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AN ANALYSIS OF THE FACTORS DRIVING HOSPITAL READMISSIONS, AND THE POTENTIAL FOR COORDINATION GAMES UNDER THE MEDICARE READMISSIONS REDUCTION ACT

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ABSTRACT

The Medicare Readmissions Reduction Act is a new piece of legislation designed to improve the quality of medical care provided to Medicare patients throughout the nation. This legislation is designed to provide Medicare patients with a higher quality of care, but in practice can lead to a coordination game between a hospital and their patients, and between different healthcare facilities. Multivariate regression was employed to isolate the socioeconomic and hospital factors which most contribute to readmissions. It was found that population size and diversity, crime rate, number of admissions from the emergency department, and the availability of nurses at long term care facilities all drive the readmission rate. Given this, analysis of the coordination game demonstrates that the legislation may incentivize hospitals to reduce care in some circumstances. Changes are proposed to improve the quality of the legislation and to remove these negative incentives before patient care is impacted too strongly.

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Chapter 1

Introduction

In the United States, approximately 20% of all Medicare patients are readmitted to the hospital after they are discharged. This trend costs Medicare billions of dollars annually, and the Center for Medicare and Medicaid sees this number as an indication that the quality of health care in the United States is not high enough.

In October 2012, the Medicare Readmissions Reduction program took effect as part of the Affordable Care Act. The goal of this program is to reduce avoidable readmissions for certain conditions by penalizing hospitals that have higher than average readmission rates. In the law, an excess readmission is defined as a patient who is readmitted within 30 days of initial discharge, after being admitted for *myocardial infarction, pneumonia,* or *heart failure.* Although there are many other conditions that might create a readmission, these are the only three currently counted towards the readmission rate.

Each hospital is held to a national average standard, which is risk adjusted for individual hospitals based on patient socioeconomics, comorbidities, and patient frailty. Hospitals whose readmission rates exceed the risk-adjusted average will have their Medicare reimbursements penalized by up to 1% in 2013, increasing to 3% by 2015.

The goal of this legislation is to place the burden of decreasing readmissions on the hospitals, by forcing them to provide higher quality of care pre and post-discharge. This could include more physician-patient interaction prior to discharge, partnering with higher quality nursing and rehabilitation facilities, and implementing more efficient means of tracking patient recovery after they return home.

In the pre-policy era, hospitals and patients engaged in strategic interaction, where the optimal effort for both parties is a function of the perceived effort of the other. While this coordination game exists inside the hospital, there was no interaction between hospitals during this time. Under the policy, a hospital's readmission rate is measured against the national average, which opens the possibility for strategic interaction between hospitals.

The goal of this paper is to assess the policy by developing a deeper understanding of the factors that drive readmissions, and to ultimately analyze how these factors may come together in the context of a coordination game. We will start by exploring the theory behind the two coordination games, and then transition into an analysis of the literature and empirical readmission data. Lastly, the potential coordination games will be analyzed, and policy implications of the data and the strategic interaction will be explored.

Chapter 2

Theoretical Framework behind the Policy

Considering the overview of the policy presented in Chapter (1), it is now possible to begin exploring a theoretical model that can explain the decisions being made by patients and hospitals. To approach this, we will consider there to be two separate maximization problems: the hospital maximizing patient care effort, and the patient maximizing effort in their own recovery.

Hospital Maximization Problem

When a patient presents at the hospital, the nurses and physicians are responsible for determining what level of care is appropriate. However, with the implementation of the Medicare Readmissions Reduction program, it is possible that the determination of appropriate care will be influenced by factors other than medical necessity. One of the biggest factors may be the patient's perceived likelihood of being compliant with the medical treatment –their effort level- and their chance of being readmitted to the hospital after the treatment. In essence, the hospital needs to determine how to maximize their utility given the perceived value of the patient. Equation (1) attempts to model this relationship, where optimal effort level should maximize:

$$(1) \qquad Value = R - C(e) + \beta[P(e,c)V^H + \left((1-P)[e,c]V^S\right)]$$

Where R is the reimbursement rate from Medicare; C(e) is the cost of providing care at effort level e; P(e,c) is the probability of the recovery from hospital effort given patient effort; V^Hrepresents the value of a patient who is healed, and $V^S$is the value of a patient who is not healed.

Simply put, value is measured by the amount they are reimbursed, minus the cost of providing care, plus the value received by the patient getting healthy given the probability that they provide effort toward their own recovery, or not healing the patient and treating them in a second period given the probability they do not provide effort toward their own recovery.

Additionally, this equation can be rearranged to solve for the value of a patient if they are readmitted in a second period:

$$V^S = max_e[R^A - C(e)] - \Gamma \tag{2}$$

The value of a readmitted patient is equal to the maximization of hospital effort given the value of R^A, a second Medicare reimbursement; C(e), the cost of the effort, and Γ, the cost (implicit and explicit) of a readmission. In the pre-policy period, this stigma would be lower, and include factors such as patient dissatisfaction. In the post-policy era, this would also include the financial implications of incurring readmissions deemed to be excessive. Ultimately, these two equations are solved for Equation 3, the first order condition:

$$C'(e) = \beta(V^H - V^S)\frac{dp}{de} \tag{3}$$

Where effort is maximized when the first derivative of C(e) equals the partial derivative of $[P(e,c)V^H + (1 - P[e,c]V^S)]$ with respect to effort.

From these equations, it is easy to see that the hospital has an incentive to toggle the level of care based on the signals they perceive from their patients. If the patient has a very high value to the hospital if they are healed, the first order condition implies that the hospital will invest more resources to cure them. On the contrary, if the value of curing them is very low, less treatment effort will be expended, as high levels of effort are no longer effort maximizing.

Given this and the structure of the second equation, we can see where the implementation of the Readmissions Reduction Act can significantly alter the optimal hospital effort response. In the pre-policy era, there was no penalty for excessive readmission rates. Because of this, it is likely that the value of a healthy patient was significantly less than a sick patient. If the patient is healed, they only provide value at their first visit. If they are not healed, they provide value at their initial visit, plus value of visits in the future captured in equation 2.

After the implementation of the policy, the optimal effort equation suggests that there will be an opposite shift. Due to the increasing penalty of avoidable readmissions, hospitals may determine that the optimal response is to treat the patient as aggressively as possible to avoid a readmission. However, certain circumstances exist that may make minimal treatment and incurring a readmission the effort maximizing optimal solution. Regardless of the hospital's effort in the first period, if the patient is readmitted, they will be counted against the hospitals record. If the hospital can say with some certainty that the patient will be readmitted regardless of the care they are provided, it would not be effort or utility maximizing to invest heavily in treatment in the first period, when they will be penalized and forced to invest into the same problem in period 2.

Patient Maximization Problem

Similarly to how the hospital chooses its effort through a utility maximization problem, the patient also decides on their optimal level of effort. There are three main factors that are argued to be part of the patients effort maximization: the maximized effort level of the hospital, socioeconomic and demographic factors unique to that patient, and the cost of the effort needed to heal themselves.

Starting with the patient-perceived effort level of the hospital, there are two possible relationships that may exist: patients may view hospital effort as either a complement or substitute to their own effort. If someone knows that a hospital puts in high effort, they might be inclined to put less effort in, knowing that the hospital probably will take care of their problem anyhow. At the same time, they might put in more effort, knowing that their chance of healing is greater when both they are the hospital work really hard.

If the two were substitutes, patient effort would be inversely related to hospital effort: $E_P = E_H^{-1}$, whereas a complementary relationship would cause the two factors to increase together, such that the patient's effort is equal to the effort they would initially provide raised to the power of hospital effort multiplied by β: $E_P = E_{P_o}{}^{\beta E_H}$. Ultimately, the stronger effect would dominate the relationship. For the purpose of simplicity, however, this paper assumes that the relationship is complementary in all instances.

Socioeconomics also plays a role, and is tied directly into the cost of effort. A patient's optimal effort level is constrained by the resources they have. If for instance, they do not have a high level of education, they may not have a strong understanding of how to treat themselves; if they have a very low income, they may be limited in their ability to recover, regardless of their understanding of what needs to be done.

The cost of effort can be a major barrier to the level of effort a patient can put forth. Income is a direct constraint, as it may make additional treatments and rehabilitation unaffordable. Additionally, those in lower income households may also be constrained by the opportunity cost of effort; the impact of lost wages may drastically reduce the efficient level of patient recovery effort.

These three factors combine into Equation (4), the patient's value function:

$$(4) \qquad Value = -C(c,\Gamma) + \beta[P(c,e)V^H + (1 - P[c,e]V^S)$$

Where C(e) is the cost of recovery effort (financial and economic) given a patient-specific bundle of socioeconomic factors, Γ. V^H is the value of getting healthy, given P[c,e], the probability that the patient recovers from their level of effort given hospital effort. V^S is the value of remaining sick given (1-P[c,e]), the probability that they do not receive care given their effort. Similar to the hospital function, the first order condition would be:

$$(5) \qquad C'(c,\Gamma) = \beta(V^H - V^S)\frac{dp}{de}$$

Where effort is maximized when the first derivative of -C(c) equals the partial derivative of $[P(c,e)V^H + (1 - P[c,e]V^S)]$ with respect to effort.

Introduction to the Coordination Framework

Since the hospital and the patient base their effort decisions in part by the perceived response of the other player, it is plausible that strategic interaction will develop between the two players. While there is some communication between the hospital and the patient, it is likely that much of the effort responses will be determined through signals. The hospital will perceive socioeconomic data about the patient to be a signal that represents the projected effort (and thus readmission risk) of the patient, and at the same time the hospital and the physician will be signaling to the patient about their projected level of effort in patient care. Ultimately, these "signals" are the different variables – the socioeconomic and hospital factors – that influence the readmission rate. The remainder of this paper will be spent exploring these different variables, illuminating the ones that actually predict readmission risk, and exploring the implications such variables have on the maximization equations and on real-world patient care. In the next section, we will explore the relationships found between these variables in the literature.

Chapter 3

Literature Review

In the study of this legislation, two important factors influencing readmissions must be considered. First are the patient specific factors, which make an individual more or less likely to be readmitted. The second are hospital factors, which dictate how sensitive a hospital is to incurring readmission penalties.

Patient Specific Factors Influencing Readmissions

The most intuitive cause of readmissions is patient health status. Severity of illness, presence of other comorbidities, and patients age all have a direct impact on the likelihood of readmission.

A second factor that influences patient readmission likelihood is the effort they exert for their own recovery. If a patient feels that they are receiving very high quality care, they will have a different effort response than a patient who is not satisfied with their care experience.

Socioeconomics play a large role in a patients readmission risk. EMTALA, the Emergency Medical Treatment and Labor Act, mandates that hospitals must provide appropriate emergency care to a patient without regard to their ability to pay. Although everyone in the country has access to hospital care, a full recovery requires ongoing care and oversight after discharge. Because the law does not mandate that these services are available to everyone, Grande, et al, proposed that readmission rates are influenced by several factors correlated with socioeconomic status.

One obvious factor that influences recovery after discharge is ability to pay for these services. Simply put, those with the means to pay for better rehabilitation and follow-up visits with specialists tend to recover faster and more fully. However, other factors limit the recovery of those in lower socioeconomic brackets. Accessibility of reliable transportation or childcare services both complicate the recovery process. Additionally, it was suggested that people with lower socioeconomic status might have less access to social support groups. These factors work together to complicate recovery.

Weissman et al. found that socioeconomic variables do correlate with readmission rates. In their empirical study, income level, employment sector and home ownership were both statistically significant predictors of readmission likelihood. They found that those patients classified as "poor", employed in unskilled or low-skilled labor markets, or rented in lieu of purchasing, had a higher probability of being readmitted to the hospital. It is likely, however, that employment sector and home ownership are both proxies for income level, as unskilled jobs pay significantly less, which would impede ones ability to own a home.

Although Grande et al. did not define what factors are considered "social support", Weismann et al. did not find a significant correlation between marital status, living situation, or availability of help at home on readmission rates, suggesting that the majority of the readmission risk in this group is generated from being economically disadvantaged. However, Amarasingham et al. did find marital status, frequent address changes, and zip-code income levels to play a role in readmission rate.

Regardless of the impact that non-monetary social factors play, there is a general consensus that socioeconomic factors do influence readmissions. For patients in lower socioeconomic brackets, it can be challenging or impossible to comply with prescribed treatment plans. Instead of actively working towards recovery with preventative and proactive medicine, these patients deteriorate at home until the point that they go to the emergency room. Frequently, they are past the point of preventative care, and are readmitted for intensive inpatient management.

Hospital-Specific Factors Influencing Readmissions

The first major component of hospital-controlled readmissions is care quality, which includes technology, availability of specialty services, staff training and patient to provider ratios.

Hospital care effort is another component of readmission risk. Hospitals and doctors who allocate more resources toward the recovery of patients will have lower readmission rates. Several factors independent of illness severity influence the effort level that a hospital might exert on a given patient. Signals from the patient that suggest they will not be compliant with treatment plans can lower care effort. If a patient is not going to exert effort to recover, some physicians may choose not to work as hard to treat them. Lack of compliance can also stem from socioeconomic struggles, causing patients with already elevated risk for readmission to receive a lower care effort. Nicholas et al. demonstrated that hospitals do maximize their effort where payoffs are largest. Hospital effort was analyzed under a pay-for-performance program, where hospitals are reimbursed based on the number of successful interventions they preform. Patients suffering from heart attacks, failure, and pneumonia were studied. Nicholas et al. found that under this type of payment program, the number of easy procedures performed for heart attack patients increased. They did not, however, find significant evidence that challenging procedures were avoided in favor of easier ones.

Hospital’s readmission rates are also highly sensitive to several factors beyond quality of inpatient care. Because socioeconomic factors influence readmissions at the individual level, it is natural that hospital’s readmissions are correlated to the socioeconomics of the population they serve.

Safi et al. found that heart failure readmission rates were significantly higher for patients in low-income urban environments than those from the suburbs. This is consistent with the patient-level socioeconomic findings of Grande et al. and Weissman et al. Safi et al. also documented that of the studied patients, African Americans and those in low-income urban households had significantly higher blood pressures and resting heart rates. This gives weight to the argument that many avoidable readmissions are a result of limited access to quality medical care in the outpatient environment. One factor that was proposed by Grande et al. that would be a fair measure of predicting these preventable readmissions is linking patients to their zip code, which could be used as a proxy for the socioeconomic factors previously discussed.

An additional factor that might influence a hospital's sensitivity to readmissions is their ownership status. In 2010, Joynt et al. discovered that readmissions are highest in for-profit hospitals. Since this was before the Readmission Reduction program was enacted, it is plausible that for-profit institutions readmitted more patients to increase revenue, as there were no incentives to avoid doing so. Additionally, it is probable that hospitals with lower ratios of Medicare patients will be less sensitive to the readmission penalties than those who deal heavily with Medicare. For both of the possibilities, a review of Medicare's fiscal year 2013 data would be prudent, although it is not currently available to the public.

Despite the fact that many readmissions are occurring on the basis of socioeconomic outpatient care barriers, the burden of the readmission penalty falls on hospitals. This has interesting implications. As Grande et al. suggested, hospitals might become more selective in who they choose to readmit, focusing on those patients with the best chance of paying for services. This assertion was supported by Weismann et al. who found a statistically significant difference in readmission rates of insured vs. uninsured patients, and in white vs. nonwhite patients.

The Model and Potential Equilibria

Understanding the different factors that play into patient and hospital-induced readmission risk is essential in the development of an accurate theoretical model. In the reviewed literature, socioeconomics has been identified as a major component of both. Kansagara et al. conducted a lengthy literature review of 26 different models designed to predict a patient's readmission risk. These models were found to have poor predictive value. While no single model was reliable at predicting readmissions, Kansagara et al. claim that readmissions are a factor of both clinical quality of care, socioeconomics, and availability of post-discharge support and primary care physicians.

In the above discussion, both hospitals and patients have factors that influence readmission risks. For a patient, these include overall health level, recovery effort level, and socioeconomic status, which include access to primary care. Hospital readmission determinants are hospital quality, effort, and socioeconomics. Because readmission is partly reliant on the effort level of hospitals and of patients, the relationship between the two parties will be explored as a coordination game.

Additionally, with the Readmissions Reduction policy in effect, a coordination game will also develop between healthcare facilities. Because the Medicare penalties are only 1% of reimbursements in the first year, it is possible that the value of the penalty does not outweigh the cost of reducing readmissions below penalty level. This is especially true for hospitals with fewer Medicare patients, who are not included in the readmission penalties. For these facilities, it is possible that the legislation will actually incentivize them to provide worse care.

While it seems unlikely that hospitals would intentionally decrease care quality, Grieco et al. demonstrated the existence of a similar equilibrium in dialysis clinics. In the trade off between treating more patients and providing higher quality of care, such clinics could treat one additional patient at the expense of a 0.8 percentage point increase in clinic infection rate. When faced with cost reduction incentives, many of these clinics have incentives to lower care quality, not patient volume.

If hospitals respond similarly to the Medicare penalties, it is possible that the care quality reduction will be widespread. If any given hospital believes that the majority of other hospitals will do this, there is the potential for a care-reducing equilibrium that would raise the readmission rates enough to shield offending hospitals from readmission penalties. Now that there is an understanding of the factors significant in the literature, we will consider empirical data from the state of Pennsylvania

Chapter 4

Empirical Analysis: Factors Driving Readmissions in Pennsylvania

The first step in analyzing the potential coordination game is to understand the different variables that influence the readmission rate in hospitals. From the literature, it is apparent readmissions are driven by both hospital factors, and socioeconomic factors of the populations they treat.

Socioeconomic status, including income level, employment sector and education level, marital status, and stability of the home environment, all may play a role in readmissions.

Hospital variables are less explicit in the literature, where it is said that readmissions are driven by overall "quality of care." As a measure of care quality, I propose that the size of the emergency department (as a proxy for the relative "busy-ness" of the hospital), physician-to-patient ratio, number of patients treated vs. number admitted, and the overall number of physicians (as a proxy for teaching status and availability of specialty services) will all influence the readmission rate. In this section, the impact these variables have on readmission rate will be explored in detail.

Data Sample

To understand the impact of these variables on readmission, all Pennsylvania hospitals listed in the Center for Medicare and Medicaid Hospital data set were initially considered. The single dependent variable of interest was the raw readmission rate, or the number of readmissions divided by the total number of discharges. While the Medicare Readmissions Reduction act focuses on the *excess readmission ratio* for their readmission penalties, that number is not sufficient for this analysis. It is already risk adjusted for socioeconomic and hospital variation, and as such, it would be impossible to draw correlations from the data as each variable's impact is already neutralized.

As such, all hospitals lacking a raw readmissions rate were removed from the data set. In addition to the CMS data, hospital-specific emergency room data was gathered from the Pennsylvania Department of Health. Any hospital that was not adequately represented in the DOH data was removed from this data set.

For the remaining hospitals, seven main socioeconomic data points relating to the hospitals geographic location were collected from various online databases: population, average annual income, racial composition, marriage rate, and unemployment rate. Additionally, measures predicted to impact hospital quality were obtained from the Pennsylvania Department of Health. For each hospital, annual emergency room visits and admissions resulting from emergency room visits were obtained, as was the number of board-certified and resident emergency physicians on staff.

In addition to the hospitals excluded for the above reason, any facilities lacking a significant amount of socioeconomic data were omitted from the study. Ultimately 111 hospitals were selected for this regression, seen below in Appendices 1 and 2, ranging from rural community hospitals to major teaching facilities in Pittsburgh and Philadelphia.

Although the Readmission Reduction Act focuses mainly on the performance of an individual hospital, it is likely that nursing homes play a large role in the readmission rate. Given that hospitals discharge some percentage of their Medicare patients to nursing homes, partnership with sub-par nursing facilities would result in an increased raw-readmission rate. For this reason, county-level nursing home data was obtained from CMS. The individual nursing homes in each county were compiled into county-level statistics for the following measures: raw number of nursing homes, average number of beds per facility, average occupied beds, average percentage of maximum capacity, average score (1-5 scale, assigned by Medicare after a holistic review of the entire facility), health inspection score (1-5), registered nurse rating (1-5), overall staff rating (1-5), daily RN, LPN, and CAN hours per resident, average annual number of reportable incidents, and average annual number of substantiated claims against the facility.

Regression Format

In order to test the impact of the abovementioned socioeconomic, nursing and hospital variables on readmission rates, several OLS regressions were done to isolate the different factors that are significant in each of the three readmission determinants (socioeconomics, hospital and nursing homes). The results can be found in tables 1-3 below:

Table 1: Socioeconomic Variables

	Raw Readmission Rate	
	coefficient	t-score
Population	3.79E-08	2.87
Income	1.54E-07	0.12
Caucasian Population (%)	0.1176	2.34
Education ≥ Bachelor's (%)	0.1276	1.58
Married Population (%)	0.0882	0.72
Crime Rate	1.28E-04	3.37
Unemployment Rate	1.13E-03	0.26
constant	-1.26E-02	-0.15
n = 88		

Table 1: Regression Results for the Socioeconomic Readmission Factors

Table 2: Hospital Variables

	Raw Readmission Rate	
	coefficient	t-score
Annual ER Visits	1.85E-06	0.9
Annual Admissions from ER	-1.49E-05	-1.3
Number of ER physicians	-1.40E-04	-0.07
ER admission ratio	1.2988	2.08
constant	4.47E-02	0.41
n = 88		

Table 2: Regression Results for Hospital Readmission Factors

Table 3: County-Level Nursing Home Variables

	Raw Readmission Rate	
	coefficient	t-score
Nursing Homes in County	1.89E-03	1.4
Certified Beds	-2.41E-04	-0.05
Occupied Beds	-1.14E-04	-0.02
CMS Score	-5.32E-02	-0.45
Health Inspection Score	2.93E-01	0.27
Overall Staff Rating	1.26E-01	0.99
RN Rating	-1.35E-01	0.99
CNA Rating	-1.86E-01	-1
LPN Hours	-8.97E-02	-0.44
RN Hours	1.52E-01	0.81
Reportable Incidents	7.50E-03	0.1
Substantiated Claims	-1.42E-03	-0.07
Number of Fines	-7.28E-03	-0.05
constant	7.66E-01	1.4
n = 88		

Table 3: Regression Results for Nursing Home Readmission Factors

Starting with Table 1, it is evident that many of the literature-suggested determinants of readmission rate may not be significant. This regression shows population size and crime rate to be positively related with raw readmission rate, and the ratio of minorities in the population is negatively related.

Table 2 shows that the ratio of ER admissions ($\frac{Admissions\ from\ ER\ visits}{total\ number\ of\ ER\ visits}$) is positively related to the raw readmission rate. Table 3 suggests that none of the measured nursing home quality variables have an influence on the readmission rates of local hospitals.

From these initial regressions, the significant variables were then compiled into a final holistic regression. Due to the fact that none of the nursing home factors significantly influenced readmissions, three measures of "overall performance" were used in the holistic regression. These were: overall score, number of RN hours per day per patient, and the ratio of occupied beds to available beds. These were deemed the three best variables to demonstrate overall performance, because each is a measure of different aspect of nursing home care. The overall score is assigned by CMS after evaluating staff quality and performance, health inspection ratings, etc. The number of RN hours per patient per day measures the availability of clinical staff, a metric independent of provider quality. Lastly, the occupancy ratio considers how full each facility is, and thus indirectly measures preference for that facility, and the capability of the facility to function efficiently for its size. The results of this regression are in Table 4 below:

Table 4: Combined Readmission Determinants

	Raw Readmission Rate	
	coefficient	t-score
Population	4.88E-08	3.63
Size of Caucasion Population	1.60E-01	3.67
Crime Rate	8.70E-05	2.65
ER Admission Ratio	-1.99E-01	-2.03
CMS Nursing Home Score	-1.75E-02	-1.98
RN Hours/Pt/Day	9.59E-02	3.65
Occupancy Ratio	1.06E-01	0.79
constant	-4.29E-02	-0.32

n = 88

Table 4: Results of Combined Readmission Factor Regression

Socioeconomic Factors

In the sample, all socioeconomic factors were significantly correlated. The positive relationship between population size and readmission rate is rather intuitive, as one would expect that communities with larger populations would have more medical problems, and more complicated socioeconomic structures stemming from increased diversity. Safi et al found that readmission rates for heart failure were much higher in low-income communities, and overall cardiac health was poorer for African Americans than for Caucasians. They argued that this could be explained by poorer access to preventative medical care. While this explanation seems valid, it directly contradicts the positive correlation in this regression, which indicates that readmission rate increases with the Caucasian population.

One way to approach this is to consider that, as documented in several papers in the literature review, white people have better access to health care. Given this fact, it would be intuitive to imagine a lower readmission rate among whites, as their conditions are not allowed to escalate to a level where hospital admission is necessary. However, the positive correlation between readmission rate and white population can be explained this way too. Given that, on average, wages are higher among whites than minorities, it may be the case that the opportunity cost of seeking medical care is lower for whites. With higher overall incomes, it may easier for this population to miss work to see the doctor; especially if they are salaried. For minorities with lower income, the impact of lost wages may make it harder to miss work for medical attention, and potentially lead to a significantly decreased overall health level compared to whites.

Recently published research supports the claim that the health status of minorities is systematically lower than it is for whites. Becker et al. conducted a study analyzing the incidents of cardiac arrest between racial groups, and the subsequent survival rates. In all age groups, they found that African Americans had a higher incidence of cardiac arrest than whites.

Additionally, despite a higher number of cardiac arrests, the survival rate was nearly two percentage points lower for blacks than whites (0.8 vs. 2.6), despite no significant different in EMS response time between racial groups.

This leads to the interesting question of why? Since the EMS response times are similar, it is arguable that there is some other sociological or physiological confounding factor that causes blacks suffer cardiac arrest more and survive less frequently.

Heart disease, myocardial infarctions, and congestive heart failure are all common medical problems that increase the risk for sudden cardiac arrest, and a physician can address all during a routine check-up. Though simple communication, a doctor can learn enough about a patient's family and medical history and lifestyle to make suggestions that reduce the risk of heart attack and coronary artery disease. Additionally, routine procedures like stress tests and cholesterol measurement can diagnose current issues and assess the risk of acquiring the issues in the future.

Knowing this, we will attempt to explain the trends observed by Beck et al. As it was asserted earlier, the higher readmission rates among communities with more white people can be explained by access to and opportunity cost of health care. For minority families, the higher opportunity cost missing work prevents them from seeking the doctor for routine checkups that could diagnose the above issues. Perhaps unconsciously, they become systematically unhealthier and more likely to suffer cardiac arrest over the course of their lives. Additionally, when they do suffer a cardiac arrest, their lower level of overall health may make them less likely to recover from the incident, and thus less likely to be admitted into the hospital.

In the data, the crime rate was defined at the number of violent crimes per 100,000 people in the population, and with statistical significance was positively correlated to readmission ratio.

Sun et al., in their paper on the social disorganization theory, argue that many socioeconomic factors influence crime rate. Their developed model predicted that crime rate is positively correlated to increasing rates of housing mobility, fewer or sparse “social friendship networks”, and family disruption.

It is interesting that many of the variables accounted for in the social disorganization theory are also included in the list of readmission predictors described in the literature review: less stable support systems, unemployment and marriage rates, and frequent zip code changes were all argued to drive readmissions up.

Despite no correlations between these variables and the raw readmission rate, positive relationships may in fact exist, buried and reflected in the crime rate correlation.

Hospital Factors

In the regression, the only factor related to the raw readmission rate was the ER admission ratio. The negative relationship initially seems counterintuitive, because it implies that as admissions go up, readmissions go down. It is possible, however, that hospitals with systematically sicker patients (hence a higher ER admission ratio) are more proficient at treating them. For instance, a community hospital with fewer specialized services may need to transfer high-acuity patients to a regional medical center where such services are available. Patients suffering from heart failure, severe cases of pneumonia, and myocardial infarctions all represent cases that may warrant such a transfer. If these patients presented at a local hospital, they would not be logged as an admission for the transferring hospital; only the receiving hospital would consider them an admission. This explanation is supported by the lack of a relationship between the raw readmissions ratio and the number of annual visits to the emergency department. Some hospitals are very busy, but still lack the resources necessary to treat every patient. A good example of this is Mount Nittany Medical Center, in State College, PA. Mount Nittany is a community hospital, and while they do provide more services than hospitals in the surrounding counties, they still rely on Geisinger Medical Center and Milton S. Hershey Medical Center to take many of their high acuity patients. From July 2011 – June 2012, 50,798 patients were seen in the emergency room, and 8,364 (16.46%) were admitted from the ER. On the contrary, Hahnemann University Hospital, the teaching affiliate of Drexel University College of Medicine, is a fully equipped medical center with the resources needed to treat any patient the encounter. While their annual ER visits are lower than Mount Nittany at 46,444, 10,950 (23.57%) of their patients are admitted. Thus, it is not necessarily the ER patient volume that drives the readmission rate, but likely the skills and services the individual facilities are capable of providing.

Nursing Home Factors

In the regression, the only significant nursing home factor was the average RN hours dedicated to each patient per day. The result was a positive relationship, suggesting that a greater availability of nursing staff directly relates to the readmission rate. Similar to other results, this appears counterintuitive, as an inverse relationship would have been expected (and was present in the nursing-home level regression). One explanation for the result is to consider that patients in facilities with high RN hour ratios are in fact receiving better care despite the increase readmissions. With more personal contact between nursing home residents and nursing staff, medical concerns can be addressed more promptly and efficiently. The positive correlation between the two may simply be the result of better communication and more efficient identification of patients who are in need of hospitalization, and not at all indicative of a lower standard of care.

Chapter 5

Analysis of the Coordination Equilibrium

Before we move forward, lets take a minute to recap the main findings from the literature and the regression values from the Pennsylvania data. Much of the research pointed to a significant socioeconomic impact on readmissions, and this was echoed in the Pennsylvania data where population size, Caucasian population size and crime rate all were positively correlated to readmission rate. Contrary to the literature, however, income, education level, and marriage rates were not related to readmissions in Pennsylvania. It is possible that these factors are included in the crime rate correlation, but it is also plausible that they in fact are independent of readmission rate. Additionally, the literature pointed to the availability of specialty services as a measure of hospital quality, and thus a factor driving the readmission rate. While the PA data did not immediately echo this assertion, the positive correlation between ER admissions and readmission rate is evidence that such a relationship exists. While nothing in the literature pointed to the relevance of nursing homes in the readmission equation, the PA data suggests that readmission rates increase with the availability of RNs at nursing homes. While counterintuitive, it is likely that the increased level of nursing availability is a result of systematically sicker patients and to the identification of more patients needing hospitalization, and thus a higher readmission rate.

With this understanding, we can look back at the coordination game that was initially proposed. We will first start with the game existing between the patients and the hospitals.

From earlier, it was asserted that:

(1) $$Value = R - C(e) + \beta[P(e,c)V^H + (1-P)(e,c)V^S]$$

(3) $$C'(e) = \beta(V^H - V^S)\frac{dp}{de}$$

The terms imply that the patient value to the hospital is a function of their probability to recover and their recovery effort given a certain level of hospital effort, and in the effort maximization, a function of the differences in recovery and readmission values. In the pre-policy period, there was no penalty to readmission, and thus the optimal value was always a readmission. With the new policy however, it is no longer the dominant strategy for the hospital to incur a readmission. This is where the game develops.

Because factors such as population size, Caucasian population, and crime rate have been shown to influence readmissions, these are the main demographic variables that should influence a hospital's effort level. Because the readmission risks are greater in large populations, areas with higher ratios of Caucasians, and higher crime rates, hospitals that serve these populations may have the incentive to decrease their level of care effort for these patients. Since they are more likely to be readmitted, the hospital should balance this risk with a smaller investment in the first period.

While these population-general variables are significant, none of the patient-specific predictors (income, educational attainment, social stability) were significant. However, crime rate can likely be extrapolated to these variables, and thus patients who live in more violent areas may be assumed to have lower incomes, education levels and unstable support systems and thus a higher readmission probability.

The same logic holds for communities that are predominantly white. Given the inverse relationship between diversity and readmission rate, less effort would be expended to residents of such communities since they are already predisposed to readmission.

In addition to the socioeconomic factors, hospitals may have to consider the nursing home factors for patients living in those facilities. As the data showed, facilities with more available nurses correlate to higher readmission risks in the compiled regression. While the government believes that the Medicare Readmission Reduction program will force hospitals to partner with higher quality nursing homes, this suggests they will be pushed away from this. If the assertion that the higher readmission rate is a result from more attentive nursing staff – or a higher quality nursing home – substituting away from these facilities in preference of those with lower nurse to resident ratios will decrease care quality.

However, the positive relationship between RN hours and readmission rate only existed in the aggregate regression. In the regression that considered nursing home factors independent of socioeconomics, there was an inverse relationship between these factors. This would imply that as RN availability increased, readmissions decreased. While the impact of socioeconomic factors should not be overlooked for most patients, a population does exist whose socioeconomic status is likely independent of readmission rate. When someone becomes a resident of a nursing home, the state entirely funds their treatment once all of their assets have been depleted. These patients are independent of external society, as the state funds their treatment regardless of the population they are in, their age, racial status, etc. In this sense, the only variation between these patients (barring different levels of health status) is the quality of the nursing care they receive. For this subset of patients, the hospital would be incentivized to partner with higher quality facilities. As it is clear, socioeconomic and nursing home factors play a large role in the hospitals choice of effort.

The patient effort function can be addressed the same way, as they choose an effort level for their own recovery based on the hospital effort. The hospital makes decisions about patient care based on the socioeconomic signals discussed above. In turn, the patient chooses their level of effort based on their perceptions of the hospitals effort. As they view care to be a complement to their effort, there will be a direct relationship between hospital effort and patient recovery effort in the presence of perfect information. This is complicated by the fact that this game is driven by signals and thus imperfect information, and that the hospital will also consider the effort of the patient in their decision. Figure 5-1 below is a depiction of this coordination game if complementarity is present:

	Hospital Maximizes Effort	Hospital Minimizes Effort
Patient Maximizes Effort	X, X	0, -X
Patient Minimizes Effort	-X, 0	0, 0

Figure 5-1: Payoff Matrix for hospital-patient coordination

As discussed, the patient and the hospital both choose their optimal levels of effort. In the top left cell, the hospital chooses a high level of effort, and the patient does the same. There is a net positive utility as a result of this; the patient has the highest chance of making a recovery, and the hospital invested wisely in avoiding a readmission. In the top right cell, the hospital perceives the patient to be of low value. The hospital determined its optimal level of effort was low, and elected to provide minimal care. Unfortunately, this patient would have expended a good amount of effort in his or her own recovery. The hospital's lack of effort may lead to a readmission, because the patient was not provided with all of the resources they would have utilized. The patient receives no utility, but the hospital loses utility with the increased readmission risk. In the bottom left, the hospital expended effort while the patient minimized. Both lose utility, as the hospital invested in a patient who is likely to be readmitted, and the patient will not recover as quick. In the last cell, both players minimize– neutralizing the costs and benefits and gaining no utility.

Looking at this matrix and assuming that the moves are made simultaneously, there are two Nash equilibria (yet only one Pareto optimal position). Given that the patient intends to maximize, it is in the best interest of the hospital to do so as well. Conversely, given that the patient plans on minimizing, the hospital is incentivized to do the same. When we consider the policy, these two equilibria make sense. If the patient is going to utilize the resources provided, it is in the best interest of the hospital to incur the expense in order to decrease the probability of a readmission as much as possible. On the other hand, given a patient who is not going to take advantage of the resources, it makes sense for the hospital to avoid providing them. This patient has a much higher probability of being readmitted, as they are not going to be facilitating their own recovery. It does not make sense for the hospital to spend money to rehabilitate a patient who will likely be readmitted regardless of the resources they are provided with.

This represents the simple model of the game occurring between hospitals and their patients under this policy. Instead of treating every patient the same and focusing on a medical solution, the policy may inherently encourage hospitals to "give up" on some patients. While the ethically desirable Pareto optimal equilibrium (mutual maximization) is attainable, the mutual minimization equilibrium is equally likely to happen, and represents an incentive in direct contrast to the motives of the policy.

The final component of this analysis is to understand how all of these factors may contribute to an inter-hospital coordination game. As it was explained earlier, the driving force for readmission penalties is a given hospitals deviation from the mean. Each individual facility's readmission rate is adjusted based on their risk, and compared to the mean. If they are above the mean readmission rate, known as having an excess readmission ratio, a penalty is assessed. The problem with this approach is the potential for a coordination game based on the patient-hospital game to develop. A given facility's choice on treating their patients will be influenced by their perceptions of which equilibrium (mutual max or mutual min) *all* other hospitals will operate at, as depicted in Figure 5-2:

	Hospital A Maximizes Effort	Hospital A Minimizes Effort
All Other Hospitals Maximize Effort	0, 0	-X, 0
All Other Hospitals Minimize Effort	2X, 0	X, X

Figure 5-2: Payoff Matrix for the Inter-Hospital Coordination Game

In the top left cell, hospital A correctly believes that all other hospitals will be operating in the Pareto optimal equilibrium of the patient –hospital game (mutual maximization). Because of this, hospital A chooses to maximize their care to avoid falling below the average (which presumably will not rise when everyone provides maximal effort). This leads to no net utility for any party, as everything remains the same. In the bottom left cell, hospital A incorrectly believes that everyone will maximize; the other hospitals will be minimizing patient care and cause an increase in the readmission rate. Hospital A will avoid the penalty and gain utility for operating so far below the average, while no utility change will occur for any other hospital. In the top right cell hospital A believes that all other hospitals will be operating at the mutual minimization equilibrium, while in reality they choose to operate at mutual maximization. Hospital A loses utility, as they incur a readmission penalty, while no other hospital realizes a utility change.

In the top right cell, the majority of hospitals do the same, while hospital A chooses to minimize effort. Hospital A incurs more readmissions than the average, and thus loses utility to a readmission penalty. In the bottom left cell, hospital A maximizes effort while most facilities minimized. The result was a net gain of utility for hospital A, as they avoided a penalty, and gained implicit value due to their isolation as one of the few facilities improving their care quality. In the bottom right cell, all hospitals choose to minimize care effort. All gain utility in this scenario; despite an increase in readmissions, resources were saved and no penalties were incurred. Because penalties are determined based on the average readmission level, decreases in the overall quality of care will lead to a spectrum wide increase in readmission rates. When everyone underperforms, nobody stands out as exceptionally bad.

In this game, when *all* hospitals operate at mutual maximization or minimization with their patients, inter-hospital Nash equilibria occur. Although it is Pareto optimal for individual hospitals to maximize with their patients, the introduction of penalties dependent on readmission rate necessitates that both the penalty and the cost of care must be minimized for the optimal equilibrium to be achieved. In the top left cell, efficiency is achieved because every hospital invested in care to avoid readmission penalties. However, Pareto optimality exists when every hospital minimizes effort: the cost of improving care and increasing effort is no longer incurred, and the penalty is avoided. This equilibrium is economically optimal, but both politically and ethically undesirable. This underscores the inherent problem with this policy: Pareto optimality is achieved at the expense of high-quality patient care. This is exactly what the policy intended to prevent.

Chapter 6

Policy Implications

Given what we have established about the nature of the coordination game, it is evident that the policy in its current form could incentivize hospitals to decrease the quality of care they provide.

The major component of this policy that drives the inter-hospital coordination is the determination of excess readmissions relative to the average. Because avoiding the penalty is as simple as beating the average, reducing care quality would serve as a dominant strategy if it were projected that many hospitals would do the same thing. Restructuring the policy such that a hospital was measured solely against its own performance would alleviate this concern. For instance, given the calculations in the current policy, assume hospital A has an excess readmission rate of 1.23, suggesting that it was 23% above the average rate for comparable hospitals in 2012. Instead of comparing the excess readmission rate of hospital A against the new average in 2013, their new rate should be compared to only their own rate in the previous period. This would incentivize every individual hospital to improve care in all cases, as only their performance in period 2 relative to period 1 impacts readmission penalties; the actions of hospital B, C, D... in period 2 have no bearing on the optimal response for hospital A. This would effectively remove the incentive to follow other hospitals as depicted in Figure 5-2, and allow a hospital to make decisions based only on the patient-hospital coordination in Figure 5-1.

With the elimination of inter-hospital coordination, policy should be directed to ensure that Pareto-optimality in Figure 5-2 (mutual maximization) is achieved. One of the underlying problems with the policy is that decisions are made with imperfect information, and hospitals are accountable for readmissions even if their root cause was exogenous to the level of care they provided. For instance, a patient who is readmitted because they did not take their medications will still be factored into the hospital's readmission rate, even if they were initially treated at the highest possible care level. Ultimately, this provides the hospital with a strong incentive to minimize effort for patients with a high-perceived likelihood of readmission. This makes the achievement of Pareto optimality unlikely, and unfortunately will lead to minimization for some patients who intend to maximize.

To circumvent this detrimental incentive, hospitals should be given immunity in the case of a readmission caused by patient-non-compliance. One way to track these readmissions is through community paramedicine. Community paramedicine is a very new approach to pre-hospital care. Paramedics who are working in the field are assigned to certain post-discharge patients on a daily basis, and make house visits to help ensure that patients are recovering. If a patient is not actively facilitating their own recovery, daily visits by the paramedic may encourage the patient to take their condition more seriously. While the most stubborn patients will be non-compliant regardless of the house visits, community paramedicine will enable adequate documentation of the non-compliance. This will protect hospital from liability should the patient be readmitted, and will make the opportunity cost of maximizing care much lower. Ultimately it will allow a hospital to maximize effort in all instances; the optimal patient response is no longer relevant to their decision. Figure 6-1 represents a payoff matrix of this new scenario:

	Hospital Maximizes Effort	Hospital Minimizes Effort
Patient Maximizes Effort	X, X	0, -X
Patient Minimizes Effort	0, 0	0, 0

Figure 6-1: Payoff Matrix After the Elimination of Patient-Induced Readmissions

This payoff matrix is identical to Figure 5-1, although the hospital has a net utility of 0 when they choose to maximize for a minimizing patient. Although they invest in the care for that patient, non-compliance induced readmissions no longer effect their readmission rate. In all instances, the hospital has an incentive to maximize effort.

In addition to being used as a means of identifying non-compliant patients, community paramedicine can also yield mutual benefits when the hospital and patients are already operating at the Pareto optimal equilibrium. Daily visits will allow providers to track progress, and identify and treat problems that could lead to readmission before they progress. Recently, after a visit by a community paramedic, a patient was found to be taking three different Coumadin pills each day, each prescribed by a different physician. Coumadin is a blood thinner, so even minor cuts lead to extensive bleeding. This patient, taking three times the normal dosage, had an incredibly high mortality risk from severe blood loss. The community paramedic who noticed this likely prevented this patient from being readmitted, but more importantly, almost certainly saved this patients life.

The benefit of community paramedicine is that it yields benefits to the hospital in all instances. In the event of a non-compliant patient, community paramedicine would enable the hospital to justify termination of expensive resources, and afford them protection in the event of a readmission. Equally, community paramedicine would benefit both parties when there is mutual cooperation, as the potential for readmission is further reduced. The program would serve to maximize the level of care the patient receives, while at the same time lowering the probability of incurring a readmission penalty.

The final component of this study that should be addressed is the penalty structure. While it is not the focus of this paper, a fine that was too small would provide an unconditional incentive to minimize care. Namely, it would be necessary for the fine to be greater than the cost of improving care to avoid it, as it would be irrational to improve care quality if this were not the case. When we consider the numbers, it seems plausible that this negative incentive might exist. Medicare plans to save $280 million in the first year through penalties levied to 2,217 hospitals with excessive readmission rates, for an average penalty of $126,296 per hospital. If the cost of reducing readmission rates below the penalty level exceeds of this figure, the hospital would be behaving rationally if their strategy was to minimize all the time and accept the penalty. As the penalty rate increases, hospitals could continue this cost benefit analysis until they are forced to improve care. With the information that is currently available, it is not possible to determine whether these negative incentives do exist, but their plausibility warrants further investigation.

Chapter 7

Conclusions

After this analysis, several main conclusions can be drawn. First, after a comparison of the literature and empirical data from Pennsylvania, it appears that there is minimal connection between the variables proposed to be significant and those actually influential in the data. Despite our full analysis of variables, only population size, Caucasian population size, crime rate, ER admission ratio and nursing home RN availability could be connected to readmission rate.

Although the literature is not wholly consistent with the empirical analysis, the variables determined to be significant allow for the possibility that optimal care is determined by observed socioeconomic factors, and patient response is influenced by their perceptions of the hospital's determination of an optimal effort level. This supports the theory that inter-hospital coordination can occur, and there is an incentive for negative patient-care-minimizing equilibria to be achieved.

The outcomes of this game – which are potentially care reducing – are not in line with the intended consequences of the Medicare Readmissions Reduction program. As a result, the policy should be amended to remove the framework for both the patient-hospital coordination and the inter-hospital coordination. By changing the policy to hold a hospital accountable only to their own readmission rate fluctuation, and eliminating the penalties incurred when noncompliant patients are readmitted, such coordination becomes unnecessary and irrelevant. Ultimately, these changes will serve to increase the quality of patient care, and help the program attain its intended goals of reducing avoidable readmissions while saving the American taxpayers hundreds of millions of dollars per year.

Appendix A

Socioeconomic Data By Hospital

Hospital	Zip Code Population	White Population	Average Income	Popuation with Bachelor's Degree	Married Pop.	Violent Crime Rate	UR
Abington Health Lansdale	15000	0.744	56233	0.31	0.483	190	6.4
Abington Memorial	56103	0.832	73738	0.221	-	-	6.4
Albert Einstein	1547647	0.369	34207	0.236	0.313	577.1	9.6
Alle Kiski	11742	0.923	39520	0.194	0.483	0	8.2
Allegheny General	306211	0.642	35947	0.331	0.326	438.7	7
Altoona	46148	0.933	34695	0.152	0.465	213.8	8
AMCH	3980	0.936	33915	0.155	0.388	121.8	9
Aria Health	1547647	0.369	34207	0.236	0.313	577.1	9.6
Berwick	10365	0.962	30389	0.116	0.445	319.9	8.4
Bloomsburg	14633	0.882	28119	0.267	0.22	146.8	8.3
Bradford Regional	8683	0.953	30925	0.162	0.368	289.5	10.1
Brandywine	5822	0.961	95126	0.251	-	-	5.6
Bryn Mawr	3779	0.711	49188	0.641	0.218	-	6.7
Butler Memorial	13620	0.924	30372	0.134	0.407	350.9	6.9
Carslisle Regional	18880	0.821	44446	0.351	0.391	208.4	6.5
Chambersburg	20360	0.706	35082	0.198	0.433	342	7.9
Chester County	18857	0.721	42284	0.453	0.24	251.1	6
Chestnut Hill	1547647	0.369	34207	0.236	0.313	577.1	9.6
Clarion	5154	0.904	24451	0.363	0.195	61.1	9.4
Clearfield	6132	0.967	35028	0.198	0.463	335.5	9.8
Conemaugh	20577	0.808	24277	0.118	0.391	293.7	10.1
Crozer Chester	3244	0.504	38812	0.112	0.343	579.4	7.5
Deleware Valley	1618	0.864	63632	0.371	0.49	-	-
Doyelstown	8365	0.942	56328	0.47	0.466	145.5	7.2
Dubois	7708	0.900	37657	0.211	0.482	-	9.8
Easton	26951	0.586	37799	0.185	0.37	317.1	9.4
Elk Regional	13354	0.972	39309	0.185	0.525	-	5.6
Ephrata Community	13506	0.895	44010	0.168	0.568	185.7	-
Evangelical	5763	0.877	32189	0.413	0.255	127.8	8.9
Geisinger Community	75809	0.811	36219	0.206	0.386	312.6	8.8
Geisinger Danville	4661	0.916	36212	0.231	0.415	219.6	6.4
Geisinger Wyoming Valley	41243	0.739	30033	0.148	0.35	330.4	9.6
Gettysburg	7645	0.796	38014	0.315	0.295	200.7	7.3
Gnaden Huetten	5435	0.940	39294	0.147	0.5	259	10
Good Samaritan	25554	0.631	34077	0.098	0.376	280	9.3
Grand View	4244	0.916	55723	0.22	0.496	-	7.3
Hahnehmann	1547647	0.369	34207	0.236	0.313	577.1	9.6
Hanover	15349	0.909	43466	0.169	0.484	254.6	8.1
Hazelton General	25224	0.638	33612	0.122	0.451	245.3	13.1
Heritage Valley Beaver	4487	0.947	53700	0.345	0.539	133.4	8
Heritage Valley Sewickley	3821	0.876	52699	0.591	0.477	90.6	6.8
Holy Redeemer	1547647	0.369	34207	0.236	0.313	577.1	9.6
Holy Spirit	7871	0.874	57616	0.465	0.535	93	6.4

Hospital	Zip Code Population	White Population	Average Income	Popuation with Bachelor's Degree	Married Pop.	Violent Crime Rate	UR
Indiana Regional	3410	0.943	39975	0.239	0.491	285.8	7.4
Jameson Memorial	22851	0.834	28514	0.139	0.457	504	10.5
Jeanes	1547647	0.369	34207	0.236	0.313	577.1	9.6
Jefferson Regional	10990	0.953	75226	0.352	0.586	-	6.8
Jennersville Regional	2864	0.645	63908	0.265	0.506	-	6.2
Lancaster Community	59360	0.437	31674	0.161	0.347	511.7	10.4
Lancaster Regional	59360	0.437	31674	0.161	0.347	511.7	10.4
Latrobe	8325	0.952	35931	0.171	0.451	166	7.7
Lehigh Valley Cedar Crest	118974	0.432	30784	0.146	0.344	512.5	11.7
Lehigh Valley Mulenberg	75103	0.653	45019	0.285	0.403	225.6	9.4
Lewistown	8360	0.931	31306	0.113	0.459	-	9.7
Lower Bucks	9686	0.745	43747	0.137	0.429	251	7.2
Meadville	13263	0.894	25719	0.243	0.372	141.8	9.7
Mercy Fitzgerald	10682	0.799	33440	0.13	0.295	1314	7.6
Mercy Suburban	13644	0.881	75853	0.323	0.576	-	6.7
Milton S. Hershey	14257	0.815	53838	0.524	0.495	-	7.5
Monogahela Valley	4264	0.938	40733	0.155	0.433	300	7.5
Montgomery	34427	0.360	42080	0.168	0.398	544.6	8.5
Moses Taylor	75809	0.811	36219	0.206	0.386	312.6	8.8
Mount Nittany	41983	0.794	22738	0.647	0.136	92.5	5.5
Nazareth	1547647	0.369	34207	0.236	0.313	577.1	9.6
Palmerton	5377	0.943	39754	0.145	0.525	191	10
Paoli	5575	0.847	75444	0.563	0.56	0	6.2
Penn	1547647	0.369	34207	0.236	0.313	577.1	9.6
Penn	1547647	0.369	34207	0.236	0.313	577.1	9.6
Penn Presbyterian	1547647	0.369	34207	0.236	0.313	577.1	9.6
Phoenixville	16518	0.780	55117	0.362	0.489	179.4	6.2
Pinnacle Health	29279	0.513	31785	0.176	0.289	743.4	10.2
Pocono	9867	0.732	41616	0.264	0.266	0	9
Pottstown	22480	0.687	41344	0.16	0.419	459.8	6.8
Reading	88102	0.584	24682	0.097	0.363	558.3	12.6
Riddle Memorial	5335	0.819	51519	0.425	0.329	146.3	7.5
Robert Packer	5557	0.951	34222	0.244	0.49	119.2	8.2
Roxboro	1547647	0.369	34207	0.236	0.313	577.1	9.6
Sacred Heart	118974	0.432	30784	0.146	0.344	512.5	11.7
Schukill	14129	0.925	37333	0.155	0.47	172	9.8
Scranton Regional	75809	0.811	36219	0.206	0.386	312.6	8.8
Sharon Regional	13815	0.819	31286	0.166	0.442	400	10.5
Somerset	6182	0.947	32103	0.245	0.432	188.9	8.4
St. Clair Memorial	306211	0.642	35947	0.331	0.326	438.7	7
St. Joeseph	88102	0.584	24682	0.097	0.363	558.3	12.6
St. Luke's	75103	0.653	45019	0.285	0.403	225.6	9.4
St. Mary	1618	0.864	63632	0.371	0.49	-	0
St. Vincent Health Center	101047	0.726	31901	0.213	0.396	307	9.4

Hospital	Zip Code Population	White Population	Average Income	Popuation with Bachelor's Degree	Married Pop.	Vio	UR
Temple	1547647	0.369	34207	0.236	0.313	577.1	9.6
Thomas Jefferson Univ.	1547647	0.369	34207	0.236	0.313	577.1	9.6
Uniontown	10231	0.785	30895	0.172	0.365	417.6	9.2
UPMC Hamot	101047	0.726	31901	0.213	0.396	307	9.4
UPMC Horizon	5895	0.941	31113	0.17	0.397	217.5	11
UPMC McKeesport	19686	0.652	27073	0.101	0.332	683.3	9.5
UPMC Mercy	306211	0.642	35947	0.331	0.326	438.7	7
UPMC Northwest	1065	0.969	53687	0.191	0.649	-	8.6
UPMC Passavent	306211	0.642	35947	0.331	0.326	438.7	7
UPMC Presbyterian	306211	0.642	35947	0.331	0.326	438.7	7
UPMC St. Margret	306211	0.642	35947	0.331	0.326	438.7	7
Warren General	9530	0.978	33334	0.233	0.457	385.9	7.7
Washington	13555	0.739	33706	0.13	0.333	-	7.6
Wayne Memorial	4341	0.948	31879	0.187	0.466	121.2	7.3
Waynesboro	10633	0.906	39804	0.15	0.499	195.6	9.8
West Penn Forbes Region	27793	0.851	57969	0.356	0.56	-	6.7
West Pennslvania	306211	0.642	35947	0.331	0.326	438.7	7
Westmoreland Regional	14736	0.909	38714	0.33	0.423	148.7	7.7
Wilkes Barre	41243	0.739	30033	0.148	0.35	330.4	9.6
Williamsport	29497	0.795	29684	0.18	0.345	294.7	9.5
Windber	4088	0.975	30120	0.164	0.452	182.6	8.5
York	43550	0.428	28270	0.101	0.341	683	13.2
York Memorial	43550	0.428	28270	0.101	0.341	683	13.2

All data was obtained through the U.S. Census Bureau, and through city-data.com

Appendix B

Hospital Data

Hospital	Excess Readmission Ratio	Predicted Readmission Ratio	Annual ER Visits	Admissions from ER	# Physicians	Admission Ratio
Abington Health Lansdale	23.2	24.2	23007	3891	11	0.169
Abington Memorial	19.1	21.1	105986	19921	26	0.188
Albert Einstein	22	24.1	120181	17487	34	0.146
Alle Kiski	23.5	26.8	-	-	-	-
Allegheny General	17.9	18.6	51290	15830	28	0.309
Altoona	19.6	18.3	66337	11463	9	0.173
AMCH	20.8	20.7	26164	4359	7	0.167
Aria Health	20.2	21.8	121713	17755	47	0.146
Berwick	23.1	22.1	13046	2087	1	0.160
Bloomsburg	23.1	22	13818	1365	6	0.099
Bradford Regional	22.8	23.2	20727	2701	3	0.130
Brandywine	19.5	18.5	28685	5191	9	0.181
Bryn Mawr	19.8	20.8	47293	11601	34	0.245
Butler Memorial	19.2	20.4	47122	8199	11	0.174
Carslisle Regional	21	18.8	28656	5048	14	0.176
Chambersburg	18.9	17.1	57526	8862	16	0.154
Chester County	19.7	20.5	41801	9229	11	0.221
Chestnut Hill	22.9	24.3	31701	5401	11	0.170
Clarion	21.7	21.7	18354	1514	4	0.082
Clearfield	22.7	23.9	26610	2582	4	0.097
Conemaugh	20.2	21	68286	19895	16	0.291
Crozer Chester	19	18.5	100403	16680	25	0.166
Deleware Valley	21.6	24.8	-	-	-	-
Doyelstown	18.4	17.2	45220	8353	17	0.185
Dubois	18.4	16.9	31824	3480	6	0.109
Easton	18.6	22.6	33889	6472	9	0.191
Elk Regional	23.2	24.1	19911	3135	12	0.157
Ephrata Community	21.4	24	31071	4440	10	0.143
Evangelical	22.8	19.9	33224	3649	9	0.110
Geisinger Community	18.3	16.5	44134	10093	10	0.229
Geisinger Danville	18.3	18.4	59222	17754	22	0.300
Geisinger Wyoming Valley	18.5	16.9	57829	7684	2	0.133
Gettysburg	20.9	19.2	28484	3735	9	0.131
Gnaden Huetten	23.3	23.1	19775	2659	11	0.134
Good Samaritan	17.8	14.9	55657	5149	11	0.093
Grand View	19.9	21.7	35260	5457	9	0.155
Hahnehmann	19.7	19.8	46444	10950	26	0.236
Hanover	21.8	19.2	31506	3976	5	0.126
Hazelton General	25.4	24.2	31716	4481	18	0.141
Heritage Valley Beaver	18	20.3	61144	10500	21	0.172
Heritage Valley Sewickley	20.4	21.6	41136	5800	23	0.141
Holy Redeemer	21.3	22.8	29529	6381	10	0.216
Holy Spirit	18.4	18.1	51918	10580	15	0.204

Hospital	Excess Readmission Ratio	Predicted Readmission Ratio	Annual ER Visits	Admissions from ER	# Physicians	Admission Ratio
Indiana Regional	21.5	21.2	45468	5443	12	0.120
Jameson Memorial	22.8	23.2	36891	7753	17	0.210
Jeanes	19.9	21.8	27547	7703	4	0.280
Jefferson Regional	18.8	18.4	54024	11189	11	0.207
Jennersville Regional	21.7	24.1	12994	2405	7	0.185
Lancaster Community	18.3	14.5	108086	18669	16	0.173
Lancaster Regional	17.8	16.2	22792	2846	4	0.125
Latrobe	20.5	22	35628	4638	28	0.130
Lehigh Valley Cedar Crest	19.6	20.4	119955	31079	59	0.259
Lehigh Valley Mulenberg	19.9	20.7	55770	8734	59	0.157
Lewistown	23.3	26.7	32921	3713	12	0.113
Lower Bucks	19.6	18.1	30139	5701	9	0.189
Meadville	19.1	20.7	37155	4074	2	0.110
Mercy Fitzgerald	20.9	25.1	38434	7515	20	0.196
Mercy Suburban	21.9	22.6	24910	4700	12	0.189
Milton S. Hershey	18.2	16.6	64421	11632	20	0.181
Monogahela Valley	21.9	22.8	34719	6004	4	0.173
Montgomery	19.2	19.9	-	-	-	-
Moses Taylor	24.8	23.7	34393	5993	9	0.174
Mount Nittany	18.9	21.1	50769	8364	14	0.165
Nazareth	24.9	27.2	35634	8613	19	0.242
Palmerton	22.3	21.4	11622	1559	12	0.134
Paoli	19.9	17.9	41309	9966	34	0.241
Penn	19.4	19.3	-	-	-	-
Penn	19	23	72835	13726	61	0.188
Penn Presbyterian	19.6	18.1	31346	7119	21	0.227
Phoenixville	18.9	23.1	26656	4916	5	0.184
Pinnacle Health	18.6	15.4	107616	18798	36	0.175
Pocono	20.2	18	85024	8870	11	0.104
Pottstown	21.7	23	43563	6229	10	0.143
Reading	18.3	15.4	130627	20859	39	0.160
Riddle Memorial	19.8	20.3	32437	7564	9	0.233
Robert Packer	17.8	18.5	30298	7886	7	0.260
Roxboro	23.8	27.1	15494	4077	4	0.263
Sacred Heart	22.8	22.4	32349	3552	17	0.110
Schukill	21.9	21.2	53394	7448	3	0.139
Scranton Regional	18.8	17.8	29419	6915	14	0.235
Sharon Regional	20.9	22.7	31285	6887	18	0.220
Somerset	21.3	21.1	19924	2327	4	0.117
St. Clair Memorial	18.8	19.2	64409	9846	26	0.153
St. Joeseph	19.1	19.5	45878	5964	15	0.130
St. Luke's	18.9	21	112193	18408	23	0.164
St. Mary	20	19.3	70199	16153	20	0.230
St. Vincent Health Center	19.6	17.2	62204	11889	17	0.191

Hospital	Excess Readmission Ratio	Predicted Readmission Ratio	Annual ER Visits	Admissions from ER	# Physicians	Admission Ratio
Temple	20.1	21	131590	16727	55	0.127
Thomas Jefferson Univ.	21.2	21.900	120423	21548	28	0.179
Uniontown	19.1	17.800	54955	7236	4	0.132
UPMC Hamot	18.9	16.600	75536	12312	13	0.163
UPMC Horizon	22.1	22.300	36908	3996	18	0.108
UPMC McKeesport	21	19.500	41347	7559	9	0.183
UPMC Mercy	19.5	21.800	72049	13176	26	0.183
UPMC Northwest	24.4	26.900	31709	4688	26	-
UPMC Passavent	19.2	18.200	59323	11087	11	0.187
UPMC Presbyterian	19.2	19.100	122064	36331	66	0.298
UPMC St. Margret	23.2	26.000	41610	9609	26	0.231
Warren General	21.9	20.100	20618	2366	11	0.115
Washington	19.5	18.800	48953	12434	9	-
Wayne Memorial	20.8	21.200	20490	2132	4	0.104
Waynesboro	21.5	22.100	23370	1814	11	0.078
West Penn Forbes Region	22.2	21.200	38884	10706	11	-
West Pennslvania	19.3	21.400	7517	1390	15	0.185
Westmoreland Regional	17.8	17.900	59350	10898	28	0.184
Wilkes Barre	19.3	16.700	58026	14813	18	0.255
Williamsport	18.4	15.300	45307	5609	14	0.124
Windber	23.2	23.600	12086	556	1	0.046
York	19.4	18.400	76501	22752	17	0.297
York Memorial	20.8	19.900	42442	2713	16	0.064

All data was obtained through the Centers for Medicare and Medicaid Services, and through the Pennsylvania Department of Health

Appendix C

Nursing Home Data by County

County level statistics representing the average value of each nursing home

County	N	B	UB	TS	HI	SR	RNR	CNAH	LPNH	RNH	IC	C	F
Adams	5	145.0	131.2	3.0	2.4	2.8	2.8	2.1	0.9	0.6	0.6	1.4	0.6
Allegheny	64	123.0	108.0	2.9	2.4	3.1	3.8	2.2	0.8	1.2	0.3	2.9	0.2
Armstrong	4	91.5	73.8	3.3	3.8	3.0	3.3	2.3	1.2	1.4	0.0	1.3	0.0
Beaver	6	199.7	175.8	2.3	2.2	3.2	3.8	2.3	0.6	1.0	0.8	2.3	0.2
Berks	15	159.9	151.3	4.1	3.9	2.4	3.3	2.1	0.8	0.8	0.0	1.5	0.0
Blair	10	147.5	136.0	4.2	4.1	3.0	3.1	2.3	1.0	0.7	0.0	2.3	0.0
Bradford	4	109.8	74.3	1.7	1.3	3.0	3.0	2.8	0.9	0.9	0.0	1.3	0.3
Bucks	30	114.6	103.4	4.3	3.7	3.3	4.1	2.3	0.6	1.1	0.1	1.3	0.0
Butler	13	119.3	103.5	3.7	3.3	2.8	3.6	2.3	0.8	1.0	0.3	1.2	0.0
Cambria	9	104.6	88.6	3.7	3.2	3.3	3.8	2.2	1.1	0.9	0.3	4.8	0.2
Carbon	3	144.3	139.3	2.7	2.3	2.3	2.0	2.8	0.8	0.6	1.0	2.7	0.3
Centre	6	117.7	104.2	2.2	1.7	3.0	3.2	2.3	0.9	0.7	0.0	2.8	0.2
Chester	21	116.5	102.2	3.0	2.2	3.8	4.0	2.4	0.9	1.1	1.1	2.7	0.0
Clarion	3	107.7	78.0	3.3	3.7	2.0	3.0	1.8	1.0	0.7	0.3	3.0	0.0
Clearfield	4	167.8	158.5	2.8	3.0	2.3	2.3	2.4	1.0	0.6	0.3	4.5	0.0
Columbia	6	127.0	105.0	2.5	2.0	2.3	2.8	2.2	0.8	0.6	0.2	1.8	0.2
Crawford	7	118.6	108.4	2.3	2.4	2.6	2.7	1.8	1.1	0.9	0.3	1.6	0.1
Cumberland	16	125.5	110.3	3.3	2.3	2.9	3.1	2.4	1.0	0.7	0.3	2.1	0.3
Dauphin	9	155.4	139.6	2.4	1.9	2.9	2.8	2.4	1.0	0.6	0.9	4.4	0.2
Delaware	30	146.1	129.2	3.2	2.5	3.4	3.9	2.4	0.7	1.1	0.6	2.4	0.1
Deleware	30	146.1	129.2	3.2	2.5	3.4	3.9	2.4	0.7	1.1	0.6	2.4	0.1
Elk	2	129.0	121.0	4.5	4.0	3.5	3.0	2.4	1.0	0.7	0.0	0.5	0.0
Erie	20	111.8	101.9	3.1	2.7	3.2	3.6	2.2	1.0	0.9	0.1	2.8	0.0
Fayetteville	7	96.0	86.6	3.3	3.1	2.7	3.3	2.1	0.9	0.8	0.0	3.3	0.3
Franklin	8	132.3	124.1	4.4	4.3	3.0	2.9	2.4	0.9	0.6	0.1	0.4	0.0
Indiana	5	97.4	91.0	4.4	4.2	2.4	3.0	2.2	0.9	0.8	0.0	1.4	0.0
Lackawanna	18	131.4	119.8	2.3	1.6	2.8	3.4	2.2	0.9	0.9	0.6	3.4	0.2
Lancaster	31	130.6	121.8	3.4	2.6	3.4	3.4	2.5	1.0	0.7	0.4	3.6	0.2
Lawrence	9	88.4	79.6	3.3	2.9	3.1	3.6	2.3	1.0	1.1	0.3	3.3	0.0
Lebanon	12	100.6	91.8	4.3	3.9	3.5	3.5	2.5	1.0	0.9	0.0	1.1	0.0
Lehigh	16	169.6	158.6	4.2	3.8	3.1	4.0	2.5	0.6	1.4	0.0	1.6	0.0
Luzerne	24	112.1	101.1	2.8	2.2	2.4	3.1	2.2	0.8	0.8	0.6	5.0	0.4
Lycoming	8	135.5	120.4	2.4	1.6	2.3	2.3	2.2	0.9	0.6	0.0	1.9	0.1
McKean	6	97.7	85.3	2.8	2.3	3.0	3.0	2.4	0.8	0.7	0.0	0.8	0.0
Mifflin	4	104.3	100.3	2.3	2.0	2.5	2.5	2.2	1.0	0.6	0.3	0.0	0.8
Monroe	4	127.5	115.8	1.0	1.0	2.0	2.3	2.2	1.1	0.6	0.0	8.3	0.0
Montgomery	62	119.9	111.3	4.1	3.5	3.3	4.0	2.3	0.6	1.1	0.2	1.6	0.0
Montour	2	131.0	112.5	1.5	1.5	2.5	2.5	2.5	1.2	0.7	0.0	1.5	1.0
Northampton	14	161.9	143.2	3.5	3.1	3.1	3.6	2.4	0.8	0.9	0.1	2.1	0.0
Philadelphia	45	163.1	150.2	4.0	3.5	3.0	3.4	2.4	0.8	1.1	0.4	1.7	0.1
Schuylkill	14	117.3	105.0	3.5	3.2	2.2	2.7	2.2	0.8	0.8	0.0	2.4	0.1
Somerset	6	110.5	101.3	3.7	3.5	3.0	3.3	2.2	1.0	0.7	0.2	2.5	0.0
Union	3	128.3	101.3	1.3	1.3	2.0	2.7	2.1	0.9	0.6	0.0	1.3	0.0
Venango	5	98.2	84.4	4.0	4.0	3.0	3.2	1.9	1.1	1.1	0.4	1.0	0.0
Warren	3	134.3	121.0	3.7	3.3	3.3	3.0	2.3	0.9	0.6	0.3	1.0	0.0
Washington	12	118.7	105.7	2.0	2.1	2.2	2.8	2.0	0.9	0.7	0.2	3.8	0.0
Wayne	3	123.7	111.3	2.3	2.0	2.3	2.7	2.2	0.8	0.6	0.0	7.0	0.0
Westmoreland	19	127.2	113.7	3.4	3.1	2.5	3.2	2.1	0.8	0.9	0.3	3.4	0.2
York	15	145.4	135.8	3.0	2.5	2.9	2.9	2.4	1.1	0.6	0.3	1.9	0.1

N= number of nursing homes
B = number of beds
UB = used beds
TS = Medicare Score
HI = health insurance rating
SR = staff rating
RNR = RN rating
CNAH = CNA hours
LPNH = LPN hours
RHR = RN hours
IC = number of reportable incidents
C = claims against facility
F = number of fines levied against each facility

Appendix D

List of Hospitals by County

Adams:
Gettysburg

Allegheny
Alle Kiski
Allegheny General
Heritage Valley Sewickley
Jefferson Regional
St. Clair Memorial
UPMC McKeesport
UPMC Mercy
UPMC Passavent
UPMC Presbyterian
UPMC St. Margret
West Penn Forbes Region
West Pennslvania

Armstrong
AMCH

Beaver
Heritage Valley Beaver

Berks
Reading
St. Joeseph

Blair
Altoona

Bradford
Robert Packer

Bucks
Delaware Valley
Doyelstown
Grand View
Lower Bucks
St. Mary

Butler
Butler Memorial

Cambria
Conemaugh

Carbon
Gnaden Huetten
Palmerton

Centre
Mount Nittany

Chester
Brandywine
Chester County
Jennersville Regional
Paoli
Phoenixville

Clarion
Clarion

Clearfield
Clearfield
Dubois

Columbia
Berwick
Bloomsburg

Crawford
Meadville

Cumberland
Carslisle Regional
Holy Spirit

Dauphin
Milton S. Hershey
Pinnacle Health

Delaware
Crozer Chester
Mercy Fitzgerald
Mercy Suburban

Elk
Elk Regional

Erie
St. Vincent Health Center
UPMC Hamot

Fayetteville
Uniontown

Franklin
Chambersburg
Waynesboro

Indiana
Indiana Regional

Lackawanna
Geisinger Community
Moses Taylor
Scranton Regional

Lancaster
Ephrata Community
Lancaster Community
Lancaster Regional

Lawrence
Jameson Memorial

Lebanon
Good Samaritan

Lehigh
Lehigh Valley Cedar Crest
Lehigh Valley Mulenberg
Sacred Heart
St. Luke's

Luzerne
Geisinger Wyoming Valley
Hazelton General
Wilkes Barre

Lycoming
Williamsport

McKean
Bradford Regional
Sharon Regional
UPMC Horizon

Mifflin
Lewistown

Monroe
Pocono

Montgomery
Abington Health Lansdale
Abington Memorial
Bryn Mawr
Holy Redeemer
Montgomery
Pottstown

Montour
Geisinger Danville

Northampton
Easton

Philadelphia
Albert Einstein
Aria Health
Chestnut Hill
Hahnehmann
Jeanes
Nazareth
Penn
Penn
Penn Presbyterian
Roxboro
Temple
Thomas Jefferson University

Schuylkill
Schuylkill

Somerset
Somerset
Windber

Union
Evangelical

Venango
UPMC Northwest

Warren
Warren General

Washington
Monogahela Valley
Washington

Wayne
Wayne Memorial

Westmoreland
Latrobe
Westmoreland Regional

York
Hanover
York
York Memorial

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