Care had a 1.4% increase in Medicaid. Non-Shifters did not demonstrate as much change with Private Pay and High Acuity Care, declining by modest amounts of 0.9% and 0.8%, respectively.

Average CMI of Admitted Patients. The overall trend among all groups was an increase of 0.01 in CMI from 2012 to 2015. Different levels of change were demonstrated with Private Pay, Long-stay Complex, Post-Acute, and High-Acuity Care groups having increases of 0.02, 0.04, 0.01, and 0.03, respectively. Long-stay and Intermediate Care had declines in the complexity of patients admitted with lower average CMIs of 0.1 each. For Shifters, the trend was similar with Long-stay and Intermediate Care groups having an average decline of 0.04 and 0.03 points, and Long-stay, Post-Acute, and High Acuity care groups increasing in average admitted CMI by 0.08, 0.01, and 0.06, respectively. For Non-Shifters, each strategy group had an increase in the average CMI of admitted patients, except for the Long-stay Complex Care group.

Referral Centrality. Overall, strategy groups demonstrated changes in referral centrality from 2012 to 2015. Private Pay, Long-stay, and Long-stay Complex Care groups increased in their levels of referral centrality, each by 0.08, and Shifters at twice that amount (0.16, 0.19, 0.18, respectively). Overall, Post-Acute, Intermediate, and High Acuity had declining levels of referral centrality of 0.09, 0.10, and 0.09, respectively. Shifters into those groups had similar declines in referral centrality of 0.18, 0.23, and 0.18, respectively. Non-Shifters did not demonstrate changes in referral centrality.

Table 21. *Classification variable means 2012 and 2015 by Strategy Group, Shifters, and Non-Shifters*

Strategy Group Classification in 2015	Overall				Shifters - Different Strategy				Non-Shifters - Same Strategy			
	2012	2015	2015-2012		2012	2015	2015-2012		2012	2015	2015-2012	
% Medicaid												
Group 1: Private Pay (N)	51.14	44.93	-6.21	***	58.79	46.76	-12.03	***	44.23	43.28	-0.95	*
Group 2: Long-stay Care (N)	70.61	72.96	2.35	***	66.08	71.66	5.58	***	73.71	73.84	0.13	
Group 3: Long-stay Complex Care (N)	67.62	67.75	0.13		67.23	67.76	0.53		68.03	67.74	-0.29	
Group 4: Post-Acute Care (W)	42.79	36.38	-6.41	***	52.96	38.87	-14.09	***	34.47	34.34	-0.13	
Group 5: Intermediate Care (W)	64.60	66.16	1.56	***	61.93	65.50	3.57	***	66.83	66.71	-0.12	
Group 6: High Acuity Care (W)	62.16	62.51	0.35		60.35	61.79	1.44	*	64.03	63.24	-0.79	*
Total	61.60	60.79	-0.81	***	62.12	60.72	-1.40	***	61.15	60.85	-0.30	*
Average CMI of Admitted Patients												
Group 1: Private Pay (N)	1.29	1.31	0.02	***	1.31	1.31	0.00		1.28	1.30	0.02	***
Group 2: Long-stay Care (N)	1.28	1.27	-0.01	***	1.31	1.27	-0.04	***	1.25	1.26	0.01	*
Group 3: Long-stay Complex Care (N)	1.39	1.43	0.04	***	1.34	1.42	0.08	***	1.44	1.44	0.00	
Group 4: Post-Acute Care (W)	1.33	1.34	0.01	**	1.34	1.35	0.01	*	1.33	1.34	0.01	*
Group 5: Intermediate Care (W)	1.30	1.29	-0.01	**	1.33	1.30	-0.03	***	1.28	1.29	0.01	***
Group 6: High Acuity Care (W)	1.42	1.45	0.03	***	1.37	1.43	0.06	***	1.46	1.47	0.01	*
Total	1.33	1.34	0.01	***	1.33	1.35	0.02	***	1.33	1.34	0.01	***
Referral Centrality												
Group 1: Private Pay (N)	0.91	0.99	0.08	***	0.82	0.98	0.16	***	0.99	0.99	0.00	
Group 2: Long-stay Care (N)	0.92	1.00	0.08	***	0.81	1.00	0.19	***	1.00	1.00	0.00	
Group 3: Long-stay Complex Care (N)	0.91	0.99	0.08	***	0.82	1.00	0.18	***	1.00	0.99	-0.01	
Group 4: Post-Acute Care (W)	0.59	0.50	-0.09	***	0.70	0.52	-0.18	***	0.49	0.49	0.00	
Group 5: Intermediate Care (W)	0.63	0.53	-0.10	***	0.77	0.54	-0.23	***	0.52	0.51	-0.01	
Group 6: High Acuity Care (W)	0.60	0.51	-0.09	***	0.71	0.53	-0.18	***	0.49	0.50	0.01	
Total	0.78	0.78	0.00		0.78	0.79	0.01		0.78	0.78	0.00	

Significance at $p < 0.05$= *, $p < 0.01$ = **, $p < 0.001$ = ***
(N) indicates Narrow Network and (W) indicates Wide Network

Performance Differences between Shifters and Non-Shifters

To test Hypothesis 3b, whether shifting from one strategy group to another strategy group is associated with a subsequent change in performance, performance measures for SNFs using different strategies are compared to those using the same strategy. Means and differences of financial measures across time for the full strategy group, Shifters, and Non-Shifters are presented in Table 22, and significance of differences between 2012 and 2015 is noted based on t-tests. Estimates from a difference-in-differences OLS regression model help identify whether the trends demonstrated by the SNFs using a different strategy in 2012 compared to 2015 are significantly different from SNFs using the same strategy from 2012 to 2015 when controlling for confounding factors. SNFs classified as changing strategy, the Shifters, represent the treatment group, and SNFs classified in the same strategy group in 2012 and 2015, the Non-Shifters, serve as the control group. Observations from 2015 are identified as post-treatment, and observations from 2012 are considered pre-treatment as a change in strategy occurred prior to 2015. Each strategy group was modeled separately based upon strategy group classifications in 2015, and a model was run for each of six performance measures, for a total of 36 regressions. The assumptions for DID are strong in this analysis, limiting confidence in its findings. However, the results are supported by the trends visible on charts of performance measures from 2012 to 2015 for Shifters and Non-Shifters included in Appendix 3. The full regression results for the Private Pay Care group for patient revenue per bed are presented in Appendix 4 as an example of the regression results.

Revenue per bed. Comparisons remain in the natural logarithm form. Overall, there was an increase in average revenue per bed across the strategy groups (0.01). Long-stay care, however, experienced a decline in revenue per bed (-0.02), and the Intermediate Care group did not experience a significant change. Among Shifters, there were increases in revenue per bed for the Long-stay Complex (0.02), Post-Acute (0.04), and High Acuity Care groups (0.03). Shifters into Long-stay Care had a decline in average revenue per bed, however, Non-Shifters in the Long-stay Care group did not have a change in revenue per bed. The Non-Shifters in the Private Pay (0.03) and High Acuity Care (0.02) groups also had increases in revenue per bed from 2012 to 2015. Difference-in-differences estimators indicate that SNFs shifting to a Private Pay or Long-stay Care strategy experienced a greater decline in revenue per bed (-2.08 % and -2.27%, respectively) than Non-Shifters. In contrast, Shifters into Long-stay Complex, Post-Acute, and High Acuity Care groups had a greater increase in revenue per bed than did Non-Shifters (1.41%, 3.15%, and 1.92%, respectively).

Patient margin. The average patient margin declined for each of the strategy groups from 2012 to 2015. Among the Shifters, the Post-Acute and High Acuity Care groups did not have a significant decline in patient margin, though the trend was downward, but the other Shifters had significantly declining margins across the study period. SNFs that did not change strategy groups also had declines in patient margin, except for the Private Pay Care group, though their patient margin trended downward. Difference-in-differences estimators indicate that SNFs shifting to a Long-stay Care strategy had a 1.27% decline in patient margin compared to Non-Shifters. In contrast, SNFs shifting to a High Acuity Care focus had a 1.32% increase in patient margin compared to Non-Shifters.

Total margin. In all strategy groups, Shifters, and Non-Shifters experienced an average decline in total margin. The exception was Shifters into the High Acuity Care group that did not have a significant decline in total margin, but the trend was downward. Difference-in-differences estimators indicate that SNFs shifting to a Long-stay Care strategy experience a 1.23% greater decline in total margin compared to Non-Shifters in the group.

Table 22. *Financial measure means 2012 and 2015 by Strategy Group, Shifters, and Non-Shifters and Difference-in-differences estimator*

Strategy Group Classification in 2015	Overall				Different Strategy				Same Strategy				DID Estimator		
	2012	2015	2015-2012		2012	2015	2015-2012		2012	2015	2015-2012		Coef.	SE	
Revenue Per Bed (Log)															
Group 1: Private Pay Care (N)	11.35	11.38	0.02	***	11.33	11.34	0.01		11.38	11.41	0.03	***	-0.021	0.009	*
Group 2: Long-stay Care (N)	11.22	11.20	-0.02	***	11.27	11.24	-0.03	***	11.18	11.18	0.00		-0.023	0.006	***
Group 3: Long-stay Complex Care (N)	11.32	11.66	0.34	***	11.29	11.31	0.02	***	11.34	11.35	0.01		0.014	0.006	*
Group 4: Post-Acute Care (W)	11.54	11.56	0.02	***	11.47	11.51	0.04	***	11.59	11.60	0.01		0.031	0.010	**
Group 5: Intermediate Care (W)	11.33	11.34	0.00		11.34	11.34	0.00		11.33	11.33	0.00		-0.001	0.007	
Group 6: High Acuity Care (W)	11.45	11.47	0.02	***	11.40	11.43	0.03	***	11.49	11.51	0.02	**	0.019	0.008	*
Total	11.35	11.36	0.01	***	11.34	11.35	0.01	***	11.35	11.36	0.01	***	0.002	0.003	
Patient Margin															
Group 1: Private Pay Care (N)	-1.36	-2.42	-1.06	*	0.58	-0.88	-1.46	**	-3.11	-3.80	-0.69		-0.556	0.759	
Group 2: Long-stay Care (N)	0.29	-1.61	-1.90	***	0.72	-2.26	-2.98	***	0.00	-1.16	-1.16	***	-1.266	0.503	*
Group 3: Long-stay Complex Care (N)	2.15	0.75	-1.40	***	1.61	0.50	-1.11	**	2.70	1.00	-1.70	***	0.649	0.541	
Group 4: Post-Acute Care (W)	-0.98	-2.17	-1.19	*	-0.90	-1.99	-1.09		-1.05	-2.32	-1.27	*	-0.100	0.832	
Group 5: Intermediate Care (W)	0.70	-1.13	-1.83	***	1.10	-1.16	-2.26	***	0.37	-1.11	-1.48	***	-0.577	0.572	
Group 6: High Acuity Care (W)	2.50	1.34	-1.16	***	1.48	0.78	-0.70		3.55	1.91	-1.64	***	1.320	0.577	*
Total	0.64	-0.84	-1.48	***	0.89	-0.77	-1.66	***	0.42	-0.90	-1.32	***	-0.094	0.253	
Total Margin															
Group 1: Private Pay Care (N)	2.41	1.14	-1.27	***	2.38	1.17	-1.21	*	2.43	1.11	-1.32	***	-0.041	0.579	
Group 2: Long-stay Care (N)	1.61	-0.20	-1.81	***	2.15	-0.75	-2.90	***	1.24	0.17	-1.07	***	-1.230	0.476	*
Group 3: Long-stay Complex Care (N)	3.14	1.87	-1.27	***	2.79	1.73	-1.06	*	3.50	2.00	-1.50	***	0.497	0.487	
Group 4: Post-Acute Care (W)	2.80	1.35	-1.45	***	2.87	1.48	-1.39	**	2.75	1.24	-1.51	***	0.039	0.559	
Group 5: Intermediate Care (W)	2.17	0.49	-1.68	***	2.31	0.60	-1.71	***	2.05	0.39	-1.66	***	0.238	0.476	
Group 6: High Acuity Care (W)	3.53	2.55	-0.98	***	2.88	2.25	-0.63		4.20	2.85	-1.35	***	1.000	0.529	
Total	2.53	1.09	-1.44	***	2.54	1.03	-1.51	***	2.53	1.15	-1.38	***	0.073	0.209	

Significance at $p < 0.05$= *, $p < 0.01$ = **, $p < 0.001$ = ***
(N) indicates Narrow Network and (W) indicates Wide Network

Means and differences of quality measures across time for the full strategy group, Shifters, and Non-Shifters are presented in Table 23.

Adjusted 30-day readmissions. All groups, Shifters, and Non-Shifters had significant absolute declines in adjusted 30-day readmissions from 2012 to 2015. Difference-in-differences estimators indicate that SNFs shifting to Long-stay Care and Long-stay Complex Care had greater declines in adjusted 30-day readmissions (0.73% and 0.83%, respectively) than Non-Shifters. Shifters into the Post-Acute Care group experienced an increase of 1.17% higher in 30-day readmissions than Non-Shifters.

Prevalence of pressure ulcers. Most groups had significant declines in the prevalence of pressure ulcers. Exceptions were the overall Post-Acute Care group not having a significant change, Shifters into the Post-Acute Care group not having a significant change, and Shifters into the Intermediate Care group not having a significant change. Difference-in-differences estimators indicate there are no significant differences between the changes in prevalence of pressure ulcers between Shifters and Non-Shifters.

Prevalence of UTIs. All groups, Shifters, and Non-Shifters had significant declines in the prevalence of UTIs from 2012 to 2015. Difference-in-differences estimators indicate that only SNFs shifting to a Private Pay group experienced a greater decline (-1.18%) than Non-Shifters.

Significant performance differences in SNFs that shifted to a different strategy compared to Non-Shifters provide mixed support for Hypothesis 3b, that changing from one strategy group to another strategy group is associated with a subsequent positive change in performance. For financial performance, Shifters into Post-Acute Care, High-Acuity Care, and Long-stay Complex strategies experienced positive changes in performance compared to Non-Shifters, however, Shifters into Private Pay and Long-stay Care groups experienced greater declines in performance compared to Non-Shifters. The comparison of quality measures is also mixed. Shifters into Long-stay Care and Long-stay Complex Care had greater reductions in adjusted 30-day readmissions, and Shifters into Private Pay Care had greater reductions in prevalence of UTIs compared to Non-Shifters of these groups. However, SNFs shifting into the Post-Acute Care group had higher increases in adjusted 30-day readmissions than Non-Shifters.

Table 23. *Quality measure means 2012 and 2015 by Strategy Group, Shifters, and Non-Shifters and Difference-in-Differences estimator*

Strategy Group Classification in 2015	Overall				Different Strategy				Same Strategy				DID Estimator		
	2012	2015	2015-2012		2012	2015	2015-2012		2012	2015	2015-2012		Coef.	SE	
Adj. 30-Day Readmissions															
Group 1: Private Pay Care (N)	17.99	16.58	-1.41	***	18.79	17.02	-1.77	***	17.27	16.18	-1.09	***	-0.599	0.409	
Group 2: Long-stay Care (N)	19.14	17.99	-1.15	***	19.37	17.90	-1.47	***	18.98	18.04	-0.94	***	-0.732	0.347	*
Group 3: Long-stay Complex Care (N)	18.79	17.59	-1.20	***	19.19	17.59	-1.60	***	18.38	17.59	-0.79	***	-0.825	0.324	*
Group 4: Post-Acute Care (W)	18.71	17.14	-1.57	***	18.40	17.43	-0.97	***	18.96	16.90	-2.06	***	1.167	0.377	**
Group 5: Intermediate Care (W)	19.16	17.97	-1.19	***	18.80	17.84	-0.96	***	19.46	18.08	-1.38	***	0.434	0.327	
Group 6: High Acuity Care (W)	19.24	17.61	-1.63	***	19.04	17.53	-1.51	***	19.45	17.69	-1.76	***	0.210	0.320	
Total	18.87	17.55	-1.32	***	18.98	17.58	-1.40	***	18.77	17.52	-1.25	***	-0.158	0.144	
Prevalence of Pressure Ulcers (Long-stay)															
Group 1: Private Pay Care (N)	5.73	5.03	-0.70	***	6.03	5.33	-0.70	*	5.46	4.76	-0.70	**	-0.060	0.377	
Group 2: Long-stay Care (N)	6.95	5.94	-1.01	***	6.84	6.01	-0.83	***	7.03	5.90	-1.13	***	0.370	0.336	
Group 3: Long-stay Complex Care (N)	7.15	6.03	-1.12	***	7.41	6.00	-1.41	***	6.89	6.07	-0.82	***	-0.534	0.341	
Group 4: Post-Acute Care (W)	5.89	5.64	-0.25		5.88	5.89	0.01		5.91	5.43	-0.48	*	0.452	0.431	
Group 5: Intermediate Care (W)	6.28	5.89	-0.39	*	6.33	6.22	-0.11		6.24	5.60	-0.64	**	0.616	0.340	
Group 6: High Acuity Care (W)	6.98	6.34	-0.64	***	6.68	6.22	-0.46	*	7.29	6.46	-0.83	***	0.311	0.380	
Total	6.57	5.83	-0.74	***	6.61	5.96	-0.65	***	6.52	5.72	-0.80	***	0.109	0.148	
Prevalence of UTIs															
Group 1: Private Pay Care (N)	7.49	5.43	-2.06	***	7.58	5.00	-2.58	***	7.40	5.82	-1.58	***	-1.182	0.506	*
Group 2: Long-stay Care (N)	7.10	4.87	-2.23	***	7.13	4.82	-2.31	***	7.07	4.91	-2.16	***	0.457	0.349	
Group 3: Long-stay Complex Care (N)	7.53	4.92	-2.61	***	7.32	4.73	-2.59	***	7.74	5.13	-2.61	***	0.101	0.401	
Group 4: Post-Acute Care (W)	8.38	5.26	-3.12	***	8.08	5.38	-2.70	***	8.63	5.17	-3.46	***	1.018	0.608	
Group 5: Intermediate Care (W)	6.96	4.79	-2.17	***	7.13	4.72	-2.41	***	6.81	4.85	-1.96	***	-0.383	0.368	
Group 6: High Acuity Care (W)	7.60	4.70	-2.90	***	7.83	5.07	-2.76	***	7.36	4.32	-3.04	***	0.059	0.451	
Total	7.43	4.97	-2.46	***	7.45	4.91	-2.54	***	7.41	5.03	-2.38	***	-0.072	0.177	

Significance at $p < 0.05$= *, $p < 0.01$ = **, $p < 0.001$ = ***
(N) indicates Narrow Network and (W) indicates Wide Network

Sensitivity Analyses

As noted in the Methods chapter, there are several aspects of cluster analysis that are subjective. Sensitivity analyses were performed to better understand outcomes under different scenarios. The choice of clustering variables is subjective and greatly impacts a cluster analysis. Sensitivity analyses are conducted using alternative staffing measures as a proxy for patient complexity to classify SNFs. First, direct-care staff hours per resident day was substituted for average CMI of admitted patients in a hierarchical cluster analysis using Ward's method. This resulted in a six-cluster solution that closely resembled the taxonomic profiles developed using in the study. Then, RN hours per resident day was substituted as a classification dimension for average CMI of admitted patients in a hierarchical cluster analysis using Ward's method. However, three- and five-cluster solutions resulted that did not resemble the study results. The sensitivity analysis suggests that direct-care staff hours per resident day serves as a better proxy of average CMI of admitted patients than does RN hours per resident day. Nursing home staffing levels are based on the acuity level of patients, but other factors may affect specific types of staffing (Mueller et al., 2006). Average CMI of admitted patients appears to be a more reliable indicator of complexity of patients than staffing levels.

Choosing a specific quality measure may not provide a full picture of quality of care and a few additional quality measures were tested for association with membership in a strategy group to broaden this assessment. Different qualitative measures were tested for association with membership in a strategic group. There was no association between prevalence of catheters and strategy group membership. Other measures were associated with group membership, with the Private Pay Care Group serving as a reference group as follows: the use of restraints was 0.26% lower in the Post-Acute Care Group; the use of antipsychotic medication was 2.59% higher in

Long-stay Care, 1.66% higher in Long-stay Complex Care, and 1.14% higher in Intermediate Care. Increase in help with activities of daily living was 1.32% higher in Long-Stay Care, 1.20% higher in Intermediate Care, and 0.92% lower in High Acuity Care groups. Except for the prevalence of catheters, these quality measures also demonstrated an association with membership in a specific strategic group.

Summary of Results

This chapter presents the results of the methods outlined in Chapter 4. A descriptive analysis of the study sample is followed by summarized results from analyses to address each of the study's three research questions. A two-stage cluster analysis resulted in a typology of six strategic groups of SNFs (Hypothesis 1). Membership in a particular strategy group was significantly associated with some financial and quality performance measures (Hypotheses 2a and 2b). Additionally, there is evidence of the composition of strategic groups changing over time, and changes in some performance measures for SNFs shifting strategies compared to SNFs that do not change strategy (Hypotheses 3a and 3b), though the direction of changes in performance measures is mixed. Sensitivity analyses regarding classification variables and performance measures are provided.

In the next chapter, these findings are summarized in the context of prior literature and implications for health policy and theory are explored. The study concludes with a review of its limitations and suggestions for future research.

Chapter 6: Discussion

This chapter summarizes and interprets the empirical results presented in Chapter 5. A summary of the study's findings is followed by a discussion of the results in the context of prior studies of strategic modeling of SNFs. The third section discusses the study's contributions and implications for policy and theory. The fourth and fifth sections address limitations and future research, and the last section provides a brief summary.

Summary of Study Findings

Changes in health care policies, competitive factors, and demand for services have added uncertainty to the environment in which nursing homes operate. This study seeks to better understand the nursing home industry through strategic group modeling and exploring the structure-performance link and changes in the structure of the industry over time. Strategic management theory informs the conceptual framework to explain how environmental and organizational factors contribute to strategic decision making by managers, which in turn leads to performance. A series of hypotheses are derived from the conceptual framework and tested. Support is found for most of the hypotheses. The study's aims, hypotheses, and results are summarized in Table 24 and discussed in the following sections.

Table 24. *Summary of study findings*

Aim 1: To better understand the behavior of SNFs by classifying SNFs into groups based on their strategic orientation.		
Hypothesis 1:	There are differences among subsets of SNFs based on: 1) the proportion of long-stay care patients, 2) complexity of admitted patients, and 3) the strength of referral relationships with hospitals.	Supported
Aim 2: To examine whether financial and quality outcomes are associated with strategic orientation.		
Hypothesis 2a:	Membership in a specific strategic group of SNFs is associated with a SNF's *financial* performance.	Supported
Hypothesis 2b:	Membership in a specific strategic group of SNFs is associated with a SNF's *quality* performance.	Supported
Aim 3: To evaluate whether SNFs change their strategic orientation during a time of environmental uncertainty indicating a change in the structure of the nursing home industry.		
Hypothesis 3a:	The composition of the strategic groups changes over time.	Supported
Hypothesis 3b:	Shifting from one strategy group to another strategy group is associated with a subsequent *positive* change in performance.	Mixed Support

Strategic groups of SNFs

The first aim of the study is to better understand the behavior of SNFs by classifying SNFs into strategic groups. Strategic group modeling provides a means of identifying groups of SNFs using similar strategies and helps to identify mobility barriers faced by strategic groups (Porter, 1979, 1980). An inductive approach is taken to classify SNFs without *a priori* expectations of the number of strategy groups. Two-step hierarchical cluster analysis using Ward's method to determine the number of clusters and then the *K*-means method is used to classify the sample into groups. Dimensions of scope of business are used for classification to represent market segment (short-stay or long-stay), services offered (complexity of admitted patients), and market reach (referral centrality). Using a limited national sample of 2015 data, a six-cluster solution of groups is found to be valid and reliable. The strategy groups of SNFs are characterized as: Private Pay Care Focus – Narrow Network, Long-stay Care Focus – Narrow Network, Long-stay Complex Care Focus – Narrow Network, Post-Acute Care Focus – Wide Network, Intermediate Care Focus – Wide Network, and High Acuity Care Focus – Wide Network. This taxonomy of SNFs provides support for Hypothesis 1, that there are differences among subsets of SNFs based on: 1) the proportion of long-stay care patients, 2) complexity of admitted patients, and 3) the strength of referral relationships with hospitals. Descriptions of each of the strategy groups are detailed in Chapter 5.

Structure – Performance Link

The second aim of the study is to examine whether financial and quality outcomes are associated with strategic orientation. A series of OLS regressions finds that there is an association between membership in a particular group and some measures of financial or quality performance in 2015. Table 25 summarizes the statistically significant results from OLS regressions testing the association of performance measures with membership in a particular strategic group. A discussion of financial and quality measures for each group follows.

Table 25. *Summary of group membership and association with performance measures*

Group	Net Patient Revenue per Bed	Patient Margin	Total Margin	Adj. 30-day Readmissions	Prevalence of Pressure Ulcers	Prevalence of UTIs
Group 1: Private Pay Care (N) (reference)	--	--	--	--	--	--
Group 2: Long-stay Care (N)	Negative	Negative	Negative	Positive	Positive	--
Group 3: Long-stay Complex Care (N)	Negative	Positive	--	Positive	Positive	--
Group 4: Post-Acute Care (W)	Positive	--	--	--	--	--
Group 5: Intermediate Care (W)	Negative	--	Negative	Positive	Positive	--
Group 6: High Acuity Care (W)	Positive	Positive	--	Positive	Positive	--

Group 1: Private Pay Care Focus – Narrow Network. The Private Pay Focus group serves as the reference group in the regression analyses as it is less likely to be influenced by Medicare policy changes. This group has mid-level patient revenue per bed and total margin, but the lowest patient margin of any group. Interestingly, low patient margins are paired with stronger quality measures as the Private Pay Care Focus group has the lowest levels of 30-day readmissions and prevalence of pressure ulcers. Perhaps this group has more incentive to focus on quality measures to compete effectively for private pay patients, or they may place greater importance on quality measures compared to other SNFs.

Group 2: Long-stay Care Focus – Narrow Network. For this group, having the highest rate of Medicaid patients is reflected in having the lowest patient revenues per bed. Patient revenue per bed and patient and total margins are negatively associated with membership in the Long-stay Care Focus group, compared to the Private Pay Care group. Lower levels of quality performance are indicated by positive association with 30-day readmissions and prevalence of pressure ulcers compared to the Private Pay Care group. This group represents SNFs providing mostly long-stay custodial care that is not very profitable.

Group 3: Long-stay Complex Care Focus – Narrow Network. The Long-stay Complex Care group has the lowest average patient revenue per bed, except for the Long-stay Care group. Interestingly, membership in the Long-stay Complex Care group is negatively associated with patient revenue per bed, but positively associated with patient margin, compared to the Private Pay Care group. Membership in this group is associated with worse quality measures for prevalence of pressure ulcers compared to the Private Pay Care group. Managers in these SNFs seem to have the ability to turn a profit on low revenues.

Group 4: Post-Acute Care Focus – Wide Network. The average patient revenue per bed in the Post-Acute Care Focus group is the highest of the strategy groups. Membership in the Post-Acute Care group is positively associated with patient revenue per bed compared to the Private Pay Focus group, however patient margins and total margins are not associated with membership in the group. Overall, the Post-Acute Care Focus group demonstrates high levels of quality performance, like the Private Pay Focus group. The Post-Acute Focus Care group seems to be able to attract high revenue referrals, but perhaps not the most profitable patients. This could be a result of lack of managerial skill in turning a profit, or a result of accepting less profitable patients in order to have working referral relationships with multiple hospitals (Shield et al., 2018).

Group 5: Intermediate Care Focus – Wide Network. Membership in the Intermediate Care Focus group is negatively associated with patient revenue per bed and total margin compared to the Private Pay Care Focus group. Membership is associated with worse quality performance in adjusted 30-day readmissions and the prevalence of pressure ulcers. The Intermediate Care Focus group appears to be less profitable because these SNFs do not admit more profitable or more complex patients as do the Private Pay Care, Post-Acute Care, High

Acuity Care, and Long-stay Complex Care Focus groups. SNFs in the Intermediate Care Focus group appear not to have a clear strategy, or struggle to effectively execute their strategy.

Group 6: High Acuity Care Focus – Wide Network. The High Acuity Care Focus group has the second highest average revenue per bed and one of the largest average bed sizes. Membership in the High Acuity Care Focus groups is positively associated with patient revenues per bed and with patient margin, but there is not an association with total margin. On average, this group has worse outcomes for 30-day readmissions and the prevalence of pressure ulcers compared to the reference group, Private Pay Focus. This is the only group that appears to turn high revenues per bed into a positive patient margin. Patients of greater acuity can produce more revenues, and this group seems to be able to manage complex patients more profitably than the other groups. Poor quality performance may reflect higher acuity patients than the other groups, or a focus on profitability at the expense of quality.

The results of the OLS regressions provide support for Hypothesis 2a, that membership in a particular strategy group is associated with financial performance, specifically patient revenue per bed, patient margin, and total margin. There is also support for Hypothesis 2b, that membership in a particular strategy group is associated with quality performance, specifically the prevalence of pressure ulcers.

Shifters versus Non-Shifters

The third aim of the study is to evaluate whether SNFs change their strategic orientation during a time of environmental uncertainty, indicating a change in the structure of the nursing home industry. First, strategic groups of SNFs in 2012 are found using discriminant analysis and changes in the composition of groups between 2012 and 2015 are assessed. Then, performance differences between SNFs that have changed strategic groups versus those that have not changed strategic groups are evaluated with a difference-in-differences model.

The results of the analysis provide support for Hypothesis 3a, that the composition of strategic groups changes over time. Among strategic groups in the current study, there is stability in the proportion of strategy groups within the industry from 2012 to 2015, but almost half of individual SNFs shift from one strategy group to another. This fluidity may be an artifact of using secondary data to classify SNFs into groups. The averages of payer proportions, patient complexity, and referral centrality are continuous variables that may fluctuate within ranges that do not represent a change in managerial strategy, but rather statistically move a SNF from one group to another that is not meaningful. Nonetheless, SNFs that shift from one strategy group to another demonstrate some interesting similarities across the strategic groups. Appendix 3 provides charts of performance measures of Shifters and Non-Shifters by group from 2012 to 2015.

SNFs that shift into the Private Pay, Long-stay Complex, Post-Acute, and High Acuity Care Focus groups have lower average levels of revenue per bed in 2012 than non-shifting SNFs in those groups. Shifters into the Long-stay Complex and High Acuity Care Focus groups have lower average patient margins and total margins in 2012. This suggests that SNFs may adapt their strategic orientation to a strategy that generates greater revenues and better margins. And, for some SNFs a change in strategic focus is beneficial. Shifting into Long-stay Complex Care and Post-Acute Care Focus groups is associated with higher revenue per bed.

In contrast, SNFs that shift into Long-stay Care Focus groups have higher average levels of revenue per bed and higher total margins in 2012 compared to Non-Shifters of these groups. Moreover, shifting into Long-stay Care Focus is associated with worse financial performance in

2015 compared to non-shifting SNFs in this group. It seems it would not be in the best financial interest of a SNF to shift its focus to Long-stay Care. On average, Shifters into the Intermediate Care Focus group have equivalent financial performance in 2012 and in 2015 with Non-Shifters. This finding aligns with the mid-range characteristics and performance demonstrated in previous review of this strategy group.

In sum, support for Hypothesis 3b, that shifting from one strategy group to another strategy group is associated with a subsequent positive change in performance, is mixed. For some SNFs, shifting strategies is associated with a subsequent positive change in performance, but for others shifting is associated with a subsequent negative change in performance, or equivocal performance.

It is not clear from the current study if shifts from one strategy group to another are intentional shifts, or if pressures from environmental changes effectively shift SNFs to different groups. The largest shifts seem to be natural extensions from one focus to another. For example, the greatest proportion of Shifters is represented by 23% of SNFs classified as Long-stay Care Focus in 2012 shifting to the Long-stay Complex Care Focus group in 2015 (see Table 20). Continuing to focus on long-stay care but providing services for more complex patients is a conceivable shift in strategic focus that may not require major investment. Both groups already focus on long-stay care and have narrow networks, and only the complexity of patients is changing. The shift to more complex admissions may be a proactive strategic choice to focus on a more profitable market segment, or it may be a consequence of external pressures such as accepting more complex patients to maintain good will in a referral relationship (Shield et al., 2018).

In contrast, the groups demonstrating the least amount of shifting from one to another would require greater adaptation of facilities, staffing, and referral relationships to accommodate a different market segment. Only 1% of SNFs shift from Post-Acute Care Focus or from High Acuity Care Focus in 2012 to Long-stay Care Focus in 2015, and only 1% of SNFs shift from Post-Acute Care Focus in 2012 to Long-stay Complex Care Focus in 2015 (see Table 20). These shifts indicate a change of focus to a very different market segment and are not immediately explicable without a better understanding of their circumstances.

More research is required to better understand the intentions and environmental pressures preceding the shift of SNFs changing from one strategy focus to another. The high level of fluidity among strategy groups suggests that, in the nursing home industry, mobility barriers may be low enough to allow movement from group to group more easily than in some other industries. Changes required in staffing, facilities, or referral relationships to focus on a different market segment may be accomplished in a relatively short time span, or at least across a three-year time span. Moreover, it appears there is variation in the height of mobility barriers within the nursing home industry. Generally, for SNFs that focus on segments of the market with similar characteristics regarding length of stay, patient complexity, or referral centrality, the barriers to movement between groups appear to be lower than barriers between groups that focus on markets that are dissimilar.

Comparison of Strategy Groups with Prior Studies and Industry Trends

Comparison with Prior Studies

Two prior studies used an inductive approach to modeling strategic groups of SNFs, Zinn, Aaronson, and Rosko (1994) and Marlin, Sun, and Huonker (1999). Each study finds seven strategic groups of SNFs using hierarchical cluster analyses similar to the analysis in the current study. A comparison of the strategic groups from Zinn et al. (1994) and Marlin et al. (1999) is presented in Chapter 2 and the comparison is extended with the addition of the current study. The strategic groups from this study are added to the comparison with Zinn et al. (1994) and Marlin et al. (1999) and summarized in Table 26.

Despite differences in samples and years and classification variables, there are six strategy groups that are consistent in each of the earlier studies and in the current study. The Post-Acute Care, Private Pay, High Acuity Care, Intermediate Care, Long-stay Care, and Long-stay Complex Care Focus groups are clearly defined in each study by distinguishing characteristics and strongly resemble one another in each study.

In Chapter 2, when comparing the strategy groups from the Zinn et al. (1994) and Marlin et al. (1999) studies, there was a seventh strategy group in each study that does not seem to align well with any group in the other study (Group E). Interestingly, the group from Zinn et al. (1994), Low-cost Skilled and Intermediate Care, which does not seem to align with another group in the Marlin et al. (1999) study, aligns with the Long-stay Complex Care Focus group in this study. The average case mix of the Zinn study's Low-cost Skilled and Intermediate Care group is the same as for their Large Municipal Facilities group. Additionally, though the average length of stay is in the mid-range, the group has the highest proportion of Medicaid patients, indicating a high level of long-stay care like the Long-stay Complex Care Focus group in this study. This suggests that the seven-strategy group solution in Zinn et al. (1994) can be rolled up into a six-strategy group solution that aligns with the strategy groups in the current study. However, the Short-term Skilled Nursing group from Marlin et al. (1999) does not appear to have a similar group in Zinn et al. (1994). Marlin et al. (1999) recognize that even though they find seven strategy groups like Zinn et al. (1994), there are differences in the taxonomies.

Therefore, although Marlin et al. (1999)'s Short-term Skilled Nursing group has some similarity to the Post-Acute Care or Private Pay or Intermediate Care groups in the current study, it is left as representing a seventh strategy group.

Table 26. *Comparison of strategy groups in the current study, Zinn et al. (1994), and Marlin et al. (1999)*

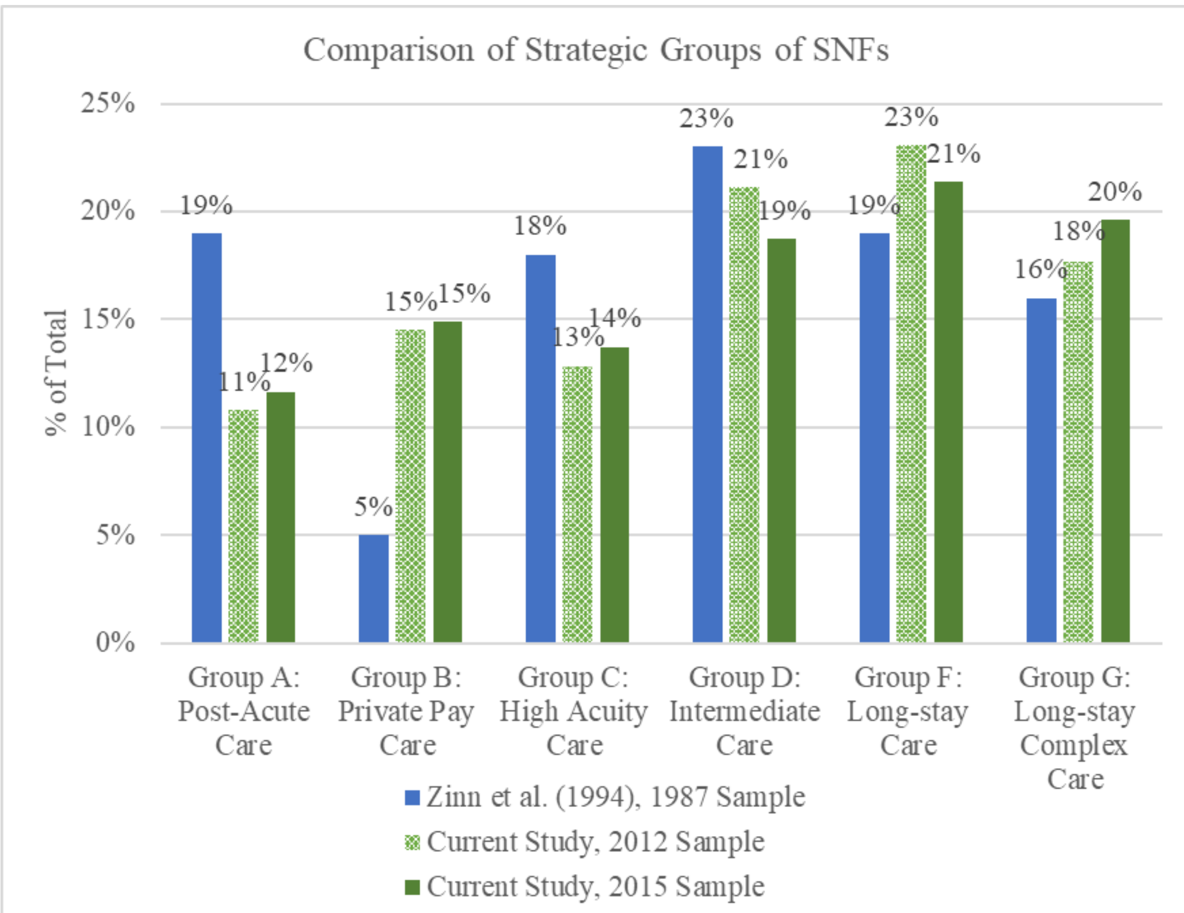
Group	Study	Study Group #	Description of Group	% of Sample	Referral Central-ity	Case Mix	% Medi-caid	% Medi-care	% Private Pay	ALOS	% For-Profit	% Chain
Group A	Current	Group 4	**Post-Acute Care Focus - Wide Network**	12%	LOW	MID	LOW	HIGH	HIGH	LOW	68%	61%
	Zinn	Group 1	Medicare Skilled Nursing Care Focus	19%	NA	HIGH	LOW	HIGH	LOW	LOW	79%	NA
	Marlin	Group 3	Medicare Skilled Nursing Care Focus	17%	NA	MID	MID	HIGH	MID	LOW	97%	97%
Group B	Current	Group 1	**Private Pay Focus - Narrow Network**	15%	HIGH	MID	MID	MID	HIGH	MID	62%	61%
	Zinn	Group 2	Differentiated Focus - Care Continuum	5%	NA	LOW	LOW	LOW	HIGH	MID	5%	NA
	Marlin	Group 7	Private Pay and Medicare Focus	6%	NA	MID	LOW	MID	HIGH	LOW	91%	74%
Group C	Current	Group 6	**High Acuity Care Focus - Wide Network**	14%	LOW	HIGH	MID	MID	MID	MID	89%	62%
	Zinn	Group 3	Generic Skilled Nursing Care	18%	NA	HIGH	MID	MID	LOW	MID	59%	NA
	Marlin	Group 5	Low-Cost Intermediate Nursing Care	9%	NA	HIGH	MID	MID	MID	LOW	83%	78%
Group D	Current	Group 5	**Intermediate Care Focus - Wide Network**	19%	LOW	MID	MID	MID	MID	MID	79%	69%
	Zinn	Group 4	Low-cost Intermediate	23%	NA	LOW	MID	LOW	LOW	MID	25%	NA
	Marlin	Group 6	Intermediate Nursing Care	11%	NA	LOW	HIGH	MID	LOW	MID	86%	72%
Group E	Current		--									
	Marlin	Group 2	Short-term Skilled Nursing Care	20%	NA	MID	MID	MID	MID	LOW	96%	91%
Group F	Current	Group 2	**Long-Stay Care Focus - Narrow Network**	20%	HIGH	LOW	HIGH	LOW	MID	HIGH	87%	66%
	Zinn	Group 6	Low-cost Focus -Care Continuum	19%	NA	LOW	MID	LOW	MID	HIGH	17%	NA
	Marlin	Group 1	Low-Cost Skilled Nursing Care	18%	NA	LOW	MID	MID	MID	MID	92%	93%

Group	Study	Study Group #	Description of Group	% of Sample	Referral Centrality	Case Mix	% Medicaid	% Medicare	% Private Pay	ALOS	% For-Profit	% Chain
Group G	Current	Group 3	**Long-stay Complex Care Focus - Narrow Network**	20%	HIGH	MID	MID	MID	MID	HIGH	87%	64%
	Zinn	Group 7	Large Municipal Facilities	3%	NA	MID	HIGH	MID	MID	HIGH	0%	NA
	Zinn	Group 5	Low-cost Skilled & Intermediate care	13%	NA	MID	HIGH	MID	LOW	MID	63%	NA
	Marlin	Group 4	Long-term Intermediate Nursing Care	19%	NA	MID	HIGH	LOW	MID	HIGH	72%	66%

Note: There are some differences in the measures of the earlier studies and the current study to note. Zinn et al. (1994) and Marlin et al. (1999) use an average CMI whereas this study includes the average CMI of admitted patients. The average CMI in the current study, though lower, has the same relative levels among strategy groups as the average CMI of admitted patients, and is used for comparison with the prior studies. An estimate of the proportion of private paying residents is measured differently in each study. In the Zinn et al. (1994) study, a measure of the percentage of independent living capacity is used to approximate the percentage of private pay patients. In the Marlin et al. (1999) study, percent of private pay is the number of private pay patient days divided by the total number of patient days. In the current study, the percentage of patient days that are not Medicaid or Medicare is used to estimate the percentage of private pay patients.

Using results from the current study and the Zinn et al. (1994) study, the structure of the industry can be compared across different time periods to identify patterns of change over time. Marlin et al. (1999) is included in the discussion, but the seventh strategy group in the study limits comparisons. Conclusions are general and must be considered with the limitation of comparing samples from different time periods and different states (Pennsylvania and Florida), and a limited national sample of SNFs. Figure 3 depicts the proportion of each strategy group in the market in the respective samples.

Figure 3. *Comparison of strategy groups across Zinn et al. (1994) and current study*



Industry Trends

Changes in policy and other environmental factors are briefly reviewed to provide some context for discussing the changes in strategy groups between the 1987 sample of SNFs used in the Zinn et al. (1994) study and the 2015 sample in the current study. A substantial change in the reimbursement method for Medicare nursing home patients occurred after the Zinn et al. (1994) and Marlin et al. (1999) years of study (1987 and 1995, respectively), but prior to the current study's timespan. The Balanced Budget Act of 1997 (BBA) implemented PPS for nursing home care to reduce increases in CMS's spending on post-acute care. PPS for nursing home care includes case-mix adjustment based on the Resource Utilization Group III (RUG-III) system, allowing SNFs to be reimbursed based on use of resources for care of more complex patients (Konetzka, Yi, Norton, & Kilpatrick, 2004). The implementation of case mix payment by CMS and its adoption by Medicaid agencies increased access to care for high acuity patients as intended (Feng, Grabowski, Intrator, & Mor, 2006), while introducing a financial incentive to provide more care to patients. Health services researchers have found a shift to greater volumes and intensity of care (Grabowski et al., 2011) and regional differences in care (Bowblis & Brunt, 2014) since the implementation of case mix adjusted PPS. MedPAC reports an increase in intensive therapy days as a share of total days from 29% in 2002 to 81% in 2014 that is not related to the frailty of members (Medicare Payment Advisory Commission, 2016). For instance, there is evidence of "thresholding behavior, which occurs when patients are provided a certain amount of therapy very close to thresholds resulting in higher reimbursement" (Prusynski, Frogner, Dahal, Skillman, & Mroz, 2020, p. 1945).

In addition to changes in reimbursement policies, there have been changes in the dynamics of the nursing home industry since the Zinn et al. (1994) study. The increasing availability of substitutes of care and the development of long-term care insurance in the late 1980s have likely contributed to the shifting focus of some SNFs over the last twenty years. SNFs operate in an industry where there are alternative sources for different levels of care. For post-acute and high-acuity patients, alternative sites of care are inpatient rehabilitation facilities (IRFs), long-term acute care hospitals (LTACHs), and home health agencies (HHA). Medicare introduced prospective payments for SNFs in 1998, for HHAs in 2000, and for IRFs in 2002. There is evidence of changes in utilization at different sites following the introduction of PPS for each of these sources of care, with reduction in utilization at a site of care once its respective PPS was implemented, as well as corresponding increases in utilization at alternative sites of care (Buntin et al., 2009), confirming the substitutability of these sites. There are fewer IRFs and LTACHs in the US than SNFs (1,182 IRFs and 391 LTACHs versus 15,052 SNFs in 2015 (Medicare Payment Advisory Commission, 2017)), but when they coexist in a market, SNFs are likely to lose some of the post-acute and high acuity patients who would otherwise be referred to a SNF. The number of HHAs has ebbed and flowed over the years. Between 1997 and 2000 the number of HHAs decreased by 31%, but between 2000 and 2015 the number of HHAs increased by 64% to 12,346 agencies (Medicare Payment Advisory Commission, 2017). HHAs can substitute for SNF care for both short-stay and long-stay patients.

For long-stay care patients, in addition to HHAs, alternative sites of care are assisted living facilities (ALFs) and continuing care retirement centers (CCRCs) which have grown in number since the 1990s. There were an estimated 30,200 assisted living providers in 2014 (Cornell, Zhang, & Thomas, 2020) and over 2,000 CCRCs in 2014 (Zebolsky, 2014). Assisted living offers a less-restrictive setting to private paying residents that may reduce the demand for private-pay care for less complex, low-care patients of nursing homes (Clement & Khushalani, 2015; Cornell et al., 2020; Silver et al., 2018). For private pay patients, CCRCs present another alternative to long-stay care in a nursing home and for patients that require post-acute or high-acuity care. Private insurance for long-term care was introduced in the late 1980s. Approximately 10% of individuals over age 60 owned a long-term care insurance policy in 2000 (Brown & Finkelstein, 2009), however, long-term care insurance has not been widely embraced (Nixon, 2014). A discussion of each strategy group and some observations about how the group may have been impacted by trends in the industry follows.

Group A: Post-Acute Care Focus.

In each study, a strategy group emerges that has the highest average proportion of Medicare patients and one of the lowest average proportions of Medicaid patients, shorter lengths of stay, and mid to high ranges of average case mix. Likely to be in urban areas, these SNFs focus on treating patients that are discharged from a hospital who need short-stay convalescent care. This strategy group appears to be successful at admitting the patients described as the most desirable referrals in the qualitative studies: short-stay, Medicare or private paying patients that are low in complexity (Lawrence et al., 2018; Shield et al., 2018). In the current study, the referral centrality for this group is low, indicating that SNFs that focus on post-acute care receive patient referrals from a wide network of hospitals.

Post-Acute Care Focus industry trend. The proportion of SNFs in the *Post-Acute Care Focus* strategy groups appears to have declined over time from 19% in Zinn et al. (1994) to 11% - 12% in both years of the current study. This group has the highest revenues per bed in the current study and its focus on less complex Medicare patients is what the qualitative literature concludes is the goal of many SNFs. MedPAC finds that after the implementation of SNF PPS, medically complex admissions are concentrated among fewer SNFs (Medicare Payment

Advisory Commission, 2011). MedPAC's finding is in accordance with the proportion of SNFs in the current study being 7% to 8% lower than in SNFs focusing on post-acute care in the Zinn et al. (1994) study.

MedPAC poses that fewer SNFs serving more complex patients is likely due to higher payments for rehabilitative therapy and the special resources required to treat more complex patients. Additionally, some areas may lack IRF or LTAC alternatives resulting in SNFs treating more acute patients (Medicare Payment Advisory Commission, 2011). This suggests that the mobility barriers for entry into this segment of the industry have become higher over time in some markets. Greater levels of resources required to provide complex care is a barrier to entry while higher reimbursements make focusing on this segment more desirable. In the current study, SNFs in this strategy group rely upon a wide network of hospital referrals for most of their patients. Local environmental factors may represent a barrier to entry into this group if a SNF is not in proximity to multiple hospitals. On the other hand, SNFs in markets without IRFs, HHAs, or LTACs may not have any competition for post-acute care referrals. Policy changes in conjunction with the ACA in 2010 incentivizing hospitals to prefer referrals to higher quality SNFs may have also increased mobility barriers for SNFs seeking to focus on post-acute patients.

Group B: Private Pay Focus.

Each study has a group that is characterized as having a high average proportion of private pay patients, mid-level lengths of stay and CMIs. SNFs in the Zinn et al. (1994) Private Pay Focus group have the lowest average level of Medicaid and highest level of Medicare, and a majority are in urban areas. The current study has mid-level rates of both payer types compared to other strategy groups, and though a majority of SNFs in the group are in urban areas, this group has a higher proportion of SNFs located in rural areas than other groups. SNFs in the Private Pay Focus group tend to receive patient referrals from a single hospital and are the smallest SNFs in terms of bed count.

Private Pay Focus industry trend. The greatest difference in the structure of the industry over time is the growth in the proportion of *Private Pay Focus* group members. The proportion of *Private Pay Focus* strategy groups increased substantially in the current study (15% in both 2012 and 2015) from the time of the Zinn study (5%). Zinn et al. (1994) does not assess financial performance, however the Marlin et al. (1999) study includes performance measures. The Private Pay Care group has the highest level of average profit per bed and operating margin and demonstrates better quality performance in Marlin et al. (1999). In the current study, the Private Pay Care group is no longer the most profitable group but has the lowest patient margin and mid-range patient revenue per bed and total margin. Instead, the High Acuity Care and Long-stay Complex Care groups have the highest average patient revenue per bed, patient margin, and total margin. It is likely that there are multiple market dynamics occurring in the private pay market. The number of CCRCs has increased over the last twenty years and most CCRCs include a licensed SNF with patients that are usually private pay (Zebolsky, 2014). In the current study, almost 20% of the SNFs in the Private Pay Care Focus group are CCRCs, the highest level of any of the strategy groups. The introduction of long-term care insurance allowing more individuals to pay for SNF care may also help explain an increase in the proportion of SNFs focusing on private pay patients.

Group C: High Acuity Care Focus.

In all three studies, this group has the highest average case mix, indicating a focus on high acuity care patients. The percent of Medicaid and Medicare patients and lengths of stay are mid-range in each of the studies in this group. In the Zinn et al. (1994) study, this group includes many of the hospital-based SNFs. It is not clear if hospital-based SNFs are included in the Marlin et al. (1999) study, and the current study excludes hospital-based SNFs. This group has low average levels of referral centrality, indicating referrals are received from multiple hospitals.

High Acuity Care Focus industry trend. The proportion of SNFs focusing on *High Acuity* is higher in the Zinn et al. (1994) study (18%) than in the current study (13% in 2014 and 14% in 2015). In the current study, this group has referral relationships with multiple hospitals, has the highest average patient margin and total margin, and is one of two groups positively associated with patient or total margins (along with Long-stay Complex Care). Like the Post-Acute Care Focus group, the increased concentration of SNFs providing care to high acuity patients may reflect the high resource requirements, making it more difficult for competitors to serve this market segment. Depending upon the market, SNFs may not face competition for high acuity referrals. Less competition and higher reimbursements contribute to the High Acuity Care Focus group being the most profitable group, on average.

Group D: Intermediate Care Focus.

In the current study, this group is not distinguished by any one characteristic and has mid-range levels of average percent of Medicaid patients, case mix of admitted patients, length of stay, and receives referrals from multiple hospitals. Although not as clearly aligned as the other five strategy groups, each of the earlier studies has a group that can be characterized as providing intermediate levels care. The Low-cost Intermediate group in Zinn et al. (1994) ranks in the mid-range of rates of Medicaid patients and average length of stay like the Intermediate Care Focus group in the current study. The Intermediate Nursing Care group in Marlin et al. (1999) has similar mid-level ranges of average percent of Medicare patients and lengths of stay.

Intermediate Care Focus industry trend. Zinn et al. (1994) find 23% of SNFs focusing on *Intermediate Level Care*, which declines to 21-19% in the current study. The Intermediate Care group appears not to have a care focus, falling in the mid-range of average characteristics compared to the other strategy groups. This group may represent what Shield et al. (2018) describe as SNFs that cast a wide net to fill their beds. Consequently, revenues per bed and total margin are negatively associated with membership in this group.

Group F: Long-stay Care Focus.

A strategy group that clearly focuses on Long-Stay Care is included in each study. SNFs in this group have high average rates of Medicaid patients, low rates of Medicare or private pay patients, longer lengths of stay, and low levels of CMI, indicating provision of long-stay custodial care. In the Zinn et al. (1994) and Marlin et al. (1999) studies, the majority of SNFs in this group are in rural areas. In the current study, the Long-Stay Care Focus group tends to receive patient referrals from a single hospital and, while the majority are in urban areas, this group has a greater proportion of SNFs located in rural areas than the other groups.

Long-Stay Care Focus industry trend. The proportion of *Long-Stay Care Focus* strategy groups has been stable across the studies, ranging from 19% in the Zinn et al. (1994) study to 23 – 21%% in the current study. This group focuses on providing long-stay custodial care for patients that are less complex and are mostly Medicaid patients. In the current study, this group is the most rural of the strategic groups, though a majority are in urban areas. SNFs in the Long-Stay Care Focus groups tend to receive referrals from a single hospital, suggesting that geographic reach or limited referral relationships may deter SNFs from moving to other strategy groups. The growth of ALFs and HHAs over the last twenty years has likely put downward pressure on the profitability of caring for long-stay care patients by diverting some private pay and low-care patients (Clement & Khushalani, 2015; Cornell et al., 2020; Silver et al., 2018).

Group G: Long-Stay Complex Care Focus.

These groups are similar to the Long-Stay Care Focus groups but have a higher average case mix compared to the Long-stay Care groups, indicating a greater complexity of care provided to long-stay patients. On average, in the current study, the Long-stay Complex Care focus group receives referrals from a single hospital, and a greater proportion of SNFs in this strategy group are in rural areas compared to most other strategy groups.

Long-stay Complex Care Focus industry trend. The proportions of *Long-Stay Complex Care Focus* groups are relatively stable in each study, ranging from 16% in the Zinn et al. (1994) study to 20% in the current study in 2015. Referral centrality is high on average in this group, again suggesting that geographic reach or limited referral relationships may deter SNFs from moving to other strategy groups. On the other hand, this group, along with the High Acuity Care group, are the only groups positively associated with patient or total margin in the current study. Having resources to care for more complex patients may act as a barrier to other SNFs seeking to enter this more profitable market segment, while SNFs in locations without substitutes for care may not need to compete for referrals.

Study Contributions and Implications

This study provides an updated taxonomy of SNFs incorporating referral patterns that had not previously been used in strategic modeling of SNFs. Strategic modeling based solely upon dimensions of scope of business, rather than scope of business *and* resource deployment as used in previous studies, resulted in a reliable, valid cluster solution. The findings of this study have implications for the study referral dynamics between hospitals and SNFs, structural changes in the nursing home industry, and policymaking. Theoretical implications are discussed in the next section.

Referral patterns for Medicare patients from hospitals to SNFs have been studied from the hospital perspective (Liao et al., 2018), but study of referrals patterns from hospitals to SNFs from the perspective of SNFs is not evident in the literature. The current study provides a unique assessment of the relational dynamics between strategy groups of SNFs and referral patterns from hospitals. The ACA of 2010 includes provisions to incentivize better coordination of post-acute care between hospitals and SNFs (Rahman et al., 2018). The expectation of Medicare programs such as the Hospital Readmissions Reduction Program, Bundled Payments for Care Improvement initiatives, and accountable care organizations is to incentivize a strong relationship between hospitals and post-acute care providers for improved post-acute care coordination and better patient outcomes (McHugh et al., 2017; Schoenfeld et al., 2016). This study finds that SNFs that focus on post-acute care and high acuity patients are more likely to have a wide referral network, except for those focusing on more complex, long-stay patients. The implications of this are not clear. A recent study by McHugh, Rapp, Mor, & Rahman, (2021) finds that SNFs with higher concentrations of hospital referrals may admit less complex patients. Their findings partially align with characterizations of strategy groups found in this study. Two of the groups with narrow referral networks, Long-stay Care and Private Pay Care, have low average CMI of admitted patients compared to the other groups. Additionally, this study found that between 2012 and 2015 referral networks became narrower for SNFs in strategy groups with narrow networks (Private Pay, Long-stay, and Long-stay Complex Focus groups), and wider for SNFs in strategy groups with wider networks (Post-Acute, Intermediate, and High Acuity Focus groups). This an area for further study by researchers, especially since some of the health reform efforts to incentivize stronger relationships between hospital and post-acute care providers have been in place for over a decade, reducing the uncertainty surrounding those policies. Post-acute care providers have had time to evaluate the landscape and then develop and implement their strategies.

This study assesses the composition across a recent three-year time span and finds that while strategy groups are stable, a large proportion of SNFs appear to shift from focusing on one strategy to focusing on another. In the current study, some SNFs that shift their scope of business focus can achieve better financial performance after shifting to a new strategy.

Although there are many limitations in comparing the current study to different studies modeling strategic groups of SNFs, results are compared to those of two similar studies conducted over twenty years ago as a basis for analysis of the industry over time. The studies demonstrate a high level of stability in the characteristics of strategic groups of SNFs. The commonalities in the strategies employed by SNFs over the last decades points to a limited number of strategies available to SNFs. Over time, however, the consequences of changes in reimbursement methods, growth in substitutes, and changing demands are apparent in shifts in the proportions of SNFs pursuing particular strategies. These shifts among strategy groups suggest structural changes have occurred within the industry. The implementation of PPS for hospitals has increased the acuity of SNF patients, but the most acute and least complex patients may choose alternative locations of care if it is available in the marketplace. Greater mobility barriers have reduced competition for high acuity patients, resulting in a lower proportion of SNFs focusing on high acuity care. The most profitable market segment in nursing home care has shifted from private pay to high acuity patients. In contrast, the proportion of SNFs focusing on private pay patients has increased in the last twenty years, possibly due to the growth in CCRCs and introduction of long-term care insurance.

As policymakers evaluate the results of the Patient-Driven Payment Model (PDPM) and other policies, it will be important to understand how the change in reimbursement policy may impact the industry. In 2019, Medicare made changes to its reimbursement policy to address the increase in volume and intensity of care that may not be necessary. The PDPM incentivizes shorter SNF stays with less therapy versus the RUG system incentivizing longer stays and more therapy (Unruh, Khullar, & Jung, 2020). Initial studies indicate that PDPM has reduced therapy hours and levels of therapy staffing, particularly among SNFs with higher proportions of Medicare patients (McGarry, White, Resnik, Rahman, & Grabowski, 2021; Prusynski, Leland, Frogner, Leibbrand, & Mroz, 2021). Possible unintended consequences of PDPM include incentivizing SNFs to selectively admit the most acute patients, as they can provide more services to clinically complex patients. Conversely, incentives for shorter stays and less therapy may result in patient discharges from SNFs sooner than appropriate (Unruh et al., 2020). Concerns for patient access to quality providers and the viability of SNFs are ongoing. Strategic modeling of SNFs provides an intermediate frame of reference for tracking shifts in the industry that can help policymakers better understand the consequences of policy changes.

This study fills a gap in the literature by providing an updated taxonomy of SNFs. By building upon previous studies to develop a longitudinal perspective, changes occurring over time because of environmental changes are more apparent than in a cross-sectional analysis. The study helps contextualize the findings of quantitative studies that explore the hospital to SNF referral process. For managers, the study can help them to better understand the nursing home industry and assess performance consequences of changing strategic focus. This study contributes to the foundation for evaluating the strategic focus of SNFs in the future. The generalizability of the study, however, is limited due the systematic exclusion of some SNFs in the sampling process.

The COVID-19 pandemic has proven to be a great environmental shock to SNFs. Policy changes including higher levels of reimbursement for patients are underway. Understanding the industry structure can help policymakers target funding and policy changes to better prepare SNFs for future public health emergencies. Subsequent monitoring of the strategic focus of SNFs can help policymakers determine whether changes in the industry occur as these new policies are implemented.

Theoretical Implications

Strategic management theory serves as the theoretical underpinning for this study and is the basis for strategic group modeling. Finding a reliable and valid taxonomy of strategy groups of SNFs supports the principles of SMT that managers make strategic choices to adapt to environmental factors and that there may be multiple strategies within an industry (Porter, 1979, 1980; Scott & Davis, 2007). Likewise, variation in performance among strategy groups supports SMT's concepts of strategic choices being the primary factor associated with performance and that some strategies result in better performance than others. This study provides evidence of strategic adaptation of SNFs shifting to different strategies and such shifts may reflect a lack of "fit" between a SNF's strategy and its environment. The question remains, however, whether SNFs shift because of managerial decisions guiding their respective SNF to shift to a different strategy (i.e., agency), or whether it is because the environment nudges or even forces some of them to shift their strategy (i.e., determinism). While SMT helps explain managerial agency in strategic decisions, it is limited in explaining environmental determinism.

Future studies of SNF strategy groups can be enhanced by integrating contingency theory (CT) as a means of exploring and explaining the fit between strategies and environmental and organizational factors. CT can help explain *why* some SNFs pursue certain strategic groups. For example, if a SNF shifts its focus from Long-stay Care to Long-stay Complex Care is it because of a strategic decision to pursue a more profitable strategy, or could it be because of rising levels of managed care in the local environment pressuring hospitals to discharge patients ‘sicker and quicker’ to SNFs, or some other environmental pressure? In sum, SMT provides the theoretical basis for strategic group modeling. CT can help explain why strategies are selected in the context of environmental and organizational factors and to conceptualize why particular strategies may, or may not, result in better outcomes for some organizations.

Limitations

There are several limitations to the study. Perhaps most importantly, this study uses secondary data for determining the strategic focus of SNFs which may not fully represent the strategic intent of managers. The comparison of this study with earlier studies may be limited as the studies use different measures for classifying SNFs. However, the general alignment of taxonomies helps provide greater confidence in the comparison of the studies.

A large number of SNFs did not match with the Torch Insight dataset and were excluded from the study. Excluded SNFs are characteristically different from SNFs that are included in the study and consequently, a segment of the industry may have been systematically excluded from the analysis. This limits the generalizability of results to facilities that have at least eleven Medicare patient referrals from a single hospital.

A large proportion of SNFs are part of chain-affiliated organizations (approximately 80% of this study’s sample). The evidence on the agency of managers to make scope of business decisions is mixed. On one hand, managers of chain-affiliated nursing homes have less autonomy than managers of independent nursing homes (Kruzich, 2005). On the other hand, managers of chain-affiliated nursing homes often have greater resources to innovate services (Castle, 2001; Castle & Banaszak-Holl, 1997). This study assumes that managers of SNFs at the facility level, or at a higher level within the chain, have agency in defining their strategy.

Finally, the choice of comparing changes across the composition of strategy groups over a three-year period from 2012 to 2015 is driven by the convenience of the dataset rather than evidence of using a specific timespan. Future research may provide evidence of a more appropriate timespan for comparing shifts across strategy groups.

Suggestions for Future Research

There are several areas for future study that could enhance the understanding of the strategic orientation of SNFs. The association of referral concentration and implications for patients, SNFs, and policy should be explored further as discussed in the Implications of the Findings section above. Better coordination of hospital and post-acute providers is a continuing goal and additional insights from the SNF perspective may help uncover barriers or successful tactics for better patient care.

Policymakers and managers could benefit from strategic modeling of SNFs on a regular basis to provide a more complete longitudinal record for assessing industry changes. MedPAC, for instance, identified that the proportion of SNFs treating more acute patients was becoming more concentrated after SNF PPS case mix reimbursement was implemented (Medicare Payment Advisory Commission, 2011), but this shift in the industry is better understood in the context of strategic group analysis. The concept of higher mobility barriers helps explain why there is less competition in the market segment treating more acute patients, and strategic modeling helps to identify alternative strategies on which SNFs may focus. Unintended consequences of policies may become apparent and adjusted, if needed. Assessing the structure of the industry on a regular basis would help policymakers to track whether policies such as the PDPM model have unintended consequences like reducing access to care for post-acute patients in SNFs or reducing the viability of SNFs focusing on more acute patients. Future studies could achieve greater validity by incorporating an expert panel composed of industry stakeholders to review findings.

Strategic modeling of SNFs could benefit from using a fuller sample for greater generalizability. The generalizability of the study is limited as a consequence of merging the Torch Insight dataset and excluding SNFs that did not have a matching observation. Obtaining a measure of referral centrality that is available for a greater number of SNFs would strengthen future studies. Many observations were also lost because of balancing the panel of data across 2012 to 2015. It may be more beneficial to have a more robust cross-sectional sample that can be compared to analyses from prior years than to have a limited balanced panel of data, but more work needs to be done assess this.

Another area of future research would be to explore more fully SNFs that shift from one strategy group to another in comparison to those that do not change strategy. The current study looks at *whether* SNFs shifted focus and associated changes in performance. A better understanding of *which* SNFs are shifting into specific groups and *why* they are shifting in terms of their strategy and organizational characteristics, and whether they are experiencing environmental changes may provide insights into organizational behavior. As discussed in the Theoretical Implications section, integrating CT into the conceptual framework of the study can inform development of hypotheses as to why SNFs shift their strategic focus. While this study has explored changes in strategic groups over time, it has not tested the fit of strategies of SNFs within their environments. Given that organizational structures such as facilities and staffing are pivotal to implementing strategies, it would be beneficial to draw upon contingency theory to better explain and test the fit of organizational and environmental factors within each strategy group.

Finally, applications of more advanced methods of cluster analysis such as application of significance tests to strategic group modeling (Carroll & Thomas, 2019) or temporal data clustering looking at changes across time (Atluri, Karpatne, & Kumar, 2018) may add more rigor to the clustering method and may help elucidate the fluidity with which SNFs shift from one strategy group to another.

Summary

This study has prioritized describing strategy groups of SNFs that exist within the nursing home industry, how those strategies are linked to the performance of groups, and whether there are changes in strategy groups over time. The inclusion of referral dynamics is a unique contribution to strategic modeling of SNFs. By comparing the taxonomy of strategy groups in the current study with taxonomies profiled in prior literature, this study establishes the stability of strategies used by SNFs over the last two decades. There are, however, structural shifts in the composition of strategy groups. Recommendations for future research include extending the study to address why shifts in strategies occur.

Managers may benefit from a better understanding of the industry at an intermediate frame of reference when making strategic decisions to improve performance. Policymakers at the federal and state levels may benefit from a clearer understanding of how to align the needs of patients with the availability of SNFs when making policy decisions, with the goal of improving patient outcomes.

References

Aldenderfer, M. S., & Blashfield, R. K. (1984). *Cluster Analysis, Sage University Papers Series. Quantitative applications in the social sciences* (Vol. 2). Beverly Hills: Sage Publications, Inc.

Alexander, J A, & Morrisey, M. A. (1989). A resource-dependence model of hospital contract management. *Health Services Research*, *24*(2), 259–284.

Alexander, Jeffrey A, Vaughn, T., Burns, L. R., Zuckerman, H. S., Andersen, R. M., Torrens, P., & Hilberman, D. W. (1996). Organizational approaches to integrated health care delivery: a taxonomic analysis of physician-organization arrangements. *Medical Care Research and Review*, *53*(1), 71–93.

Atluri, G., Karpatne, A., & Kumar, V. (2018). Spatio-temporal data mining: A survey of problems and methods. *ACM Computing Surveys (CSUR)*, *51*(4), 1–41.

Barnett, M. L., & Grabowski, D. C. (2020). Nursing homes are ground zero for COVID-19 pandemic. In *JAMA Health Forum* (Vol. 1, pp. e200369–e200369). American Medical Association.

Bazzoli, G. J., Harless, D. W., & Chukmaitov, A. S. (2017). A taxonomy of hospitals participating in Medicare accountable care organizations. *Health Care Management Review*, *44*(2), 93.

Bazzoli, G. J., Shortell, S. M., Dubbs, N., Chan, C., & Kralovec, P. (1999). A Taxonomy of Health Networks and Systems: Bringing Order Out of Chaos. *Health Services Research*, *33*, 1683–1717.

Berlowitz, D. R., Bezerra, H. Q., Brandeis, G. H., Kader, B., & Anderson, J. J. (2000). Are we improving the quality of nursing home care: the case of pressure ulcers. *Journal of the American Geriatrics Society*, *48*(1), 59–62.

Bogner, W. C., & Mahoney, J. T. (1998). Paradigm shift: the parallel origin, evolution, and function of strategic group analysis with the resource-based theory of the firm. *Advances in Strategic Management*, *15*, 63–102.

Bostick, J. E., Rantz, M. J., Flesner, M. K., & Riggs, C. J. (2006). Systematic review of studies of staffing and quality in nursing homes. *Journal of the American Medical Directors Association*, *7*(6), 366–376.

Bowblis, J. R., & Brunt, C. S. (2014). Medicare skilled nursing facility reimbursement and upcoding. *Health Economics*, *23*(7), 821–840.

Boyd, B. K., Takacs Haynes, K., Hitt, M. A., Bergh, D. D., & Ketchen, D. J. (2012). Contingency Hypotheses in Strategic Management Research. *Journal of Management*, *38*(1), 278–313. https://doi.org/10.1177/0149206311418662

Brown, J. R., & Finkelstein, A. (2009). The Private Market for Long-Term Care Insurance in the U.S.: A Review of the Evidence. *The Journal of Risk and Insurance*, *76*(1), 5–29. https://doi.org/10.1111/j.1539-6975.2009.01286.x

Buntin, M. B., Colla, C. H., & Escarce, J. J. (2009). Effects of payment changes on trends in post-acute care. *Health Services Research*, *44*(4), 1188–1210.

Cai, S., Rahman, M., & Intrator, O. (2013). Obesity and pressure ulcers among nursing home residents. *Medical Care*, *51*(6), 478.

California Health Care Foundation. (2020). Infographic — US Health Care Spending: Who Pays? Retrieved March 2, 2021, from https://www.chcf.org/publication/us-health-care-spending-who-pays/#related-links-and-downloads

Carroll, C., & Thomas, H. (2019). Strategic categories and competition: significant clustering for strategic groups. *Journal of Strategy and Management*, *12*(4), 505–521.

Castle, N. G. (2001). Innovation in nursing homes: which facilities are the early adopters? *The Gerontologist*, *41*(2), 161–172.

Castle, N. G. (2003). Strategic Groups and Outcomes in Nursing Facilities. *Health Care Management Review*, *28*(3), 217–227.

Castle, N. G., & Banaszak-Holl, J. (1997). Top management team characteristics and innovation in nursing homes. *The Gerontologist*, *37*(5), 572–580.

Castle, N. G., & Ferguson, J. C. (2010). What is nursing home quality and how is it measured? *The Gerontologist*, *50*(4), 426–442.

Caves, R. E., & Porter, M. E. (1977). From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition. *The Quarterly Journal of Economics*, 241–261.

Chang, C.-H., Mainor, A., Colla, C., & Bynum, J. (2021). Utilization by Long-Term Nursing Home Residents Under Accountable Care Organizations. *Journal of the American Medical Directors Association*, *22*(2), 406–412.

Chen, A. T., Ryskina, K. L., & Jung, H.-Y. (2020). Long-term care, residential facilities, and COVID-19: an overview of federal and state policy responses. *Journal of the American Medical Directors Association*, *21*(9), 1186–1190.

Child, J. (1972). Organizational Structure, Environment and Performance: The Role of Strategic Choice. *Sociology*, *6*(1), 1–22. https://doi.org/10.1177/003803857200600101

Clement, J. (2016). Value and nursing home profitability. *Health Services Management Research*, *29*(3), 62–69.

Clement, J. P., & Khushalani, J. (2015). Does Assisted Living Capacity Influence Case Mix at Nursing Homes? *Gerontology and Geriatric Medicine*, 1–8. https://doi.org/10.1177/2333721415587449

CMS. (2012). Minimum Data Set 3.0 Public Reports. Retrieved November 10, 2020, from https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/Minimum-Data-Set-3-0-Public-Reports

CMS. (2018). Quality, Safety & Oversight - General Information. Retrieved November 10, 2020, from https://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/SurveyCertificationGenInfo

CMS. (2019). Medicare Provider Cost Report Public Use Files. Retrieved November 10, 2020, from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Cost-Report

Comondore, V. R., Devereaux, P. J., Zhou, Q., Stone, S. B., Busse, J. W., Ravindran, N. C., … Cook, D. J. (2009). Quality of care in for-profit and not-for-profit nursing homes: systematic review and meta-analysis. *British Medical Journal, 339*.

Cool, K., & Schendel, D. (1988). Performance differences among strategic group members. *Strategic Management Journal*, *9*(3), 207–223.

Coomer, N. M., Ingber, M. J., Coots, L., & Morley, M. (2017). *Using Medicare Cost Reports to Calculate Costs for Post-Acute Care Claims*. Research Triangle Park, NC: RTI Press.

Cornell, P. Y., Zhang, W., & Thomas, K. S. (2020). Changes in long-term care markets: Assisted living supply and the prevalence of low-care residents in nursing homes. *Journal of the American Medical Directors Association*, *21*(8), 1161–1165.

Creswell, J. W., Klassen, A. C., Plano Clark, V. L., & Smith, K. C. (2011). Best practices for mixed methods research in the health sciences. *Bethesda (Maryland): National Institutes of Health*, 2094–2103.

Demsetz, H. (1973). Industry structure, market rivalry, and public policy. *The Journal of Law and Economics*, *16*(1), 1–9.

Denham, A. C. (2018). Community Care Alternatives for Older Adults. In *Chronic Illness Care* (pp. 259–270). Springer.

Dobbin, F., & Baum, J. A. C. (2014). Introduction: Economics meets sociology in strategic management. *Advances in Strategic Management*, *17*.

Donabedian, A. (1966). Evaluating the quality of medical care. *The Milbank Memorial Fund Quarterly*, *44*(3), 166–206.

Donaldson, L. (2001). *The contingency theory of organizations*. Thousand Oaks, CA: Sage.

Donaldson, L. (2006). The contingency theory of organizational design: challenges and opportunities. In *Organization design* (pp. 19–40). Springer.

Drazin, R., & Van de Ven, A. H. (1985). Alternative forms of fit in contingency theory. *Administrative Science Quarterly*, 514–539.

Dubbs, N. L., Bazzoli, G. J., Shortell, S. M., & Kralovec, P. D. (2004). Reexamining organizational configurations: An update, validation, and expansion of the taxonomy of health networks and systems. *Health Services Research*, *39*(1), 207–220.

Eskildsen, M., & Price, T. (2009). Nursing home care in the USA. *Geriatrics & Gerontology*

International, *9*(1), 1–6. https://doi.org/10.1111/j.1447-0594.2008.00513.x

Feng, Z., Grabowski, D. C., Intrator, O., & Mor, V. (2006). The effect of state Medicaid case-mix payment on nursing home resident acuity. *Health Services Research*, *41*(4p1), 1317–1336.

Gadbois, E A, Tyler, D. A., Shield, R. R., McHugh, J. P., Winblad, U., Trivedi, A., & Mor, V. (2018). Medicare Advantage Control of Post-Acute Care Costs: Perspectives from Plans, Hospitals, and Skilled Nursing Facilities. *Innovation in Aging*, *2*(suppl_1), 409.

Gadbois, Emily A, Tyler, D. A., Shield, R. R., McHugh, J. P., Winblad, U., Trivedi, A., & Mor, V. (2018). Medicare Advantage control of postacute costs: perspectives from stakeholders. *The American Journal of Managed Care*, *24*(12), e386.

Gaudet Hefele, J., Wang, X., Bishop, C. E., & Barooah, A. (2019). Multitasking in Nursing Homes: Differences Between For-Profit and Nonprofit Quality Outcomes. *The Gerontologist*, *59*(6), 1034–1043.

Geng, F., Mansouri, S., Stevenson, D. G., & Grabowski, D. C. (2020). Evolution of the home health care market: the expansion and quality performance of multi-agency chains. *Health Services Research*, *55*, 1073–1084.

Goldfeld, K. S., Stevenson, D. G., Hamel, M. B., & Mitchell, S. L. (2011). Medicare expenditures among nursing home residents with advanced dementia. *Archives of Internal Medicine*, *171*(9), 824–830.

Grabowski, D. C., Afendulis, C. C., & McGuire, T. G. (2011). Medicare prospective payment and the volume and intensity of skilled nursing facility services. *Journal of Health Economics*, *30*(4), 675–684. https://doi.org/10.1016/j.jhealeco.2011.05.014

Grabowski, D. C., Angelelli, J. J., & Mor, V. (2004). Medicaid payment and risk-adjusted nursing home quality measures. *Health Affairs*, *23*(5), 243–252.

Grabowski, D. C., Feng, Z., Hirth, R., Rahman, M., & Mor, V. (2013). Effect of nursing home ownership on the quality of post-acute care: An instrumental variables approach. *Journal of Health Economics*, *32*(1), 12–21.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis, 6th edition*. Upper Saddle River, NJ: Pearson Prentice Hall.

Harris-Kojetin, L. D., Sengupta, M., Lendon, J. P., Rome, V., Valverde, R., & Caffrey, C. (2019). *Long-term care providers and services users in the United States, 2015-2016*. *Vital Health Stat* (Vol. 3).

Hillmer, M. P., Wodchis, W. P., Gill, S. S., Anderson, G. M., & Rochon, P. A. (2005). Nursing home profit status and quality of care: Is there any evidence of an association? *Medical Care Research and Review*, *62*(2), 139–166.

Hirth, R. A., Zheng, Q., Grabowski, D. C., Stevenson, D. G., Intrator, O., & Banaszak-Holl, J. (2017). The Effects of Chains on the Measurement of Competition in the Nursing Home Industry. *Medical Care Research and Review*, 107755871770177. https://doi.org/10.1177/1077558717701771

Hoskisson, R. E., Wan, W. P., Yiu, D., & Hitt, M. A. (1999). Theory and research in strategic management: Swings of a pendulum. *Journal of Management*, *25*(3), 417–456.

Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of Classification*, *2*(1), 193–218.

Huckfeldt, P. J., Sood, N., Romley, J. A., Malchiodi, A., & Escarce, J. J. (2013). Medicare payment reform and provider entry and exit in the post-acute care market. *Health Services Research*, *48*(5), 1557–1580. https://doi.org/10.1111/1475-6773.12059

Huckfeldt, P. J., Weissblum, L., Escarce, J. J., Karaca-Mandic, P., & Sood, N. (2018). Do skilled nursing facilities selected to participate in preferred provider networks have higher quality and lower costs? *Health Services Research*, *53*(6), 4886–4905.

Hurd, M. D., Martorell, P., Delavande, A., Mullen, K. J., & Langa, K. M. (2013). Monetary costs of dementia in the United States. *New England Journal of Medicine*, *368*(14), 1326–1334.

IBISWorld Industry Report. (2017). *Nursing Care Facilities in the US*.

Jacobson, G., Damico, A., Neuman, T., & Gold, M. (2015). Medicare Advantage 2015 Spotlight: Enrollment Market Update. Retrieved from http://www.nasuad.org/sites/nasuad/files/Medicare Advantage Brief.pdf

Jaul, E., Barron, J., Rosenzweig, J. P., & Menczel, J. (2018). An overview of co-morbidities and the development of pressure ulcers among older adults. *BMC Geriatrics*, *18*(1), 1–11.

Kelley, A. S., McGarry, K., Gorges, R., & Skinner, J. S. (2015). The burden of health care costs for patients with dementia in the last 5 years of life. *Annals of Internal Medicine*, *163*(10), 729–736.

Ketchen, D. J., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: an analysis and critique. *Strategic Management Journal*, *17*(6), 441–458.

Ketchen Jr, D. J., Thomas, J. B., & Snow, C. C. (1993). Organizational configurations and performance: A comparison of theoretical approaches. *Academy of Management Journal*, *36*(6), 1278–1313.

Kimberly, J. R., & Zajac, E. J. (1985). Strategic adaptation in health care organizations: Implications for theory and research. *Medical Care Review*, *42*(2), 267–302.

Klecka, W. R. (1980). *Discriminant analysis* (Vol. 19). Beverly Hills, CA: Sage Publications.

Konetzka, R. T., Stuart, E. A., & Werner, R. M. (2018). The effect of integration of hospitals and post-acute care providers on Medicare payment and patient outcomes. *Journal of Health Economics*.

Konetzka, R. T., Yi, D., Norton, E. C., & Kilpatrick, K. E. (2004). Effects of Medicare payment changes on nursing home staffing and deficiencies. *Health Services Research*, *39*(3), 463–488.

Kruzich, J. M. (2005). Ownership, chain affiliation, and administrator decision-making autonomy in long-term care facilities. *Administration in Social Work*, *29*(1), 5–24.

Lawrence, E., Casler, J.-J., Jones, J., Leonard, C., Ladebue, A., Ayele, R., … Burke, R. E. (2018). Variability in skilled nursing facility screening and admission processes: Implications for value-based purchasing. *Health Care Management Review*. https://doi.org/10.1097/HMR.0000000000000225

Leavitt Partners. (n.d.). Torch Insight. Retrieved June 15, 2019, from www.torchinsight.com

Lee, S., & Lee, D. K. (2018). What is the proper way to apply the multiple comparison test? *Korean Journal of Anesthesiology*, *71*(5), 353.

Lepore, M., & Leland, N. E. (2015). Nursing Homes That Increased The Proportion Of Medicare Days Saw Gains In Quality Outcomes For Long-Stay Residents. *Health Affairs (Project Hope)*, *34*(12), 2121–2128. https://doi.org/10.1377/hlthaff.2015.0303

Lewis, E., Eiken, S., Amos, A., & Saucier, P. (2018). The growth of managed long-term services and supports programs: 2017 update. *Truven Health Analytics.*, *18*, 2018.

Li, Y., Yin, J., Cai, X., Temkin-Greener, H., & Mukamel, D. B. (2011). Association of race and sites of care with pressure ulcers in high-risk nursing home residents. *JAMA*, *306*(2), 179–186.

Liao, J. M., Konetzka, R. T., & Werner, R. M. (2018). Trends in hospital-SNF relationships in the care of Medicare beneficiaries. *Healthcare*, *6*, 175–179. https://doi.org/10.1016/j.hjdsi.2018.05.001

Linhart, H. A. (2020). *Hospital Investment in Urgent Care: Impacts on Emergent, Outpatient, and Ambulat Outpatient, and Ambulatory Surgery Volumes (Doctoral dissertation)*. Virgnia Commonwealth University.

Lix, L. M., Keselman, J. C., & Keselman, H. J. (1996). Consequences of assumption violations revisited: A quantitative review of alternatives to the one-way analysis of variance F test. *Review of Educational Research*, *66*(4), 579–619.

Long-term Care: Facts on Care in the US. (2017). Retrieved July 1, 2018, from http://ltcfocus.org

Luke, R. D., & Begun, J. W. (1988). Strategic orientations of small multihospital systems. *Health Services Research*, *23*(5), 597.

Luke, R. D., Walston, S. L., & Plummer, P. M. (2004). *Healthcare strategy : in pursuit of competitive advantage*. Chicago, IL: Health Administration Press.

Marlin, D., Huonker, J. W., & Sun, M. (2002). An examination of the relationship between strategic group membership and hospital performance. *Health Care Management Review*, *27*(4), 18–29.

Marlin, D., Lamont, B. T., & Hoffman, J. J. (1994). Choice situation, strategy, and performance: A reexamination. *Strategic Management Journal*, *15*(3), 229–239.

Marlin, D., Sun, M., & Huonker, J. W. (1999). Strategic Groups and Performance in the Nursing Home Industry: A Reexamination. *Medical Care Research and Review*, *56*(2), 156–176. https://doi.org/10.1177/107755879905600203

McGarry, B. E., White, E. M., Resnik, L. J., Rahman, M., & Grabowski, D. C. (2021).

Medicare's New Patient Driven Payment Model Resulted In Reductions In Therapy Staffing In Skilled Nursing Facilities: Study examines the effect of Medicare's Patient Driven Payment Model on therapy and nursing staff hours at skilled nursing facilities. *Health Affairs*, *40*(3), 392–399.

McGee, J., & Thomas, H. (1986). Strategic Groups: Theory, Research and Taxonomy. *Strategic Management Journal*, *7*(7), 141–160. Retrieved from http://www.jstor.org/stable/2486163

McHugh, J. P., Foster, A., Mor, V., Shield, R. R., Trivedi, A. N., Wetle, T., … Tyler, D. A. (2017). Reducing hospital readmissions through preferred networks of skilled nursing facilities. *Health Affairs*, *36*(9), 1591–1598. https://doi.org/10.1377/hlthaff.2017.0211

McHugh, J. P., Rapp, T., Mor, V., & Rahman, M. (2021). Higher hospital referral concentration associated with lower-risk patients in skilled nursing facilities. *Health Services Research*.

Mechanic, R. (2014). Post-acute care—the next frontier for controlling Medicare spending. *New England Journal of Medicine*, *370*(8), 692–694.

Medicare Payment Advisory Commission. (2011). *Report to the Congress Medicare Payment Policy*. Washington, DC. Retrieved from http://medpac.gov/docs/default-source/reports/Mar11_EntireReport.pdf

Medicare Payment Advisory Commission. (2016). *Report to the Congress: Medicare Payment Policy*. Washington, DC. Retrieved from http://www.medpac.gov/docs/default-source/reports/march-2016-report-to-the-congress-medicare-payment-policy.pdf

Medicare Payment Advisory Commission. (2017). *A Data Book: Health Care Spending and the Medicare Program*. Retrieved from http://medpac.gov/docs/default-source/data-book/jun17_databookentirereport_sec.pdf

Medicare Payment Advisory Commission. (2018a). *A Data Book: Health Care Spending and the*

Medicare Program. Retrieved from http://www.medpac.gov/docs/default-source/data-book/jun18_databookentirereport_sec.pdf

Medicare Payment Advisory Commission. (2018b). *Report to the Congress: Medicare Payment Policy*. Washington, DC. Retrieved from http://www.medpac.gov/docs/default-source/reports/mar18_medpac_entirereport_sec.pdf

Menachemi, N., Mazurenko, O., Kazley, A. S., Diana, M. L., & Ford, E. W. (2012). Market factors and electronic medical record adoption in medical practices. *Health Care Management Review*, *37*(1), 14–22.

Mick, S. S., Morlock, L. L., Salkever, D., & de Lissovoy, G. (1993). Rural hospital administrators and strategic management activities. *Journal of Healthcare Management*, *38*(3), 329.

Miles, R. E., Snow, C. C., Meyer, A. D., & Coleman Jr, H. J. (1978). Organizational strategy, structure, and process. *Academy of Management Review*, *3*(3), 546–562.

Mor, V., Intrator, O., Feng, Z., & Grabowski, D. C. (2010). The revolving door of rehospitalization from skilled nursing facilities. *Health Affairs*, *29*(1), 57–64. https://doi.org/10.1377/hlthaff.2009.0629

Mor, V., Zinn, J., Angelelli, J., Teno, J. M., & Miller, S. C. (2004). Driven to tiers: socioeconomic and racial disparities in the quality of nursing home care. *The Milbank Quarterly*, *82*(2), 227–256.

Mueller, C., Arling, G., Kane, R., Bershadsky, J., Holland, D., & Joy, A. (2006). Nursing home staffing standards: Their relationship to nurse staffing levels. *The Gerontologist*, *46*(1), 74–80.

Navathe, A. S., & Grabowski, D. C. (2020). Will Medicare’s New Patient-Driven Postacute Care

Payment System Be a Step Forward? In *JAMA Health Forum* (Vol. 1, pp. e200718–e200718). American Medical Association.

Nelson, S. T., & Flynn, L. (2015). Relationship between missed care and urinary tract infections in nursing homes. *Geriatric Nursing*, *36*(2), 126–130.

Newhouse, J. P. (1970). Toward a theory of nonprofit institutions: An economic model of a hospital. *The American Economic Review*, *60*(1), 64–74.

Newman, H. H. (1978). Strategic groups and the structure-performance relationship. *The Review of Economics and Statistics*, 417–427.

Nixon, D. C. (2014). State tax subsidies to bolster the long-term care insurance market. *Journal of Public Policy*, *34*(3), 415–436.

Ouslander, J. G., & Grabowski, D. C. (2020). COVID-19 in nursing homes: calming the perfect storm. *Journal of the American Geriatrics Society*, *68*(10), 2153–2162.

Park, J., Konetzka, R. T., & Werner, R. M. (2011). Performing well on nursing home report cards: does it pay off? *Health Services Research*, *46*(2), 531–554. https://doi.org/10.1111/j.1475-6773.2010.01197.x

Pfeffer, J., & Salancik, G. (2003). *The external control of organizations: A resource dependence perspective*. Stanford University Press.

Porter, M. E. (1979). The structure within industries and company performance. *Review of Economics and Statistics, 61*, 214–227.

Porter, M. E. (1980). *Competitive strategy: techniques for analyzing industries and competitors*. New York, NY: The Free Press.

Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strategic Management Journal*, *12*(S2), 95–117.

Prusynski, R. A., Frogner, B. K., Dahal, A. D., Skillman, S. M., & Mroz, T. M. (2020). Skilled nursing facility characteristics associated with financially motivated therapy and relation to quality. *Journal of the American Medical Directors Association*, *21*(12), 1944–1950.

Prusynski, R. A., Leland, N. E., Frogner, B. K., Leibbrand, C., & Mroz, T. M. (2021). Therapy Staffing in Skilled Nursing Facilities Declined after Implementation of the Patient-Driven Payment Model. *Journal of the American Medical Directors Association*. https://doi.org/10.1016/j.jamda.2021.04.005

Rahman, M., Gadbois, E. A., Tyler, D. A., & Mor, V. (2018). Hospital-Skilled Nursing Facility Collaboration: A Mixed-Methods Approach to Understanding the Effect of Linkage Strategies. *Health Services Research*. https://doi.org/10.1111/1475-6773.13016

Ryan, A. M., Burgess, J. F., & Dimick, J. B. (2015). Why We Should Not Be Indifferent to Specification Choices for Difference-in-Differences. *Health Services Research*, *50*(4), 1211–1235.

Saliba, D., Weimer, D. L., Shi, Y., & Mukamel, D. B. (2018). Examination of the new short-stay nursing home quality measures: rehospitalizations, emergency department visits, and successful returns to the community. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, *55*, 1–11. https://doi.org/10.1177/0046958018786816

Schoenfeld, A. J., Zhang, X., Grabowski, D. C., Mor, V., Weissman, J. S., & Rahman, M. (2016). Hospital-skilled nursing facility referral linkage reduces readmission rates among Medicare patients receiving major surgery. *Surgery*, *159*(5), 1461–1468.

Scott, W. R., & Davis, G. F. (2003). *Networks in and around organizations*. *Organizations and Organizing*. Pearson Prentice Hall.

Scott, W. R., & Davis, G. F. (2007). *Organizations and Organizing; Rational, Natural and*

Opens System Perspectives. Pearson Prentice Hall.

Shay, P. D. (2014). *More than just hospitals: An examination of cluster components and configurations (Doctoral dissertation)*. Virginia Commonwealth University.

Shay, P. D., & Mick, S. S. (2013). Post-acute care and vertical integration after the patient protection and Affordable Care Act. *Journal of Healthcare Management*, *58*(1).

Shay, P. D., & Mick, S. S. F. (2017). Clustered and distinct: a taxonomy of local multihospital systems. *Health Care Management Science*, *20*(3), 303–315. https://doi.org/10.1007/s10729-016-9353-7

Shield, R., Winblad, U., McHugh, J., Gadbois, E., & Tyler, D. (2018). Choosing the Best and Scrambling for the Rest: Hospital–Nursing Home Relationships and Admissions to Post-Acute Care. *Journal of Applied Gerontology*, 073346481775208. https://doi.org/10.1177/0733464817752084

Short, J. C., Ketchen Jr, D. J., Palmer, T. B., & Hult, G. T. M. (2007). Firm, strategic group, and industry influences on performance. *Strategic Management Journal*, *28*(2), 147–167.

Short, J. C., Payne, G. T., & Ketchen Jr, D. J. (2008). Research on organizational configurations: Past accomplishments and future challenges. *Journal of Management*, *34*(6), 1053–1079.

Shortell, S. M., Gottlieb, D. J., Martinez Camblor, P., & O'Malley, A. J. (2021). Hospital-based health systems 20 years later: A taxonomy for policy research and analysis. *Health Services Research*, *56*(3), 453–463.

Shortell, S. M., & Zajac, E. J. (1990a). Health care organizations and the development of the strategic management perspective. *Innovations in Health Care Delivery*, 144–180.

Shortell, S. M., & Zajac, E. J. (1990b). Perceptual and archival measures of Miles and Snow's strategic types: A comprehensive assessment of reliability and validity. *Academy of*

Management Journal, *33*(4), 817–832.

Silver, B. C., Grabowski, D. C., Gozalo, P. L., Dosa, D., & Thomas, K. S. (2018). Increasing prevalence of assisted living as a substitute for private-pay long-term nursing care. *Health Services Research*, *53*(6), 4906–4920.

Sinsky, C., & Linzer, M. (2020). Practice And Policy Reset Post-COVID-19: Reversion, Transition, Or Transformation? Commentary examines possible policy and practice changes for health professionals, regulators, and payers after the COVID-19 pandemic. *Health Affairs*, *39*(8), 1405–1411.

Spetz, J., Trupin, L., Bates, T., & Coffman, J. M. (2015). Future Demand For Long-Term Care Workers Will Be Influenced By Demographic And Utilization Changes. *Health Affairs*, *34*(6), 936–945. https://doi.org/10.1377/hlthaff.2015.0005

Trinh, H. Q., & O'Connor, S. J. (2000). The strategic behavior of US rural hospitals: a longitudinal and path model examination. *Health Care Management Review*, *25*(4), 48–64.

Trinh, H. Q., & O'Connor, S. J. (2002). Helpful or Harmful? The Impact of Strategic Change on the Performance of U.S. Urban Hospitals. *Health Services Research*, *37*(1), 143–169. https://doi.org/10.1111/1475-6773.99208

Tyler, D. A., Feng, Z., Leland, N. E., Gozalo, P., Intrator, O., & Mor, V. (2013). Trends in Postacute Care and Staffing in US Nursing Homes, 2001-2010. *Journal of the American Medical Directors Association*, *14*, 817–820. https://doi.org/10.1016/j.jamda.2013.05.013

Unruh, M. A., Khullar, D., & Jung, H.-Y. (2020). The patient-driven payment model: addressing perverse incentives, creating new ones. *The American Journal of Managed Care*, *26*(4), 150–152.

Wagner, L. M., Katz, P., Karuza, J., Kwong, C., Sharp, L., & Spetz, J. (2020). Medical Staffing

Organization and Quality of Care Outcomes in Post-acute Care Settings. *The Gerontologist*, *61*(4), 605–614.

Wagner, L. M., McDonald, S. M., & Castle, N. G. (2012). Joint commission accreditation and quality measures in US nursing homes. *Policy, Politics, & Nursing Practice*, *13*(1), 8–16.

Wang, X. J., & Hefele, J. G. (2021). A Rising Tide Lifts "Related" Boats—Post-Acute Care Quality Improvement is Associated With Improvement in Long-Term Care Quality in Nursing Homes. *Journal of the American Medical Directors Association*, *22*(3), 706–711.

Weech-Maldonado, R., Laberge, A., Pradhan, R., Johnson, C., Yang, Z., & Hyer, K. (2012). Nursing home financial performance. *Health Care Management Review*, *37*(3), 235–245. https://doi.org/10.1097/HMR.0b013e31823dfe13

Weech-Maldonado, R., Lord, J., Pradhan, R., Davlyatov, G., Dayama, N., Gupta, S., & Hearld, L. (2019). High Medicaid nursing homes: Organizational and market factors associated with financial performance. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, *56*, 1–9. https://doi.org/10.1177/0046958018825061

Weech-Maldonado, R., Neff, G., & Mor, V. (2003). Does quality of care lead to better financial performance?: the case of the nursing home industry. *Health Care Management Review*, *28*(3), 201–216.

Weech-Maldonado, R., Pradhan, R., Dayama, N., Lord, J., & Gupta, S. (2019). Nursing home quality and financial performance: is there a business case for quality? *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, *56*, 1–10. https://doi.org/10.1177/0046958018825191

Yeager, V. A., Menachemi, N., Savage, G. T., Ginter, P. M., Sen, B. P., & Beitsch, L. M. (2014). Using resource dependency theory to measure the environment in health care organizational studies: a systematic review of the literature. *Health Care Management Review*, *39*(1), 50–65. https://doi.org/10.1097/HMR.0b013e3182826624 [doi]

Young, H. M., Quinn, W., Brassard, A., Gualtieri, C., & Reinhard, S. (2020). COVID-19 pandemic spurs policy changes benefiting older adults. *Journal of Gerontological Nursing*, *46*(6), 19–23.

Zajac, E. J., Kraatz, M. S., & Bresser, R. K. F. (2000). Modeling the dynamics of strategic fit: A normative approach to strategic change. *Strategic Management Journal*, *21*(4), 429–453.

Zajac, E. J., & Shortell, S. M. (1989). Changing generic strategies: Likelihood, direction, and performance implications. *Strategic Management Journal*, *10*(5), 413–430.

Zebolsky, G. T. (2014). An introduction to continuing care retirement communities. Retrieved from https://us.milliman.com/en/insight/an-introduction-to-continuing-care-retirement-communities

Zimmerman, D. R., Karon, S. L., Arling, G., Clark, B. R., Collins, T., Ross, R., & Sainfort, F. (1995). Development and testing of nursing home quality indicators. *Health Care Financing Review*, *16*(4), 107.

Zinn, J. S., Aaronson, W. E., & Rosko, M. D. (1994). Strategic groups, performance, and strategic response in the nursing home industry. *Health Services Research*, *29*(2), 187.

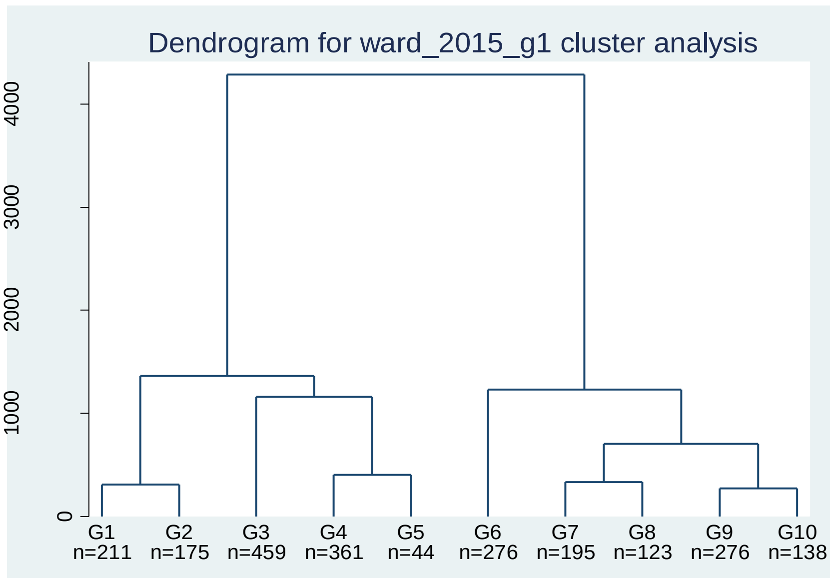
Zinn, J. S., Mor, V., Feng, Z., & Intrator, O. (2007). Doing better to do good: the impact of strategic adaptation on nursing home performance. *Health Services Research*, *42*(3 Pt 1), 1200–1218. https://doi.org/10.1111/j.1475-6773.2006.00649.x

Zinn, J. S., Spector, W. D., Weimer, D. L., & Mukamel, D. B. (2008). Strategic Orientation and Nursing Home Response to Public Reporting of Quality Measures: An Application of the Miles and Snow Typology. *Health Services Research*, *43*(2), 598–615.

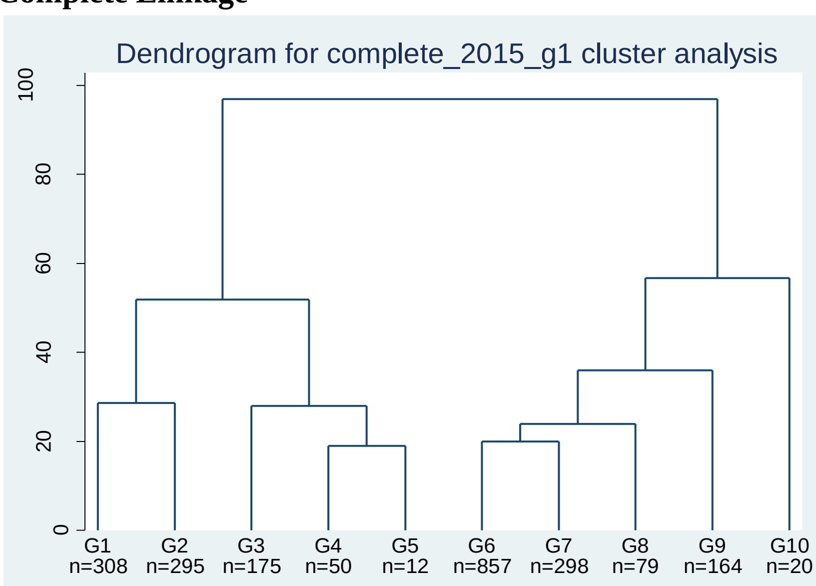
https://doi.org/10.1111/j.1475-6773.2007.00781.x

Appendix 1: Hierarchical Cluster Analysis Dendrograms

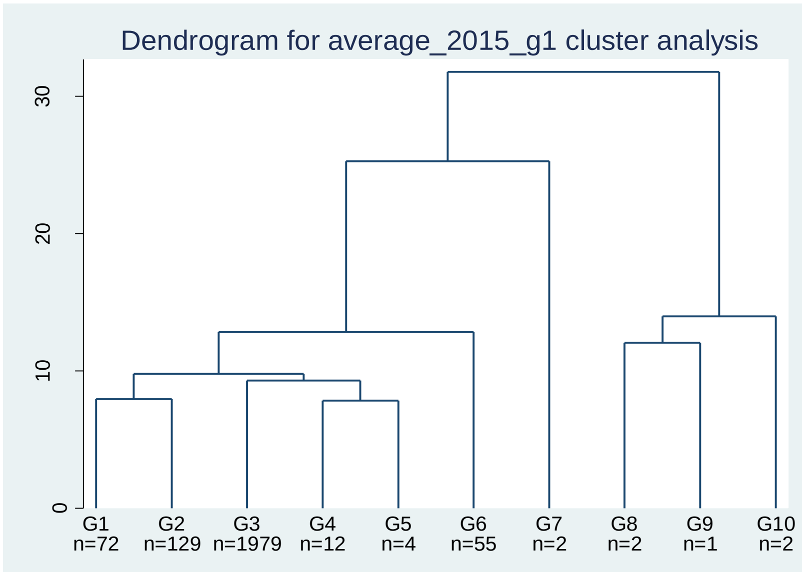
Ward's Method



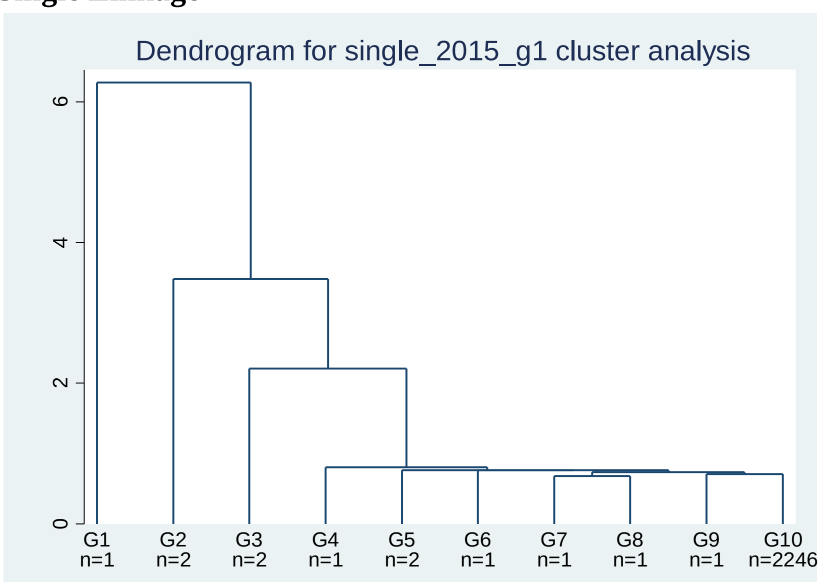
Complete Linkage



Average Linkage

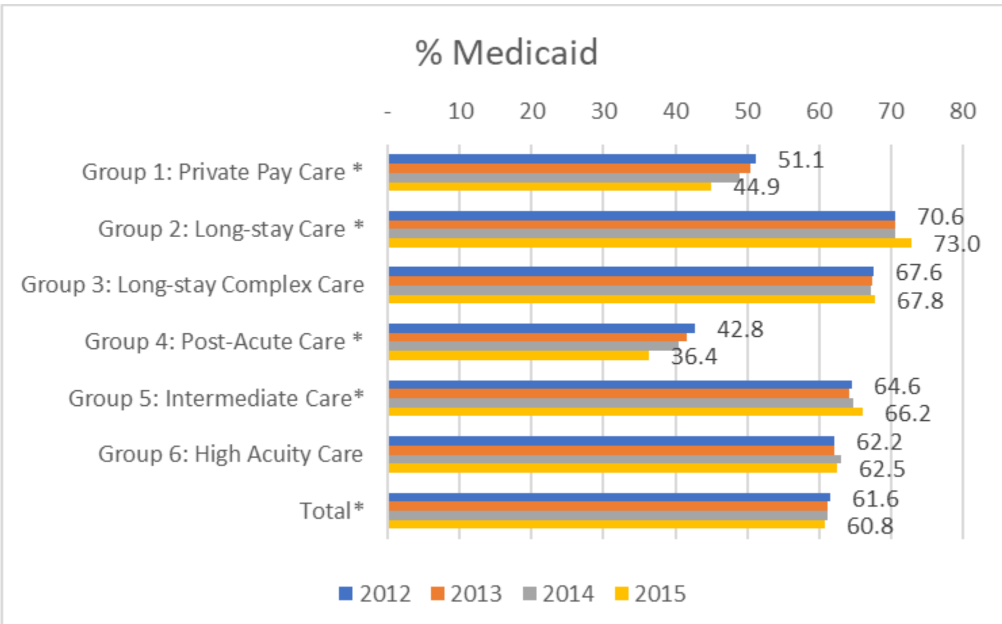


Single Linkage



Appendix 2: Measures of classification variables from 2012 to 2015

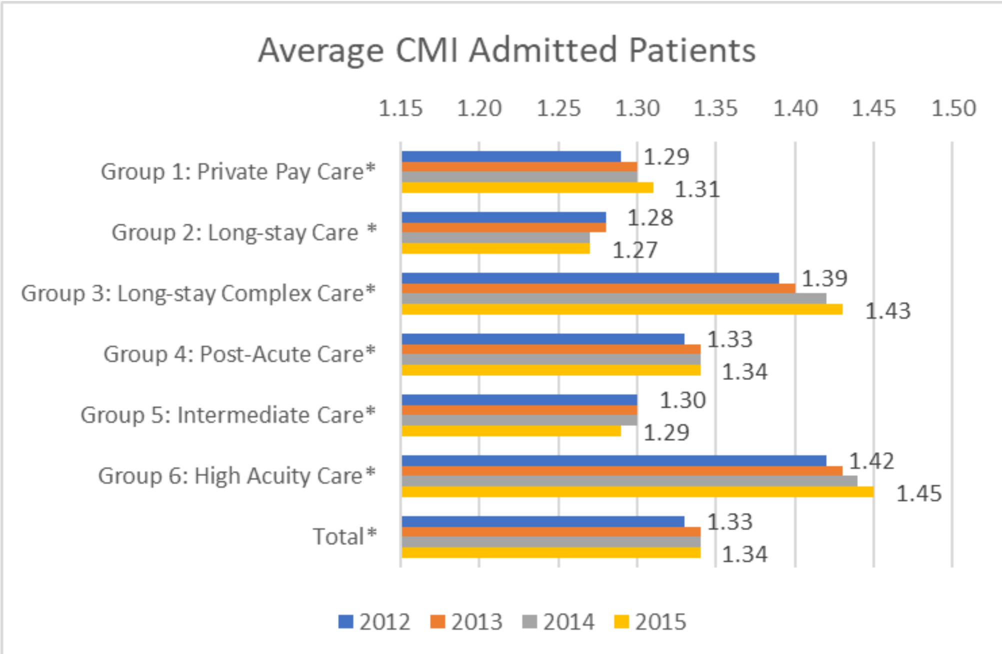
% Medicaid across groups from 2012 to 2015



% Medicaid				
Strategy Groups 2015	2012	2013	2014	2015
Group 1: Private Pay Care *	51.1	50.4	49.0	44.9
Group 2: Long-stay Care *	70.6	70.6	70.6	73.0
Group 3: Long-stay Complex Care	67.6	67.3	67.2	67.8
Group 4: Post-Acute Care *	42.8	41.5	40.5	36.4
Group 5: Intermediate Care*	64.6	64.2	64.8	66.2
Group 6: High Acuity Care	62.2	62.2	63.2	62.5
Total*	61.6	61.2	61.1	60.8

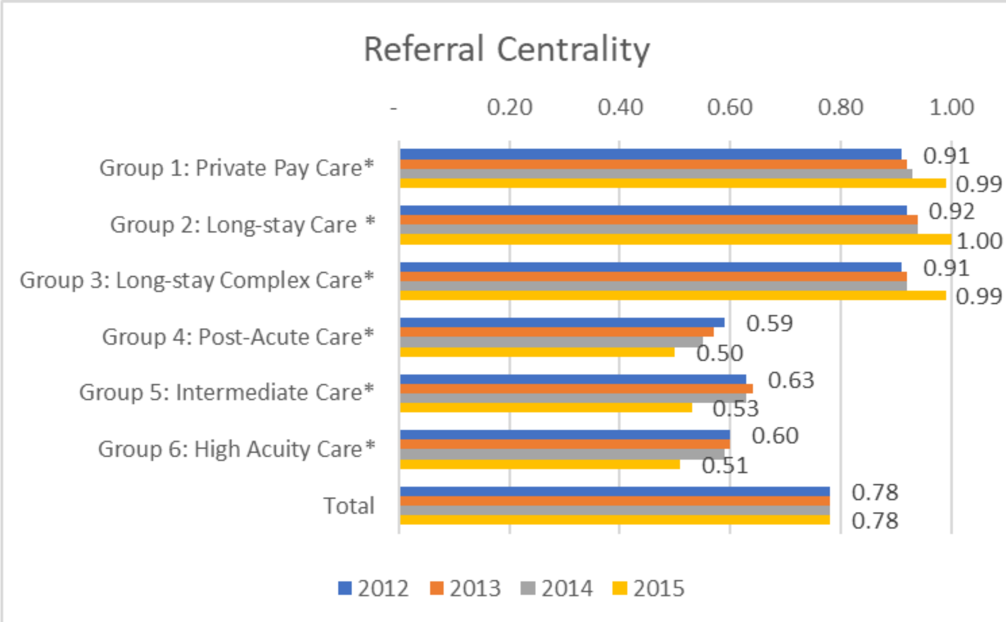
* Difference between 2015 and 2012 significant at $p < 0.001$

Average CMI of Admitted Patients across groups from 2012 to 2015



Average CMI Admitted Patients				
Strategy Groups 2015	2012	2013	2014	2015
Group 1: Private Pay Care*	1.29	1.30	1.30	1.31
Group 2: Long-stay Care *	1.28	1.28	1.27	1.27
Group 3: Long-stay Complex Care*	1.39	1.40	1.42	1.43
Group 4: Post-Acute Care*	1.33	1.34	1.34	1.34
Group 5: Intermediate Care*	1.30	1.30	1.30	1.29
Group 6: High Acuity Care*	1.42	1.43	1.44	1.45
Total*	1.33	1.34	1.34	1.34
* Difference between 2015 and 2012 significant at $p < 0.001$				

Referral Centrality across groups from 2012 to 2015

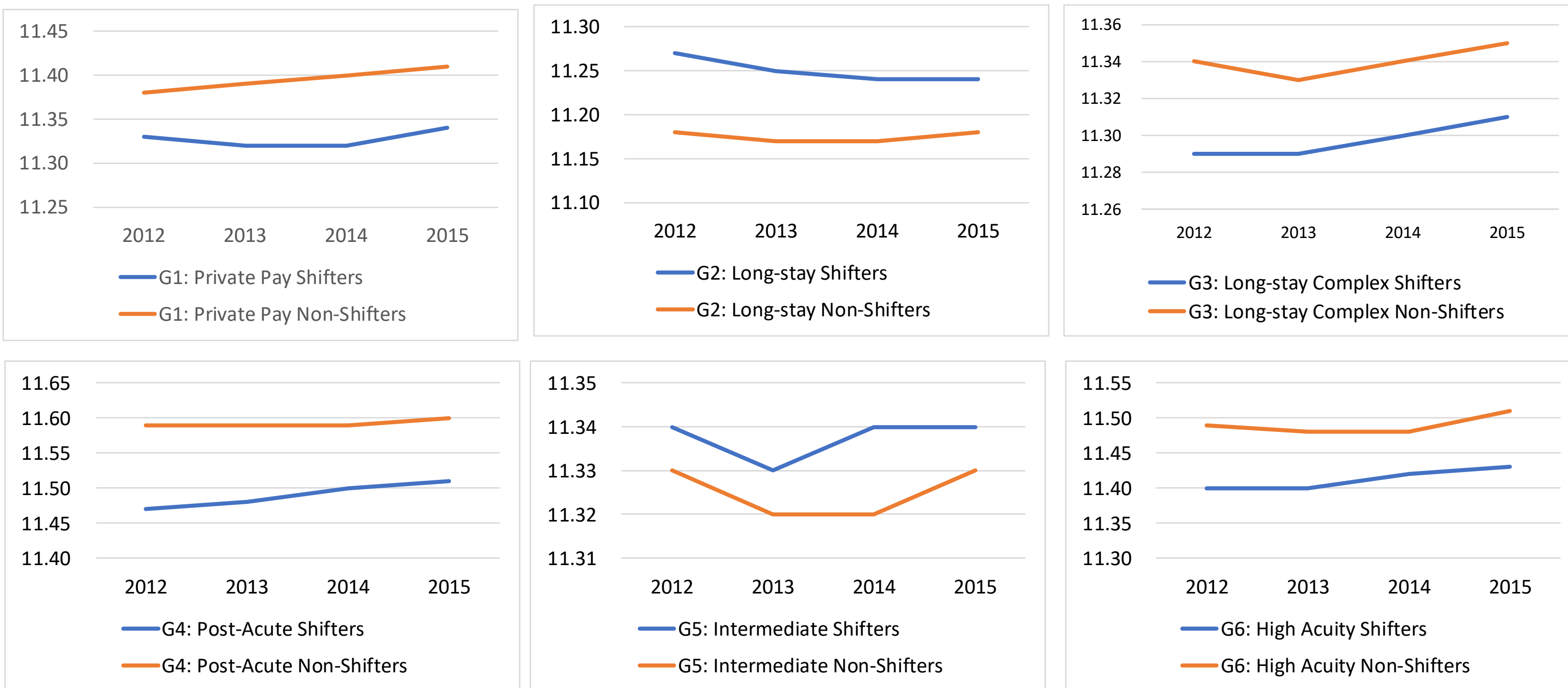


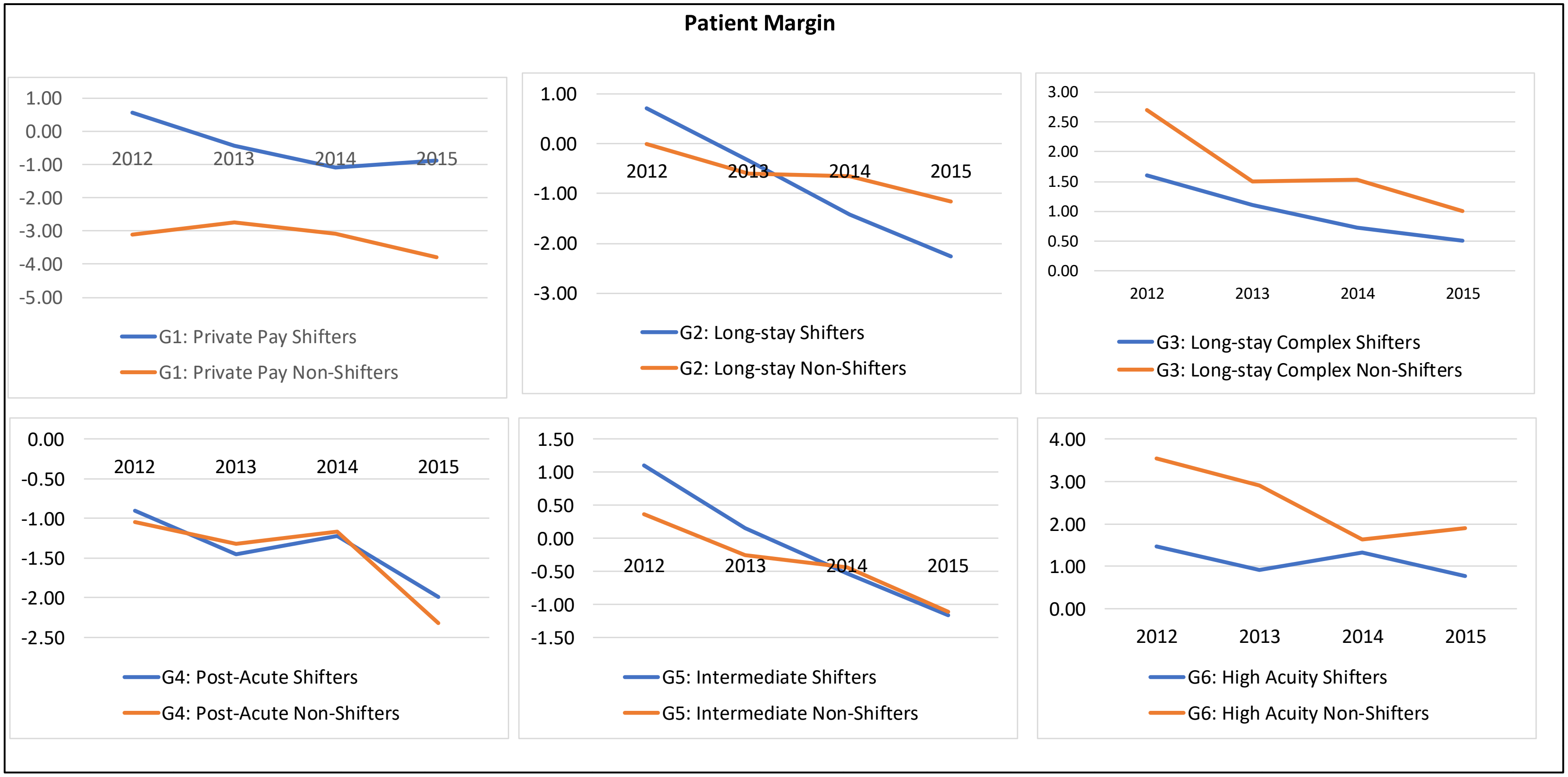
Referral Centrality				
Strategy Groups 2015	2012	2013	2014	2015
Group 1: Private Pay Care*	0.91	0.92	0.93	0.99
Group 2: Long-stay Care *	0.92	0.94	0.94	1.00
Group 3: Long-stay Complex Care*	0.91	0.92	0.92	0.99
Group 4: Post-Acute Care*	0.59	0.57	0.55	0.50
Group 5: Intermediate Care*	0.63	0.64	0.63	0.53
Group 6: High Acuity Care*	0.60	0.60	0.59	0.51
Total	0.78	0.78	0.78	0.78

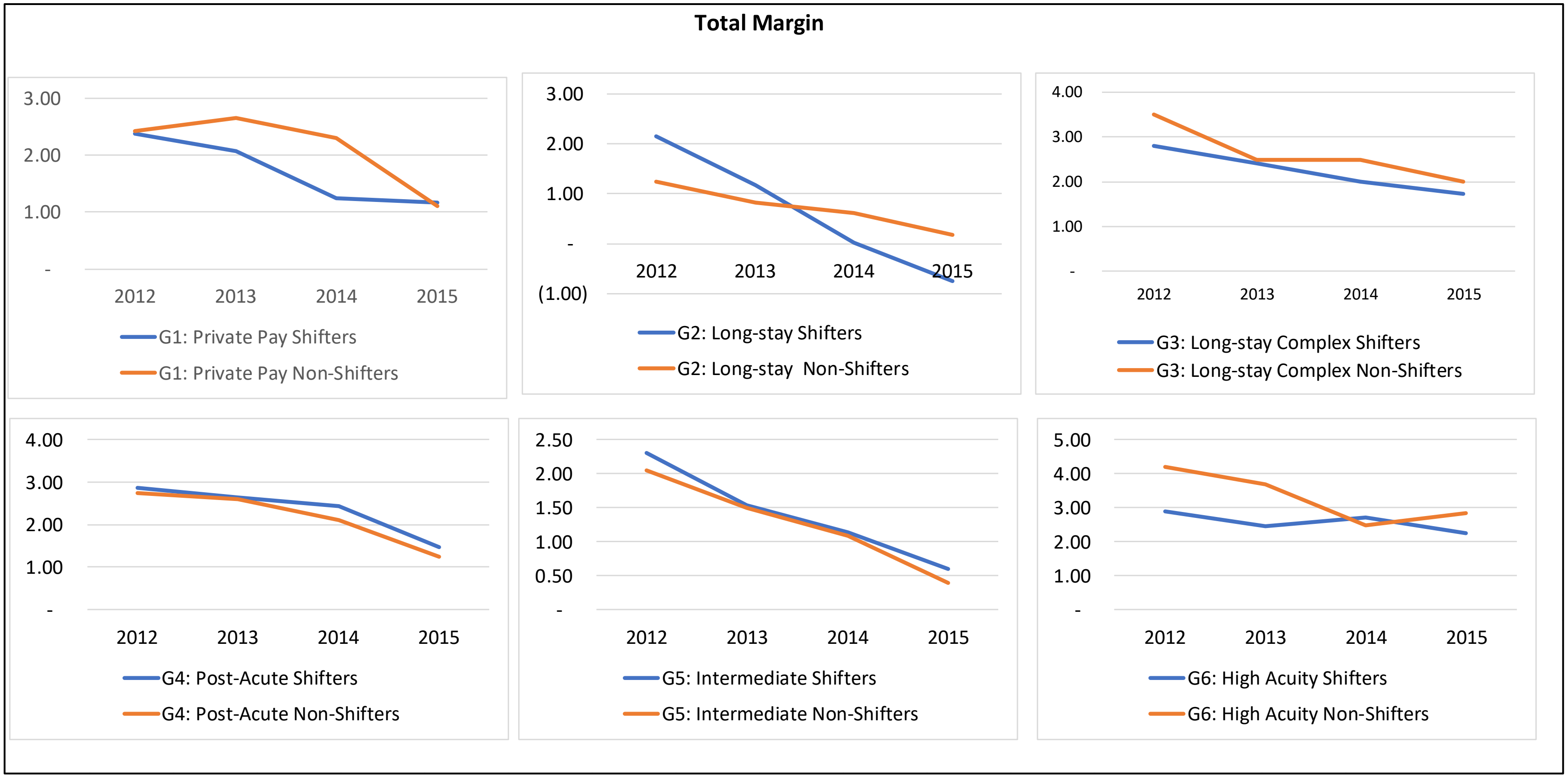
* Difference between 2015 and 2012 significant at $p < 0.001$

Appendix 3: Performance of Shifters and Non-Shifters by group from 2012 to 2015

Net Patient Revenues per Bed (log)




Patient Margin
1.00
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
2012
2013
2014
2015
G1: Private Pay Shifters
G1: Private Pay Non-Shifters
1.00
0.00
-1.00
-2.00
-3.00
G2: Long-stay Shifters
G2: Long-stay Non-Shifters
3.00
2.50
2.00
1.50
1.00
0.50
0.00
G3: Long-stay Complex Shifters
G3: Long-stay Complex Non-Shifters
-0.50
-1.50
-2.50
G4: Post-Acute Shifters
G4: Post-Acute Non-Shifters
1.50
0.50
G5: Intermediate Shifters
G5: Intermediate Non-Shifters
4.00
G6: High Acuity Shifters
G6: High Acuity Non-Shifters


Total Margin
3.00
2.00
1.00
-
2012
2013
2014
2015
G1: Private Pay Shifters
G1: Private Pay Non-Shifters
3.00
2.00
1.00
-
(1.00)
G2: Long-stay Shifters
G2: Long-stay Non-Shifters
4.00
3.00
2.00
1.00
G3: Long-stay Complex Shifters
G3: Long-stay Complex Non-Shifters
G4: Post-Acute Shifters
G4: Post-Acute Non-Shifters
2.50
1.50
0.50
G5: Intermediate Shifters
G5: Intermediate Non-Shifters
5.00
G6: High Acuity Shifters
G6: High Acuity Non-Shifters

Appendix 4: Difference-in-Differences Regression Result Sample

Group 1 - Revenue/Bed ($) (in 2015 dollars) (log)	Coef.	Robust Std. Err.	t	P>t	[95% Conf. Interval]	
SHIFT (0,1)	0	(omitted)				
POST	0.044	0.014	3.060	0.002	0.016	0.072
SHIFT * POST	-0.021	0.009	-2.450	0.015	-0.039	-0.004
% Population > 65	0.003	0.011	0.260	0.792	-0.018	0.024
Per capita income ($) (log)	-0.118	0.077	-1.540	0.124	-0.269	0.032
Urban (0,1)	0.000	(omitted)				
Suburban (0,1)	0.000	(omitted)				
Large Rural Town (0,1)	0.000	(omitted)				
Rural (0,1)	0.000	(omitted)				
% Medicare HMO Penetration	-0.001	0.001	-0.760	0.448	-0.003	0.001
% ACO Penetration	0.000	(omitted)				
HHI (SNF Beds)	0.088	0.112	0.790	0.432	-0.132	0.309
Home Health Availability / Population > 65 per 1000 (log)	-0.022	0.017	-1.270	0.204	-0.055	0.012
Size (# Beds) (log)	-0.687	0.111	-6.200	0.000	-0.904	-0.469

Group 1 - Revenue/Bed ($) (in 2015 dollars) (log)	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
Occupancy	0.005	0.001	7.960	0.000	0.004	0.006
Ownership (FP 0,1)	0.013	0.083	0.160	0.872	-0.150	0.176
Chain Affiliation (0,1)	-0.004	0.016	-0.220	0.822	-0.035	0.028
constant	15.469	1.028	15.050	0.000	13.451	17.487

Vita

Jennifer Palazzolo was born in Richmond, Virginia. She graduated with a Bachelor of Science in Commerce from the University of Virginia in 1988. Jennifer worked as a data analyst at Thompson, Siegel, and Walmsley, an investment management firm, and later as an independent consultant until completing a Master's in Public Health at Virginia Commonwealth University in 2011. Afterwards, she worked for Virginia Health Information as a program manager, where she was inspired to pursue a doctorate degree. Jennifer currently serves as a Senior Economic Researcher at the Virginia Department of Medical Assistance Services.

Jennifer celebrated thirty years of marriage to Daniel Palazzolo in 2021, and they have two adult daughters, Sarah La Euna Palazzolo and Elena Gwendolyn Palazzolo.