A MULTILEVEL ANALYSIS OF ORGANIZATIONAL AND MARKET PREDICTORS
OF PATIENT ASSESSMENTS OF INPATIENT HOSPITAL CARE

A Dissertation in
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by
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ABSTRACT

This dissertation was motivated by the limited research on macro-level predictors of patient assessments of care. A theoretical model for studying multilevel predictors of patient assessments of care was developed, based on Donabedian’s structure-process-outcomes model and resource dependency theory, to guide this study. Overall, the sample included 24,887 medical/surgical patients from 173 hospitals, nested in 46 counties in CA; the data were derived from the 2002 NRC Picker Patients’ Evaluation of Performance in California (PEP-C) survey, the American Hospital Association (AHA) Annual Survey, and the Area Resource File (ARF). The study employed three-level hierarchical linear models, where patient, organizational (hospital), and market predictors were introduced in a sequential model-building approach to explain variations across data levels in process quality and overall satisfaction with care. Six of the ten hypotheses were either completely or partially supported by the results, providing support for the theoretical model. This study found that variations in all domains of patient assessments of care abound. Strikingly, however, most of the overall variations (95% - 99%) were within-hospitals, rather than between-hospitals or between-markets. Patient characteristics accounted for up to 13% of variations at the within-hospital level. Interestingly, despite the relatively small between-hospital and between-market variations, net of patient characteristics, organizational-and market- level characteristics predicted a sizable amount of the true variations in process quality and overall satisfaction with care domains. The findings of this study suggest that most of the variations in patient assessments exist within the patient-health-care-provider relationship. Overall, this study supports the robustness of patient assessments of care in elucidating and explaining sources of variations across data levels. Other implications are discussed.
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DEDICATION

I dedicate this work to the human being that I love the most – after Muhammad, the prophet of Islam – my mother Fathia AbuDagga. My mother is the most giving and forgiving person that I have ever met in my life. Born and raised as a Palestinian refugee in three different countries, my mother was never able to go to school; however, she sacrificed and endured to make it possible for me and my siblings to pursue our educational goals, to the extent that each one of us wanted.
CHAPTER 1: BACKGROUND

INTRODUCTION

The robustness of patient assessments of care as measures of health care quality has been largely supported (Finkelstein, Hulka, & Rosenthal, 1999). Nonetheless, the literature on patient assessment of care is viewed to be less developed than the consumer satisfaction research found in the general marketing literature. O'Connor and Shewchuk (2003) describe the patient satisfaction literature as generally comprised of “substantively shallow empirical reports that address circumscribed, idiosyncratic, and context-specific questions (p. 21).” Furthermore, the literature cites three major weaknesses in the work on patient assessments of care: (1) Lacking theoretical foundations (Patterson, 1998); (2) Being mostly based on simple descriptive and correlational analyses (O'Connor & Shewchuk, 2003; Otani, Kurz, Burroughs, & Waterman, 2003); and, (3) Being limited to a single or few health care organizations (Finkelstein, Singh, Silvers, Neuhauser, & Rosenthal, 1998; Greenley & Schoenherr, 1981; Rogut, Newman, & Cleary, 1996; Rosenheck, Wilson, & Meterko, 1997; Young, Meterko, & Desai, 2000). The fact that this literature had rarely used multi-hospital samples of patients (Greenley et al., 1981) is of particular importance, for this sampling practice has been implicated in the discrepancy of research findings; the discrepant findings on the sociodemographic predictors of patient assessments of care (Finkelstein et al., 1998; Young et al., 2000) is one such major example. Another downside of this sampling practice is that studies that are limited to few hospitals preclude investigating macro-level predictors – at the organizational (Jimmieson & Griffin, 1998; Rogut et al., 1996; Rosenheck et al., 1997) and market levels.
Driven by the need to address these three limitations and capitalizing on data from a large multi-hospital sample from the Patients’ Evaluations of Performance in California (PEP-C) survey of the NRC Picker, this study made several contributions to the area of research on predictors of patient assessments of care. Firstly, it conceptualized and validated patient assessments of care as multidimensional process quality and overall satisfaction with care composite scores. Secondly, building on Donabedian’s structure-process-outcome model and resource dependency theory, this study developed a theoretical model for studying the data structure of patient assessments of care. This theoretical model suits the multilevel nature of patient assessments of care, given that variations are likely to exist at the three data levels: patients, hospitals, and markets. Thirdly, this study employed three-level hierarchical linear models to decompose and explain multilevel variations using organizational and environmental characteristics, net of patient characteristics.

This study addressed three major research questions:

1. Do patient assessments of inpatient care (process quality and overall satisfaction composite scores) vary within hospitals, between hospitals, and between markets?
2. Do hospital organizational characteristics predict the mean patient assessments of hospital care, controlling for patient-level characteristics? How much of the hospital variations at this level are explained by organizational characteristics?
3. Do hospital environmental characteristics predict the mean patient assessments of hospital care, controlling for patient and organizational characteristics? How much of the hospital variations at this level are explained by environmental characteristics?
LITERATURE REVIEW

A vast body of research has been devoted to the concept of patient assessments of care. This study focused on patient assessments of hospital care. A review of this literature showed three major strands of research: the usefulness of patient assessments of care, measurement of patient assessments of care, and predictors of patient assessments of care.

Usefulness of Patient Assessments of Care

As early as the 1960s, researchers have documented that patients have different reactions to their experiences with medical care (Hulka, Zyzanski, Cassel, & Thompson, 1971). Over the last three decades, patient perceptions of medical care have increasingly gained attention among researchers (Sitzia & Wood, 1997; Van Campen, Sixma, Friele, Kerssens, & Peters, 1995; Van Campen, Sixma, Kerssens, Peters, & Rasker, 1998). The rise of consumer-oriented approaches as superior models for health care delivery (Finkelstein et al., 1999; O'Connor et al., 2003) and the emergence of the information on the quality of health care providers movement (Barr & Banks, 2002) have contributed to the proliferation of work on patient assessments of care.

Traditionally, some physicians and administrators raised doubts that patient perceptions can accurately measure quality, let alone provide actionable information (Mack, File, Horwitz, & Prince, 1995). Surprisingly however, these suspicions have “beyond any doubt” largely contributed to the proliferation of the measurement of patient satisfaction industry (O'Connor & Shewchuk, 2003). As indicated by Hays, Larson, et al. (1999), patient perceptions of health care have already been shown to be highly related to patient intentions to recommend, brag about, and return to the hospital if care is needed in the future. Patients perceptions of care have been documented to predict whether patients seek medical advice, comply with treatment, maintain a
continuing relationship with a practitioner, as well as the willingness of patients to initiate a malpractice litigation (Finkelstein et al., 1999). It has also been shown that patient ratings of hospital quality closely match those of hospital employees (Jimmieson et al., 1998; Nelson et al., 1992). Moreover, recent research suggest that patient assessments of care are related to organizational financial performance (Press, Ganey, & Malone, 1991). For example, one study showed that patient satisfaction accounts for almost one third of the variance in hospital profitability (Nelson et al., 1992).

Implicit in the argument that patient assessments of care are useful means for evaluating the performance of health care providers and improving health care quality is that patients have a common idea about how health care providers should operate (Sixma, Spreeuwenberg, & Van Der Pach, 1998). In reality, it has also been found that patients can discriminate between different aspects of care (Hays, Larson, Nelson, & Batalden, 1991) and between the care provided at different hospitals, and that patient ratings of care are reproducible over time (Finkelstein et al., 1999). An additional strength of patient assessments of care is that previous studies have established that patient surveys are feasible (Hays et al., 1991). Taken together, all these findings affirm the usefulness of patient assessments of care for evaluating health care quality (Finkelstein et al., 1999).

Quality improvement efforts, in both the service and manufacturing industries, have embraced consumer assessments to evaluate product quality (Rubin, 1990b). In fact, the health care quality improvement movement had long adopted patient assessments of care in quality assessment (Kane, Maciejewski, & Finch, 1997) even before their robustness was supported empirically.
Although most of the uses of consumer assessments data in health care have traditionally been limited to internal organizational purposes, such as quality improvement activities (Rosenheck et al., 1997; Young et al., 2000), their use has progressively expanded over the last two decades. For example, in the managed care industry, information from the Consumer Assessments of Health Plans Survey (CAHPS®) has been used in most of the publicly available managed care report cards (National Committee for Quality Assurance (NCQA), 2004). Similarly, the hospital industry is subjected to unprecedented market and policy pressures to comply with public disclosure of their performance data, in order to inform the purchasing decisions of consumers (Rosenheck et al., 1997; Young et al., 2000). In fact, several reports that compare hospitals based on patient assessments of care have been publicly available for several years (Barr et al., 2002). The importance of patient evaluations of hospital care is most exemplified by the Centers for Medicare and Medicaid Services (CMS) effort to promote the collection and reporting of patient experiences with hospital care (Hays, Eastwood, Spritzer, & Cowan, 2006) in the CHAPS® Hospital Survey effort (Goldstein, Farquhar, Crofton, Darby, & Garfinkel, 2005).

**Measurement of Patient Assessments of Care**

Of the vast body of literature on patient assessments of care, patient satisfaction is the most commonly used/studied term. In fact, one literature review (Sitzia et al., 1997) found that over a thousand studies addressed the concept of patient satisfaction worldwide. Sitzia and Wood (1997) noted that patient satisfaction with care has been operationalized in so many different ways that made them conclude that the literature lacks attention to the meaning of the concept of patient satisfaction. Ironically, discussions of conceptual and theoretical issues
related to patient satisfaction have typically come after measurements and analyses of patient satisfaction have taken place (Finkelstein et al., 1999).

A major reason for lacking consistent conceptualization of patient satisfaction is the fact that until recently, standardized and validated instruments of patient satisfaction were lacking. A review of the patient satisfaction instruments (Van Campen et al., 1995) revealed that of the existing one hundred and thirteen instruments, only forty one were tested for validity and/or reliability and just eight instruments were tested twice or more in published studies. The authors also noted that most of these instruments were developed in-house by hospital staff. The authors proposed five requirements for an instrument to be suitable for quality assessments from the consumer’s perspective: the tool has to be theoretically sound; reliable and valid; structured around sub-scales; easily feasible; and applicable to outpatient settings. According to the authors, none of the eight tools that had been used more than two times met all these requirements and only five met at least three of these criteria. Indeed, the lack of validated and standardized instruments in the patient assessments of care literature limits the generalizability of the findings of these studies.

Another limitation is the tendency to conceptualize patient assessments of care too broadly. Early work using factor analyses and other similar methods supported the presence of several different dimensions underlying the patient assessments of care construct (Ware & Snyder, 1975). However, researchers have started to consider the multidimensional nature of patient assessments of care in empirical studies only recently. Furthermore, consensus on the specific dimensions that comprise patient assessments of care has been lacking (Greenley et al.,
Ware and Snyder’s review of the patient satisfaction (assessments) literature indicated the prevalence of eight major dimensions of satisfaction: art of care, technical quality of care, accessibility of/convenience, finances, physical environment, availability, continuity, and efficacy/outcome of care (Ware, Davies-Avery, & Stewart, 1978). Clearly, failure to conceptualize patient assessments of care multidimensionally has implications for the findings on predictors of this construct. In addition, various dimensions of patient assessments can have different predictors. More variations in predictors can also exist among various patient groups and/or organizations (Greenley et al., 1981). Therefore, unless researchers look at multiple dimensions of patient assessments of care, complete understanding of the factors that influence patient assessments will not be attained.

**Predictors of Patient Assessments of Care**

The literature on predictors of patient assessments of care has focused primarily on patient-level characteristics (Greenley et al., 1981): such as, health status, age, gender, socioeconomic factors, disease severity, and health care access measures including availability of health insurance. In fact, combinations of these patient-level predictors have been effectively used in case-mix adjustments of some health care outcomes, with the purpose of making equitable comparisons among different providers.

A significant amount of research indicates that age (Jaipaul & Rosenthal, 2003) and health status (Hargraves et al., 2001) are important predictors of patient assessments of care, independent of the characteristics of the care provided. However, research remains equivocal about the role of other patient factors, such as gender and race (Barr et al., 2002). The availability of health insurance has been found to be positively related to satisfaction with care
(Finkelstein, 1998; Rogut et al., 1996). The importance of including health insurance status in the study of patient assessments of care is supported by the mounting evidence on the link between the availability of health insurance and health status (Hadley, 2003). Moreover, poor health status has been found to be negatively related to patient assessments of care (Westaway, Rheeder, Van Zyl, & Seager, 2003).

Interestingly, patient characteristics appear to account for a rather small amount (3% - 7%) of the overall variance in measures of patient assessments of care in published studies (Barr et al., 2002). As such, some researchers, such as Finkelstein, et al. (1998) have concluded that hospital ratings based on patient assessments of care are not substantially affected by case-mix differences.

In the patient assessments of care literature, there are instances where researchers indicated that patient assessments of care differed across individual hospitals, yet no attempts were made to correlate these differences with hospital characteristics. The work of (Nelson et al., 1989) is such a case in point. The fact is, compared to work on patient characteristics, a small number of studies have examined the influence of hospital organizational characteristics on patient assessments of care (Greenley et al., 1981; Jimmieson et al., 1998; Rosenheck et al., 1997; Young et al., 2000). Additionally, despite the existence of a multitude of potentially influential and measurable hospital organizational variables, the following variables were examined, albeit narrowly, by researchers in this area: size, teaching status, ownership status, Medicaid volume, nurse staffing, total margin, and service type. Studies seldom included combinations of more than three of these variables. Thus, the findings on these organizational variables are generally too inconsistent to provide a good understanding of their influence.
With respect to organizational size, (Rosenheck et al., 1997; Young et al., 2000) found that patient assessments of care were worse in hospitals with higher number of beds. However, Finkelstein, et al. (1998) found that size was not related to patient assessments of care among obstetric patients. While Fleming 1981 found that teaching status was negatively related to patient assessments of hospital care, in general, another study found it to be negatively related to coordination of care, timeliness, and accessibility of care, in particular (Rosenheck et al., 1997). However, Young et al. (2000) found teaching status was negatively associated with patient ratings of care only in surgical settings. In terms of hospital ownership status, Baker et al.’s (2000) review of the literature found that among the six studies that examined the relationship between patient assessments of care and ownership, the relationship was confirmed in only one study and suggested in another. Nonetheless, Baker et al. (2000) noted that little attention has been given to the relationship between hospital ownership status and patient outcomes, in general, not just regarding patient assessments of care. Therefore, the authors recommended that future research of patient outcomes should include ownership status. While Rogut et al. (1996) found that Medicaid volume was negatively related to patient assessments of care, Finkelstein et al. (1998) found it not at all related to patient assessments of care. Rogut et al. (1996) also found nurse staffing (measured as the number of nurse full-time equivalents per occupied beds) not predictive of patient ratings of care, controlling for patient characteristics. With respect to total margin, Rogut et al. (1996) found it not related to patient assessments of hospital. In contrast to other organizational characteristics, hospital service type seems to be a more consistent predictor of patient assessments of care. For example, (Cleary et al., 1991; Young et al., 2000) found that obstetric patients and surgical patients tend to rate their care higher than medical patients.
Similarly, (Hargraves et al., 2001) recommended disaggregating patient assessments data by service type, as opposed to combining data from all types of hospital care.

While the general organizational and strategic management literature give emphasis to market (environmental) characteristics, as significant predictors of organizational performance, very few studies have researched their link to patient outcomes, let alone patient assessments of care. Incidentally, one study (Young et al., 2000) examined the role of one market factor (rural location), alongside hospital-level predictors of patient assessments of care; this study found rural location of hospitals to be a favorable predictor of patient assessments of care. On the other hand, the few available findings from the health care industry suggest that market characteristics do influence patient outcomes. For example, some studies have found that higher Health Maintenance Organizations (HMO) penetration and HMO competition in hospital markets are related to better clinical outcomes (Mukamel, Zwanziger, & Bamezai, 2002; Mukamel, Zwanziger, & Tomaszewski, 2001). Similar to the managed care industry, where the market characteristics were found to be related to plan quality (Scanlon, Swaminathan, Chernew, & Lee, 2006), we can justifiably posit (as illustrated under the theoretical framework) that market characteristics can also influence the quality of hospital care, as assessed by patients.

Apparently, not enough research studied macro-level predictors of patient assessments of care. An obvious major reason for this knowledge gap is the fact that most studies have typically sampled too few hospitals (Finkelstein et al., 1998; Fleming, 1981; Rosenheck et al., 1997; Young et al., 2000) or failed to gather sufficient data on the structure and processes of sampled hospitals (Greenley et al., 1981). As explained by (Sixma et al., 1998), the representation of an
adequate range of health care organizations in the patient assessments of care research stems
from the fact that structural variables, such as the characteristics of the health care professionals,
can be predictive of the quality of care and how the care can be improved. Therefore, unless
patient assessments of care data are collected from samples that resemble the hierarchical
structure of the health care system, it becomes unclear whether differences in patient assessments
of care are due to differences between patients or the hospitals where health care was provided.
Along those lines, differences in patient assessments could be due to differences in the markets
where hospitals exist.

Another limitation in this research is failing to simultaneously account for patient and
organizational predictors. For example, Fleming’s (1981) study of organizational predictors of
patient assessments of care did not control for patient characteristics. Young et al. (2000)
advocated for the combined analyses of patient and organizational factors, because these
variables may be correlated across data levels as in the case of teaching hospitals and sicker
patients. Additionally, Finkelstein et al. (1998) and others asserted that the discrepant findings
on patient characteristics could be due to the methodological failure to account for organizational
characteristics. Moreover, the absence of data analyses of both patient and organizational
predictors makes it difficult to distinguish the relative contribution of each predictor to the
overall variability in patient assessments of care (Veenstra & Hofoss, 2003).

Aside from sampling issues, further research that takes into account the multidimensional
and multilevel nature of patient assessments of care is urgently needed. With the recent
availability of standardized and validated measures of patient assessment of care, such as the
NRC Picker instruments, and the advancements in multilevel methods, health services
researchers have a unique opportunity to provide a better understanding of the predictors of patient assessments of hospital care across patient, organizational, and environmental levels. The findings of this research are particularly instrumental in the realm of adjusting quality information, for more equitable comparisons among health care providers (Young et al., 2000).
CHAPTER 2: THEORETICAL FRAMEWORK

This section describes the theoretical foundation for the hypothesized relationships between patient assessments of care and organizational and market factors. Firstly, the relevance of Donabedian’s structure-process-outcomes model to the conceptualization of patient assessments of care is explained. Secondly, the relevance of market characteristics is illustrated. Thirdly, the conceptual model that guided this study is presented. Finally, the usefulness of the resource dependency theory to understanding macro-level predictors of patient assessments of care is illustrated and specific study hypotheses are derived.

The Structure-Process-Outcome (SPO) Model

The SPO model for assessing health care quality (Donabedian, 1966, 1980, 1992) provided an overall conceptual basis for this study. The health services research and the quality improvement communities have used the SPO model widely (Romano & Mutter, 2004). A number of studies of patient assessments of care have also used the SPO model (Chang, 1997; Crall & Morris, 1988; Oropesa, Landale, & Kenkre, 2002; Patterson, 1998; Westaway et al., 2003). Thus, a preponderance of support exists for the appropriateness of the SPO model for understanding organizational phenomena, such as patient assessments of care.

Donabedian defined *structure* as the professional and organizational resources associated with the provision of care, such as staffing levels and credentials, and facility operating capacities. *Process* refers to the things done to and for the patient, and includes both technical quality and process quality. Technical quality represents the *clinical quality* of the medical
procedures delivered to the patient. In contrast, *process quality* concerns with how the care was created and delivered (Marley, Collier, & Goldstein, 2004). Examples of *process quality* include the level of care personalization and patient-care provider interaction, the delivery of medication, the efficiency of admission and checkout, and the timeliness and accuracy of hospital bills (Marley et al., 2004). According to Donabedian, *Outcomes* are the conditions resulting from care processes, which may include clinical outcomes, functional well being, as well as patient satisfaction with care. In applications of the SPO model, researchers, such as Romano and Mutter (2004) had further distinguished between two types of outcomes as: *clinical outcomes*, as those outcomes encompassing mortality, morbidity, and functional status; and *process outcomes*, as those encompassing patient behaviors, knowledge, and satisfaction with care.

Donabedian indicated that there is a direct relationship among the three components of the SPO model, whereby a good structure promotes appropriate processes of care and better patient outcomes, and vice versa. Research findings had repeatedly supported the link between structural measures and processes and outcomes of care in health care applications of the SPO model (Mitchell & Shortell, 1997).

The general practice in applications of SPO model in health services research has been to use either process or outcome measures; seemingly due to data limitations considering that existing datasets are mostly tailored to either process or outcome measures, and rarely combine both types of data. Representing tangible end results of care, *outcomes* appeal to researchers, more than process measures (Crombie & Davies, 1998), and are currently dominant in health services research. On the other hand, some researchers assert the usefulness of *process quality* measures in the realms of quality improvement and health policy (Crombie et al., 1998).
Particularly, *processes quality* measures are directly actionable by health care providers, as they offer “opportunities for intervention” by reflecting how providers evaluate and treat patients (Romano et al., 2004).

This study used both process quality and outcome measures, as opposed to the traditional practice, for two reasons. The first reason is to offer a more comprehensive application of the SPO model and the second is to see if there is a pattern for the associations between the organizational and market characteristics and various aspects of care, at the process level of care as well as overall satisfaction. For example, overall ratings of care were found to measure aspects of care that are not captured in process of care measures (Hendriks, Vrielink, Van Es, De Haes, & Smets, 2004). Thus, one can presume that satisfaction with care may have different predictors than process of care.

With respect to defining patient assessments of care, this study borrowed from the work of (Marley et al., 2004). According to (Marley et al., 2004), *patient satisfaction* refers to “how patients judge the overall hospital experience and whether they would return to a future visit.” The authors also stated that *process quality* “concerns with patient perceptions of how the care was created and delivered,” however they did not provide a formal definition of process quality. Although the literature seems to share a general understanding of the concept of process quality, formal definitions do not seem to exist. In this study, *process quality* was defined as validated multidimensional evaluations of the health care experience in terms of coordination of care, continuity and transition of care, physical comfort, emotional support, information and education, involvement of family and friends, and respect for patient preferences.
In this study, the *structure* component of the SPO model pertained to the organizational characteristics of hospitals: teaching status, nurse-staffing mix, ownership status, payor mix, occupancy rate, and financial resources committed to patient care. The *process* component pertained to the Picker composite scores of process quality: coordination of care, continuity and transition of care, physical comfort, emotional support, information and education, involvement of family and friends, and respect for patient preferences. The *outcome* component pertained to the overall satisfaction with care composite score.

**Role of Environmental Factors**

The SPO model is apparently limited with respect to explicating the relevance of macro-level predictors of patient assessments of care. In fact, the SPO model does not capture factors beyond the hospital level that can also relate to patient assessments of care. This limitation represents a serious conceptual and methodological challenge, given that variations in patient assessments of hospital care are likely to exist between hospital markets, not only within hospitals.

There are two compelling rationales behind considering market-level factors in the study of patient assessments of care. The first rationale comes from the findings of the small area variation (SAV) in health care utilization research. Although predictors of SAV were long believed to be entirely attributable to differences in practice style among individual providers, this understanding has been changed radically by findings from recent research that incorporated market-level predictors. Evidently, market-level socio-economic and health care supply and demand factors have been found to account for a sizable amount of variations in SAV.
(Alexander et al., 1999; Komaromy et al., 1996).

The second rationale for considering market-level predictors of patient assessments of care is provided by the fundamental environmental – political and economic – changes that have taken place in the American health care system since the introduction of the SPO model. Major examples of these changes include the proliferation of managed care, shortages in professional health care staff, and changes in reimbursement structures. In addition, patients are increasingly becoming more educated about their health care needs and are also being more involved in planning their health care. In effect, hospitals have responded with several strategies to changes in their environments. Commonly-cited examples of hospital responses include the decrease in length of stay, increased emphasis on outpatient care, hospital downsizing, and the emergence of new hospital structures.

Theoretical support for the influence of the environment on the organizational behavior of hospitals is available from several organizational theories. Most notably, resource dependency theory is one such theory that has been extensively used by researchers interested in studying organizational response to external factors (Zinn, Mor, Castle, Intrator, & Brannon, 1999). The relevance of resource dependency theory is discussed later in this chapter.

**Role of Patient Characteristics**

Existing research on predictors of patient assessments of care has primarily focused on patient-level predictors. Despite the discrepant findings on the direction and size of association of patient-level predictors, the literature almost unequivocally supports the influence of these predictors on various measures of patient assessments of care. Thus, conceptual models of
patient assessments of care that fail to include patient-level predictors would evidently be incomplete.

**Adapted Conceptual Model**

This study hypothesized that hospital organizational and market characteristics are related to *process quality* and *overall satisfaction with care*. As discussed, the SPO model was instrumental in the conceptualization of the components of patient assessments of care. The SPO model also provided a theoretical foundation for the association between organizational characteristics, as structural factors, and measures of patient assessments of care. Support for the potential role of market and patient-level\(^1\) factors was discussed. Consequently, the conceptual framework for this study added relevant characteristics of the hospital market as well as relevant patient characteristics to the three basic components of the SPO model (Figure 1).

Therefore, this adapted model offers a more comprehensive framework to studying multilevel predictors of various aspects of patient assessments of care and captures the complexity of the current hospital industry.

This study left testing the relationship between process quality and overall satisfaction with care to future research. Nonetheless, direct association between patient perceptions of process quality and overall patient satisfaction with care had been supported in the work of (Marley et al., 2004).

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\(^1\) Given that organizational and market characteristics were the predictors of interest in this study, patient characteristics were used as control variables, but no hypothesis were formulated for them.
Figure 1: An Adapted Model of Studying Multilevel Predictors of Patient Assessments of Care

Relevance of Resource Dependency Theory

Resource dependency theory is an open systems theory that posits that the environment is the source of scarce and critical resources (Pfeffer & Salancik, 1978). Organizations depend on resources in the environment, beside their internal resources, for survival and must interact with their environments in order to obtain needed resources. The scarcity of resources and the uncertainty of the environment determine the nature and extent of organizational dependency (Scott, 1998). In turn, influential environmental factors prompt organizations to respond. In order to ensure their own survival, organizations take rational operational and/or strategic actions to respond to environmental factors and demands of key constituencies, while organizational characteristics determine the ability of organizations to respond to environmental factors and
demands of constituencies (such as, payors, patients, etc.).

Similar to other health care organizations, hospitals are facing increased complexity in their external environments. While health care payors have emphasized cost-effective health care services, exemplified in stringent reimbursement mechanisms by both government and managed care organizations, health care payors have increasingly been emphasizing quality of care as well over the last decade or so. One strategy for health care organizations to respond to these new environmental demands and to improve their market position is differentiation based on quality of care (Baker Starkey, Weech-Maldonado, & Mor, 2005). This study views differentiation of hospitals based on quality of care, as measured in patient assessments of care, as rational adaptive response to changing environmental conditions intended to secure a stable flow of resources.

Higher patient assessments of care would help hospitals distinguish themselves from their competitors. If hospitals demonstrate higher levels of patient assessments of care, they can generate more revenue and secure more resources from their environments. Therefore, hospitals will respond to the increasing complexity of external environment by increasing patient assessments of care. The ability to provide higher process quality and patient satisfaction with care is constrained by organizational and environmental factors.

Research Hypotheses

The conceptual model posited that hospital organizational and environmental characteristics, net of patient characteristics, influence hospitals’ ability to offer high process quality and increase overall patient satisfaction of care. Specific hypotheses for each hospital
Nurse Staffing

Comprising about 30-40% of overall hospital Full Time Equivalent (FTE) personnel and about 30% of hospital budget (Mark, Harless, & Mcue, 2005), nurse staffing is an important resource used in the delivery of hospital care. Hospitals with higher nursing staff, particularly more skilled staff, such as registered nurses are more likely to have better outcomes because they have access to adequate personnel resources and hence fewer personnel resource constraints. Studies have demonstrated that the more the staff and the more skilled staff, the better patient outcomes. Although the influence of nurse staffing levels on patient assessments of care have not been adequately investigated in large hospital samples, findings from studies using other quality of care outcomes, such as mortality, length of stay, and adverse outcomes, generally show favorable effects for higher nursing staffing levels (Needleman, Buerhaus, Stewart, Zelevinsky, & Mattke, 2006). This study posited that higher nurse staffing levels will enable hospitals to provide quality care (with the purpose of securing more resources). While few studies have investigated skill mix and others looked at aggregate nurse staffing levels (Patterson, 1998), this study tested the influence of both types of nursing staffing: RNs and LPNs. Therefore,

*Hypothesis 1A: At the hospital level, higher RN and LPN staffing levels are favorably associated with perceived process quality and overall satisfaction with care.*

Similarly, the more nursing staff that exist in a market, the larger the pool of nurses available to hospitals and the lesser uncertainty experienced by local hospitals in hiring more nurses. The availability of nursing staff in local markets is particularly critical to hospitals, given
the documented shortages of nurses in the United States. The nursing shortage has generated concerns among various health care stakeholders. In fact, legislations on minimum staffing levels in licensed health facilities have been recently passed in California in response to the concerns over quality of care (Mobley & Magnussen, 2002). Therefore,

Hypothesis 1B: At the market level, higher RN and LPN staffing levels are favorably associated with perceived process quality and overall satisfaction with care.

**Resources Directed to Patient Care**

In addition to nurse-staffing levels, another important dimension of the internal resources available in the hospital structure is how much of the total hospital expenses are allocated to labor. Labor expenses are important because they reflect the amount of resources dedicated to direct patient care. In fact, labor costs accounts for approximately half of the operational cost of hospitals (Centers of Medicare and Medicaid, 2003). Similar to nurse staffing levels, greater ratios of labor expenses (of total expenses) will enable hospitals to increase process quality and overall patient satisfaction with care, in order to distinguish the hospital from other competitors in the market. Therefore,

Hypothesis 2A: At the hospital level, higher ratios of resources directed to patient care are favorably associated with perceived process quality and overall satisfaction with care.

Extending the same logic to the market level, having more of the total hospital resources in a given market directed to patient care, through higher investments in labor, is expected to be associated, on average, with better patient care. Therefore,

Hypothesis 2B: At the market level, higher levels of resources directed to patient care are favorably associated with perceived process quality and overall satisfaction with care.
Payor mix

According to resource dependency theory, hospitals that depend on small pools of resources for survival are more vulnerable to environmental uncertainties compared to hospitals that have access to several pools of resources (Pfeffer et al., 1978). Hospitals take revenue resources into account when making operational and strategic decisions. Clearly, higher revenues generated from payors create more resources for hospitals and are also likely to affect patient experiences, such as better process quality and satisfaction. The hierarchy of insurance reimbursement rates for hospitals suggests that hospitals will pursue patients based on their source of reimbursement as follows: Medicare, private insurance, and then Medicaid. In acute care hospitals, Medicare is the *single* largest payor for hospital care (covering 30% of hospital care expenditures in 2001) followed by private insurance (34%) and Medicaid (17%) of hospital care expenditures (Centers of Medicare and Medicaid, 2003). Also, Medicare payments for hospitalization are more generous than Medicaid payments. Additionally, the impact of payor mix has been linked to the amount of internal resources generated in hospitals. Higher proportions of Medicare inpatient days (than Medicaid) in a hospital have been found to be associated with staffing levels, other factors held constant (Harrington & Swan, 2003). Also, higher Medicaid inpatient days are associated with negative effect on total staffing levels (Harrington et al., 2003). As such, this payment structure prescribes hospital ability to provide better patient care. Therefore,

*Hypothesis 3A: At the hospital level, a greater percentage of Medicare days of total days is favorably associated with perceived process quality and overall satisfaction with care, whereas a greater percentage of Medicaid days of total days is unfavorably associated with perceived process quality and overall satisfaction with care.*
Given that Medicaid is a less favorable payor of hospital care than other insurers, markets where Medicaid is a dominant payor of hospital care have fewer revenue resources from which local hospitals can draw resources. Following the premises of resource dependency theory, markets with constrained pools of resources, where Medicaid is a major payor (Baker Starkey et al., 2005), means that hospitals operating in these markets will have a hard time generating resources that are necessary for their survival and thus will have a lesser ability to compete based on, and provide quality care. Therefore,

\textit{Hypothesis 3B: At the market level, a greater ratio of Medicaid days to total days is unfavorably associated with perceived process quality and overall satisfaction with care.}\footnote{Notice that Medicare Days was not included as a predictor at the market level in this study, due to high multicollinearity with the nurse staffing variables – thus, no hypothesis was formulated for it.}

\textbf{Teaching Status}

Teaching hospitals enjoy a good reputation among various constituencies, including payors and patients. Moreover, teaching status affords hospitals more resources internally with combinations of patient care, research, and teaching capabilities. Thus, teaching hospitals will be able to attract more patient revenue resources. Research shows that patients are willing to travel farther to receive care in more reputable hospitals than their local hospitals (Bronstein & Morrisey, 1990). Additionally, hospitals in which intensive teaching is performed may act as institutional leaders dictating use of care in neighboring facilities (Alexander et al., 1999). For all these reasons, teaching hospitals will be able to offer better care and attain higher patient assessments of care as a strategy to generate even more resources from their environments. Therefore,

\textit{Hypothesis 4A: At the hospital level, teaching status is favorably associated with perceived process quality and overall satisfaction with care.}
Because teaching hospitals place more emphasis on patient care in their missions more than non-teaching hospitals, we can deduce that markets with higher concentration of teaching hospitals will have more cumulative focus on patient care than markets with fewer teaching hospitals. Additionally, more critical resources will be concentrated in market with higher teaching intensity, as patients tend to travel to these markets to seek treatment. Thus, according to resource dependency theory, markets with higher teaching intensity will be expected to have more resources and will be able to provide, and compete based on better patient care, as a strategy to ensure their survival.

*Hypothesis 4B: At the market level, teaching status is favorably associated with perceived process quality and overall satisfaction with care.*

**Occupancy Rate**

According to resource dependency theory, the higher patient occupancy rate, the more resources afforded to hospitals and the less environmental constraints imposed on them; thus, the higher the ability of the hospital to provide higher process quality care and increase overall patient satisfaction with care. A high occupancy rate means higher capacity utilization and more resources accessible to the hospital. Higher resources within a hospital will increase hospital ability to provide better process quality and satisfaction levels. Therefore,

*Hypothesis 5A: At the hospital level, higher occupancy rate is favorably associated with perceived process quality and overall satisfaction with care.*

At the market level, the higher excess capacity in a given market, the more resources available in it. In order for local hospitals to fill more of their beds, they will compete based on the quality of their hospital care. Thus, markets with higher excess capacity will have better process quality and patient overall satisfaction of care. Therefore,
Hypothesis 5B: At market level, excess bed-capacity is favorably associated with perceived process quality and overall satisfaction with care.

Hospital Ownership

Government-owned (state and local) hospitals accounted for 16% of community hospitals in 2000, non-government non-profit hospitals accounted for 61% and for-profit (investor-owned) hospitals accounted for the remainder 13% of hospitals (Centers of Medicare and Medicaid, 2003). Government hospitals have a more complex set of objectives than non-government hospitals, such as serving the indigent populations, providing community outreach and education programs, and are less motivated to by financial incentives (Tirole, 1994). In addition, community needs place constraints on acceptable responses for managing operating pressures in the organization. Government hospitals are often subject to soft budget constraints; while the government will likely subsidize the hospitals following poor performance, the hospital also remit any surpluses to the governing agency (Guggan, 2000). On the other hand, for-profit and non-government non-profit hospitals are more likely to emphasize profit strategies in response to environmental pressures as they are self-sustaining organizations that cannot rely on subsidies for operations. It is noteworthy, however, that non-profit hospitals often articulate a social objective; so profit is not the sole driver of managerial/operational actions compared to for-profit hospitals. Nonetheless, revenue from operations must fund costs and thus managers of non-profit non-government hospitals have similar pressures as for-profit managers, i.e., a profitability return on services provided. Thus, conceivably, more focus on process quality and

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3 Community hospitals are nonfederal short-term general and special hospitals whose facilities and services are available to the public.
overall satisfaction with care are more congruent with the mission and objectives of government-owned hospitals. Therefore,

**Hypothesis 6:** Government ownership is favorably associated with perceived process quality and overall patient satisfaction with care\(^4\).

**Hospital Competition**

Market share is taken into consideration by hospitals when determining internal resources and capacity utilization (Magnussen & Mobley, 1999). Moreover, in competitive markets, organizations share a limited resource pool and survival depends even more, compared to less competitive markets, on how resources are allocated across competitors (Proenca, Rosko, & Zinn, 2000). Thus, in more competitive markets, hospitals are more likely to emphasize higher levels of patient care (better process quality and overall satisfaction with care) as an adaptive strategy to distinguish themselves from their competitors and secure and stabilize resource flows (Oliver, 1990). As such, hospitals will seek to improve patient experiences of care, as a competitive strategy. Not to have high patient assessments of care could result in loss of market share and revenues to more aggressive competitors. Therefore,

**Hypothesis 7:** Markets with higher rates of hospital competition have favorable perceived process quality and overall patient satisfaction with care.

**HMO Penetration Rate**

For hospitals, managed care organizations are a key constituency that expects hospitals to provide good hospital care to enrolled populations and that enforces its demands through contractual agreements. Compliance with HMOs’ demands is likely to increase among hospitals

\(^4\) Because market-level information on the ownership status of hospitals was not available in ARF, it was not feasible to study the role this variable at the market level. Thus, no market-level hypothesis was feasible in this study.
that depend on these HMOs for scarce resources or for resources needed for survival. HMOs influence which hospitals their members will use, how many services they will utilize, and what price will be paid for these services. Because of HMOs’ ability to obtain information about quality of their enrollees’ providers, hospitals have an incentive to increase quality in order to attract patients and not lose potential revenue sources to competitors. Hospitals that are highly dependent on managed care revenue (exist in markets of high penetration) are more likely to respond by emphasizing high process quality and satisfaction with care than hospitals that are less dependent. Therefore,

Hypothesis 8: Markets with higher HMO penetration rates are favorably associated with perceived process quality and overall satisfaction with care.

Socio-Economic Factors

The socio-economic status of a market area is a crude indicator of the amount of resources available for hospitals operating in this market area. Research has shown that more affluent populations use more health care. Moreover, markets with low socio-economic status present an added challenge for their local hospitals, because the health care needs of the population will be more complicated than those of markets with higher socio-economic status. In fact, some researchers found that the socio-economic characteristics of markets are more important in explaining variations in use of health services than the practice style of health care providers (Komaromy et al., 1996).

These facts suggest that the socio-economic conditions of hospital markets can influence hospital performance and planning, which is the perspective of resource dependency theory. Similar to other studies in health services research that examined market effects (Iwashyna, Chang, Zhang, & Christakis, 2002), this study hypothesized a relationship between the socio-
economic conditions of hospital markets and process quality and overall patient satisfaction with hospital care. Specifically, this study used two key commonly-used proxy measures of market-level socio-economic status: percentage of minority population and per-capita income\(^5\).

Therefore,

\begin{quote}
Hypothesis 9: Markets with higher per-capita incomes have higher perceived process quality and overall patient satisfaction with care.
Hypothesis 10: Markets with lower percentages of minority population have higher perceived process quality and overall patient satisfaction with care.
\end{quote}

\(^5\) These two variables were also highly correlated with other market-level socio-economic variables in this study, e.g. population and housing densities, etc.
CHAPTER 3: DATA AND METHODS

A theoretical model that relates hospital and market (environment) characteristics to the processes and outcomes of care guided this study. Therefore, this study addressed the important research question of how organizational and market characteristics influence multi-dimensional processes quality and the outcome of overall satisfaction with care, as perceived by patients, using three-level hierarchical linear models (Raudenbush & Bryk, 2002).

Research Questions

1. Do patient assessments of inpatient care (process quality and overall satisfaction composite scores) vary within hospitals, between hospitals, and between markets?

2. Do hospital organizational characteristics predict the mean patient assessments of hospital care, controlling for patient-level characteristics? How much of the hospital variations at this level are explained by organizational characteristics?

3. Do hospital environmental characteristics predict the mean patient assessments of hospital care, controlling for patient and organizational characteristics? How much of the hospital variations at this level are explained by environmental characteristics?

Data Sources

There were three data sources for this study. Firstly, patient-level data were derived from the 2002 Patients’ Evaluation of Performance in California (PEP-C) adult survey. PEP-C data were collected through a collaborative project between the California Institute for Health
Systems Performance (CIHSP) and the National Research Corporation Picker (NRC Picker) to gather information about patient experiences with hospital care and to enhance quality improvement efforts in California hospitals. Secondly, hospital-organizational characteristics data were derived from the 2002 American Hospitals Association’s (AHA) survey of hospitals. Thirdly, market (environmental) characteristics were derived from the 2002 Area Resource File (ARF) data.

Refinement of the PEP-C Sample

The PEP-C survey targeted all general acute care hospitals in California; however, hospital participation was entirely voluntary. Participating hospitals provided NRC Picker with complete lists of their adult medical, surgical, and maternity patient discharges. NRC Picker randomly selected and surveyed a sample of 600 patients from each hospital list (NRC Picker & CIHSP, 2003). For each hospital, the sample was equally divided among the three: medical, surgical, and maternity/obstetric service units. For hospitals with less than 300 eligible discharges during the sample period, a census study of their patient population for the given year was conducted. The PEP-C survey excluded patients admitted for psychiatric and substance abuse treatment, those admitted purely for observational purposes, those who died or whose baby died, and patients who were discharged to a setting other than home.

The PEP-C adult survey data included patients admitted in the participating hospitals where they stayed for at least one night in any of the three service units of interest and were discharged between July 1, 2002 and October 31, 2002. According to NRC Picker & CIHSP (2003), a total of 181 hospitals participated in the PEP-C survey in 2002; thus, accounting for 47% of eligible hospitals, 51% of hospital discharges, and 54% of the licensed beds in
California. The average patient response rate (RR) within hospitals was 45%, with a total of 137 hospitals recorded response rates of 40% or better (NRC Picker et al., 2003).

For the purpose of this study, the PEP-C sample was refined in order to enhance the representation of the data. Some additional refinements of the sample were also necessitated by the other data sources of this study, in order to better address the research questions of this study. For instance, this study excluded pediatric hospitals, due to the inherent differences between adult and pediatric patient populations. Thus, the number of PEP-C hospitals was reduced to 179. Furthermore, given that obstetric services differ in numerous ways from medical and surgical services (Finkelstein et al., 1999; Finkelstein et al., 1998), this study excluded all maternity cases. As such, the PEP-C data used in this study were limited to medical and surgical patients.

Furthermore, due to differences with respect to both patient characteristics and the nature of services provided between short-term and long-term hospitals and the fact that there was only one PEP-C participating hospital that was designated in the AHA data as a long-term hospital, this single hospital was deleted from the PEPC data. Hence, the PEP-C hospital sample size was reduced to 175. Another justification for limiting the sample in this study to short-term hospitals was supported by the fact that the majority of all hospitals in CA (about 96%) were short-term hospitals (as supported by findings based on length of stay variable in the AHA data).
Variables and Measures

Patient Characteristics

All patient-level variables, including patient characteristics and measures of patient assessments of process quality and overall impression of care, were derived from the 2002 PEP-C data. The dependent variables were patient assessments of care (process quality reports and patient satisfaction with care domains). The PEP-C survey contained 33 items (reports) that tap 7 distinctive dimensions/domains of care processes: coordination of care, continuity and transition, emotional support, information and education, involvement of family and friends, physical comfort, and respect for patient preferences (See Appendix A for a list of these items grouped by domain; Appendix B for the PEP-C survey instrument). Patients were typically asked to respond to these questions using a three-likert scale type questions, whereby, a totally positive or non-problem response= “1”; a semi-positive/negative response= “2”; and, a negative response= “3.” Therefore, a lower score on these items was indicative of a favorable patient experience (in other words, we can think of these scales as problem scores).

PEP-C also contained seven ratings of care items (which are the satisfaction items in this study): courtesy of staff, courtesy of doctors, availability of doctors, courtesy of nurses, availability of nurses, how well doctors and nurses worked together, rating of the care received at the hospital, and whether one recommends the hospital to others. These items used a 5-point-likert scale: poor= “1”, fair= “2”, good= “3”, very good= “4”, and excellent= “5”, except for the hospital recommendation question, which was rated on a simple “yes” or “no” response options. As such, a higher score on the overall impression of care domain was indicative of favorable response.
As discussed in the next section, prior to creating summative composite-score scales for each of the eight outcomes of interest in this study, I first empirically validated the suitability of Picker grouping methodology for the data of this study.

Patient characteristics (level-one predictors in HLM conditional models) were constructed using the PEP-C data, as follows. White race was coded as a dummy variable with a value of “1” for white and “0” for non-white. Age was a continuous variable measured in years. Education was coded as a dummy variable, taking a value of “1” for less than high school and “0” for high school or beyond. Gender was a dummy variable taking a value of “1” for female and “0” for male gender. Self-perceived health status was coded as a dummy variable with a value of “1” for fair or poor health status, and a value of “0” for excellent, very good, or good health status. Patient’s primary health insurance consisted of two main dummy variables (Medicare and Medicaid) and private insurance served as the reference group. Since there were few observations who reported lack of health insurance (2.27% of the sample) or not being sure whether they have insurance or not (2.77%), these observations were coded as missing on health insurance. Type of inpatient service was a dummy variable taking a value of “1” for surgical and “0” for medical service.

Hospital Characteristics

Hospital characteristics were used as level-two predictors in the HLM conditional models. The AHA data provided three sets of measures for volume data: hospital-unit; nursing-home unit; and, overall-facility measures. Due to the fact that the PEP-C data concern inpatient stay, it was intuitive to use only hospital-unit data. Nevertheless, this approach was not feasible, due to a serious degree of data missingness with all of the hospital-unit measures. For
example, the measure with the least degree of missingness at the hospital unit (inpatient days) had 13% missingnesses. On the other hand, up to about a third of the PEP-C hospitals were missing on other hospital-unit measures. For example, 28% of the PEP-C hospitals were missing on Medicaid inpatient days at the hospital-unit level. Furthermore, some variables, such as nurse-staffing variables were only available at the total facility unit in the AHA data. Therefore, I opted to use the total facility measures to derive hospital-level predictors. Nonetheless, in order to control for the influence of non-hospital unit component (in other words, the nursing-home component) of hospital measures, I used the indicator variable in the AHA data of whether a hospital maintained a separate nursing-home unit, as a control variable in the HLM models.

In terms of hospital volume, I used total inpatient days, rather than discharges or admissions, because inpatient days reflect the heterogeneity in labor usage across patients (Magnussen et al., 1999). Additionally, although both bed size and nurse staffing were predictors of interest in this study, these measures were highly collinear\(^6\). Therefore combinations of these variables (such as, the number of staff per inpatient days) were better suited for HLM models.

Overall, I derived/constructed nine measures of hospital-organizational characteristics using the AHA data, as follows. Teaching status was measured via a summative scale (ranging from 0-3) constructed using three teaching-status indicators in the AHA data: whether a hospital is a member of the Council of Teaching Hospitals; whether a hospital’s residency training program is approved by the Council for Graduate Medical Education (GME); and whether a hospital’s medical school reported to the American Medical Association (AMA). I also considered using the ratio of residents per inpatient days as a measure of teaching status, as suggested by (Navathe, Zhu, Silber, Rosenbaum, & Volpp, 2007). While the ratio of residents

\(^6\) Predictors with bivariate correlation coefficients of 0.7 or higher were considered collinear.
per inpatient days sounded like a suitable measure of teaching status (given that for nursing staffing, RN and LPN ratios to inpatient days were used), it was heavily skewed with 95 hospitals (54.60%) reported having zero residents and overall 94.83% had lower than 1 resident per 1000 inpatient days. On the other hand, the teaching status composite was related to the ratio of residents (r=.54). The teaching status composite also showed more variations among hospitals on this measure. The only caveat was that one hospital was missing on this variable, thus the number of hospitals in the HLM models was reduced to 173.

In terms of ownership status, AHA data measured this variable through three main categories: government owned (federal and nonfederal); non-government owned non-profit; and investor owned. Occupancy rate is a measure of technical efficiency and was calculated as total inpatient days/ (staffed beds times 365). Two measures of payor mix were constructed based on the AHA data: (1) the percentage of Medicare inpatient days of total inpatient days; and, (2) the percentage of Medicaid inpatient days of total inpatient days. Two measures of nurse staffing were constructed based on the AHA data: (1) ratio of RN FTEs to total inpatient days; and, (2) ratio of LPN FTEs to total inpatient days. Finally, a measure of financial resources committed to patient care was constructed as the labor expense per total FTEs: (hospital total payroll expenses + employee benefits expense)/ total FTEs. One hospital characteristic I considered was whether a hospital was a general or non-general (i.e., a specialty) hospital. However, since the majority of PEP-C hospitals were general hospitals, there were not enough variations in this variable to be included among the hospital predictors of interest in this study. Another hospital characteristic that I could not include due to lack of hospital variations was whether a hospital was a community hospital, as approximately 98% of the PEP-C hospitals were designated as
community hospitals in the AHA data.

I have also considered the use of other hospital characteristics from the AHA data that have been suggested in the literature to be related to organizational outcomes, such as health system membership (Bazzoli, Shortell, Dubbs, Chan, & Kralovec, 1999), degree of community orientation (Proenca et al., 2000)\(^7\), involvement in quality improvement (self-assessment against Baldrige-like criteria for sustained continuous improvement). However, due to serious problems with missing values with these measures in the AHA, to an extent that would minimize hospital sample size up to about 30% if I included such measures, I opted not to include them in this study.

**Market Characteristics**

Market characteristics were the predictors of interest at level three of the HLM conditional models. I conceived of market characteristics to include characteristics pertinent to the structure of competing organizations (hospitals), key factors of supply and demand of hospital care, as well as key socio-economic characteristics of the population served. The operationalization of these market-level predictors was to some extent dictated by the ARF data. However, to the extent possible, I tried to refine these market measures to correspond to the way the organizational characteristics were measured in the AHA data in order to enable closer comparisons between the organizational and market levels. All of the market-level characteristics, with exception of hospital index of competition, were derived from the ARF data. The ARF data generally used the county as the unit of analysis for most measures, although in some cases, such as HMO penetration rate, it presented measures at the MSA level. As such, for

\(^7\) 19.5% missing values on this variable.
the most part, this study used the county as the approximation of market area for a given hospital. Another fact worthy of mention here too is that ARF data presented measures related to hospital characteristics at the county level separately for short-term and long-term care hospitals. Moreover, in some cases, measures for short-term general hospitals were further disaggregated for general and non-general hospitals. Given that the PEP-C hospital sample excluded long-term hospitals, ARF measures for long-term hospitals were also excluded from the market-level data for this study. In addition, since the vast majority of hospitals in the PEP-C sample were general hospitals, I subsequently used the measures pertinent to the short-term general hospitals upon construction of the market variables of interest in this study. However, in the event that short-term hospital measures were not available at the short-term general hospital level (but rather aggregated for both general and non-general hospitals), I was constrained to use these measures. A final note in this regard is that I used the 2001-estimated population data in ARF for the population measures of interest at the market level.

With respect to market characteristics pertinent to hospital structure, I derived the following variables: teaching status, excess capacity, resources committed to patient care, and hospital index of competition. Teaching status was measured in this study as the number of short-term general hospitals per county that were members of the council of teaching hospitals. Excess capacity of short-term general hospital beds was calculated as the county’s occupancy rate subtracted from 100%. Occupancy rate was constructed as the total number of inpatient days for short-term-general hospitals in a county divided by the product of the total number of the county’s short-term-general hospital beds and 365. The resources-committed-to-patient-care

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8 Unlike the hospital-level, it was not feasible to use affiliation with the AMA and membership in the Council for GME. The ratio of residents per population was severely skewed with significant number of hospitals with zero observations, thus could not be used in this study.
variable was measured as the ratio of total payroll expense in thousands for short-term-general hospitals in a county divided by total per 1000 short-term-general inpatient days. Unlike the AHA data, while the ARF data reported total payroll expense, they did not report any information about employee benefits expense. Therefore, this distinction needs to be taken in consideration upon drawing comparisons about this construct between the hospital- and market-levels. It also should be noted that the ARF data included total hospital expense for short-term general hospitals as one measure and aggregated the corresponding measures for both long-term and short-term non-general hospitals.

Consistent with the majority of the hospital competition literature, I calculated the Herfindahl-Hirschman Index (HHI) of competition among hospitals as the measure of the intensity of hospital competition (Gaynor & Voget, 2000). HHI is a geopolitical measure of competition and one of its strengths is that it reflects both the number of hospitals and the market shares across hospitals (Wong, Zhan, & Mutter, 2005). Consistent with most of the literature in this area as well (Iwashyna et al., 2002), I calculated the HHI for hospital markets at the county level. I calculated HHI in the AHA data and imported it to the ARF data and linked it back to the respective hospital level data at level three in the HLM Models using county identifiers. I chose to calculate the HHI using the AHA, rather than the ARF data for several reasons: I used both general short-term and non-general short-term hospital inpatient days in the construction of this variable, unlike the way this variable was constructed in the ARF data (as ARF also includes long-term hospitals in the calculation of this measure). Worthy of mention here is that I calculated this variable using market share information from both PEP-C and non-PEP-C participating hospitals. I also created two additional sets of the HHI using the hospital’s health
service area (HSA) and hospital referral region (HRR) codes as defined in the Dartmouth Atlas of Health Care, as the units of measurement in addition to the county-based HHI. However, there was a significant degree of missingness on the HSA and HRR code identifiers for hospitals in the AHA data, as hospitals were asked to self-report their respective identifiers for these two codes; not surprisingly, therefore, these codes were not reported by all hospitals. The HHI of hospital competition was calculated as the sum of the squares of the individual hospital market shares per county. The market share for a given hospital consisted of the proportion of a hospital’s inpatient days of the total inpatient days in a market area. This means that a highly-competitive hospital market had an HHI approaching zero (since each hospital had fractional percentages of market share, which became even smaller when squared), while a perfectly-monopolistic market (with one hospital) had an HHI of 1.

Key factors of supply and demand of inpatient care used in this study were: HMO penetration rate, nurse-staffing mix per population count, and, payor mix per population count. The HMO penetration rate variable was already calculated in ARF as total HMO enrollment divided by the total population in the hospital’s county and was derived from InterStudy’s 1998 data. Consistent with the way nurse-staffing variables were measured at the organizational-(hospital) level, I constructed two measures of nurse staffing using the ARF data: (1) RN FTEs per 1000 population, and, (2) LPN/LVN FTEs per 1000 population. Similarly, I constructed two measures of payor mix: (1) Medicare inpatient days in a hospital market area, which was calculated as the total number of short-term-general-hospital Medicare inpatient days in a county divided by the per-thousand count of the county’s population and (2) Medicaid inpatient days, which was calculated as the ratio of Medicaid short-term-general-hospital inpatient days divided
by the per-thousand count of the county’s population.

In terms of key socio-economic characteristics of the population in hospital markets, I examined two key predictors: per capita income and percentage of minority population. Per capita income was defined in ARF as the per capita income in the hospital’s county. I calculated the percentage of racial/ethnic minorities as one minus the percentage of the white population (one race alone) variable given in the ARF data. Thus, minority status of a county represented the percentage of racial/ethnic minorities (nonwhites) of total population in a hospital’s county.

Although I was interested in including a measure of rural/urban status of hospital markets, as suggested by previous research that studied market characteristics in relation to health care outcomes (Mobley et al., 2002), all possible measures of this construct that I examined were highly collinear with other essential market predictors (namely, hospital HHI and HMO penetration). Some of the measures of rural/urban status I considered were: whether a county was located in an MSA area; 2003 and 1995 codes of rural continuum; and percentage of urban population in 2000. Given that multicollinearity among predictors is a serious violation to assumptions of the HLM models, I was compelled to exclude these measures of rural/urban status from the market level models. Multicollinearity among market-level predictors also hindered the inclusion of several other relevant predictors, such as, population and housing densities, percentage of population who are 65 and older, and index of competition among HMOs.
Validating Picker Domains

The survey instrument used to collect the PEP-C data was the NRC Picker inpatient questionnaire, which evolved from the 1987 Picker/Commonwealth Program for Patient-Centered Care. This instrument has been widely used in assessing patient experiences with hospital care (Cleary et al., 1991; Cleary, Edgman-Levitan, Walker, Gerteis, & Delbanco, 1993; Rosenheck et al., 1997; Young et al., 2000) in the U.S and other developed countries, such as the Canada, Germany and the UK (Coulter, 2001). The Picker instrument was scientifically validated based on rigorous survey research methods and extensive field testing. Accordingly, the ability of Picker’s questions and response scales to capture meaningful variations between patients and hospitals had been established (NRC Picker et al., 2003).

SEM Models

Given that this study used the Picker PEP-C survey data, it follows that the Picker methodology for grouping various survey items to Picker eight domains was used in this study. Due to the fact that these domains were used as outcomes in the three-level hierarchical models, it was imperative to test how well the Picker grouping methodology fits the data of this study. Factor analyses are typically employed to determine grouping approaches in such cases. There are two types of factor analyses: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA is associated with theory development, whereas CFA is associated with theory testing. CFA is done to test hypothesized models rather than for exploratory purposes. Essentially, there was no need to reinvent the wheel and undertake an exploratory investigation of new domains that can underlie the survey items. Therefore, CFA was the appropriate technique here since the purpose was to validate whether/how well the correlations [grouping
scheme] among individual items were consistent with hypothesized factor [domain] structures (Tabachnick & Fidell, 2000).

CFA models were estimated in this study using Structural Equation Modeling (SEM) techniques. SEM serves purposes similar to multiple regression analysis, but in a more powerful way which takes into account the modeling of measurement error. Moreover, the power and precision of data analysis for SEM is better than traditional methods of analysis, because many variables (both observed and latent variables) may easily be brought into the analysis. Within structural equation modeling, hypotheses are translated into a series of regression equations that can be solved simultaneously to generate an estimated covariance matrix. By means of various goodness-of-fit indices, the estimated matrix can be evaluated against the observed sample covariance matrix to determine whether the hypothesized model is an acceptable representation of the data.

In order to test the Picker grouping scheme, CFA models were estimated separately for each of the eight domain structures using the following steps:

1. Each domain structure representing hypothesized relationships between the observed measures and the underlying “latent” domain (such as, coordination of care, etc.) was fitted to the data; and,

2. Models were evaluated in terms of their parameter estimates and goodness of fit.

For each latent variable, the loading (regression coefficient) of one indicator variable (called “anchor” or “reference” variable) was fixed to unity (1.0) in order scale the loadings of all other items/indicators in the same factor. Sometimes the different scales of the measured variables make the unstandardized coefficients difficult to interpret and often the scales of the
measured variables lack inherent meaning. Therefore, standardized estimates were presented in the results section for ease of interpretation. The t-value for each regression weight indicated the degree of statistical significance for the relative contribution of each variable to the corresponding factor.

Estimating CFA models was performed using full information maximum likelihood (FIML) estimates. FIML does not use any method of data imputation. Several studies suggest that FIML estimates tend to be less biased than the other methods (Little and Rubin, 1989; Schafer, 1997). In contrast, mean imputation, list-wise deletion, and pair-wise deletion methods can all produce severely biased results independent of sample size. One of the assumptions underlying maximum likelihood estimation is that the data conform to multivariate normality. However, results of numerous studies indicate that maximum likelihood estimation is robust even in cases of serious departure of data from multivariate normality (Wang, Fan, & Wilson, 1996).

Assessing CFA Model Fit

The next step in estimating each CFA model was to evaluate how well each hypothesized model matched the observed data. One of the robust features of CFA is that in addition to calculating regression weights for each item hypothesized to predict the latent domain is that is also calculates model goodness of fit indices. These indices assess whether a given model as a whole confirmed the theoretical construct (Picker domains, in this case); thus, serving as a check for the construct validity of CFA models.

In terms of evaluating overall model fit, one key model fit index is the chi-square ($\chi^2$) test statistic. The null hypothesis for the chi-square test is that the implied covariance matrix is
equivalent to the observed covariance matrix. Therefore, failure to reject the null hypothesis is a sign of a good model fit. However, it is well known in the SEM literature that the likelihood of rejecting a SEM model based on the chi-square statistics increases with sample size. Recalling that the sample size for the PEP-C data is quite large, with more than 24,000 observations, it was imperative to use incremental fit indices, as these indices have been largely recommended as better measures of model fit in cases of large sample size. Indeed, a large class of incremental model-fit indices exists for determining overall model fit. There is also a wide range of variations in what incremental indices to use and how many should be reported. Although several studies typically report at least a couple of such indices, the recent trend is to report a large number of them. It is also suggested that good-fitting models produce consistent results on many different indices, in many, if not most cases. Therefore, if different indices lead to similar conclusions, this is considered a good sign. Accordingly, I evaluated the following model fit indices, that has been largely used in the SEM literature, in this work: (1) Normed Fit Index (NFI), also known as the Bentler-Bonett Normed Fit Index, DELTA1; (2) Relative Fit Index (RFI), also known as RHO1; (3) Incremental Fit Index (IFI), also known as DELTA 2; (4) Tucker-Lewis Index (TLI), also called the NNFI (non-normed fit index) by Bentler and colleagues; (5) Comparative Fit Index (CFI); and, (6) the Root Mean Square Error of Approximation (RMSEA). For all these indices, with exception of RMSEA, values of .90 or above indicate a good model fit (Arbuckle & Wothke, 1999). On the other hand, RMSEA values of about .05 or less indicate a close fit of the model to the data, in relation to the degrees of freedom, and values up to about .08 signify a reasonable model fit, while models with RMSEA values greater than .1, should not be employed (Browne & Cudeck, 1993). In particular, for
comparison of full and reduced models, I also evaluated a measure of absolute fit: Akaike Information Criterion (AIC). AIC directly assesses how well a priori model reproduces the sample data. There are no cutoffs, such as .90, for AIC. Rather, upon comparing models, a model with the lower AIC value is considered to have a better fit.

**Improving CFA Model Fit**

The SEM literature suggests the use of a number of strategies to improve model fit, in the event that an original model did not fit the data according to the model fit indices. Obviously, the tradition is to first drop out predictors that are not significant. However, in the case of the Picker domains, all of the predictors were significant. Hence, dropping items did not seem the right strategy one can begin with in attempting to obtain adequately-fitting models. However, dropping items was reserved as a last strategy, if model improvement was not obtained using other more conservative strategies, as discussed below. The SEM literature suggests the use of post-hoc model modifications in such cases. Examples of such modifications include adding constraints to a model, as implied by the modification indices and critical ratio-differences test statistics. Unfortunately, the use of modification indices was not feasible in this study, because the AMOS program does not generate this information in the presence of missing data.\(^9\)

Alternatively, adding constraints to a model based on results from critical ratio difference tests was the approach I employed in this study. Basically, I considered adding equality constraints to some model parameters, if such constraints were supported by results from critical ratio difference tests. The critical ratio is the difference between two parameters divided by the

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9 I opted not to perform any imputations on the missing data for two reasons: a) Ambiguity of basis for missing-value imputation (i.e. which patient characteristics to use in MI models), for example Hays, et al., (2006), did not indicate such info although they used Picker measures with missing data; and b) AMOS automatically uses ML for fitting CFA models.
estimated standard error of this difference. Under the distributional assumptions, the critical ratio statistic can be compared to a table of the standard normal distribution to test whether the two parameters are equal in the population. If two parameter estimates turned out to be nearly equal, one might be able to improve model fit by postulating a new model where those two parameters were hypothesized to be exactly equal. Subsequently, a proposed constrained model is then evaluated for their fit to the data, above and beyond the fit of the original (more general) model (Arbuckle et al., 1999). In this regard, the SEM literature warns that adding such constraints needs to be based on theoretical grounds rather than being purely driven by exploratory observations. Thus, it is not appropriate to propose unsubstantiated model constraints just to improve the fit. Therefore, in all cases where I attempted to use this method to improve the fit of CFA models, I first postulated a theoretical basis for possible equality of parameters and then proceeded to examining related critical ratio tests accordingly.

**Reliability of Picker Domains**

In addition to construct validity (established using CFA models), reliability is an equally important criterion for evaluating the suitability of a grouping methodology. For this reason, I ascertained adequate internal-consistency reliability for all Picker domains. In keeping with the literature, cronbach alpha values of .70 or higher were considered acceptable (Cronbach, 1951) in this study.
HLM Models

The preceding sections of this chapter described how Picker domains (outcomes of interest) were tested and validated and how relevant predictors were constructed across the three levels of data: patients, hospitals, and markets. The multi-level-nesting structure of the data implies that variances in Picker domains exist within hospitals, between hospitals, and between markets. Furthermore, the conceptual foundation of this study suggests that the variability in the data can be explained or accounted for by predictors at each level. Therefore, the appropriate predictive methods to employ in this study were three-level hierarchical linear models.

Hierarchical Linear Modeling (HLM), version 6, statistical program (Raudenbush, Bryk, Congdon, & Congdon Jr, 2004) was used to estimate all multilevel models. The following steps were followed in order to answer the research questions of this study. First, the amounts of true variance across the three levels of the data were measured using a null model for each outcome. Second, a sequential approach to conditional-model building across the three data levels was established. Third, conditional models were specified and revised, as such for each outcome. Fourth, the amounts of variance explained by the final conditional models were evaluated across all data levels for each outcome. A detailed description of these four steps follows.

Null Models and Variance Decomposition

Overall true variance in a given domain (outcome) was estimated via a null model with a random intercept. A null model is fully unconditional; that is, no predictor variables are specified at any level. Null models estimated how variations in an outcome measure were allocated as into within-hospital, between-hospital, and between-market components. An
additional statistic of importance computed based on decomposition of variance was the intraclass correlation (ICC), which represented the proportion of variance attributable to between-hospital variations. Estimating overall variance and how it was partitioned across the three levels of the data were crucial prerequisite pieces of information; for these variance compartments served as baselines against which subsequent conditional models were compared. To the extent that a conditional model was able to reduce (i.e., explain) these variances, such a model had high significance.

A sample null model looks like model 3.1:

\[ Y_{ijk} = \gamma_{000} + u_{00k} + r_{0jk} + e_{ijk} \]

\text{Model 3.1}

Where, \( Y_{ijk} \) represented the assessment of patient \( i \) in hospital \( j \) in market \( k \); \( \gamma_{000} \) was the grand mean; \( u_{00k} \) was a random “market effect” (the deviation of the market \( k \)’s mean from the grand mean); \( r_{0jk} \) was a random “hospital effect” (the deviation of hospital \( jk \)’s mean from the market mean); and, \( e_{ijk} \) was a random “patient effect” (the deviation of patient \( ijk \) score from the hospital mean).

\textbf{Approach to Conditional-Model Building}

After estimating the null model for each outcome, multilevel regression models were estimated in three major stages: conditional models at level one; conditional models at level two; and, conditional models at level three, as follows.
**Level-One Conditional Model**

First, patient characteristics were specified in a within-hospital model at level one. Specifying the within-hospital model enabled me to estimate the adjusted within-hospital, between-hospital, and between-market variances. That is, these were the residual variances after controlling for the characteristics of patients who received care in hospitals. Driven by the concern about the bias that might arise from failing to specify a predictor, rather than about the lack of efficiency that arises when the model is slightly overfit, I used the relatively liberal criterion of $t$-ratio of 1.5 for a predictor to be retained in the model, as proposed by (Raudenbush, Rowan, & Cheong, 1993). Although patient-level predictors were not of interest in this study (rather organizational and market characteristics were), yet patient characteristics were potentially influential factors that needed to be controlled for, given the nested structure of the data. Thus, the refined conditional models at level one served as baseline models, in addition to the null models, against which conditional models at levels two and three were compared for the amount of variance explained by predictors of interest.

**Level-Two Conditional Model**

At this stage, between-hospital predictors hypothesized to influence the outcomes were added at level two, to the refined conditional level-one models per above. Similar to the practice at level one, level-two predictors with coefficients found to be less than 1.5 times their estimated standard errors were dropped and the model was re-estimated using retained predictors according to this criterion.
Level-Three Conditional Model

Thirdly, market-level predictors were introduced at level three, to the refined conditioned organizational-model per above. Again, only market-level predictors with \( t \)-ratios of 1.5 or higher were retained. As such, for each outcome, I sequentially built up a final good-fitting model that included predictors related to the outcome and excluded predictors unrelated to the outcome (Raudenbush et al., 1993).

Model Specifications

Model 3.2 presents a sample fully-conditional three-level model for outcomes used in this study. Notice that I grand-mean centered predictors at the three data levels in order to make the intercept more meaningful. I also grand-mean centered dummy variables, in order to adjust for the fact that proportions of these predictors (such as, female gender and Medicaid insurance, etc.) differed across hospitals and markets.

\[
Y_{ijk} = \gamma_{000} + \sum \gamma_{00x} \cdot \text{(Market-level predictors)}_k + \sum \gamma_{0x0} \cdot \text{(Hospital-level predictors)}_{jk} + \sum \gamma_{x00} \cdot \text{(Patient-level predictors)}_{ijk} + u_{00k} + r_{0jk} + e_{ijk}
\]

Model 3.2

Where, \( \gamma_{000} \) was interpreted as the adjusted average of hospital means on the outcome across the population of hospitals in markets; the terms \( \gamma_{00x}, \gamma_{0x0}, \) and \( \gamma_{x00} \) were the simple effects of individual market-, hospital-, and patient-level predictors. In other words, \( \gamma_{00x} \) was the average degree to which a given market-level variable predicted the mean outcome; \( \gamma_{0x0} \) was the average degree to which a given hospital-level variable predicted the mean outcome; \( \gamma_{x00} \) was the average degree to which a patient-level variable predicted the mean outcome. On the other hand,
\( u_{00k}, r_{0jk}, e_{ijk} \) represented the residual (unexplained) between-market, between-hospital, and within-hospital variances, respectively. It should be noted that the relationship (effect) of each predictor was net of the other predictors. For example, the effect of government-hospital ownership status in market \( k \) represented the adjusted mean difference between government and non-government hospitals in market \( k \), after controlling for the effects of other hospital predictors.

**Examining the Explanatory Power of Organizational and Market Characteristics**

In order to determine the extent of variance explained by conditional models, the types of variances explained by each model were compared against their counterpart variances in the respective base models. Reductions in residual variances are typically expected in conditional models with relevant predictors. More specifically, the extent to which residual variances were reduced was indicative of the strength of a particular model in predicating the outcome of interest. While variances of the conditional models at level one were compared against variances of the null models, these conditioned level-one models, in turn, served as the baseline models for variance comparisons for the conditional level-two and-three models. The proportions of variances explained were calculated using equation 3.1:

\[
\frac{(R^2_{Base\ model} - R^2_{Conditional\ model})}{R^2_{Base\ model}}
\]

Equation 3.1

Where, \( R^2_{Base\ model} \) represented the estimated variance in the basic model and \( R^2_{Conditional\ model} \) represented the estimated variance in the adjusted model.
CHAPTER 4: RESULTS

Using PEP-C patient survey data, I examined patient assessments of care in a sample of 24,887 medical and surgical patients from 173 hospitals in 46 markets in CA. The three-level structure of the data suggests that patient assessments of care vary at each of the three data levels: within hospitals, as a function of the characteristics of the patients; between hospitals, as a function of the characteristics of hospitals; and between markets as a function of the characteristics of hospital markets. Accordingly, I employed a three-level hierarchical linear model with the purpose of decomposing variations in patient assessments of care across these three components. I then employed predictor variables at their respective levels in an sequential model-building approach, in an attempt to account for unit-specific variations in eight multidimensional domains of patient assessments of care: coordination of care, continuity & transition of care, physical comfort, emotional support, information & education, involvement of family & friends, respect for patient preferences, and overall impression of care.

Data:

Number of Patients, Hospitals, and Markets

The PEP-C data were obtained from medical and surgical patients who received inpatient care in 179 hospitals in CA in 2002. However, there were four hospitals in the PEP-C data that were not found in the AHA data. Attempts to retrieve hospital identifiers for those four hospitals from AHA were not successful; therefore they were dropped from this study. Additionally, one
hospital was designated as a long-term hospital, according to the AHA’s length of stay variable; therefore this hospital was also dropped from the sample along with its patient-level observations. Finally, one hospital was missing on the teaching-status composite. Thus, when the Multivariate Data Matrix (MDM) file was constructed in the HLM program, this hospital was automatically dropped from the data (because HLM does not currently support computation in presence of missing data at higher levels). Consequently, the final PEP-C data used in this study pertained to 24,887 patients, nested within 173 hospitals, nested within 46 counties (market units) in the State of California. As described in the methods section, all of these 173 hospitals were short-term hospitals.

Characteristics of Patients

Table 1 presents the main characteristics of patients (n=24,887). Slightly over half (53%) of the respondents received surgical services during their hospitalization compared to the rest of the sample (47%), who received medical inpatient services. Females comprised 57% of the respondents. Because the survey was administered to adult patients in this sample, the participants were relatively old (M= 63 years; SD= 17.04 years), as 37% were less than 55 years old, 33% were 55 to 17 years old, and 30% were older than 74. Approximately, one third of the participants (31%) described their health status as poor or fair. While 36% reported being insured by Medicare, 13% reported having Medicaid insurance, and about 5.5% reported that they either had no insurance or not sure whether they had insurance or not. As characteristic of the population in California, racial minorities constituted a sizeable portion of the sample, as only 68% of participants characterized their race/ethnicity as white. On the other hand, most of the participants were educated, as only 16% had lower than high school education.
As demonstrated in Table 2, most patient characteristics were weakly correlated with each other, with exception of less than high school education and Medicare insurance, which were moderately correlated with each other.

**Characteristics of Hospitals**

Table 4 presents the main characteristics of the 173 hospitals included in this study. As discussed in the methods section, all of these hospitals were short-term hospitals. Almost all of these hospitals were general hospitals (97%). Of the sample, 19% were government-owned (federal/non-federal) hospitals. On the other hand, only 7% of the hospitals were investor-owned (for-profit) and 74% were non-government-owned non-profit hospitals\(^{10}\). Therefore, the HLM models used a government-owned dummy variable as a predictor, and the other two categories (non-government) were aggregated as the reference group. There were three indicator variables in the AHA data that measured the teaching status of hospitals: whether a hospital was a member of the Council of Teaching Hospitals; whether a hospital’s residency training program was approved by the Council for Graduate Medical Education (GME); and whether a hospital’s medical school reported to the American Medical Association (AMA). Respectively, 8%, 25%, and 29% of the hospital sample indicated a positive answer (question response “yes”) on these three items. On a summative scale (ranging from 0-3), constructed using these three teaching-status indicators, 70% of the hospitals were not members/affiliates with any of these three programs (teaching score=0), 6% reported membership/affiliation with only one program (score=1), 17% were members of two programs (score=2), and only 8% reported being members of all three programs (score=3). The mean occupancy rate for the hospital sample was 66%

\(^{10}\) Results are not shown in the table.
with only 5 hospitals reported an occupancy rate of 100% or higher. Medicare and Medicaid were major payors for the participating hospitals: the mean percentage of Medicare inpatient days was 44% (SD= 16%) and the mean percentage of Medicaid inpatient days was 20% (SD= 18%). The mean ratio of full-time-equivalent (FTE) RNs to per-thousand inpatient days was 5.52 (SD= 2.91) and the ratio of full-time-equivalent LPNs to per-thousand inpatient-days was 0.73 (SD= 0.76). The mean ratio of financial resources committed to patient care was $60,980 (SD= $17,886). Nurse-staffing and labor-expense variables in the AHA data were available only for the total facility (rather than separately for the hospital-unit) and there was also a significant degree of missingness with other variables (such as, payor mix and inpatient days) at the hospital-unit level. Therefore, I have decided to include the total facility variables rather than those of the hospital-unit for hospital-level predictors. In order to account for the fact that facility variables in AHA include measures of long-term care (mainly nursing-home-unit operated by the hospital) beside hospital-unit inpatient care, I included an indicator variable (whether a hospital maintained a nursing-home unit) as a control variable in HLM regression models to account for possible non-short term inpatient care effect. Overall, 40% of the hospitals reported maintaining a separate nursing-home unit. As demonstrated in table 5, most hospital characteristics were weakly correlated with each other, although the two nurse staffing measures were moderately associated with each other.

Characteristics of Markets

Table 6 presents characteristics of the market units (counties). The hospitals that participated in the PEP-C survey in 2002 (included in this study) belonged to 46 counties (representing 81% of counties in CA). Market characteristics were classified into the structure
of the market area of hospitals (teaching status, excess capacity\textsuperscript{11}, resources committed to patient care, and, hospital Herfindahl-Hirschman Index (HHI) of competition); key factors of supply and demand (payor mix, nurse staffing, and, HMO penetration rate); and, population characteristics (percentage of minority population and per capita income).

The hospital HHI of competition was calculated as the sum of squared market shares of short-term inpatient hospital days. As described in the method’s chapter, HHI was constructed using the AHA hospital data including the entire short-term hospital population in CA (not only the hospitals that participated in the PEP-C survey) and was then imported to the ARF county-level data. The mean hospital HHI was 0.52 (SD= 0.27). The mean of the Medicare inpatient days variable was 188.43 (SD= 74.05). On the other hand, the mean of the Medicaid inpatient days variable was 132.94 (SD= 141.84). The mean RN FTEs per 1000 population was 2.34 (SD= 0.87) and the mean LPN/LVN per 1000 population was 0.42 (SD= 0.30). Teaching status had a mean of 0.52 (SD= 1.52). The mean excess capacity was 37.60% (SD= 5.78%). The mean of the resources committed to patient care variable was $1,096 (SD= $734.35). The mean HMO penetration rate in a county was 0.33 (SD= 0.22). In terms of population characteristics, the mean of per-capita income was $29,207 (SD= $10,710) and the mean of county’s percentage of minority (non-white) population was 29.07% (SD= 14.13%). As demonstrated in Table 7, several market-level characteristics were moderately correlated with each other, although not to an extent that can pose a multicollinearity threat upon using these predictors in the HLM models.

\textsuperscript{11}Although Medicare days/population is an important variable of payor mix, it was not included in the HLM models because it was highly collinear with the ratio of RN staffing levels per population.
Outcome Measures:

Items and Domains (Composite Scores)

There were 41 specific patient-assessments of care items in the PEP-C survey. Most of these questions (k=33) asked patients to indicate whether they had a problem with a specific aspect of their care using three-option response scales: no problem at all= “1”, a problem sometimes= “2”, and a problem all the time= “3”. According to the Picker methodology, these 33 items map 7 domains, conceptualized as the “process quality of care composite scores” in this study. Items belonging to each domain were summed up and the resulting composite scores (scales) were used as outcomes in HLM predictive models. Therefore, items that listed the report of a problem in a reverse direction (where 3 indicated the occurrence of a problem all the time and 3 indicated lack of a problem) were recoded to conform to the intended coding scheme described above. For example, a score of 18 on the coordination of care domain infers having a problem all the time on all encompassing items.

On the other hand, there were 8 items that asked patients to rate their experiences with aspects of their care on a 5-point likert scale: poor= “1”; fair= “2”; good= “3”; very good= “4”; excellent= “5”. The exception of these rating items was “whether you recommend the hospital for inpatient stay,” which used a simple “yes” or “no” options. Therefore, a higher score with “overall impression of care” domain is similar to a satisfaction scale where the higher score, the higher-level of satisfaction.

The means and standard deviations for the eight composite scores were as follows: coordination of care (M= 6.94; SD= 2.32); continuity and transition of care (M= 4.54; SD= 1.96); physical comfort (M= 4.23; SD= 2.09); emotional support (M= 6.32; SD= 2.64);
information and education (M= 5.62; SD= 2.40); involvement of family and friends (M= 4.55; SD= 1.49); respect for patient preferences (M= 3.55; SD= 1.14); and, overall impression of care (M= 21.49; SD= 5.12).

I also calculated bivariate correlations for these composite scores (see Table 3). As can be observed from these correlations, although these domains were weakly to moderately correlated with each other, none of them were highly correlated. This finding implied that while interrelated, each measure of patient assessments of care captures a somewhat different and unique aspect of care; thus, lending support to the multi-dimensional notion for the conceptualization of patient experiences of care - the position adopted in this study.

Factor Analyses and Reliabilities

Confirmatory Factor Analysis (CFA) models were tested using AMOS (Version 7) computer program. No missing-data imputations were done on the data because AMOS has the advantage of estimating SEM models in the presence of missing data using Maximum-Likelihood estimation (the same estimation method used in the HLM program for fitting the predictive hierarchical models).

Because of the likelihood of rejecting a model based on the chi-square test increases with sample size, incremental measures of fit were more appropriate indicators of goodness of fit (Arbuckle et al., 1999) and I used them as the model-fitting criteria in this work. As discussed in the methods section, I used NFI; RFI; IFI; TLI; CFA; and, RMSEA indices. Values of .90 or higher for NFI; RFI; IFI; TLI; and, CFA and values of .08 or less for RMSEA were considered indicative of a good-fitting model. I also used an additional measure of absolute-model fitting criteria (AIC), in cases where a reduced model was sought, if an original full model (i.e., a
model with all hypothesized items) failed to achieve adequate fit. Therefore, I compared the AIC value across different models (full and reduced), in conjunction with other indices mentioned above, in order to arrive at the best CFA solution. Cronbach’s-alpha values of .70 or higher have been accepted universally to be indicative of internal-consistency reliability; this practice was adopted in this study.

As discussed in detail in the methods section, CFA model were estimated for each of the eight domains to test whether each group of items taped its underlying domain, per the Picker Methodology. CFA models were tested separately for each domain and the model-fit criteria were evaluated. Where applicable, modifications to the models using critical ratio difference statistics were used to improve model fit, if a model did not generate the appropriate model fit criteria. Alternatively, and as a last resort, I considered removing items from a CFA model (generally one/or two items at most) if adequate model fit was not obtained via the critical ratio differences improvements. Model fit indices and internal consistency reliabilities for the original and final CFA models are presented in Table 8.

1. *Coordination of Care*

According to the Picker methodology, six items tap this domain. A chi-square test of the CFA model that tested the hypothesis that these items did not adequately fit this domain was rejectable statistically because of large sample size, $\chi^2 = 654$, p-value= .00. However, the model fitted the data well in terms of the incremental model-fit indices: NFI= .96; RFI= .91; IFI= .96; TLI= .91; CFA= .96; RMSEA= .05. Moreover, the cronbach’s alpha for this model was 0.69, which just meets the minimum value for adequate internal-consistency reliability. Therefore, the CFA results for this model supported the hypothesis that all of these items belong to the coordination of care domain. Thus, creating a composite score using these items (summative
score in this case) was supported in terms of both validity and reliability. A graphical depiction of this measurement (CFA) model, along with the estimated standardized coefficients for each path, is presented in Figure 2.

Figure 2: SEM Model for the Coordination of Care Domain

2. Continuity and Transition of Care

Per the Picker methodology, four items belong to this domain. However, the CFA model that encompassed these four items failed to meet the desired levels for three of the six incremental model-fit indices (RFI=.75; TLI=.75; and RMSEA=.16). However, the values for the other indices (NF; IFI; and CFI) were acceptable with corresponding values over .90. Efforts to improve model fit using results from critical-ratio differences statistics were not successful in producing a better-fitting model. Therefore, I had to resort to deleting one of the four items and then tested whether a reduced model could fit the data better. Upon reviewing the standardized
regression coefficients from the full CFA model, I decided to remove the item with the lowest SMC and standardized regression values. Applying these criteria, I dropped “staff explained purpose of home medicines” item from the model, which had a SMC value of = .40 and a standardized regression coefficient in the path predicting the latent domain of .63. Although the beta for this regression path seemed high, it was the lowest coefficient of all items predicting this domain.

On the other hand, the reduced CFA model (with three items)\(^\text{12}\) met the entire incremental-model fit and the internal-consistency reliability criteria: NFI= .99; RFI= .98; IFI= .99; TLI= .98; CFA= .99; RMSEA= .04; cronbach’s alpha= .76. A graphical depiction of this measurement (CFA) model, along with the estimated standardized coefficients for each path, is presented in Figure 3.

![Figure 3: SEM Model for the Continuity and Transition of Care Domain](image)

\(^{12}\) In order to achieve identification for this model, I imposed one constraint (supported by the CR differences test statistics), whereby I assumed equal variance for the “discussion of medication side effects” and “discussion of when you can resume normal activities,” since it is theoretically conceivable to assume that these two aspects of discharge instructions will have equal variances. This hypothesis was also supported empirically, since the value of the critical-ratio difference statistics for these two parameters was below 1.96.
3. **Physical Comfort**

The Picker methodology conceptualizes that five items uniquely tap this domain. Unfortunately, a CFA model with these five items did not yield acceptable values for RFI or TLI (with value of .78 for both indices), although the values for the remaining indices (NFI; IFI, and CFI) ranged acceptably from .92 to .93, the RMSEA value was also acceptable (.08), and, the cronbach’s alpha was .72. Therefore, I first considered improving model fit by imposing several constraints using the CR differences tests. The model improved a little bit with the added constraints, yet it did not reach the required model-fit values (and the AIC value was actually higher than that in the baseline model). Subsequently, I resorted to dropping the least predictive item from the original model (“minutes for help after call button”).

The resulting reduced model improved upon the previous two models substantially (with an AIC value of 181) and NFI=.98; RFI=.92; IFI=.98; TLI=.92; CFA=.98; RMSEA=.05; cronbach’s alpha=.73. A graphical depiction of this measurement model, along with the estimated standardized coefficients for each path, is presented in Figure 4.
4. Emotional Support

The original CFA model for this domain, conceptualized following the Picker methodology consisted of six items. While this original model was reliable according to the cronbach’s alpha criterion (.78), it failed to attain adequate RFI and TLI levels (with values of .71) and had a yet poorer fit with respect to RMSEA (value was .13). None of the model improvement constraints using the CR differences tests yielded a better-fitting model. A reduced CFA model that excluded the “help pay bill” item from its structure was considered first, since the beta for the path of this item predicating the latent variable was the smallest of all other items (b = .26) and the SMC was only 0.04. Although this alternative model seemed plausible, the RFI, TLI, and RMSEA values were even worse than the full model (corresponding values were .62, .62, and .18, respectively). As result, I estimated other reduced models by dropping other items,
one at a time (the results of all these models were not presented here, but available upon request). As a result, the best-fitting reduced model was the one without the “doctor discussed anxieties/fears.” In the full CFA model, the “doctor discussed anxieties/fears” item had a regression weight of (b= .64) for the path predicting the emotional support domain and a SMC value of (.40). The model fit indices for this final model were all acceptable, as follows: NFI= .97; RFI= .90; IFI= .97; TLI= .90; CFA= .97; RMSEA= .07; cronbach’s alpha= .74. A graphical depiction of this revised measurement model along with the estimated standardized coefficients for each path is presented in Figure 5.

![SEM Model for the Emotional Support Domain](image)

**Figure 5: SEM Model for the Emotional Support Domain**

5. **Information and Education**

The original CFA model with the five items that tap this construct (according to the Picker methodology) fitted the PEP-C data very well and better than any of all other Picker domains and therefore no changes to this original model were necessary. The model fit indices were as follows: NFI= .98; RFI= .95; IFI= .98; TLI= .95; CFA= .98; RMSEA= .04;
cronbach’s alpha = .76. A graphical depiction of this measurement (CFA) model, along with the estimated standardized coefficients for each path, is presented in Figure 6.

Figure 6: SEM Model for the Information and Education Domain

6. Involvement of Family and Friends

This domain is comprised of just three items according to the Picker methodology. Therefore, the model was just identified in AMOS with regression paths estimable but not enough degrees of freedom existed in the model for the fit indices to be estimated. Therefore, I had to impose one constraint on this model to render it overidentified. Conceptually, one can hypothesize that “whether family was given information” and “amount of information given to family” have equal variances given that these two items are related to each other conceptually. In addition, the CR difference test for the variances of these items was below 1.96, lending support for the hypothesis that these two variances are equal. Therefore, I estimated a second CFA model for this 3-item domain structure after imposing an equality constraint on those two
variances. Not surprisingly, this model fitted the PEP-C data very well: NFI= .99; RFI= .97; IFI= .99; TLI= .97; CFA= .99; RMSEA= .05; cronbach’s alpha= .69. A graphical depiction of this measurement (CFA) model, along with the estimated standardized coefficients for each path, is presented in Figure 7.

Figure 7: SEM Model for the Involvement of Family and Friends Domain

7. Respect for Patient Preferences
The original Picker methodology hypothesizes that this domain is comprised of four items. This hypothesized model did not fit the data according to any of the model fit indices (value of about 0.80 on all of the 5 indices) and a cronbach’s alpha of .60. Attempts to improve the model via imposing equality constraints were not substantiated empirically. Therefore, I had to consider dropping an item. Since “enough say about treatment” had the lowest standardized path weight with the latent domain (b=0.2) and the lowest SMC of all items (0.04), it was logically the first item to consider for dropping from the model. Accordingly, a reduced CFA model without “enough say about care” was estimated. All of the model fit indices for this
model were all very satisfactory: NFI= .99; RFI= .98; IFI= .99; TLI= .98; CFA= .99; RMSEA= .04\(^\text{13}\). The only exception to the acceptability of this reduced model was the low cronbach’s alpha of .60. However, recalling that the corresponding value for the original model was not any better (in fact it was the same as that of this reduced model), it did not seem that reliability could get any better for this domain. Thus, although this reduced model was used as the composite score for this domain, its low reliability was noted as a limitation when inferences related to domain were made. A graphical depiction of this measurement (CFA) model, along with the estimated standardized coefficients for each path, is presented in Figure 8.

![Figure 8: SEM Model for the Respect for Patient Preferences Domain](image)

\(^\text{13}\)Since this CFA model had only three indicators, it was just identified and an additional constraint had to be imposed to render it overidentified for model fit indices to be computed. Incidentally, this model had a negative value for the variance of the “nurses talked in front of you” item (-0.04), which is considered a type of model anomaly. The recommended course of action in this case is to fix this parameter to its nearest non-negative value (i.e., zero). Hence, fixing this variance parameter to zero eliminated this model anomaly and also attained the required model over-identification status.
8. Overall Satisfaction with Care

This domain is comprised of eight items according to the Picker methodology. A CFA model with these eight items was reliable (with cronbach’s alpha of .92), however four of the incremental fit indices did not meet acceptable levels: RFI= .75; TLI= .75; RMSEA= .20. Therefore, I attempted several model improvement strategies using the results of the critical ratio differences tests (such as, assuming equal variances for the “availability of nurses” and “courtesy of nurses”; “availability of doctors” and “courtesy of doctors,” beside other modifications as well). While such model improvements had theoretical grounding and were also supported by the CR differences tests (values below 1.96), none of them were successful in achieving better model fit on all incremental indices compared to the original model. As a result, I had to resort to dropping one item at a time. As this approach was not successful, I was left with the only option of having to drop two items at a time in search for a better fitting model. A reduced model without “courtesy of doctor” and “courtesy of nurses” was the best fitting model among all rested reduced models. While this reduced model makes some but no huge elimination of the component aspects of this domain (since there are other indicators of nurses and doctors in the model), it met the entire model fit criteria: NFI= .98; RFI= .95; IFI= .98; TLI= .95; CFA= .98; RMSEA= .09; cronbach’s alpha= .90. Therefore, this reduced model was used for the construction of the composite score for this domain. A graphical depiction of this measurement model, along with the estimated standardized coefficients for each path, is presented in Figure 9.
Decomposing Variations among Data Levels:

To gauge the magnitude of true variances across the three levels of the data in each domain (outcome), I estimated a null model (with no predictors) with random effects for each outcome. Decomposition of variance in the composite scores of patient assessments of care domains across the three levels of data (within hospitals, between hospitals, and between markets) is important because it has strong implications for at what level of the data one needs to look to explain why patients varied on these domains.

1. Decomposing the Variance in Coordination of Care

Column 1 of Table 9 details the exact values for the amounts of variations across the three levels of the data. A null model with random effects demonstrated a statistically significant variance component of 5.20 for the intercept at level 1, indicating significant variations exist.
within hospitals on this domain, when no predictors are included in the model. The between-hospital variance was estimated at .18, and the between-market variance was estimated at .04. Therefore, 95.9% of the variance was within-hospitals, 3.35% was between-hospitals, with a small proportion of the variance (.75%) was between markets. Two other statistics were helpful in interpreting these variance components. First, Table 9 presents chi-square tests of the hypothesis that the true variance between hospitals was null, in which case the estimated variance of .18 would be an artifact of chance. This hypothesis was easily rejected because of the observed size of the chi-square of 732.3 far surpassed the critical value at the .01 level based on 127 degrees of freedom. Similarly, the hypothesis that the true between-market variance was null was rejected, as the chi-square of 80.2 exceeded the critical ratio at the .01 level, based on a 45 degrees of freedom.

Table 9 also provides information about the reliability of estimates at the hospital and market levels. The reliability of discriminating between hospitals within markets was estimated to be .80, whereas the reliability of discriminating between markets was estimated to be .33. The three-level program does not calculate estimated of the reliability of the within-hospital level differences. However, we know that the internal consistency of the coordination of care composite-score was .69, implying that the majority of the variance was not due to measurement error.

In sum, the majority of the variance on the coordination of care composite score was within hospitals, 3.35% was between hospitals, and only .75% of the true variance was attributed to differences between hospital markets. These results support the need for controlling patient-level differences (within hospitals) prior to including organizational and market-level predictors.
While the variations between hospitals and between markets were small in magnitude, compared
to the within-hospital variations, investigation of specific predictors at the organizational and
market level was of enough measurable size to warrant investigation.

2. Decomposing the Variance in Continuity and Transition of Care

The results for continuity and transition of care are listed in column 2 of Table 9. The estimated true within-hospital variance was 3.79; the estimated true between-hospitals variance was .02; and the estimated true between-market variance was about .01. As such, 99.12% of the variance in this domain was within hospitals, and the less than 1% remaining segment of the true total variance was partitioned between hospitals (.65%) and between markets (.23%).

Regardless of the minute amounts of variation that were attributed to between-hospital and between-market differences, the hypotheses that hospitals did not vary at these levels were strongly rejected (chi-square value at level 2 was 237.6 on a 127 degrees of freedom was significant at the .01 level; chi-square value at level 3 was .82.9 on 45 degrees of freedom was significant at the .01 level). Likewise, the reliability estimates of these between-hospital and between-market variances were .45 and .31, respectively.

3. Decomposing the Variance in Physical Comfort

The results for the physical comfort domain are listed in column 3 of Table 9. Similar to the results from the continuity and transition of care, the unconditional model of the physical comfort composite score revealed that almost all of the true variance was within hospitals. The variance attributed to between-hospital differences was estimated to constitute .77% of the true overall variance. The variance attributed to between-market differences constituted .23% of the overall variance, while 99.10% of the overall variance was confined within hospitals. The
between-hospital variance had a reliability estimate of .46 that was statistically significant at the .01 level. On the other hand, the between-market variance had a relatively lower reliability (.20) and was marginally significant at the .05 level.

4. Decomposing the Variance in Emotional Support

The results for the emotional support domain are presented in column 4 of Table 9. About 1.25% of the true overall variance in this domain was between hospitals and 1% was between markets, while the vast 97.76% of the variance was within hospitals. Both between-hospital and between-market variances were highly significant at the .01 level and the reliability estimates for these variances were .61 and .54, respectively.

5. Decomposing the Variance in Information and Education

The results for the information and education domain are shown in column 5 of Table 9. Of the true overall variance in this domain, 2.44% existed between hospitals, .53% was between markets, whereas most of the variance (97.03%) was within hospitals. Hypotheses that between-hospitals and between-market variances are not statistically significant were rejected at the .01 level. The reliability estimates for between-hospital and between-market variances were .64 and .32, respectively.

6. Decomposing the Variance in Involvement of Family and Friends

The results for this domain are listed in column 6 of Table 9. Less than 1% of the overall true variance in this domain existed between hospitals and between markets (.49% and .34%, respectively) while a massive 99.17% of the variance was due to differences within hospitals. Estimates of between-hospital and between-market variances had reliability estimates of .38 and
.40, respectively, and both estimates were statistically significant at the .01 level.

7. Decomposing the Variance in Respect for Patient Preferences

The results for this domain are listed in column 7 of Table 9. While .58% of the total true variance in this outcome existed between-markets, 2.34% was between hospitals, and 97.08% was within hospitals. Both between-hospital and between-market variances were statistically significant at the .01 level and had reliability estimates of .74 and .34, respectively.

8. Decomposing the Variance in Overall Satisfaction with Care

The results for this domain are listed in column 8 of Table 9. The variability between markets accounted for only .59% of the overall true variance, whereas 3.24% of the true variance was between hospitals, and a considerable 96.17% of the variance was attributed to patient differences (within hospitals). Between-hospital variance had an estimated reliability of .80 and between-market variance had an estimated reliability of .29 and both estimates were statistically significant and the .01.

9. Summary

Decomposition of variance at these scales is important because it has strong implications for where one might look to explain why hospitals varied in terms of the experiences of patients about their care. Having identified the components of variance in each outcome, the next step of the analysis was to employ three level regression models to predict these variations.
Conditional Models

The approach I took to estimate the three-level conditional models was detailed in the methods chapter. In brief, baseline models (conditional only at level-one) were fitted first, then conditional models at level two were fitted, and finally conditional models at level three were fitted. The results for the three final conditional models for each outcome are shown in Table 10. Predictors of interest are listed in the first column. If a predictor was not related to an outcome, the Table leaves its estimate blank. The results are also described separately for each outcome as follows.

I. Results for Process Measures

1. Results for Coordination of Care

   a. Patient-Level Predictors

       Although organizational and market characteristics were the predictors of prime interest in this study, their estimates would not have been accurate unless relevant patient-level predictors were also controlled for in the same conditional models. Therefore, patient-level predictors (k=9) were added to models at level one. Furthermore, models with patient characteristics also served as baseline models (beside null models) against which subsequent models were compared, to measure the effect of organizational and market characteristics on the outcome, net of the effects of patient characteristics.

       The coordination of care composite score ranged from 1-18, whereby the lower the score, the fewer the problems reported by patients; conversely, the higher the score, the more problems reported by patients on this domain. The grand mean for coordination of care, adjusted for mean differences in patient characteristics, was 6.88, which was statistically significant at the .01 level.
This grand mean represented the mean for male, medical, with more than high school education, private health insurance, good to excellent health status, and non-white patients.

As presented in Table 10, on average, the gap between surgical and medical patients (b = -1.22) was the largest in magnitude of all level-one predictors. This means that surgical patients reported 1.22 fewer problems with this domain compared to medical patients, controlling for other predictors. Recalling that the standard deviation for the coordination of care composite score was 2.32, thus the effect of surgical service can be interpreted as .52 decrease in standard deviation units of the outcome. With an effect size of (b= .62), lower health status corresponded to a .26 increase in standard deviation units of the coordination of care composite score, all else equal. Medicaid insurance was associated with .31 unit increase in the coordination of care scale, compared to non-Medicaid insurance (b= .31), controlling for other predictors. The gap between nonwhite and white patients was .26 and the gap between female and male patients was -.20, all else equal. Age had a small effect size on this domain (b= -.01). Neither high school education nor Medicare insurance was uniquely associated with the coordination of care domain.

b. Hospital-Level Predictors

Per the model-building approach of this study, predictors at level 1 with t-ratios of 1.5 or higher were retained in the model, as level-two predictors were added. Net of each other, only four level-two predictors were significant according to the same t-ratio criterion used at level 1. Teaching Status was unfavorably associated with coordination of care (b= .14), although the effect was rather small in magnitude (.06 increase in standard deviation units); this translates to an effect of 3 *.06= .18 increase in standard deviation units of the coordination of care score for hospitals with the highest level of teaching-status level. RN/inpatient days had a favorable effect of just .01 decrease in standard deviation units (b= -.03). Occupancy rate had a small effect
(b= 0.004), indicating that a 10% increase in occupancy rate was unfavorably associated with a .02 increase in standard deviation units of the outcome. The last significant predictor at the organizational level was resources directed to patient care (b= -.00001). Recalling that the average ratio was 60,980; thus, an increase of 10,000 in this ratio was associated with a favorable .1 decrease in the coordination of care score (an effect equal to .04 decrease in standard deviation units).

c. Market-Level Predictors

Market-level predictors were added at level three. Significant predictors from models 1 and 2 were retained in this model, with the exception of RN/inpatient days as it was rendered insignificant by the addition of the level-three predictors. I performed a likelihood ratio test to compare conditional market-level models with and without RN/inpatient days. The results showed that the model with RN/inpatient days did not improve model fit in the fully-conditional model; therefore, this predictor was removed from the final model.

Although the proportion of variance at level three was the smallest of variances at the three data levels, six market-level predictors, net of each other and other predictors, were significant in predicting this variance. The market-level predictor with the highest effect size was LPN/population (b= -.68), indicating that as the LPN/population ratio increased by one unit, there was a corresponding favorable decrease of .68 in the coordination of care problem score domain (equivalent to a .29 decrease in standard deviation units). HHI was unfavorably associated with this domain (b= -.57), indicating that as the HHI increased by one unit (and hospitals were less competitive), the coordination of care problem score decreased by .24 standard deviation units. HMO penetration rate had an equal effect size as HHI (b= -.55), although it was in the opposite direction, since a one unit increase in HMO penetration rate
was associated with a .55 lesser problems on the coordination of care scale. Contrary to the organizational-level model, teaching status at the market level was associated with lower problem scores. However, this effect was small ($b = -.03$), corresponding to a .01 decrease in standard deviation units. Percentage of minority population had a tiny favorable effect ($b = .001$), indicating that the higher the minority population, the fewer problems reported with coordination of care, contrary to the effect of white race at the patient level. Medicaid days/population has a minute unfavorable effect ($b = .0007$), which means as that as this ratio increased, there was a minute increase in the composite score. Excess capacity had a borderline unfavorable effect ($b = 0.004$), thus it was not included in the final model because of its low $t$-ratio of 1.4.

\[d. \text{Variance Explained by Models}\]

Most of the true overall variance in the coordination of care problem score existed within hospitals (95.9%) and the remaining variance existed between hospitals (3.35%) and between markets (.75%). As shown in Table 11, patient-level predictors accounted for 12.79% of the within-hospital variance at level 1, 23% of the true variance at the organizational level, and 38.29% of the true variance at the market level of the coordination of care composite score.

At model two, the addition of organizational-level predictors further explained 11.63% of the between-hospital variance in the baseline model. Recalling that the baseline model was conditional at level 1 (with patient-level predictors), it was expected that this model also accounted for some of the between-hospital and between-market variances (since predictors at level one were grand-mean centered, as described earlier). Remarkably, model 2 explained a sizable 80.56% of the true between-market variance in the baseline model.

At model three (with market predictors added), an impressive 98.96% of the between-market variance in the baseline model was explained. Furthermore, model 3 improved the
baseline model’s explained between-hospital variance to 27.12%.

2. Results for Continuity and Transition of Care

   a. Patient-Level Predictors

      On average, the adjusted mean score for continuity and transition of care across patients, hospitals, and markets was 4.53 and was statistically significant at the .01 level. Results for tested predictors, net of each other, are presented below. The gaps between surgical and medical service (b = -.28), Medicaid and non-Medicaid insurance (b = -.08), Medicare and non-Medicare insurance (b = -.06), and less than high school and high school or more education (b = -.31) were all favorably associated with this domain. Nonetheless, predictors with unfavorable relationships with this domain were: low health status (b = .49), female gender (b = .19), non-white race (b = .07), and, age (b = .002).

   b. Hospital-Level Predictors

      Only two organizational predictors were associated with the continuity and transition of care composite score: RN/inpatient days and resources directed to patient care, net of other predictors. RN/inpatient days was favorably associated with this domain (b = -.02), corresponding to a .01 decrease in standard deviation units of the outcome for every unit increase in this predictor. On the other hand, the size of the relationship with resources directed to patient care (b = -.000001) was very small, yet favorable.

   c. Market-Level Predictors

      The results of the conditional level-three model for the continuity and transition of care need to be taken with caution, because the reliability for the level-2 intercept (which was modeled at level-three as a function of level-3 predictors) was reduced from .002 (when all level-
3 predictors are added) to .000 when predictors with less than 1.5 \( t \)-ratios were dropped. However, of all potential market-level predictors, only percentage of minority population was associated with the continuity and transition composite score (\( b = .007 \)); this effect was not favorable and translate to about .004 increase in standard deviation units of the outcome per one unit increase in this predictor.

\[ d. \text{Variance Explained by Models} \]
As presented in Table 11, the conditional level-one model (with patient characteristics as the only predictors in the model) explained 4.15\% of the true within-hospital variance in the null model. The conditional level-two model (with organizational predictors added at level-two) explained 6.54\% of the residual between-hospital variance in the baseline model (conditional level-one model). This model also explained 25\% of the residual between-market variance in the null model. Nonetheless, the conditional level-three model explained almost all of the between-market variance (99.91\%) in the baseline model. However, the findings from this market-level model should be taken with caution due to the lack of reliability at this level.

3. Results for Physical Comfort
   
   \[ a. \text{Patient-Level Predictors} \]
   On average, the mean score for the physical comfort domain across patients, hospitals, and markets was 4.2 and was statistically significant at the .01 level. Net of each other, all patient-level variables included in this study were associated with the physical comfort composite score. By far, lower health status had the highest association with this outcome (\( b = .49 \)), indicating that patients with lower health status had .49 higher problem score compared with patients with good or better health status. The effect of lower health status was equivalent
to a .23 increase in standard deviation units of the physical comfort composite score. The gaps between surgical and medical service, female and male gender, Medicaid insurance and non-Medicaid insurance were .31, .27, and .23, respectively, which correspond to .15, .13, and .11 increase in standard deviation units. The gaps between lower than high school education and high school education and over, and Medicare and non-Medicare insurance were favorable and of comparable magnitude (b= -.16) and (b= -.14), corresponding to about .07 decrease in standard deviation units. The gap in white and non-white race was small (b= .07). Age had the smallest association with the physical comfort domain of all level-one predictors (b= -.02), indicating that a 10-year increase in age corresponds to a tiny .1 decrease in standard deviation units of the physical comfort domain, which is a favorable, albeit weak effect.

b. Hospital-Level Predictors

Both nursing staffing variables were associated with the physical comfort composite score. However, the effect of LPN staffing was unfavorable (b= .06), while the effect of RN staffing was favorable (b= -.03). Nonetheless, the effect of both staffing variables was rather small, with only .03 and .02 standard deviation change in the physical comfort score for every unit change in these predictors. Teaching status had an unfavorable effect with this domain (b= .04), which equals about .02 increase in standard deviation units of the physical comfort composite score for every unit increase in teaching status. Finally, the only other hospital-level predictor associated with physical comfort was resources directed to patient care (b= -.000002), a favorable, yet very small, association.

c. Market-Level Predictors

At the market level, 5 predictors were associated with the physical comfort composite score, net of each other and other predictors. LPN/population and HMO penetration were both
unfavorably correlated with this domain (b= .34) and (b= .28), with respective effects of .16 and .14 increase in standard deviation units for every unit change in these predictors. Likewise, the effect of hospital HHI was unfavorable (b= -.20), which is equivalent to a .09 increase in standard deviation units of the outcome for every decrease in hospital HHI. Medicaid days/population had a favorable, though small, association with physical comfort (b= -.0009). Finally, there was a favorable minuscule association between resources directed to patient care and this domain (b= -.0001).

*d. Variance Explained by Models*

As presented in Table 11, only .77 % of the true overall variance in the physical comfort composite score was between hospitals, with even a tinier amount of .13% existed between markets, and the almost the exclusive majority (99.10%) of the true variance was within hospitals.

Patient-level predictors at level one explained only 5.9% of the massive within-hospital variance. Incidentally, patient-level predictors also accounted for 27.45% of the true between-hospital variance and another sizable 54.93% of the true between-market variance. Organizational-level predictors explained 14.24% of the between-hospital variance in the baseline model. In total, the conditional-level-two model explained 37.78% of the null-model’s between-hospital variance. The conditional market-level model explained 99.62% of the true between-market variance in the baseline model. It also explained 50.64% of the true between-hospital variance in the null model (and also explained 31.97% of the baseline model’s between-hospital variance).
4. Results for Emotional Support

a. Patient-Level Predictors

On average, the mean of the emotional support composite score across patients, hospitals, and markets was 6.25 and was statistically significant at the .01 level. Net of each other, patient-level predictors, with exception of education and Medicaid insurance, were associated with this domain. The largest association at this level was that with lower health status (b= .70), which constitutes about a .26 increase in the emotional support problem score, an unfavorable effect. The surgical and medical service gap was favorable (b= -.34) and translates to about a .13 decrease in standard deviation units. The female and male gap in emotional support was (b= -.11); which was favorable and equivalent to a .04 decrease in standard deviation units. Both the gaps of Medicare and non-Medicaid, and white and non-white race were favorable with estimated effects of (b= -.30) and (b= -.26), respectively, translating to about a .11 decrease in standard deviation units.

b. Hospital-Level Predictors

Net of other predictors, there was a favorable association with RN staffing (b= -.04) translating to a .02 decrease in standard deviation units of the emotional support composite score. There was an unfavorable effect of more than twice the size of RN staffing for teaching status (b= .11). Once more, resources directed to patient care had a slight, yet favorable, association with patient assessments of care (the emotional support domain, in this case) (b= -.000002).

c. Market-Level Predictors

Results for these predictors are presented below net of other predictors and net of each other. While HMO penetration rate had a favorable association with the emotional support composite score (b= -.42) (.16 decrease in standard deviation units per one unit increase in this
predictor), hospital HHI was unfavorably associated with it (b= -.34) (a .13 decrease in standard deviation units per one unit increase in this predictor). Both nurse-staffing variables at this level were associated with the emotional support composite score. However, the association was favorable and over 3 times higher for LPN/population with an effect size of (b= -.23), which was about .09 decrease in standard deviation units, for every unit increase in LPN ratio. On the other hand, the effect of RN/population was unfavorable (b= .06). The following predictors were associated with this composite, although these associations were minute in magnitude: teaching status (b= -.01), percentage of minority population (b= .01), excess capacity (b= .004), and per capita income (b= .000003). Notably, of these three predictors, teaching status was the only one with favorable effect. It was also notable that this favorable effect of teaching status at the market level contradicts its unfavorable effect at the hospital level for this domain.

\[ d. \textit{Variance Explained by Models} \]

As presented in Table 11, the between-market variance constituted 1% of the overall true variance in the emotional support composite score and the between-hospital variance constituted 1.24% of overall variance. However, the rest of overall variance (97.76%) was within hospitals. The conditional level-one model accounted for 5.28% of the true within hospital variance, 31.31% of the between-hospital variance, and 41.4% of the between-market variance.

Conditional level-two model (with organizational characteristics) explained 11% of the true between-hospital variance of the baseline model, and a total of 38.87% of the between-hospital variance of the null model. Conditional level-three model (with market characteristics) explained an impressive 99.9% of the between-market variance in the baseline model.
5. Results for Information and Education

a. Patient-Level Predictors

The intercept for the information and education domain was 5.59, indicating that, on average, the mean score for the average patient in an average hospital in an average market was 5.59 and was statistically significant at the .01 level. Net of other predictors, the gap between surgical and medical service was favorably associated with this domain. Also, predictors with favorable association were female (b= -.19), white (b= -.22), Medicare insurance (b= -.08), and age (b= -.09). However, predictors with unfavorable relationship with this domain were: lower health status (b= .63), Medicaid insurance (b= .27), and less than high school education (b= .08).

b. Hospital-Level Predictors

Net of each other and other predictors, only three organizational- (hospital) level predictors were associated with the information and education composite score: teaching status; RN staffing; and resources directed to patient care. The effect of teaching status was unfavorable (b= .09); corresponding to about .04 increase in standard deviation units for every unit increase in teaching status) and was more than twice as large in magnitude as the effect of RN staffing. Conversely, the effect of RN staffing was favorable (b= -.04). Thirdly, the effect of resources directed to patients care was negligible in magnitude, yet favorable (b= -.000003).

c. Market-Level Predictors

Of the ten market-level variables tested at level 3, seven were associated with the information and education composite score, all else equal. The largest of these associations pertained to hospital competition (HHI index), HMO penetration rate, and LPN/population: respective slopes were (b= -.64), (b= -.55), and (b= -.52). In standard deviation units of the information and education composite score, these effects translate to .27, .23, and .22 decreases
for every unit increase in these predictors, respectively. These associations were favorable except for hospital HHI. Another predictor that had a favorable association here was teaching status, despite its tiny size, (b= -.02), which corresponds to a .01 decrease in standard-deviation units. The other three significant predictors (percentage of minority population, Medicaid days, and, resources directed to patient care) had minimal unfavorable effects of (b= .008), (b= .0008), and (b= .0001), respectively.

\textit{d. Variance Explained by Models}

As shown in Table 11, the majority of the variance in the information and education composite score was within hospitals (97.03%), while 2.44% was between hospitals, and only .53% was between markets. The conditional patient-level model explained 11.41% of the variance at level one (the within-hospital variance). This model also accounted for 30.81% of the variance at level 2 (between hospitals) and 40.89% of the variance at level 3 (between markets). The conditional organizational-level model explained 6.81% of the residual between-hospital variance in the baseline model, thus the explained between-hospital variance at the null model increased to 35.52%. The conditional market-level model explained 99.67% of the of the between-market variance in the null model and also explained 23.92% of residual between-hospital variance in the baseline model.

6. Results for Involvement of Family and Friends

\textit{a. Patient-Level Predictors}

On average, the mean score of involvement of family and friends was 4.57 and was statistically significant at the .01 level. Net of other predictors, whilst female gender (b= .07) and lower health status (b= .27) were unfavorably associated with this domain, surgical service
(b= -.18), Medicaid insurance (b= -.14), Medicare insurance (b= -.11), age (b= -.09), and less than high school education (b= -.05), were favorably associated with this domain. White race was not associated with this domain.

b. Hospital-Level Predictors

All else equal, three hospital-level variables were predictive of the involvement of family and friends composite score. Teaching status was associated unfavorably with this domain, with a small association of (b= .03), which is equivalent to about .02 increase in standard deviation units per one unit increase in the teaching status. On the other hand, LPN staffing, and resources directed to patient care were favorably associated with this domain, (b= -.06) and (b= -.000003), respectively. Notably, the size of the association of LPN staffing corresponded to a .04 decrease in standard deviation units for every unit increase in this predictor.

c. Market-Level Predictors

All else equal, the largest associations at the market level with the involvement of family and friends composite pertained to LPN staffing and HMO penetration rate as both relationships were also favorable (b= -.26) and (b= -.13) translating to a decrease of .18 and .09 in standard deviation units for every unit increase in these predictors, respectively. There were also smaller, yet favorable, relationships with this domain and teaching status, excess capacity, and per capita income with respective associations of (b= -.01), (b= -.0010), and (b= -.000003). The only predictor that had an unfavorable association at this level was percentage of minority population (b= .004).

d. Variance Explained by Models

As shown in Table 11, very small amounts of the true overall variance in this domain existed between markets (.34%) and between hospitals (.49%), whereas the vast majority of the
variance (99.17%) existed within hospitals. Despite the large amount of within-hospital variance, patient characteristics at level 1, explained only 3.4% of this variance. However, the conditional level-1 model also explained 18.12% of the between-hospital variance and 64.48% of the between-market variance. The conditional level-two model (with organizational characteristics) explained 16.74% of the baseline model’s residual between-hospital variance. Therefore, a total of 31.12% of the null model’s between-hospital variance was explained by the addition of organizational characteristics at level two. The conditional level-three model (with market-level characteristics) explained a tremendous 99.48% of the true between-market variance in the null model.

7. Results for Respect for Patient Preferences

a. Patient-Level Predictors

On average, the mean of the respect for patient preferences composite score across patients, hospitals, and markets was 3.55 and it was statistically significant at the .01 level. There was no association between surgical service and this domain, all else constant, unlike results from the process quality domains. White race (b = -.27), female gender (b = -.03), and age (b = -.004) were the only predictors with favorable relationships with this domain at level one of the model, all else constant. On the other hand, Medicaid insurance (b = .23), lower health status (b = .19), less than high school education (b = .05), and Medicare insurance (b = .03) were all unfavorably related to this domain, controlling for other predictors.

b. Hospital-Level Predictors

Controlling for other predictors, teaching status and the percentage of Medicare share of inpatient days were unfavorably associated with the respect for patient preferences composite
score: (b= .05) and (b= .001), respectively. The effect of Medicare payor mix corresponded to about .04 increase in standard-deviation units of the outcome per one-unit increase in this predictor (b= .001). RN/inpatient days and resources committed to patient care had favorable relationships with this domain, (b= -.02) and (b= -.000001), respectively, all else constant.

c. Market-Level Predictors

The largest association at the market-level predictors pertained to HHI (b= -.15). However, this relationship was unfavorable and corresponded to about .13 increase in standard-deviation units of this domain for every unit increase in hospital HHI, all else constant. Similarly, unfavorable association was found for HMO penetration (b= .10), corresponding to a .09 increase in standard deviation units, per one-unit increase in this predictor. The remaining significant predictors at this level (teaching status, percentage of minority population, excess capacity, and Medicaid days) were also unfavorably associated with this domain, except for teaching status, (b= -.01), (b= .003), (b= .001), and (b= .0002), respectively, all else constant.

d. Variance Explained by Models

As shown in Table 11, although a miniscule amount of .58% of the true overall variance in the respect for patient preferences composite score existed between markets, a slightly larger amount of variance (2.34%) existed between hospitals. However, the majority of the true variance (97.08%) was within hospitals. Patient characteristics in the conditional level-one model explained only 6.77% of the true variance at the within-hospital level. Nonetheless, this model explained as much as 49.38% of the between-hospital and 93.98% of the between-market variances. Organizational predictors explained 23.52% of the baseline model’s between-market variance (which is the residual variance from the null model). Overall, organizational predictors explained 61.28% of the null model’s between-hospital variance. Market characteristics in the
conditional level-three model explained 99.60% of the null model’s between-market variance. This model also explained 70.26% of the null model’s true between-hospital variance.

II. Results for Overall Satisfaction with Care

a. Patient-Level Predictors

On average, the mean overall satisfaction composite score across patients, hospitals, and markets was statistically significant at the .01 level, and was estimated at 21.9. It is notable that this mean score was rather high compared to the mean scores for the process-quality domains, which were problem-score scales. This finding is not surprising because previous research had noted that satisfaction scores tend to be commonly high (Hays et al., 2006). Recalling that items of overall satisfaction with care were measured in the Picker questionnaire using a satisfaction-type likert scales (not problem scores), higher values on this outcome are considered favorable, as opposed to the seven process-quality composite scores. All other predictors held constant, lower health status (b= -1.60) and female gender (b= -.45) were both unfavorably associated with this domain. Conversely, three other predictors were favorably associated this domain: surgical service (b= .54), less than high school education (b= .38), and age (b= .01). There were no relationships between this domain and Medicare insurance, Medicaid insurance, and white race.

b. Hospital-Level Predictors

As discussed in the methods section, total facility-level predictors where used at the hospitals level (which means that measures of hospital characteristics used in this study were not net of non-short term inpatient components). Therefore, at the organizational level, I decided to include the dummy variable of whether a hospital maintained a nursing home unit or not (as a control variable at this level). Overall satisfaction with care was the only domain among the
eight patient assessments of care domains where this control variable was significant and thus should have been indeed controlled for when the relationship between predictors and the outcomes was examined at the organizational level (b= .20). Therefore, controlling for maintenance of a separate nursing home unit, three hospital-level predictors were associated with the overall satisfaction with care, all else constant. RN staffing and resources directed to patient care had favorable relationships with overall impression of care, estimated at (b= .14) and (b= .000008), respectively. Conversely, teaching status had an unfavorable relationship (b= - .22), which corresponds to a .04 decrease in standard deviation units per one unit increase in this predictor.

**c. Market-Level Predictors**

All other predictors held constant, only four predictors were associated with overall satisfaction with care, at the market level; the largest of which was hospital HHI (b= 0.90), which corresponds to .18 increase in standard deviation units of overall satisfaction with care per one unit increase in HHI; an unfavorable relationship, since the higher the HHI index (means the lesser degree of competition among hospital), the higher the satisfaction score. Likewise, the percentage of minority population had an unfavorable relationship (b= -0.03). Conversely, teaching status and per capita income had favorable relationships with overall satisfaction with care, estimated as (b= .04) and (b= .000007), respectively.

**d. Variance Explained by Models**

As shown in Table 11, most of the true variance in the overall satisfaction with care composite score was within hospitals (96.17%), as opposed to proportions of between-hospital (3.24%) and between-market (.59%) variances. Of the within-hospital variance, 10.97% was accounted for by patient characteristics. Level-1 predictors also accounted for 12.66% of the
hospital-level variance and 2.28% of the market-level variance in the null model.

The conditional model at level two (with organizational-level predictors) explained 20.68% of
the between-hospital variance in the null model and it also explained 9.18% of between-hospital
variance in the baseline model. The conditional model at level three (with market-level
predictors) explained 99.55% of the true between-market variance. It also improved the
explained between-hospital variance of the baseline model to 25.53%.
CHAPTER 5: DISCUSSION

A major finding of this study was that true variations in patient assessments of care – in terms of multidimensional domains of process quality, as well as overall satisfaction with care – are abundant. Strikingly, most of the overall true variations in various measures of patient assessments of care (95.9% - 99.17%) were predominately within hospitals (i.e., due to differences among patients at the hospital level). On the other hand, a maximum of 3.35% of the true overall variations existed between hospitals and up to 1% of the variations were attributed to differences between hospital markets.

Having established the existence of true variations in process quality and overall patient satisfaction with care, this study proceeded by testing several hypotheses of organizational and market predictors in order to explain these variations. Despite the relatively small amount of between-hospital and between-market variations, net of patient characteristics, organizational- and market-level characteristics predicted a sizable amount of them: 9.76% - 61.28% of between-hospital variations, and up to 99% of the between-market variations. Table 12 contrasts the findings on each predictor to its respective directional hypothesis. Furthermore, the interpretation and significance of the findings of these predictors are discussed below.

Discussion of Findings on Predictors

Taken together, nurse-staffing variables were favorably associated with almost all domains of patient assessments of care, as predicted by resource dependency theory. At the organizational (hospital) level, RN staffing had a much more pronounced effect than LPN
staffing; as RN staffing was predictive of most process quality domains as well as overall satisfaction with care. LPN staffing was predictive of involvement of family and friends (while RN staffing was not) and physical comfort. At the market level, the role of nurse staffing variables was also favorable. However, the role of LPN staffing was much more pronounced at the market level (than RN staffing). While RN staffing was only associated with emotional support at the market level, LPN staffing was further associated with four additional process quality domains: coordination of care, physical comfort, information and education, and, involvement of family and friends.

As hypothesized, resources directed to patient care was a favorable predictor of all domains of process quality and overall satisfaction with care, at the organizational level. However, this relationship was rather small in size. At the market-level, this variable was favorably predictive of physical comfort. Conversely, the relationship was unfavorable for information and education.

At the organizational level, Medicare days was associated with only one domain of patient assessments of care (respect for patient preferences), albeit this association was not favorable, contrary to the hypothesis. On the other hand, there was no association between Medicaid days and any of the patient assessments of care domains of this study. At the market level, Medicaid days was unfavorably associated with four process quality domains, as hypothesized: coordination of care, physical comfort, information and education, and, respect for patient preferences.

At the organizational level, teaching status was unfavorably associated with overall satisfaction with care and all process quality domains (except continuity and transition of care).
This unfavorable association was highest for coordination of care. This finding contradicted the hypothesis of this study, but it agreed with the findings of (Fleming, 1981) and others. Conversely, at the market level, teaching status was favorably associated, as hypothesized, with overall satisfaction with care and several domains of process quality. Teaching status at the market level was not related to continuity and transition of care (similar to results from the organizational level) and also was not related to physical comfort. The conflicting direction of association of teaching status between the organizational and market levels is puzzling. One may be able to envision the relationship manifesting differently using different outcomes or samples (given the mixed findings in the literature on this predictor), but it is hard to reconcile such conflicting results across data levels of the same outcomes. However, given the lack of examples in the literature, where teaching status is modeled at both the organizational level and the market level, it is hard to exclusively argue against the tenability of this finding.

Furthermore, the results could partly be an artifact of not using identical measures of teaching status at both levels. At the market level, membership in the council of teaching hospitals was the only teaching-status measure used. However, at the organizational level, I also included other measures of teaching membership in this predictor (such as AMA membership). Therefore, future research that examines alternative measures of teaching status is called upon to better understand the influence of this important predictor.

At the organizational level, coordination of care was the only measure of patient assessment of care predicted by occupancy rate. Additionally, this relationship was rather small and unfavorable, contrary to the hypothesis. At the market level, excess capacity was associated with only three process quality domains and this association was favorable for involvement of
family and friends. However, it was unfavorable for emotional support and respect for patient preferences; indicating that the higher excess capacity in a market, the higher the problem scores reported on these two domains.

A trade-off clearly exists between quality of care and technical efficiency, as measured in occupancy rate. For example, high occupancy rate while representing higher efficiency, typically means some sacrificing of quality of care because higher occupancy rate means less time spent with patients (Bates, Mukherjee, & Santerre, 2006). This logic could present another explanation to this finding.

No relationship with ownership status was found in this study, controlling for other predictors. Perhaps the fact that the sample of hospitals were primarily non-profits (government and non-government hospitals); with only 7% investor-owned hospitals, there were not enough variations in this variable to detect an effect for for-profit hospitals. So the comparison here becomes mostly between government and non-government non-profit hospitals. However, the findings of this study are also justifiable in the sense that they agree with some studies that suggested that non-profit (government and non-government) hospitals react in similar ways to market pressures; thus, perhaps they also behave similarly with respect to processes of care.

Hospital HHI of competition was highly correlated with overall satisfaction and process quality domains (except continuity of care and involvement of family and friends). This relationship was consistently unfavorable across various domains, indicating that patients reported more problems with process quality domains and lower satisfaction of care in more competitive (than less competitive) markets. Obviously, this finding contradicts the hypothesis of this study and the predictions of resource dependency theory; resource dependency theory
predicts that hospitals in competitive markets will respond to competition from local hospitals by offering better health care, as measured by patient assessments of care domains. Nonetheless, this finding agrees with the finding of (Shortell & Hughes, 1988), who also found an unfavorable relationship between hospital competition and hospital mortality. As Shortell and Hughes (1988) concluded, when hospitals are faced with intense competition, they attempt to cut costs through reduction in staff, elimination of selected services, and consolidation of services and postponement of capital improvements. Hospitals may also forgo the development of new programs and services that could improve the quality of care. Some of these initiatives, undertaken in the name of efficiency could have a negative effect on the quality of patient care, which in turn could lead to poorer processes of care and lower patient satisfaction.

Although HMO penetration rate was not associated with satisfaction with care, it was highly associated with all process quality domains, with exception of continuity of care. However, findings on the direction of association were mixed; as the relationship was favorable for the most part (as hypothesized), physical comfort and respect for patient preferences were unfavorably associated with it.

The fact that California has typically been one of the highest states in the country with respect to HMO penetration rates could have some bearing on the unfavorable relationship of HMO penetration and patient assessments of care. As argued by (Rivers & Fottler, 2004), high rates of HMO growth may reduce quality because HMOs encourage hospitals to cut costs (by forcing price competition), which reduces profit margins. Through selective contracting and volume discounts, these lower margins might subsequently reduce resources (such as nursing) used in patient care, thus reducing hospital quality of care. Indeed this line of reasoning can
justify the unfavorable assessments of care in market with high HMO penetration. Moreover, such justification also does not contradict with resource dependency theory. Nonetheless, it contradicts with the strategic action taken by hospitals. Specifically, this study posited that higher process quality and overall patient assessments of care are the strategic action taken by hospitals in response to the environmental factor of growth in HMO penetration. However, the logic of Rivers and Fottler (2004) implies that cost reduction, rather than quality, is the strategic action that hospitals pursue. Nonetheless, existing research has not yet established claims of superior quality overall for managed care versus traditional plans (Mark et al., 2005). Therefore, future research that also takes into account more information on the financial performance of hospitals and the nature of the contractual agreements between HMOs and hospitals also need to be incorporated when studying quality outcomes.

With regards to socio-economic market factors, percentage of minority population was consistently unfavorably associated with overall satisfaction with care and almost all process quality domains, as hypothesized. On the other hand, the higher the per-capita income of a county, the more problems reported on two process quality domains: emotional support and involvement of family and friends. However, county-level per capita income was favorably associated with overall satisfaction with care.

Implications for Practice and Policy

There are substantial variations in health outcomes and the roots of these variations are complex (Iwashyna et al., 2002). This study supported the robustness of patient assessments of care in elucidating sources of variations within hospitals, between hospitals, and between
markets. A direct implication of this finding is that more attention should be given to patient-centered, as opposed to the traditional mortality and morbidity, measures for elucidating sources of variations in patient outcomes across patients, organizations, and markets. Patient-centered measures can now be derived from several reporting systems of patient experiences, such as the NRC Picker/California Hospitals Assessment and Reporting Taskforce (CHART) surveys and the more recent and larger CAHPS® Hospital Survey effort. The CHART project began in 2004, as an extension of the PEP-C project to broaden the voluntary public reporting initiative in California to include a variety of clinical measures, in addition to the patient experience survey (California Health Care Foundation, 2005). On the other hand, the CAHPS® Hospital Survey effort is a result of the partnership between the Centers of Medicare and Medicaid (CMS) and the Agency for Healthcare Research and Quality (AHRQ) to help consumers make more informed choices when selecting a hospital and to create incentives for hospitals to improve the quality of care they provide (Goldstein et al., 2005). The CAHPS® Hospital Survey has been piloted in three states (Goldstein et al., 2005) and is soon to be in use across the country. Comprised of 16 questions assessing specific aspects of care and two hospital rating questions (plus demographic and screener questions), the CAHPS® Hospital Survey taps seven domains of care: nurse communication, doctor communication, nursing services, physical environment, pain control, communication about medicines, and discharge information. Although there is much overlap between the NRC Picker items (questions) and the CAHPS® Hospital Survey items, the NRC Picker survey (i.e., CHART) added more questions items to improve reliability and create a coordination of care domain, because this domain was emphasized by the Institute of Medicine, as a key aspect of patient care (Anderson Rothman, Park, Hays, Edwards, & Dudley, 2008). In
fact, Anderson Rothman et al. (2008) found that the CHART survey improved reliabilities (beyond CAHPS® Hospital Survey) and that the coordination of care domain was more closely associated with overall rating of care and the willingness to recommend the hospital than several other CAHPS® domains. While the PEP-C/CHART surveys offer the advantage of having more items/domains of patient assessments of care from hospitals across California, the CAHPS® Hospital Survey offers a standardized core of items/domains from hospitals across the country. Therefore, where researchers are more interested in predicting core measures of patient assessments of care, then the CAHPS® Hospital Survey would be ideal, because it will also allow for studying variations across a variety of market areas and possibly more market-level predictors. Nonetheless, the CHART survey and similar localized surveys would allow for in-depth study of predictors of more specialized (non-core) measures of patient assessments of care, such as coordination of care or interpreter services.

In addition to elucidating sources of variations across patients, hospitals, and markets, this study was motivated by the limited research on macro-level (hospital-level and market-level) predictors that can explain variations in patient assessments of care. Remarkably, macro-level predictors accounted for a small portion of the true variations at the between-hospital and between-market levels. Unexpectedly, however, the majority of the overall true variations in patient assessments of care existed within hospitals. Furthermore, while patient demographic and health insurance characteristics accounted for some of these variations, the majority of the true variances at this level remained unexplained. This finding highly suggests that factors within the health care provider experience (such as physician-patient relationship and nurse-patient relationship) are the more likely determinants of the patient perceptions of care. The
implications of this conclusion are immense for hospital administrators, who want to improve patient experiences at their hospitals, and for policy makers. Indeed, one would be tempted to think that the characteristics of the hospital or the market, which are fairly hard to change, account for most of the variations in patient experiences with care. Rather, variations in the health-care-provider relationship seem to be more influential, than macro-level characteristics, and are also very amenable to change by emphasizing a patient-centered-care culture among hospital staff. Ironically, the move toward patient-centered quality measurement and reporting systems of hospital care should have been preceded by a comparable move towards patient-centered care, whereby patients are more involved in all aspects of their care.

On the other hand, as more evidence accumulates from similar studies regarding significant predictors of patient assessments of care, there are policy implications for such findings. For example, evidence on significant predictors need to be taken into account (or adjusted for) upon making comparisons across hospitals (as in quality report cards or the hospital compare website launched by CMS) in order to achieve more equitable comparisons of hospitals. In light of the finding of this study that patient-level case-mix predictors predict more of the true overall variance in patient assessments of care than all macro-level predictors combined, this study takes the position that future work needs to control/adjust for these characteristics; contrary to suggestion of Finkelstein, et al., (1998) on this issue.

Moreover, if future studies support the findings of this study regarding what/how macro-level predictors are associated with better process quality and higher overall satisfaction with care, then policy makers can target these predictors in order to induce change. For example, if intense competition among hospitals is indeed bad for patients experiences with care, as this
study found, then regulations to reduce competition among hospitals (such as eliminating Certificate of Need (CON) laws) can be pursued to increase quality of care (Baker Starkey et al., 2005) and improve assessments of care. Similarly, if nurse-staffing levels prove to be critical for improving patient experiences of care, then policies that dictate acceptable (or minimum staffing levels) need to be put in place and enforced by policy makers. Other macro-level characteristics, such as occupancy rate and how much excess capacity hospitals are allowed to have or can exist in a given market could be subject to change by policy makers, or even hospital administrators who want to improve patient experiences.

Theoretical Implications

On the theoretical side, a particular strength of this study and an extremely helpful tool in conceptualizing it was the theoretical model for examining multilevel predictors of patient assessments of care. This model was developed based on Donabedian’s SPO model and resource dependency theory, and sought to advance the SPO model in order to reflect the complexity of the hospital industry. Of the ten hypotheses derived in this study, three were fully supported and another three were partially supported. In turn, support for these hypotheses yields support for the theoretical model of the study as well as the usefulness of resource dependency theory in understanding the link between organizational and market predictors of care and patient assessments of care as both an outcome (overall satisfaction) and process of care. On the other hand, the fact that three hypotheses were not supported in this study indicates that more work is needed in order to understand the processes of organizational response to the environmental factors with respect to patient-centered outcomes. As discussed in regards to the
relationship of HMO penetration rate, while the principles of resource dependency theory still apply, alternative (to the response studied) reactionary or adaptive organizational actions could be driving organizational responses.

Furthermore, this study is one of few studies that adopted the long-recognized notion of multidimensionality of patient assessments of care. Apparently, there appears to be a good consequence to this decision, because various dimensions (domains) of process quality showed some differences, to an acceptable extent, in terms of significant predictors. This variety in the patterns of relationships between different predictors and dimensions of patient assessments of care supports the view to adopt multidimensional measures in future research. Nonetheless, more research is needed to understand the reasons and/or underlying mechanisms by which these predictors relate to certain dimensions of care, but not to others, as seen in this study.

**Study Limitations and Ways to Overcome them in Future Research**

Because this study used observational cross-sectional data and methods, the findings cannot infer causality (Babbie, 2001) and can be biased, if there are unobserved, time-invariant factors that affect hospital quality, and these factors are correlated with exploratory variables of the model (Mark et al., 2005). Therefore, the relationships of interest in this study would be best examined using longitudinal designs and larger sample sizes. Unfortunately, longitudinal data with reasonable sample sizes did not exist at the time when this work was conceived of/commenced. Nonetheless, as more waves of data from the CHART and CAHPS® Hospital Survey projects become available, it will become more feasible to test the hypotheses of this study using longitudinal designs.
Considering the voluntary nature of hospital participation in this study, possible selection biases at the hospital level present a validity threat. However, the participation rate of CA hospitals in the PEP-C effort is sizable, if not among the highest in state-level quality measurement efforts. Also, there is indeed a large representation of hospitals from most (80%) of CA markets. Statistical comparisons of PEP-C participant and non-participant hospitals show no significant differences (at the 0.05 level) in terms ownership status, teaching status, occupancy rate, nurse-staffing levels, and maintenance of a separate nursing home unit. However, PEP-C-participating hospitals had slightly more resources than non-participants. Specifically, PEP-C participants had 6% higher mean of percentage of Medicare days, 8% lower mean of percentage of Medicaid days, and 11% higher mean of resources directed to patient care; all of these differences were statistically significant at the 0.05 level.

Likewise, low response rates at the hospital level could be another validity concern, since it has been suggested that non-respondents are more likely to have negative experiences of care than respondents (Rubin, 1990a). However, a study that examined the impact of non-response bias among patients in a multi-hospital sample (Lasek, Barkley, Harper, & Rosenthal, 1997) found that this impact was relatively small and not systematically greater in hospitals with lower response rates. Moreover, obtaining high response rates from surveys of hospital patients is a well-known challenge and will continue to be a challenge to researchers in the future.

The AHA data are self-reported and not independently verified. However, there is no a priori reason to suspect that the data reliability is correlated with the predictors of this study or the outcomes. Furthermore, the response rate has typically increased to at least 80% by hospitals. Notably, missing data in AHA survey precluded testing hospital memberships in
health systems or networks (Bazzoli et al., 1999); these two variables were of interest in this study given the opinion of Bazzoli, Shortell et al. (1999) that describing hospitals in terms of their individual characteristics alone is no longer adequate given the consolidation in the hospital industry. However, in univariate models ran on valid (non-missing) system membership data, I found no relationship with patient assessments of care domains.

A common theme of discussion (and controversy) with respect to the market-level analyses in health services research is deciding what constitutes a hospital market (Wong et al., 2005). Consistent with numerous prior studies (Zinn et al., 1999) and because the data were derived from only one state (thus had a small number of market units), this study used counties to approximate hospital markets. Moreover, as indicated by Iwashyna et al. (2002), providers tend to view their markets in terms of counties. However, others argue that the use of MSAs, as a geopolitical measure of competition, is more defensible, because MSAs are designed to enclose an area with a high degree of economic cohesion (Wong et al., 2005). Therefore, future research of market-level predictors of patient assessments of care that includes large samples of MSAs could fare better, from the perspective of measuring hospital competition, by using MSAs or HRRs, instead of counties, to approximate hospital markets.

Finally, here are few more areas of research for future studies. It would be interesting to examine whether specialty hospitals differ from general hospitals with respect to patient assessments of care. Given that specialty hospitals comprise just a small fraction of hospitals, large and multi-state samples will be needed to examine this research question.

Although this study controlled for race as a potential predictor of patient assessments of care, it failed to control for language differences, considering that the PEP-C survey was
administered in three languages: English, Spanish, and Chinese. Given that previous studies of patient assessments of care found that language groups differ on measures of patient assessments of care (Carrasquillo, Orav, Brennan, & Burstin, 1999; Weech-Maldonado et al., 2003), future research that includes ethnic/racial subgroups need to take language differences into consideration.

Although this study examined the validity of the Picker domains using the PEP-C data, it did not assess equivalence of the Picker domains across various racial/ethnic groups or contexts, such as rural and urban areas. Although previous studies established equivalence of similar patient assessments of care domains, such as the Health Plan CAHPS 1.0 survey (Marshall, Morales, Elliott, Spritzer, & Hays, 2001) among racial/ethnic groups, evidence of group equivalence using the Picker domains is not available in the published literature. Therefore, future studies using hospital-based patient assessments of care need to examine the equivalence of these measures across groups and contexts.

Despite being one of the few studies that included measures of resources directed to patient care, due to data limitations, this study failed to control for potential variations in the costs of medical care across markets. Additionally, because of the small amounts of true variations in patient assessments of care that existed at the market level, this study did not consider more sophisticated analyses, such as deviance from market norms/averages or cross-level interactions. However, such analyses are recommended for future research.

Another area of importance for future research is to test the hypotheses of this study on the uninsured. There were few cases of uninsured patients in the sample, of which the results presented here make no inferences, whatsoever; as I dropped them from the analysis, due to strict
sample size reasons. Indeed, the uninsured are likely to have the most to say in terms of experiences of care and, because of their greater need, they are even the most worthy of study; I hope future studies in this area will address this shortcoming, before all others.

Conclusions

Notwithstanding its limitations, this study adds to the current literature on patient assessments of hospital care, by addressing the three major limitations identified by O'Connor & Shewchuk (2003) and others; in order to bridge the gap between the patient assessments of care research and the consumer assessments research found in the general marketing literature. It demonstrated the robustness and richness of patient assessments of care and presented numerous issues for future research.
Table 1: Descriptive Statistics for Patient-Level Variables (n=24,887)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coding and Range</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>0=no</td>
<td>.57</td>
<td>.49</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surgical service</td>
<td>0=no</td>
<td>.53</td>
<td>.50</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>(18, 102)</td>
<td>63</td>
<td>17.04</td>
</tr>
<tr>
<td>&lt; High school</td>
<td>0=no</td>
<td>.16</td>
<td>.36</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare insured</td>
<td>0=no</td>
<td>.36</td>
<td>.48</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicaid insured</td>
<td>0=no</td>
<td>.13</td>
<td>.33</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower health status</td>
<td>0=no</td>
<td>.31</td>
<td>.46</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0=no</td>
<td>.68</td>
<td>.46</td>
</tr>
<tr>
<td></td>
<td>1=yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coordination of care</td>
<td>6 items</td>
<td>6.94</td>
<td>2.32</td>
</tr>
<tr>
<td>Continuity and transition of care</td>
<td>3 items</td>
<td>4.54</td>
<td>1.96</td>
</tr>
<tr>
<td>Physical comfort</td>
<td>4 items</td>
<td>4.23</td>
<td>2.09</td>
</tr>
<tr>
<td>Emotional support</td>
<td>5 items</td>
<td>6.32</td>
<td>2.64</td>
</tr>
<tr>
<td>Information and education</td>
<td>5 items</td>
<td>5.62</td>
<td>2.40</td>
</tr>
<tr>
<td>Involvement of family and friends</td>
<td>3 items</td>
<td>4.55</td>
<td>1.49</td>
</tr>
<tr>
<td>Respect for patient preferences</td>
<td>3 items</td>
<td>3.55</td>
<td>1.14</td>
</tr>
<tr>
<td>Overall satisfaction with care</td>
<td>6 items</td>
<td>21.49</td>
<td>5.12</td>
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</table>
Table 2: Correlations of Patient-Level Variables

<table>
<thead>
<tr>
<th></th>
<th>Female</th>
<th>Surgical service</th>
<th>Age</th>
<th>&lt; High school</th>
<th>Medicare insured</th>
<th>Medicaid insured</th>
<th>Low Health status</th>
<th>White</th>
</tr>
</thead>
<tbody>
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<td>Female</td>
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<td>-.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surgical service</td>
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<td>-.07</td>
<td>-.10</td>
<td>-.08</td>
<td>-.23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>.10</td>
<td>.58</td>
<td>-.07</td>
<td>.18</td>
<td>.21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; High school</td>
<td></td>
<td>.03</td>
<td>.25</td>
<td>.15</td>
<td>-.26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare insured</td>
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<td>.11</td>
<td>.17</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>.14</td>
<td>-.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower health status</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.06</td>
</tr>
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</table>

Table 3: Correlations of Process Quality and Overall Satisfaction with Care Domains

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<th></th>
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</thead>
<tbody>
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<td>Coordination of care</td>
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<td>.47</td>
<td>.71</td>
<td>.35</td>
<td>.36</td>
<td>-.43</td>
<td></td>
</tr>
<tr>
<td>Continuity &amp; transition of care</td>
<td>.23</td>
<td>.43</td>
<td>.39</td>
<td>.44</td>
<td>.24</td>
<td>-.46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical comfort</td>
<td>.36</td>
<td>.27</td>
<td></td>
<td>.26</td>
<td>.28</td>
<td>-.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional support</td>
<td></td>
<td>.61</td>
<td></td>
<td>.48</td>
<td>.42</td>
<td>-.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information and education</td>
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<td>.44</td>
<td></td>
<td>.37</td>
<td>-.49</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Involv. of family &amp; friends</td>
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<td>.26</td>
<td></td>
<td></td>
<td>-.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Respect for patient preferences</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.36</td>
<td></td>
</tr>
</tbody>
</table>

* Where there is no statistically significant correlation, the table leaves the entry blank.
Table 4: Descriptive Statistics for Hospital-Level Variables (n= 173)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coding and Range</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maintain a NH unit</td>
<td>0= no</td>
<td>.40</td>
<td>.49</td>
</tr>
<tr>
<td></td>
<td>1= yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RN/inpatient days</td>
<td>(.58, 24.38)</td>
<td>5.52</td>
<td>2.91</td>
</tr>
<tr>
<td>LPN/inpatient days</td>
<td>(0, 7.73)</td>
<td>.73</td>
<td>.76</td>
</tr>
<tr>
<td>Government hospital</td>
<td>0= no</td>
<td>.19</td>
<td>.39</td>
</tr>
<tr>
<td></td>
<td>1= yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupancy Rate</td>
<td>(23.81%, 178.26%)</td>
<td>66%</td>
<td>18.73%</td>
</tr>
<tr>
<td>Pct Medicare</td>
<td>(0%, 88.40%)</td>
<td>44%</td>
<td>15.50%</td>
</tr>
<tr>
<td>Pct Medicaid</td>
<td>(0%, 93.31%)</td>
<td>20%</td>
<td>17.88%</td>
</tr>
<tr>
<td>Teaching Status</td>
<td>(0, 3)</td>
<td>.62</td>
<td>1.02</td>
</tr>
<tr>
<td>Resources pt care</td>
<td>(4776, 121099)</td>
<td>60980</td>
<td>17886</td>
</tr>
</tbody>
</table>

Table 5: Correlations of Hospital-Level Variables +

<table>
<thead>
<tr>
<th></th>
<th>Maint. a NH unit</th>
<th>RN/ inpat. days</th>
<th>LPN/ inpat. days</th>
<th>Gov. hospital</th>
<th>Occup. rate</th>
<th>Pct Medicare</th>
<th>Pct Medicaid</th>
<th>Teach. status</th>
<th>Resour. pt care</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maintain a NH unit</td>
<td>-0.33</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RN/inpatient days</td>
<td></td>
<td>0.52</td>
<td>-0.31</td>
<td>-0.28</td>
<td>-0.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LPN/inpatient days</td>
<td></td>
<td></td>
<td>-0.27</td>
<td>-0.18</td>
<td>-0.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gov. hospital</td>
<td></td>
<td></td>
<td></td>
<td>-0.38</td>
<td>0.42</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupancy rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>Pct Medicare</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.51</td>
<td>-0.20</td>
</tr>
<tr>
<td>Pct Medicaid</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teaching status</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resources pt care</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

+ Where there is no statistically significant correlation, the table leaves the entry blank.
### Table 6: Descriptive Statistics for Market-Level Variables (n=46)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coding and Range</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHI hospital competition</td>
<td>(.06, 1)</td>
<td>.52</td>
<td>.27</td>
</tr>
<tr>
<td>Pct minority pop</td>
<td>(6.6%, 51.3%)</td>
<td>29%</td>
<td>14.13%</td>
</tr>
<tr>
<td>No. RN FTEs/pop.</td>
<td>(.99, 4.93)</td>
<td>2.34</td>
<td>.87</td>
</tr>
<tr>
<td>No. LPN FTEs/pop.</td>
<td>(.074, 1.73)</td>
<td>.42</td>
<td>.30</td>
</tr>
<tr>
<td>Resources pt care</td>
<td>(482.24, 5376)</td>
<td>1096</td>
<td>734.35</td>
</tr>
<tr>
<td>Excess capacity</td>
<td>(-15.23, 76.95)</td>
<td>37.60</td>
<td>15.78</td>
</tr>
<tr>
<td>Teaching status</td>
<td>(0, 9)</td>
<td>.52</td>
<td>1.53</td>
</tr>
<tr>
<td>HMO penetration</td>
<td>(.0009, .74)</td>
<td>33</td>
<td>22</td>
</tr>
<tr>
<td>Per-capita income</td>
<td>(16,112, 60,618)</td>
<td>29,207</td>
<td>10,710</td>
</tr>
<tr>
<td>Medicaid days/pop</td>
<td>(15.87, 680.52)</td>
<td>132.94</td>
<td>141.84</td>
</tr>
</tbody>
</table>

### Table 7: Correlations of Market-Level Variables *

<table>
<thead>
<tr>
<th></th>
<th>HHI hosp. compet.</th>
<th>Pct min. pop.</th>
<th>No. LPN FTEs/pop.</th>
<th>Resour. pt care</th>
<th>Excess capacity</th>
<th>Teach. status</th>
<th>HMO Penet.</th>
<th>Per-capita income</th>
<th>Medicaid days/pop</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHI hosp. compet.</td>
<td>-.49</td>
<td>.34</td>
<td>-.41</td>
<td>-.64</td>
<td>-.47</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pct minority pop</td>
<td>-.33</td>
<td></td>
<td>.41</td>
<td>.38</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>No. RN FTEs/pop.</td>
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<td>.29</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. LPN FTEs/pop.</td>
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<td>.67</td>
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<td></td>
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</tr>
<tr>
<td>Resources pt care</td>
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<td>.53</td>
<td>-.29</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Excess capacity</td>
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<td>.37</td>
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<td></td>
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<tr>
<td>Teaching status</td>
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<td></td>
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<td>-.31</td>
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<tr>
<td>HMO Penetration</td>
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<tr>
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</tbody>
</table>

* Where there is no statistically significant correlation, the table leaves the entry blank.
Table 8: Results of Model Fit Indices and Reliabilities for Picker Domains

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Domain Solution</th>
<th>Chi-Square</th>
<th>NFI</th>
<th>RFI</th>
<th>IFI</th>
<th>TLI</th>
<th>CFI</th>
<th>RMSEA</th>
<th>AIC</th>
<th>Cronb. Alpha</th>
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<td>.978</td>
<td>.090</td>
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1 Dropped Staff explained purpose of home medicine - q008206. A constraint based on CR differences was imposed to achieve model identification.
2 Dropped minutes for help after call button - q008648.
3 Dropped Doctor discussed anxieties/fears - q008177.
4 In order to estimate model fit indices for this model, assumed equal variance for 2 items (family given info & amount of info given to family).
5 Dropped Enough say about treatment - q008185 (standardized B=0.20, squared multiple correlations =4%).
6 Dropped courtesy of Dr q008098 and courtesy of nurses q008104 - tried dropping only one item; none worked.
Table 9: Variance Components Estimates for the Null Models

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Reliability Estimates

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Components of Variance Tests

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<td>p-value</td>
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<td>.000</td>
<td>.001</td>
</tr>
<tr>
<td></td>
<td>Coordination of care</td>
<td>Continuity &amp; transition of care</td>
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</tr>
<tr>
<td><strong>Level 1 predictors</strong></td>
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<tr>
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<td>6.9168(0.0343)</td>
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<td>-0.1958(0.0236)</td>
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<td>-1.2264(0.0491)</td>
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<tr>
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<td>-0.0097(0.0009)</td>
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<td>0.3077(0.0659)</td>
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<td>0.6164(0.0422)</td>
<td>0.6139(0.0414)</td>
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<td>White</td>
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<tr>
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<td></td>
</tr>
<tr>
<td>RN Inpatient days</td>
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<td>-0.0223(0.0097)</td>
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<tr>
<td>LPN Inpatient days</td>
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<tr>
<td>Gov hospital</td>
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<tr>
<td>Occupancy rate</td>
<td>0.0036(0.0016)</td>
<td>0.0049(0.0015)</td>
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<tr>
<td>Pct Medicare</td>
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<tr>
<td>Pct Medicaid</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teaching status</td>
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<td>0.0950(0.0152)</td>
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<tr>
<td>Resources pt care</td>
<td>-0.00001(0.0000)</td>
<td>-0.000003(0.000001)</td>
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<tr>
<td><strong>Level 3 predictors</strong></td>
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<tr>
<td>HHI hosp. competition</td>
<td>-0.5660(0.2047)</td>
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<tr>
<td>Per-capita income</td>
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<tr>
<td>Pct minority pop.</td>
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<tr>
<td>Medicaid days/pop.</td>
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<tr>
<td>No. RN FTEs/pop.</td>
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<td>No. LPN FTEs/pop.</td>
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<tr>
<td>Resources pt care</td>
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Table 10: Regression Results for Multilevel Models, Cont’d.

<table>
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<tr>
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<td>Intercept</td>
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<td>Female</td>
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<td>Surgical service</td>
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<td>RN/inpatient days</td>
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<td>Occupancy rate</td>
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<td>Pct Medicare</td>
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</tr>
<tr>
<td>Pct Medicaid</td>
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<td>-0.000002(0.000002)</td>
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<td>HHI hosp. competition</td>
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<tr>
<td>Per-capita income</td>
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<tr>
<td>Pct minority pop.</td>
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<td>No. RN FT Es/pt pop.</td>
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<td>No. LPN FT Es/pt pop.</td>
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<td>Excess capacity</td>
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<td>Teaching status</td>
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Regression Coefficient Estimates (with Standard Error Estimates in Parentheses)
Table 10: Regression Results for Multilevel Models, Cont’d

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<th>Involvement of family &amp; friends</th>
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<td>Female</td>
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<td>RN/inpatient days</td>
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<td>Gov hospital</td>
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<td>HHI hosp. competition</td>
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<tr>
<td>Per-capita income</td>
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<tr>
<td>Pct minority pop</td>
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<tr>
<td>Medicaid days/pop.</td>
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<tr>
<td>No. RN FTES/pop.</td>
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<td>No. LPN FTES/pop.</td>
<td>-0.5229(0.1697)</td>
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<td>Resources pt care</td>
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<td>Excess capacity</td>
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<td>Teaching status</td>
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Regression Coefficient Estimates (with Standard Error Estimates in Parentheses)
Table 10: Regression Results for Multilevel Models, Cont’d

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<th>Level 3</th>
<th>Level 1</th>
<th>Level 2</th>
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<td>3.5536(0.0110)</td>
<td>3.5094(0.0092)</td>
<td>21.8975(0.1045)</td>
<td>21.7978(0.0798)</td>
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<tr>
<td>Female</td>
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<td>-0.0311(0.0180)</td>
<td>-0.0313(0.0179)</td>
<td>-0.4475(0.0686)</td>
<td>-0.4489(0.0679)</td>
<td>-0.4487(0.0676)</td>
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<td>Surgical service</td>
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<td>Age</td>
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<td></td>
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<tr>
<td>&lt; High school</td>
<td>0.0538(0.0301)</td>
<td>0.0534(0.0302)</td>
<td>0.0536(0.0299)</td>
<td>0.3760(0.0979)</td>
<td>0.3769(0.0981)</td>
<td>0.3871(0.0962)</td>
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<tr>
<td>Medicare insured</td>
<td>0.0347(0.0197)</td>
<td>0.0363(0.0197)</td>
<td>0.0397(0.0198)</td>
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<tr>
<td>Medicaid insured</td>
<td>0.2327(0.0310)</td>
<td>0.2302(0.0309)</td>
<td>0.2341(0.0309)</td>
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<td>Lower health status</td>
<td>0.1882(0.0189)</td>
<td>0.1856(0.0187)</td>
<td>0.1850(0.0188)</td>
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<td>-1.5940(0.0713)</td>
<td>-1.5918(0.0704)</td>
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<tr>
<td>White</td>
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<td>Level 2 predictors</td>
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<tr>
<td>Maintain a NH unit</td>
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<td>0.2013(0.1341)</td>
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<td>RN/inpatient days</td>
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<td>0.1034(0.1289)</td>
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<td>LPN/inpatient days</td>
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<td>0.0014(0.0006)</td>
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<td>Pct Medicaid</td>
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<td>Teaching status</td>
<td>0.0488(0.0079)</td>
<td>0.0333(0.0093)</td>
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<td>-0.2240(0.0544)</td>
<td>-0.1140(0.0595)</td>
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<td>-0.000001(0.0000)</td>
<td>-0.000001(0.0000)</td>
<td>0.000008(0.000004)</td>
<td>0.0000007(0.000004)</td>
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<td>Level 3 predictors</td>
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<td>HHI hosp. competition</td>
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<td>-0.153093(0.0640)</td>
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<td>0.8961(0.5308)</td>
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<td>Per-capita income</td>
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<td>0.0001(0.000005)</td>
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<td>Pet minority pop</td>
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<td>-0.0272(0.0059)</td>
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<td>Medicaid days/pop.</td>
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<td>0.00020(0.0001)</td>
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<td>No. RN FTEs/pop.</td>
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<td>No. LPN FTEs/pop.</td>
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<td>Resources pt care</td>
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<td>Excess capacity</td>
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<td>Teaching status</td>
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<tr>
<td>HMO penetration</td>
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</table>

Regression Coefficient Estimates (with Standard Error Estimates in Parentheses)
Table 11: Variances and Variances Accounted for at the Three Levels

<table>
<thead>
<tr>
<th></th>
<th>Null model</th>
<th>Null model % of total variance</th>
<th>Patient predict. only Model 1</th>
<th>Pat./hosp. pred. Model 2</th>
<th>Pat/hosp/mkt pred. Model 3</th>
<th>% var. explain. by Model 1</th>
<th>% var. explain. by Model 2</th>
<th>% var. explain. by Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coordination of care</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Within-hospitals</td>
<td>5.19681</td>
<td>95.90%</td>
<td>4.532</td>
<td>4.53188</td>
<td>4.53095</td>
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<tr>
<td>Between-hospitals</td>
<td>0.18144</td>
<td>3.35%</td>
<td>0.13971</td>
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<td>0.10182</td>
<td>11.63%</td>
<td>27.12%</td>
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<tr>
<td>Between-markets</td>
<td>0.04059</td>
<td>0.75%</td>
<td>0.02505</td>
<td>0.00487</td>
<td>0.00026</td>
<td>80.56%</td>
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<tr>
<td><strong>Continuity and transition of care</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Within-hospitals</td>
<td>3.79394</td>
<td>99.12%</td>
<td>3.63663</td>
<td>3.63678</td>
<td>3.636</td>
<td>4.15%</td>
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<td>Between-hospitals</td>
<td>0.02479</td>
<td>0.65%</td>
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<td>0.00889</td>
<td>0.23%</td>
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<tr>
<td><strong>Physical comfort</strong></td>
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<td>Within-hospitals</td>
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<td>0.03359</td>
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<td>0.00588</td>
<td>0.13%</td>
<td>0.00265</td>
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<td>80.75%</td>
<td>99.62%</td>
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<td><strong>Emotional support</strong></td>
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<tr>
<td>Within-hospitals</td>
<td>6.82111</td>
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<td>6.46128</td>
<td>6.46077</td>
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<td>0.06969</td>
<td>1.00%</td>
<td>0.04084</td>
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<td>0.00004</td>
<td>55.63%</td>
<td>99.90%</td>
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<tr>
<td><strong>Information and education</strong></td>
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<tr>
<td>Within-hospitals</td>
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<td>Between-hospitals</td>
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<td><strong>Involvement of family and friends</strong></td>
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<td>Within-hospitals</td>
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<td>Between-hospitals</td>
<td>0.01087</td>
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<td>0.0089</td>
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<td><strong>Overall satisfaction with care</strong></td>
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<tr>
<td>Within-hospitals</td>
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<td>0.74581</td>
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<td>0.55538</td>
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<tr>
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<td>0.15093</td>
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<td>0.0007</td>
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Table 12: Contrasting Findings to Hypotheses

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<td>Nurse Staffing</td>
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<tr>
<td>Hospital level</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Market level</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Resources directed to patient care</td>
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</tr>
<tr>
<td>Hospital level</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Market level</td>
<td>+</td>
<td>Mixed</td>
</tr>
<tr>
<td>Payor mix</td>
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<td></td>
</tr>
<tr>
<td>Medicare Days - Hospital level</td>
<td>+</td>
<td>–</td>
</tr>
<tr>
<td>Medicare Days - Market level</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Medicaid days - Hospital level</td>
<td>–</td>
<td>NS</td>
</tr>
<tr>
<td>Medicaid days - Market level</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Teaching status</td>
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<td></td>
</tr>
<tr>
<td>Hospital level</td>
<td>+</td>
<td>–</td>
</tr>
<tr>
<td>Market level</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Occupancy rate</td>
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<tr>
<td>Hospital level</td>
<td>+</td>
<td>–</td>
</tr>
<tr>
<td>Market level</td>
<td>+</td>
<td>Mixed</td>
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<tr>
<td>Government ownership</td>
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<td>Hospital level</td>
<td>+</td>
<td>NS</td>
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<tr>
<td>Market level</td>
<td>NA</td>
<td>NA</td>
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<tr>
<td>Hospital competition</td>
<td></td>
<td></td>
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<tr>
<td>Market level</td>
<td>+</td>
<td>–</td>
</tr>
<tr>
<td>HMO penetration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market level</td>
<td>+</td>
<td>Mixed</td>
</tr>
<tr>
<td>Socio-economic conditions</td>
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<td></td>
</tr>
<tr>
<td>Market’s per capita income</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Market’s percent. minority pop.</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

NA= Hypothesis was not applicable. NS= Relationship was not significant.
Mixed= Results were mixed
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suppl, 56S-89S.


Race/Ethnicity, Language, and Patients' Assessments of Care in Medicaid Managed Care. 


### Appendix A: NRC Picker Domains of Patient Assessments of Care and Comprising Items

<table>
<thead>
<tr>
<th>Domain</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coordination of care</td>
<td>1. How organized was the care you received in the emergency room?</td>
</tr>
<tr>
<td></td>
<td>2. How organized was the admission process?</td>
</tr>
<tr>
<td></td>
<td>3. Do you feel you had to wait an unnecessarily long time to go to your room?</td>
</tr>
<tr>
<td></td>
<td>4. Was there one particular doctor in charge of your care in the hospital?</td>
</tr>
<tr>
<td></td>
<td>5. Sometimes in the hospital, one doctor or nurse will say one thing and another will say something quite different. Did this happen to you?</td>
</tr>
<tr>
<td></td>
<td>6. Were your scheduled tests and procedures performed on time?</td>
</tr>
<tr>
<td>Continuity and transition of care</td>
<td>1. Did someone from the hospital staff explain the purpose of the medicines you were to take home in a way you could understand?</td>
</tr>
<tr>
<td></td>
<td>2. Did someone tell you about medication side effects to watch for when you went home?</td>
</tr>
<tr>
<td></td>
<td>3. Did they tell you what danger singles about your illness or operation to watch for after you went home?</td>
</tr>
<tr>
<td></td>
<td>4. Did they tell you when you could resume your usual activities, such as when to go back to work or drive a car?</td>
</tr>
<tr>
<td>Physical comfort</td>
<td>1. When you needed help getting to the bathroom, did you get it in time?</td>
</tr>
<tr>
<td></td>
<td>2. How many minutes after you used the call button did it usually take before you got the help you needed?</td>
</tr>
<tr>
<td></td>
<td>3. How many minutes after you requested pain medicine did it usually take before you got it?</td>
</tr>
<tr>
<td></td>
<td>4. Do you think the hospital staff did everything they could to help you control you pain?</td>
</tr>
<tr>
<td>Emotional support</td>
<td>1. If you had any anxieties or fears about your condition or treatment, did a doctor discuss them with you?</td>
</tr>
<tr>
<td></td>
<td>2. Did you have confidence and trust in the doctors treating you?</td>
</tr>
<tr>
<td></td>
<td>3. If you had any anxieties or fears about your condition or treatment, did a nurse discuss them with you?</td>
</tr>
<tr>
<td></td>
<td>4. Did you have confidence and trust in the nurses treating you?</td>
</tr>
<tr>
<td></td>
<td>5. Was it easy for you to find someone on the hospital staff to talk to about your concerns?</td>
</tr>
<tr>
<td></td>
<td>6. Did you get as much help as you wanted from someone on the hospital staff in figuring out how to pay your hospital bill?</td>
</tr>
<tr>
<td>Domain</td>
<td>Item</td>
</tr>
<tr>
<td>------------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Information and education</td>
<td>1. While you were in the emergency room, did you get enough information about your medical condition and treatment?</td>
</tr>
<tr>
<td></td>
<td>2. If you had to wait to go to your room, did someone from the hospital explain the reason for the delay?</td>
</tr>
<tr>
<td></td>
<td>3. When you had important questions to ask a doctor, did you get answers you could understand?</td>
</tr>
<tr>
<td></td>
<td>4. When you had important questions to ask a nurse, did you get answers you could understand?</td>
</tr>
<tr>
<td></td>
<td>5. Did a doctor or nurse explain the results of tests in away you could understand?</td>
</tr>
<tr>
<td>Involvement of family and</td>
<td>1. Did your family or someone close to you have enough opportunity to talk to your doctor?</td>
</tr>
<tr>
<td>friends</td>
<td>2. How much information about your condition or treatment was given to your family or someone close to you?</td>
</tr>
<tr>
<td></td>
<td>3. Did the doctors and nurses give your family or someone close to you all the information they needed to help you recover?</td>
</tr>
<tr>
<td>Respect for patient</td>
<td>1. Did doctors talk in front of you as if you were not there?</td>
</tr>
<tr>
<td>preferences</td>
<td>2. Did nurses talk in front of you as if you were not there?</td>
</tr>
<tr>
<td></td>
<td>3. Did you have enough say about your treatment?</td>
</tr>
<tr>
<td></td>
<td>4. Did you feel like you were treated with respect and dignity while you were in the hospital?</td>
</tr>
<tr>
<td>Overall satisfaction with</td>
<td>1. How would you rate the courtesy of the staff who admitted you?</td>
</tr>
<tr>
<td>care</td>
<td>2. How would you rate the courtesy of your doctors?</td>
</tr>
<tr>
<td></td>
<td>3. How would you rate the courtesy of your nurses?</td>
</tr>
<tr>
<td></td>
<td>4. How would you rate the availability of your doctors?</td>
</tr>
<tr>
<td></td>
<td>5. How would you rate the availability of your nurses?</td>
</tr>
<tr>
<td></td>
<td>6. How would you rate how well the doctors and nurses worked together?</td>
</tr>
<tr>
<td></td>
<td>7. Overall, how would you rate the care that you received at the hospital?</td>
</tr>
<tr>
<td></td>
<td>8. Would you recommend this hospital to your friends and family?</td>
</tr>
</tbody>
</table>
Appendix B: The Patients’ Evaluations of Patient Assessments of Care (PEP-C) Survey Instrument

Your hospital stay...

Please fill in the bubble that best describes your experience during your recent hospital stay ending on __________. Only the patient who was hospitalized should fill out this questionnaire.

EMERGENCY ROOM...
1. How organized was the care you received in the emergency room?
   - Not at all organized
   - Somewhat organized
   - Very organized
   - Didn’t use emergency room
2. While you were in the emergency room, did you get enough information about your medical condition and treatment?
   - Yes, definitely
   - No
   - Didn’t use emergency room

ADMISSION...
3. How organized was the admission process?
   - Not at all organized
   - Somewhat organized
   - Very organized
4. Do you feel you had to wait an unnecessarily long time to go to your room?
   - Yes, definitely
   - Yes, somewhat
   - No
5. If you had to wait to go to your room, did someone from the hospital explain the reason for the delay?
   - Yes
   - No
   - Didn’t have to wait
6. How would you rate the courtesy of the staff who admitted you?
   - Poor
   - Fair
   - Good
   - Very Good
   - Excellent

DOCTORS...
7. Was there one particular doctor in charge of your care in the hospital?
   - Yes
   - No
   - Not sure
8. When you had important questions to ask a doctor, did you get answers you could understand?
   - Yes, always
   - Yes, sometimes
   - No
   - Didn’t have questions
9. If you had any anxieties or fears about your condition or treatment, did a doctor discuss them with you?
   - Yes, completely
   - Yes, somewhat
   - No
   - Didn’t have anxieties or fears
10. Did you have confidence and trust in the doctors treating you?
    - Yes, always
    - Yes, sometimes
    - No
11. Did doctors talk in front of you as if you weren’t there?
    - Yes, often
    - Yes, sometimes
    - No
12. How would you rate the courtesy of your doctors?
    - Poor
    - Fair
    - Good
    - Very Good
    - Excellent
13. How would you rate the availability of your doctors?
    - Poor
    - Fair
    - Good
    - Very Good
    - Excellent

NURSES...
14. When you had important questions to ask a nurse, did you get answers you could understand?
    - Yes, always
    - Yes, sometimes
    - No
    - Didn’t have questions
15. If you had any anxieties or fears about your condition or treatment, did a nurse discuss them with you?
    - Yes, completely
    - Yes, somewhat
    - No
    - Didn’t have anxieties or fears
16. Did you have confidence and trust in the nurses treating you?
    - Yes, always
    - Yes, sometimes
    - No
17. Did nurses talk in front of you as if you weren’t there?
    - Yes, often
    - Yes, sometimes
    - No
18. How would you rate the courtesy of your nurses?
☐ Poor ☐ Fair ☐ Good ☐ Very Good ☐ Excellent
19. How would you rate the availability of your nurses?
☐ Poor ☐ Fair ☐ Good ☐ Very Good ☐ Excellent

HOSPITAL STAFF...
20. Sometimes in the hospital, one doctor or nurse will say one thing and another will say something quite different. Did this happen to you?
☐ Yes, always ☐ Yes, sometimes ☐ No
21. Did you have enough say about your treatment?
☐ Yes, definitely ☐ Yes, somewhat ☐ No
22. Did your family or someone else close to you have enough opportunity to talk to your doctor?
☐ Yes, definitely ☐ No ☐ Family didn't want or need to talk
☐ Yes, somewhat ☐ No family or friends were involved
23. How much information about your condition or treatment was given to your family or someone close to you?
☐ Not enough ☐ Too much ☐ Family didn't want or need information
☐ Right amount ☐ No family or friends involved
24. Was it easy for you to find someone on the hospital staff to talk to about your concerns?
☐ Yes, definitely ☐ Yes, somewhat ☐ No ☐ Didn't want to talk/no concerns
25. When you needed help getting to the bathroom, did you get it in time?
☐ Yes, always ☐ Yes, sometimes ☐ No ☐ Didn't need help
26. How many minutes after you used the call button did it usually take before you got the help you needed?
☐ 0 minutes/right away ☐ 6-10 minutes ☐ 16-30 minutes ☐ Never used call button
☐ 1-5 minutes ☐ 11-15 minutes ☐ More than 30 minutes ☐ Never got help
27. Did a doctor or nurse explain the results of tests in a way you could understand?
☐ Yes, completely ☐ Yes, somewhat ☐ No ☐ No tests were done
28. Were your scheduled tests and procedures performed on time?
☐ Yes, always ☐ Yes, sometimes ☐ No ☐ No tests/procedures
29. Did you feel like you were treated with respect and dignity while you were in the hospital?
☐ Yes, always ☐ Yes, sometimes ☐ No

PAIN...
30. Were you ever in any pain?
☐ Yes ☐ No (Go to #37)
31. When you had pain, was it usually severe, moderate, or mild?
☐ Severe ☐ Moderate ☐ Mild
32. Did you have a machine that you could use to give yourself pain medicine?
☐ Yes (Go to #35) ☐ No
33. Did you ever request pain medicine?
☐ Yes ☐ No (Go to #35)
34. How many minutes after you requested pain medicine did it usually take before you got it?
☐ 0 minutes/right away ☐ 6-10 minutes ☐ 16-30 minutes ☐ Never got medicine
☐ 1-5 minutes ☐ 11-15 minutes ☐ More than 30 minutes
35. Do you think that the hospital staff did everything they could to help control your pain?
☐ Yes, definitely ☐ Yes, somewhat ☐ No
36. Overall, how much pain medicine did you get?
☐ Not enough ☐ Right amount ☐ Too much

SURGERY...
37. Did the surgeon explain the risks and benefits of the surgery in a way you could understand?
☐ Yes, completely ☐ No ☐ I didn't want anything explained
☐ Yes, somewhat ☐ Explained to spouse or someone else
38. Did the surgeon or any of your other doctors answer your questions about the surgery in a way you could understand?
☐ Yes, completely ☐ Yes, somewhat ☐ No ☐ I didn't have any questions
39. Did a doctor or nurse tell you accurately how you would feel after surgery?
   ○ Yes, completely ○ Yes, somewhat ○ No

40. Were the results of the surgery explained in a way you could understand?
   ○ Yes, completely ○ Yes, somewhat ○ No ○ Explained to spouse or someone else

GOING HOME...
41. Did someone on the hospital staff explain the purpose of the medicines you were to take at home in a way you could understand?
   ○ Yes, completely ○ Yes, somewhat ○ No ○ Didn't need explanation ○ No medicines at home

42. Did someone tell you about medication side effects to watch for when you went home?
   ○ Yes, completely ○ Yes, somewhat ○ No ○ Didn't need explanation ○ No medicines at home

43. Did they tell you what danger signals about your illness or operation to watch for after you went home?
   ○ Yes, completely ○ Yes, somewhat ○ No

44. Did they tell you when you could resume your usual activities, such as when to go back to work or drive a car?
   ○ Yes, completely ○ Yes, somewhat ○ No

45. Did the doctors and nurses give your family or someone close to you all the information they needed to help you recover?
   ○ Yes, definitely ○ No ○ Family didn't want or need information
   ○ Yes, somewhat ○ No family or friends involved

46. While you were in the hospital, how worried were you about how you would pay your hospital bill?
   ○ Very worried ○ Somewhat worried ○ Not at all worried

47. Did you get as much help as you wanted from someone on the hospital staff in figuring out how to pay your hospital bill?
   ○ Yes, definitely ○ Yes, somewhat ○ No ○ Didn't want or need any help

OVERALL IMPRESSION...
48. How would you rate how well the doctors and nurses worked together?
   ○ Poor ○ Fair ○ Good ○ Very Good ○ Excellent

49. Overall, how would you rate the care you received at the hospital?
   ○ Poor ○ Fair ○ Good ○ Very Good ○ Excellent

50. Would you recommend this hospital to your friends and family?
   ○ Yes, definitely ○ Yes, probably ○ No

The next questions are used to make sure we hear from all our patients. Please tell us a little about yourself.

YOUR BACKGROUND...
51. In general, how would you rate your health?
   ○ Poor ○ Fair ○ Good ○ Very good ○ Excellent

52. During the past month, how many days did illness or injury keep you in bed all or part of the day?
   ○ None ○ Two Days ○ Four Days ○ Eight-to-Ten Days
   ○ One Day ○ Three Days ○ Five-to-Seventeen Days ○ More than Ten Days

53. Including this hospital stay, how many times in the last six months have you been in a hospital overnight or longer?
   ○ Only this time ○ This time and one other time ○ This time and more than one other time

54. Do you belong to an HMO or health plan that has a list of people or places you go to, in order for the plan to cover your health care costs?
   ○ Yes ○ No ○ Not sure

55. What health insurance plan do you use to cover most or all of your medical care?
   ○ Medicare ○ Medicaid ○ Something else ○ I have no insurance ○ Not sure

56. What was the last year of school you completed?
   ○ Less than high school graduate ○ High school graduate or GED ○ College graduate or Post college graduate education
   ○ Some college, trade, or tech school

57. What is your current marital status?
   ○ Married ○ Divorced ○ Separated ○ Widowed ○ Never married
58. Are you of Hispanic or Spanish family background?
   ○ No
   ○ Yes, North American (Mexican, Mexican American, Chicano)
   ○ Yes, Central American
   ○ Yes, South American
   ○ Yes, Other Spanish/Hispanic/Latino

59. Which of the following best describes your racial background?
   ○ White
   ○ Black, African American, or Negro
   ○ American Indian or Alaska Native (North, South, and Central American Indian)
   ○ Native Hawaiian
   ○ Guamanian
   ○ Samoan
   ○ Other Pacific Islander
   ○ Asian Indian
   ○ Cambodian

   ○ Chinese
   ○ Filipino
   ○ Japanese
   ○ Hmong
   ○ Korean
   ○ Laotian
   ○ Vietnamese
   ○ Other Asian
   ○ Other

60. What language do you speak at home most of the time?
   ○ English
   ○ Chinese
   ○ Korean
   ○ Russian
   ○ Other
   ○ Spanish
   ○ Vietnamese
   ○ Tagalog
   ○ Armenian

MORE QUESTIONS ABOUT YOUR NURSES...
61. How often did a nurse ask you if you had pain?
   ○ At least once a day
   ○ Less than once a day
   ○ Don't remember

62. Did you receive information from your nurses about your care and treatment?
   ○ Yes
   ○ No

63. Was it as much information as you needed or would you have liked more?
   ○ Enough assistance was provided.
   ○ Additional assistance would have been helpful.

64. Did you need help planning for your needs after discharge from the hospital?
   ○ Yes
   ○ No
   ○ (Go to comment question)

65. Did you receive help from your nurses in planning for your needs after discharge?
   ○ Yes
   ○ No

66. Was the help you received as much as you needed or would you have liked more?
   ○ As much as I needed
   ○ Would have liked more

67. An interpreter is someone who repeats or signs what one person says in a language used by another person. Did you need an interpreter to help you speak with doctors or other health providers?
   ○ Yes
   ○ No

68. When you needed an interpreter to help you speak with doctors or other health providers, how often did you get one?
   ○ Never
   ○ Sometimes
   ○ Usually
   ○ Always
   ○ I didn't need an interpreter

69. If you could change one thing about the hospital, what would it be?


Thank you for taking the time to complete this questionnaire! Your answers are greatly appreciated.

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VITAE

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