A RETROSPECTIVE ANALYSIS OF THE EFFECTS OF THREE 2013 PENNSYLVANIA HOSPITAL ACQUISITIONS

GEORGE SALEEBY
SPRING 2019

A thesis
submitted in partial fulfillment
of the requirements
for baccalaureate degrees
in Economics and Finance
with honors in Economics

Reviewed and approved* by the following:

Robert C. Marshall
Distinguished Professor of Economics
Thesis Supervisor

Russell Chuderewich
Teaching Professor of Economics
Honors Adviser

* Signatures are on file in the Schreyer Honors College.
ABSTRACT

In the years since 2010, the US has experienced record levels of consolidation in the hospital industry. This paper examines the impacts of three specific Pennsylvania hospital acquisitions from 2013 on prices, markups for specific services, and quality of care. Difference-in-differences methodology is used to compare trends in the three acquired hospitals to a control group of hospitals located throughout Pennsylvania. My findings provide evidence that these three transactions resulted in higher markups on electrocardiograms (EKGs) and computerized tomography (CT) scans, as well as a decrease in quality of care, indicated by inpatient survey results. Results of price level regressions are insignificant, and no relationship between average price levels and the acquisitions is discernible.
TABLE OF CONTENTS

LIST OF FIGURES ........................................................................................................................................ iv
LIST OF TABLES ........................................................................................................................................... v
ACKNOWLEDGEMENTS ................................................................................................................................. vi

Chapter 1 Introduction ................................................................................................................................. 1
  1.1 Trends in the US Hospital Market ........................................................................................................ 2
    - Consolidation ................................................................................................................................. 2
    - Prices ............................................................................................................................................. 4
    - Charge-to-cost Ratios (Markups) ................................................................................................ 8
    - Quality of Care ........................................................................................................................... 10
  1.2 Transactions in Question ....................................................................................................................... 12
    - Allegheny Health Network Acquires Jefferson & Saint Vincent Hospitals .................... 12
    - UPMC Acquires Altoona Regional Health System ............................................................. 13
  1.3 Government Guidelines and Legislation ............................................................................................ 14

Chapter 2 Literature Review ......................................................................................................................... 17
  2.1 Legal Precedent ..................................................................................................................................... 17
  2.2 Findings of Retrospective Analyses ................................................................................................... 19
    - The Evanston – Highland Park Merger .................................................................................... 20
    - The Sutter – Summit Merger ................................................................................................... 21
    - Hospital Quality ....................................................................................................................... 22
  2.3 Considerations and Takeaways ......................................................................................................... 22

Chapter 3 Methodology ............................................................................................................................... 24
  3.1 Determination of Control Group ......................................................................................................... 24
  3.2 Estimation of Prices ........................................................................................................................... 26
    - Case-mix Index ........................................................................................................................... 28
  3.3 Charge-to-cost Ratios ......................................................................................................................... 29
  3.4 Measuring Quality of Care ................................................................................................................. 30
  3.5 Model Specifications ......................................................................................................................... 32

Chapter 4 Results ......................................................................................................................................... 34
  4.1 Prices .................................................................................................................................................. 34
  4.2 Charge-to-cost Ratios ......................................................................................................................... 36
  4.3 Quality of Care .................................................................................................................................. 38

Chapter 5 Conclusion and Discussion ......................................................................................................... 42
Appendix  Select Figures and Tables................................................................. 44
REFERENCES .............................................................................................. 50
LIST OF FIGURES

Figure 1. Number of Hospital and Health System Mergers & Acquisitions Deals Announced, 2000-2018 ..................................................................................................................................................3

Figure 2. Consumer Price Indexes for All Items, Medical Care, and Hospital and Related Services, 1985-2018 ........................................................................................................................................4

Figure 3. Annual Percent Change for All Items, Medical Care, and Hospital and Related Services CPIs, 1985-2018 ........................................................................................................................................5

Figure 4. Difference in Annual Percent Change, Hospital and Related Services CPI and All Items CPI, 1985-2018 ........................................................................................................................................6

Figure 5. Percent "Top-box" responses needed to achieve 25th, 50th, and 75th Percentiles Nationally in Overall Hospital Rating ..............................................................................................................................11
LIST OF TABLES

Table 1. Average Charge-to-cost Ratios for Selected Hospital Patient Care Departments, 2013 ................................................................. 9

Table 2. HCAHPS "Box" Classifications ................................................................................ 31

Table 3. Coefficient Estimates for Price Regression ............................................................... 35

Table 4. Coefficient Estimates for Charge-to-cost Ratio Regressions ..................................... 37

Table 5. Coefficient Estimates for High-box Survey Response Regressions ......................... 39

Table 6. Coefficient Estimates for Bottom-box Survey Response Regressions ................. 40
ACKNOWLEDGEMENTS

I would like to thank Dr. Robert Marshall and Dr. James Tybout for the active roles they took in guiding me through every step of completing this thesis, from planning to writing. I would also like to thank my family for supporting me throughout my life and academic career.
Chapter 1

Introduction

In the United States, any merger or acquisition deal valued at more than $90 million must be reported to the Federal Trade Commission or the Department of Justice for review (FTC, n.d.). Using guidelines and regulations such as the 2010 Horizontal Merger Guidelines, these regulatory agencies decide whether or not to challenge a merger in federal court by assessing if the transaction is likely to result in any anticompetitive effects. For example, if an acquisition substantially increases a firm’s market share, conceivable anticompetitive effects could include exploiting increased pricing power to raise prices, or taking advantage of decreased competition by cutting down on innovation (DOJ & FTC, 2010). The FTC and DOJ’s overarching goal in this function is to protect American consumers from such anticompetitive outcomes (FTC, n.d.).

In transactions involving the health care industry, the implications of anticompetitive effects are arguably more serious and detrimental to consumers than those of any other sector, by virtue of the products/services provided by the merging parties. A radical increase in the prices of life-saving surgeries and drugs is naturally more concerning than a proportional rise in the prices of any consumer good. Likewise, an abatement in medical advancement is more concerning than a stagnation in smartphone innovation.

Although there is notable merger activity across the health care industry, this study focuses on a key type of health care service provider: general acute care hospitals. More specifically, we examine trends involving inpatient services, as opposed to outpatient services and procedures. The retrospective analysis examines the impact of three hospital transactions in
Western Pennsylvania, all consummated in 2013: (1) Allegheny Health Network’s acquisition of Jefferson Hospital in Pittsburgh, (2) Allegheny Health Network’s acquisition of Saint Vincent Hospital in Erie, and (3) the University of Pittsburgh Medical Center’s (UPMC) acquisition of Altoona Regional Health System (now known as UPMC Altoona). Please note that throughout this study, these three hospitals will collectively be referred to as “treatment” hospitals, and the “hospitals in question.”

1.1 Trends in the US Hospital Market

Consolidation

While the effects of hospital mergers and acquisitions are a subject of debate, the relatively high frequency of transactions in recent years is widely noted (see Gaynor, 2018, and Schmitt, 2018). Figure 1 displays how the total number of M&A deals in this space has evolved since 2000. Pennsylvania, the state examined herein, has been especially active in health care provider consolidation, with 19 announced deals between 2017 and 2018, the most of any state over these two years (Kaufman Hall, 2018, 2019).
In addition to an increase in the volume of deals, health care provider M&A has been trending towards bigger, more expensive deals. In 2014, the average seller (with seller defined as the smaller of the two parties in a transaction) in the 102 transactions that took place brought in about $250 million in annual revenues (Kaufman Hall, 2019). By contrast, the average deal in 2018 involved a seller with yearly revenues of $409 million (Kaufman Hall, 2019), a trend dubbed “the growth of mega mergers” by consulting firm Kaufman Hall.

When speculating about a relationship between hospital prices and the industry’s consolidation, there are some trends to keep in mind. Although figures for the number of hospital and health system M&A deals differ slightly between sources, there are several broadly acknowledged trends. The 1990’s and early 2000’s are recognized as times of especially heavy consolidation, in comparison to the 1980’s and presumably earlier (see Thompson, 2011, & Mutter et al., 2011). The years since 2010 contain the other substantial flood of merger deals, and higher volume of deals than ever before, as shown in Figure 1.
Prices

While this study examines price changes in several specific hospitals, it is informative to examine price trends on a macro scale. Figure 2 displays Consumer Price Indexes for all items, medical care, and hospital and related services, with 1982-1984 as the base years. The CPI for medical care is constructed using prices of medical care commodities (drugs, equipment, and supplies) and medical care services (such as private practice services, dental services, hospital services). The hospital and related services CPI comprises 30% of the medical care CPI, and is constructed using prices of hospital inpatient/outpatient services and nursing home/elderly care services. The hospital and related services CPI is most relevant, and should serve as an appropriate indicator for hospital prices, as inpatient/outpatient service prices comprise 90% of this index, with nursing/elderly care weighted at only 10%.

Figure 2. Consumer Price Indexes for All Items, Medical Care, and Hospital and Related Services, 1985-2018

Several striking observations can be drawn from Figure 2. While general prices (as measured by the all items CPI) are roughly 250% of what they were nominally in 1950, medical care is apparently five times as expensive, and hospital services are almost nine times as expensive. Those critical of consolidation in health care often attribute this price rise to consolidation, at least in part (Gaynor, 2018, and Gaynor et al., 2013). However, simply examining these indexes alone can be misleading, since it is difficult to determine the rate at which an indexed variable is changing over time. Furthermore, very few conclusions can be drawn without considering things like technological advancement, innovation, and quality of care.

Figure 3. Annual Percent Change for All Items, Medical Care, and Hospital and Related Services CPIs, 1985-2018


Figure 3 provides additional insight into how hospital prices have evolved over the years. As one would expect given Figure 2, hospital services prices have been growing at a faster rate
than medical care prices and overall prices. Also, hospital services prices since 2010 are growing at slower rate relative to the past, especially compared to the late 1980’s and the 2000’s. This would appear to contradict a correlation between hospital prices and increased consolidation, since the 2010’s have been the period of heaviest consolidation. However, since general inflation has been lesser in recent years (as displayed by the all item CPI), one would expect all indexes of this type show less growth. Indeed, changes in the hospital services CPI appear to move in tandem with changes in the all item CPI.

**Figure 4. Difference in Annual Percent Change, Hospital and Related Services CPI and All Items CPI, 1985-2018**


Figure 4 provides perhaps the best indication of trends in hospital prices over the last forty years. It displays the difference in annual percent changes for the hospital services and all items CPIs; that is, the yearly percent change in hospital services prices minus the yearly percent change in general prices as indicated by the all items CPI. This demonstrates how prices for hospital services have changed relative to prices in general. The periods when hospital prices outpaced the general CPI most are the late 1980’s into the early 1990’s, 2002-2003, and 2009-2010.
As previously noted, the two widely recognized periods of hospital consolidation in the US are the 1990’s into the early 2000’s, and the years since 2010. In Figure 4, the extreme spike in hospital service price growth could be perceived as a reaction to the flurry of mergers in the earlier of the two consolidation periods; the apparent lag is reasonable, as the effects of M&A deals should not be expected to show up immediately. However, data from the years since 2010 tell a different, possibly contrary story. Although these recent years have seen record levels of hospital consolidation, even in comparison with the 1990’s, the hospital services CPI has outpaced the all items CPI by less than usual. The difference measure from Figure 4 is 3.7% on average for the whole sample, and 2.8% on average from 2011 forward. Interestingly, the late 1980’s and early 1990’s show hospital service price changes exceeding inflation most substantially of all, during a period not noted for a great deal of hospital M&A activity.

While these observations provide some background information on the evolution of prices in American hospitals, drawing any conclusions about how a specific merger, or even hospital mergers in general affect prices is imprudent. These overarching trends fail to present any specific reasons for price changes, and do not take into account factors such as innovation, quality of care, government policies, or any number of elements affecting these prices. However, there is some circumstantial evidence suggesting that on a macro scale, increased consolidation does not necessarily cause increased prices, especially in most recent years.

Despite this, there are many who maintain that consolidation of health care providers leads to significant price increases (see Gaynor, 2018 for example). Undoubtedly, the effects of a merger vary on a case-by-case basis, and nobody is claiming that all hospital mergers cause price increases. However, those denouncing the uptick in hospital merger transactions on the basis of rising prices are implying that post-merger price hikes are the norm, rather than exceptions. With
Figure 4 in mind, that claim does not seem to hold up on a national scale. Part of this study’s aim is to determine whether the three specific mergers in question lead to price increases, and broadening any results more than that is unjustifiable.

**Charge-to-cost Ratios (Markups)**

Hospitals in the US must submit annual cost reports to the government, detailing statistics like charges to patients, expenses, number of discharges, and countless other figures. The information in these reports is housed in the Healthcare Cost Report Information System (HCRIS), maintained by the Centers for Medicare & Medicaid Services (CMS), and is accessible for use by researchers and the public through CMS’s website. These cost reports include statistics called cost-to-charge ratios, reported for a number of services that hospitals provide. One part of this ratio is a service’s Medicare-allowable cost, or the overall cost for all patients that are deemed to be directly related to patient care by Medicare, including operating costs and administrative expenses, all of which must be directly traceable or allocatable to the department. The other part is called the chargemaster price, or the price indicated by the hospital’s comprehensive list of billable items/services and their prices, with this list sometimes being known as the chargemaster (Bai & Anderson, 2016). The cost-to-charge ratio that hospitals report for each service is Medicare-allowable cost divided by chargemaster price. By inverting this calculation, we can obtain a hospital’s charge-to-cost ratio on a given service, how much they charge over how much providing the service actually costs.
Table 1. Average Charge-to-cost Ratios for Selected Hospital Patient Care Departments, 2013

<table>
<thead>
<tr>
<th>Rank</th>
<th>Department</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Computed tomography scan (CT scan)</td>
<td>28.5</td>
</tr>
<tr>
<td>2</td>
<td>Anesthesiology</td>
<td>23.5</td>
</tr>
<tr>
<td>3</td>
<td>Magnetic resonance imaging (MRI)</td>
<td>13.6</td>
</tr>
<tr>
<td>4</td>
<td>Electocardiology (EKG)</td>
<td>12.4</td>
</tr>
<tr>
<td>5</td>
<td>Electroencephalography (EEG)</td>
<td>9.3</td>
</tr>
<tr>
<td>6</td>
<td>Cardiac catheterization</td>
<td>8.7</td>
</tr>
<tr>
<td>7</td>
<td>Laboratory</td>
<td>8.5</td>
</tr>
<tr>
<td>8</td>
<td>Medical supplies charged to patients</td>
<td>8.3</td>
</tr>
<tr>
<td>9</td>
<td>Radiosotope</td>
<td>7.2</td>
</tr>
<tr>
<td>10</td>
<td>Renal dialysis</td>
<td>6.5</td>
</tr>
</tbody>
</table>

Source: Bai & Anderson, 2016

Table 1 shows the hospital departments that a 2016 study found to have the highest charge-to-cost ratios, using data from 2013 for 2,409 general acute care hospitals (Bai & Anderson, 2016). Fairly routine services, such as CT scans and MRIs, seem to provide hospitals with the highest margins. Another study from the same researchers found that the fifty hospitals with the highest average charge-to-cost ratios in 2012 were distributed across only thirteen states (Bai & Anderson, 2015). Pennsylvania contained seven of the hospitals in this top 50, trailing only Florida, which contained twenty. Given this, I also use charge-to-cost data for specific services to determine whether these three Pennsylvania acquisitions had an effect on how much the hospitals marked up their prices.
Quality of Care

The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) is a standardized survey aimed at measuring patients’ perspectives on hospital care. The survey was developed by the Federal Agency for Healthcare Research and Quality (AHRQ) and CMS, and has been implemented nation-wide by CMS since 2006. It is administered to a random sample of adult inpatients between 48 hours and six weeks after discharge, either by a survey vendor approved by CMS or a hospital itself if approved by CMS, through mail, telephone, or automated phone calls. Every hospital in this study achieved their required 300 completed surveys each year.

HCAHPS has recently discharged patients address crucial aspects of any hospital, including communication with doctors and nurses, timeliness of care, and cleanliness, finally having them rate the hospital overall and state whether or not they would recommend it to friends and family. Survey results are then aggregated into “boxes,” where “top-box” scores represent the most positive response to a survey item, “bottom-box” scores represent the least positive response, and “middle-box” scored capture intermediate responses. For example, when dealing with whether or not a patient would recommend a hospital, “Definitely yes” is a “top-box” score, while “Definitely no” and “Probably no” are “bottom-box” scores. These specific details regarding the aggregation of the survey items used in this study are detailed in Chapter 3.

There is evidence that quality of care provided in American hospitals has steadily risen over the last decade, at least insofar as quality can be measured through patient satisfaction and the HCAHPS survey. Multiple studies have used HCAHPS data to come to similar conclusions (see Press Ganey, 2017, and Mann et al., 2016). Figure 5 displays how the percent of “top-box” scores hospitals needed to achieve the 25th, 50th, and 75th percentiles nationally in overall hospital
From 2008 to 2017, the percent of “top-box” responses required for each quartile rose 9-10%, indicating a clear increase in average patient satisfaction on a national scale. The increases are so significant that a hospital scoring above the 75th percentile in 2008 would drop below the 50th percentile in 2017 if “top-box” scoring rate stayed the same, as the median hospital would drop to the bottom quartile. In 2008, a hospital could score in the top quartile with 70% of respondents giving the most positive response, while in 2017, a seemingly comparable 68% would only put them at the 25th percentile. Considering these changes, it is apparent that Americans are noticing positive changes in the quality of care they receive as hospital inpatients. This is a somewhat unsurprising finding, as technological advancement in medicine should provide for more patient satisfaction. The question addressed in this study is whether the three mergers in question caused deviations from this trend.
1.2 Transactions in Question

Firms choose to engage in M&A activities for any number of reasons. Motives for these activities include synergistic benefits (such as increased efficiency or product/service quality), diversification, relief of economic distress, and entrance into new markets (El Zuhairy et al., 2015). Hospitals’ motivations to merge, acquire, and be acquired are no different. Here, I provide an introduction to the factors that caused, or were cited as causes for, the three Pennsylvania hospital acquisitions to be examined. All three transactions consist of a larger health system acquiring a specific hospital. Each acquisition took place in 2013, during the recent/ongoing string of hospital and health care mergers.

Allegheny Health Network Acquires Jefferson & Saint Vincent Hospitals

In April of 2013, Pittsburgh based health insurer Highmark finalized its acquisition of West Penn Allegheny Health System, a system that included five acute care hospitals in western Pennsylvania. Originally announced in late 2011, the deal went through after a year and a half of doubt and contention, mainly centered on West Penn’s mismanaged finances and bungling operations (Evans, 2013). In September 2012, many labeled the deal dead when West Penn officials called it off after discovering that Highmark allegedly planned to restructure the health system through bankruptcy (VMG Health, 2013). In the end, a deal was struck that involved Highmark purchasing West Penn’s debt at a discount, and the agreement worth roughly $1 billion was approved by regulators and consummated (Commins, 2013). Today, AHN controls eight hospitals, and brings in yearly revenues of almost $3 billion (AHN, 2019a).
The newly integrated health provider/insurer system was promptly rebranded as Allegheny Health Network (AHN). At the time of the deal’s approval, Highmark had already reached an agreement to acquire Jefferson Regional Medical Center, in Jefferson Hills, a suburb of Pittsburgh. Now simply called Jefferson Hospital, AHN’s website claims its board of directors “recognized an opportunity to expand Jefferson’s service offerings and better serve the needs of those living in the South Hills communities” (AHN, 2019b). AHN also asserted plans to commit up to $100 million to fund capital projects, and $75 million in funding to the Jefferson Regional Foundation, a charitable grantmaking foundation (AHN, 2013). All public communications, prior and recent, from both Highmark/AHN and the acquired hospital include claims of a better hospital for the community. Several months later, in July of 2013, AHN finalized its acquisition of St. Vincent Hospital in Erie, PA, taking a controlling stake for $65 million (Mamula, 2013). The deal was announced alongside plans for AHN to invest $40 million over three years to improve facilities and acquire assets, and $20 million for financial purposes (Mamula, 2013).

In both cases, the acquisitions were approved by state regulators (the Pennsylvania Insurance Department) with no apparent intervention from federal agencies or regulators. While competitive concerns about the hospital deals as well as the deal forming AHN were brought up in public discourse (see Evans, 2013, and Commins, 2013), there was not sufficient concern for any federal entities to get involved.

**UPMC Acquires Altoona Regional Health System**

UPMC is a Pittsburgh-based integrated health system with 40 hospitals, bringing in $16 billion of revenue in 2017, making it considerably larger than AHN (UPMC, 2019). In July of
2013, UPMC officially acquired Altoona Regional Health System, redubbed UPMC Altoona, in Altoona, PA, a small city about 100 miles east of Pittsburgh. With the deal, UPMC committed $250 million over ten years, to go towards enhanced services and facilities (Twedt, 2013). This action, like the two AHN acquisitions, was approved at the state level without intervention by federal regulators. The hospital’s president and CEO at the time, Jerry Murray, said the deal would “enable Altoona Regional to further enhance our quality of care and breadth of medical services. (Twedt, 2013). Three years after the acquisition, UPMC Altoona issued a press release touting progress made since the merger, including $50 million dollars of investment in facilities and services, expansion of several clinical services, and recruitment of 53 new physicians (UPMC Altoona, 2016).

In addition to investigating price changes, a goal of this study is to determine the accuracy of claims like these made by the hospitals and health networks involved in these acquisitions. The fact that federal regulators were not involved in the approval of these deals does not inhibit scrutiny, and does not necessarily mean patients have benefitted.

1.3 Government Guidelines and Legislation

None of these three acquisitions were valued above the $90 million threshold at which federal review is required. Although federal agencies were not involved in the transactions to be examined, the laws and rules they implement are relevant. State regulators presumably approach their M&A approvals in the same way as federal agencies. Also, anticompetitive concerns maintained by the FTC and DOJ must be acted on preemptively, prior to a merger being
consummated, before any actual effects can be observed. Retrospective analysis can be more straightforward, and federal rules and guidelines provide a useful lens for it.

Section 7 of the Clayton Antitrust Act of 1914 is the preeminent grounds on which government entities such as the FTC and DOJ challenge mergers and acquisitions. This section prohibits mergers whose effect “may be substantially to lessen competition, or to tend to create a monopoly.” The government’s task in the simplest terms is to show that this phrase applies to the merger in question.

The Sherman Antitrust Act of 1890 is perhaps the most eminent piece of American antitrust legislation, and was the first to protect consumers by prohibiting arrangements such as cartels and monopolies. In 1914, the aforementioned Clayton Act and the Federal Trade Commission Act (which formed the FTC) were passed, assembling what the FTC dubs “the three core federal antitrust laws still in effect today” (FTC, n.d.). It is on the basis of these pieces of legislation that the FTC and DOJ attempt to challenge mergers and acquisitions they deem anticompetitive or somehow illegitimate.

The DOJ and FTC also maintain and make public a set of guidelines by which they approach mergers and acquisitions, whose most recent edition is the 2010 Horizontal Merger Guidelines (“the guidelines”). These guidelines are internal instructions (as opposed to enforceable law) that outline the government’s methodology in assessing the competitive effects of mergers. The guidelines define two distinct types of anticompetitive effects the government looks for in potential mergers. “Unilateral effects” are those which arise as a direct result of eliminating competition between merging parties, without changes in the behavior of other firms in the market (DOJ & FTC, 2010). These effects are probably the more commonly considered, and include changes in pricing, bargaining power, output, and innovation. Referred to by the
guidelines as “coordinated effects,” the other type of anticompetitive outcomes involves
“enabling or encouraging post-merger coordinated interaction among firms in the relevant
market that harms customers” (DOJ & FTC, 2010). Hospital merger studies focus mainly on
unilateral price effects (Ashenfelter et al., 2011).
Chapter 2

Literature Review

A large portion of the literature presented is the direct output of the FTC’s Hospital Merger Retrospective Project (“the retrospective project”), announced in 2002. A joint Bureau of Competition/Bureau of Economics initiative, this project launched as a result of a succession of failed hospital merger challenges by the FTC, and aimed to “[study] consummated hospital mergers to determine whether particular hospital mergers have led to higher prices” (Haas-Wilson & Vita, 2011).

2.1 Legal Precedent

As previously noted, the FTC launched the retrospective project after a series of failed attempts to block hospital mergers. In fact, at the 2002 Competition in Health Care Forum, the then-Chairman of the FTC, Timothy Muris, noted that “in the last eight years the Commission and Department of Justice are 0 for 7 in hospital merger cases” (Muris, 2002). Such a losing streak is understandably alarming, and part of the retrospective project’s intentions likely included determining what the FTC was doing wrong. Ashenfelter et al. (2011) accurately points out the compounding harm of a string of legal losses due to methodological mistakes: “Because the US legal system is based on precedent, the consequence of making invalid assumptions that, in turn, lead to poor enforcement decisions is often persistent.”
The FTC’s losing streak in the 1990’s was due mostly to the methods used to define relevant geographical markets in litigation (Ashenfelter et al., 2011). That is to say, the courts accepted definitions of geographical markets that were too large, resulting in underestimation of market share and competitive harm. In practically all failed challenges, both sides defined the relevant geographic market using the Elzinga-Hogarty (E-H) statistic, an approach based upon in- and out-migration of patients from a geographic market area (Ashenfelter et al., 2011). Ashenfelter criticizes the E-H statistic as “an ad hoc rule of thumb lacking a solid theoretical foundation.”

Another criticism of the E-H statistic was dubbed the “silent majority fallacy” by Capps et al. (2001), and claims that the E-H approach “draws a conclusion about the entire market from the behavior of those consumers who express displeasure with their local sellers by traveling elsewhere.” So, hospitals that are relatively far apart are deemed substitutes and in the same “relevant geographical market” by the E-H statistic, just because some consumers choose to travel the longer distance to receive care. However, such behavior (traveling to a farther hospital) may indicate that the hospitals are not close substitutes, since it is more than possible that patients are traveling farther because of a difference in services (Ashenfelter et al., 2011). A farther hospital is thereby wrongfully included in a geographical market, causing a larger definition of market area.

The so-called “payer problem” presents yet another limitation of the E-H test when it comes to health care: Patients are unlikely to notice a hospital’s price hike as their health insurance plans pay the difference, resulting in no change in out-of-pocket costs (Elzinga & Swisher, 2011). This does not, however, mean there is no harm inflicted upon the consumer, as health insurers will pass through their increased costs with pricier insurance. The E-H approach
has no way of accounting for the extra degree of removal health insurance provides patients from price increases.

Ashenfelter et al. (2011) cites the not-for-profit status that most American hospitals possess as the second most consequential reason for the FTC’s unfortunate losing streak of the 1990’s. The FTC’s retrospective project, Ashenfelter points out, resulted in multiple pieces of empirical evidence that the “not-for-profit defense” is invalid.

Recently, however, the FTC has been more successful challenging hospital mergers and acquisitions. In 2016, John J. Miles from law firm Baker Donelson noted that since successfully nullifying Evanston Northwestern Healthcare Corporation’s acquisition of Chicago provider Highland Park Hospital in 2007, the FTC went “undefeated” with several abandoned acquisition attempts and a few victories in matters that went to trial. Apparently, the FTC improved its methodologies, and these victories can at least partially be attributed to the employment of “complex econometric evidence and economic theories not employed in previous hospital-merger cases” (Miles, 2016).

2.2 Findings of Retrospective Analyses

The retrospective analyses presented in this section are results of the FTC’s Hospital Merger Retrospective Project, and all studies use the difference-in-differences (DID) framework to come to their conclusions. Although the DID method has clear drawbacks as it can never perfectly simulate a true experiment, it provides useful insights and “has become the standard empirical approach for retrospectively estimating the price effects of consummated mergers” (Haas-Wilson & Vita, 2011).
Haas-Wilson & Garmon (2011) examines the effects of two consummated hospital consolidations from 2000 in Chicago: the aforementioned Evanston Northwestern-Highland Park merger (nullified in 2007) and the merging of two community hospitals to form an entity called Vista Health. The study uses prices paid by private health insurers for inpatient hospital services to complete its DID analysis, and found that the Evanston merger, but not the Vista Health merger, resulted in an increased ability of the merged hospital to raise its prices. This result is not unexpected, considering the FTC’s success in challenging the Evanston merger.

However, in a comment on the paper, Adams & Noether (2011) claim that the DID methodology employed by Haas-Wilson and Garmon “does not produce credible results when applied to an assessment of the merger of Evanston and Highland Park Hospital, north of Chicago.” It is argued that price levels alone (the only variable analyzed by the DID method) are insufficient in judging the competitive effects of a merger, and that data deficiencies and an inability to control for certain variables that could affect price render the results unreliable. In addition, pre-merger prices at Evanston were well below those of competitors and post-merger prices were not higher than those of comparable hospitals, so any price increases can be considered the result of the merged entity’s prices “catching up” with those of its competitors (Adams & Noether, 2011).

When mergers are challenged, a common defense for the price increases that often follow is an improvement of the products/services being offered. The defense can be a convincing one; a merged entity has more resources and may be more efficient, or may have the means to make purchases that allow for improvements. In the case of a hospital, this takes of the form of improvements in patient care through expensive undertakings such as new medical record
computer systems or state-of-the-art equipment acquisitions. The Evanston case is no exception, but the FTC determined that any such improvements were more than offset by the competitive harm caused by the acquisition (Adams & Noether, 2011).

**The Sutter – Summit Merger**

In 1999, Sutter Health, a not-for-profit health system in Northern California, acquired Summit, a not-for-profit hospital in Oakland, California. This effectively combined Summit with Sutter Health’s larger Alta Bates Hospital, approximately 2.5 miles away, forming an entity known today as Alta Bates Summit Medical Center (Tenn, 2011). In August of that year, the California Attorney General filed a federal complaint to block the merger, and the motion for a preliminary injunction was denied that December. Tenn (2011) uses insurance claims data and the DID method, coming to the conclusion that “Summit’s price increase was among the largest of any comparable hospital in California, indicating this transaction may have been anticompetitive.” Among the issues addressed by Tenn are inaccuracies in geographical market definition, the Elzinga-Hogarty test, and the non-profit status of the merging entities.

Specifically, Tenn (2011) finds that while Summit exhibited statistically significant price increases, Alta Bates, the close-by facility already run by Sutter Health, did not. Tenn posits that this result could stem from an asymmetry in the size of the two facilities: Pre-acquisition, Alta Bates’ larger size could make for a significant constraint on Summit’s prices, while Summit would have a relatively minor effect on Alta Bates’ prices (Tenn, 2011). Another notable claim from this study is that “mergers involving nonprofit hospitals should perhaps attract as much antitrust scrutiny as other hospital mergers” (Tenn, 2011).
Mutter et al. (2011) uses the DID framework to examine the effects of hospital mergers on 25 measures of quality, including various mortality rates, incidence of infections and other complications, and incidence of certain traumas related to childbirth. The study uses a sample of 42 hospital consolidations across 16 states from 1999 and 2000, with over 400 “control group” hospitals for each of the two years (Mutter et al., 2011). Ultimately, Mutter et al. (2011) finds that “consolidations have no consistent effect on quality, although there is suggestive evidence that acquiring hospitals may achieve some limited quality benefits.”

In a comment on Mutter et al. (2011), Robert Town lauds the study for making a valuable contribution to the literature, but offers a slightly different, more nuanced interpretation of its results. Town says that although there is evidence that the average impact of hospital mergers on quality is not statistically significant, the highly heterogeneous nature of market and hospital characteristics means a paper with the scope of Mutter et al. (2011) may not detect the true impact of these mergers (Town, 2011).

2.3 Considerations and Takeaways

This study uses the concepts presented, conclusions reached, and empirical methods employed by this literature as a guide for retrospectively examining the three mergers in question. The methodology detailed in Chapter 3 relies on the studies above as examples of the DID framework applied to hospital mergers, drawing on models, sampling methods, and control variables presented in these papers and others.
Haas-Wilson & Garmon (2011) and Tenn (2011) are relevant because of their examination of a few specific mergers, as opposed to using merger data across many transactions. However, this study differs in a few ways worth noting. The above studies concerned with price effects use claims data from private insurers, which is not publicly available and practically inaccessible to a student researcher. My price estimations rely on annually aggregated, self-reported hospital cost report data, which are accompanied by serious concerns that are addressed later. My sample size of sixteen control hospitals is also worth addressing, as Tenn (2011) uses between 40 and 71 control hospitals (depending on the insurer providing the claims data) and Haas-Wilson & Garmon (2011) presents results across four different control group specifications of hospitals in the Chicago area. As a consequence, my results should be approached with increased caution.

On the other hand, some drawbacks of Mutter et al.’s (2011) analysis of how hospital quality is impacted by mergers are corrected for in this study. For example, eleven of the 25 quality measures used by Mutter et al. (2011) are various in-hospital mortality rates, which have since been deemed unreliable for gauging quality by some researchers (see Goodacre et al., 2015, and Drye et al., 2012). I use HCAHPS survey data, described above, to measure quality of care. Also, the heterogeneity concern brought up by Town (2011) is partially abated by my focus on three specific hospital acquisitions in one state from 2013, as opposed to tens or hundreds of mergers across various years and locations.
Chapter 3
Methodology

Using difference-in-differences (DID), post-merger price changes for three hospitals are compared to price changes in a “control” group (hence the labeling of the acquired hospitals as the “treatment” group) of comparable Pennsylvania hospitals that underwent no merger/acquisition activity during the period in question. All data used for price estimations and presentations of trends come from the CMS’s publicly available data sets, and span a seven-year period from the beginning of 2010 to the end of 2016.

3.1 Determination of Control Group

When attempting to determine the effects of a merger, the DID method’s purpose is to serve as a proxy for a controlled experiment, since a true controlled experiment is impossible in many circumstances. In a true controlled experiment, the effects of a given treatment are substantiated by the use of a control group, whose only difference from the treatment group is the treatment itself. In the case of a retrospective merger study, one attempts to simulate an experiment by comparing the merged entities in question with other firms that are ideally as similar as possible, less the treatment, which in this case is merger/acquisition activity. Methodical and unbiased selection of such a control group is central to the ability to draw any inferences from the results of a retrospective study. The assumption implied is that the outcomes being considered for treatment and control groups would have followed parallel paths absent any
treatment (in this case, a merger), an idea that has been descriptively been referred to as the common trends assumption (Kwoka, 2015).

Determining a control group for a retrospective hospital merger analysis is a balance between attaining a large enough sample size to minimize the effects of any number of unique circumstances that affect a given hospital, while maintaining a group of hospitals that are similar enough to be suitable controls. I only considered hospitals as candidates for the control group if they were general acute care facilities located in Pennsylvania. The merging entities in question are general acute care hospitals whose prices and characteristics can only reasonably be compared to hospitals that offer a similar general array of services, rather than facilities that specialize in psychiatric care or rehabilitation, for example. Only Pennsylvania hospitals are in the control group because hospitals must comply with laws and rules enforced at the state level, namely those related to federal programs.

While many retrospective merger studies focus on the effects of a merger on an entire market, the focus of this study is the effects on the newly merged entities themselves. I exclude hospitals in the same county as any treatment hospital, as they are undoubtedly affected by a nearby competitor’s merger activity, as well as any hospitals that had any merger activity between the years 2010 and 2016. Similarly, no hospitals in the Allegheny Health Network or UPMC medical systems are in the control group, as they are the parties who “administered” the treatment of interest.

Finally, hospitals were disqualified from the control group if they averaged less than 10,000 or more than 22,000 total discharges per year during 2010-2016. During this period, Jefferson, Saint Vincent, and UPMC Altoona averaged about 13,700, 14,500, and 18,000 discharges per year, respectively. As detailed later in this section, each hospital’s prices pre- and
post-merger are estimated by the ratio of total private payer inpatient charges to total private payer discharges (charges per inpatient), adjusted for contractual discounts and case-mix. Only hospitals with a similar number of discharges as the treatment hospitals provide a reasonable comparison. After imposing these restrictions, there are 16 hospitals across Pennsylvania that serve as suitable members of the control group.

3.2 Estimation of Prices

Ideally, a hospital’s average price level would be measured by detailed claims data across all patients and all payers, including Medicare, Medicaid, and private insurers. Unfortunately, Pennsylvania is not one of the few states that collects all-payer claims data of this kind. Some past retrospective hospital merger studies have utilized detailed claims data from several large commercial health insurers (see Tenn, 2011, and Haas-Wilson & Garmon, 2011). Such data are presumably not realistic for an undergraduate student researcher to purchase or obtain.

I estimate average hospital prices using the data sets and procedures described in Dafny (2009) and utilized again in Garmon (2017). The estimates are generated using financial measures in the HCRIS, a database containing yearly hospital level data, maintained and updated annually by the CMS. HCRIS files for 2017 and 2018 are currently far too incomplete to be useful, as they are apparently not updated, so the data used only spans to the end of the 2016 fiscal year. A hospital’s estimated case-mix adjusted price for a given year, as expressed in Dafny (2009), is:

$$\hat{P}_h = \frac{IPC_h \left( 1 - \frac{CD_h}{TPC_h} \right) - MCR_h}{(DIS_h - MDIS_h)CMI_h}$$
where \( IPC_{ht} \) is the hospital’s total inpatient service charges in the fiscal year, \( CD_{ht} \) is contractual discounts, \( TPC_{ht} \) is total patient charges, \( MCR_{ht} \) is total reimbursement to the hospital for Medicare inpatients, \( DIS_{ht} \) is total inpatient discharges, \( MDIS_{ht} \) is Medicare inpatient discharges, and \( CMI_{ht} \) is the hospital’s case-mix index (described below).

The term \( 1 - \frac{CD_{ht}}{TPC_{ht}} \) can be defined as a “discount factor,” as it represents the percentage of total patient charges not accounted for by contractual discounts (Dafny, 2009).

Every commercial insurer accepted at a given hospital enters a contract with negotiated terms that differ between insurers, and estimated prices must be adjusted to reflect these discounts. Then, the product of total inpatient charges and the discount factor represents the portion of inpatient charges actually charged to payers. Although the discount factor is calculated based on all patients, this price calculation applies it to inpatient specific charges. The implied assumption is that the composition of payers for inpatients is the same as the composition of payers at the hospital overall.

Dafny’s calculation deducts charges to Medicare patients as well as Medicare discharges, since the federal government determines these patients’ prices. Garmon (2017) points to the inclusion of Medicaid revenue/discharges as the primary source of potential bias in this price estimation because Medicaid provider reimbursement rules are generally determined at the state level. Since all control and treatment group hospitals in this study are located in Pennsylvania, this variation is non-existent.
A major aspect of this method of price estimation is the adjustment of discharges using case-mix index (CMI), an indexed measure of the makeup of a hospital’s inpatient cases in a given year. According to the State of California (the only state that releases CMI data across all hospitals and all inpatients), CMI reflects the diversity, clinical complexity, and resource needs of all patients in the hospital. The CMS calculates CMI yearly for Medicare patients for hospitals across the country, and serve as a proxy for overall CMI, as they do in Dafny (2009). A higher CMI means a more complex, time and resource consuming case load, so using it to adjust discharges captures the fact that every discharge should not be weighted equally between hospitals. Facilities that take on more complicated and resource intensive cases have their discharge figure adjusted upward; on average, one of their discharges is more costly in time and resources than that of a competitor with a lower CMI, and their price estimation is altered to reflect it.

CMS starts CMI’s calculation by assigning a relative weight to over 900 distinct diagnoses groups requiring inpatient care, called Medicare Severity-Diagnosis Related Groups (MS-DRGs). Each MS-DRG reflects not only a diagnosis (such as pneumonia or cardiac arrest), but also the patient’s degree of severity and whether or not complications and comorbidities occurred. MS-DRG relative weights are assigned based on the average cost to the provider of the MS-DRG (as calculated by the CMS). For example, for the year of 2019, CMS has assigned the MS-DRG titled “Simple Pneumonia & Pleurisy without complications or comorbidities” a relative weight of about 1, and the MS-DRG “Lung Transplant” a relative weight of about 26 (CMS, 2018). This means they have determined that the average lung transplant costs a hospital 26 times more than the average pneumonia patient without complications. CMS computes each
hospital’s CMI by summing every MS-DRG weight for every Medicare inpatient in the given year, and dividing by total Medicare discharges that year. Note that this study, like most of its counterparts, is using Medicare CMI as a proxy for overall hospital CMI. The underlying assumption is that a hospital’s typical Medicare inpatient case-mix is representative of its typical inpatient case-mix in general.

CMI was originally conceived as a way to adjust cost per patient in order to compare efficiency across hospitals with differing case-mixes. A hospital with a relatively high CMI would have their average cost per patient adjusted downwards, to account for the fact that their inpatients’ conditions were inherently more costly. This was simply used as a measure of a hospital’s efficiency. More recently, researchers like Dafny and Garmon have utilized CMI as an indicator of the severity and costs of a hospital’s average inpatient. By including CMI in the denominator, the price estimation formula adjusts for the idea that hospitals whose average inpatient is more costly to them will inherently charge more per patient/discharge.

### 3.3 Charge-to-cost Ratios

Using cost report data from HCRIS, I examine how the acquisitions in question affected how much these hospitals charge-to-cost ratios changed for three services: Electrocardiograms (EKGs), computed tomography scans (CT scans), and magnetic resonance imaging (MRI). These three services were chosen because they are common and should be relatively homogeneous across hospitals. The routine nature of these tests makes them more pertinent to the general American, who will likely be subject to at least one of these tests over the course of their life. Homogeneity is also important; since these services likely do not vary across hospitals,
disparities in charge-to-cost ratios cannot be attributed to differences in quality of care. There is really only one way to place a patient in an MRI machine, for example.

Including regressions on charge-to-cost ratios gives insight into whether, for instance, the newly-acquired hospitals were able to take advantage of a hypothetical decrease in competition by hiking up margins on specific, routine services. Please note that UPMC Altoona is not included in the regressions for charge-to-cost ratios for CT scans and MRIs, due to large gaps in the data, presumably caused by a reporting mistake/omission on the hospital’s part. Those two regressions contain only two treatment hospitals.

### 3.4 Measuring Quality of Care

Using HCAHPS results for three survey items, I analyze how quality of care has changed in the three merged hospitals relative to my control group. The three survey items deal with: (1) The hospital’s overall rating, (2) whether patients would recommend the hospital, and (3) the timeliness of inpatient care. Overall rating and recommendation are examined because they give a valuable look into inpatients’ general perception of a given hospital after actually staying there, making them ideal indicators of quality of care. I consider how quickly patients receive care when they wanted it as well, as it should be a suitable indicator of how efficient a hospital is, at least when it comes to inpatient care. These three survey items, more accurately than other HCAHPS items, demonstrate aspects of hospital services that mergers are likely to affect. Table 2 displays how specific responses are classified by the surveyors into “boxes,” as touched on in Chapter 1. Note that data is only released in these specific boxes; that is, I cannot determine
whether a hospital with a “top-box” overall rating received a “9” or “10,” only that their score was classified as “top-box.”

### Table 2. HCAHPS "Box" Classifications

<table>
<thead>
<tr>
<th>Bottom-box</th>
<th>Middle-box</th>
<th>Top-box</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 6</td>
<td>7 - 8</td>
<td>9 - 10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Would you recommend this hospital to your friends and family?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom-box</td>
</tr>
<tr>
<td>Probably no or Definitely no</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>During this hospital stay, after you pressed the call button, how often did you get help as soon as you wanted it?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom-box</td>
</tr>
<tr>
<td>Sometimes or Never</td>
</tr>
</tbody>
</table>

Source: HCAHPSonline.org

I use HCAHPS survey data from 2010-2016 to compare treatment and control hospitals’ respective trends in quality of care and patient satisfaction. There were no gaps or apparent errors in any of the data. Specifically, I use the percentage “top-box” and “bottom-box” scores for each question, to determine the proportion of patients who were very satisfied with their inpatient experience, and the proportion of patients who were very unsatisfied with their inpatient experience.
3.5 Model Specifications

The basis of the difference-in-differences technique is the estimation of the DID parameter, which captures the difference between the variable of interest’s change over time for the treatment group, and its change over time for the control group. In the case of a merger, a simple representation of this parameter $\delta$ for prices is:

$$\delta = (\bar{P}_{tr, post} - \bar{P}_{tr, pre}) - (\bar{P}_{c, post} - \bar{P}_{c, pre})$$

This is simply the difference between the merging parties’ changes in price and the control group’s changes in price, as measured by their average prices before and after the merger took place. To estimate this parameter and its standard error to determine its significance, regression analysis is convenient (Kwoka, 2015). The different variables detailed above (prices, charge-to-cost ratios, and survey results), represented by $Y_{it}$, will be estimated by the following model:

$$Y_{it} = \alpha + \beta_1 Post_i + \beta_2 Trt_i + \delta Post_i Trt_i + \beta_n X_{it} + \epsilon_{it}$$

Where $Post_i$ is a dummy variable for the post-merger period, $Trt_i$ is a dummy variable for whether the hospital is in the treatment group, $Post_i Trt_i$ is an interaction variable equal to one for a treatment hospital in the post merger period, $X_{it}$ represents control variable(s), and $\delta$ is the DID parameter. As the coefficient on the interaction between the treatment and post-merger dummy variables, $\delta$ and its standard error should indicate whether the data suggest that these mergers had a significant effect on the prices paid by patients in the treatment hospitals. The control variable(s) used in each regression will be detailed in Chapter 4.

Four years of pre-merger (2010-2013) and three years of post-merger (2014-2016) data are used to estimate case-mix adjusted prices, charge-to-cost ratios, and inpatient survey results.
for each hospital in each of the six years, which are then used to determine the effects of the mergers as detailed above.
Chapter 4

Results

This chapter presents the coefficient estimates of the model specified in Chapter 3, obtained using panel data from the years 2010-2016. All regressions use data from the three hospitals of interest and sixteen “control” hospitals in an attempt to isolate the effects of the acquisitions. Coefficients significant at $p < 0.05$ are marked with one asterisk on the error term (*), and coefficients significant at $p < 0.01$ are marked with two asterisks on the error term (**).

4.1 Prices

Table 3 presents the coefficient estimates for the above-described model, with the independent variable being natural log of case-mix adjusted price of inpatient services, as calculated by the formula originally introduced by Dafny (2009). The coefficient on the interaction between the dummies for post-merger period (2014-2016) and treatment hospitals is the DID parameter. The natural log of beds is used as a control variable in an attempt to control for each hospital’s size, as number of beds is a prevailing way of describing the size of a hospital. This is a common control variable for such regressions, and has been included by other studies using this price estimation formula (see Dafny, 2009, and Schmitt, 2018). The percent of inpatients made up by Medicaid is also a regressor, because while the price estimation formula effectively excludes Medicare patients, Medicaid inpatients cannot be excluded because the information in HCRIS is insufficient to do so (again consistent with Dafny, 2009, and Schmitt, 2018, who utilized the same price estimation formula).
Table 3. Coefficient Estimates for Price Regression

<table>
<thead>
<tr>
<th></th>
<th>Price</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Trt</td>
<td>-0.024</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Post</td>
<td>0.001</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Trt</td>
<td>-0.233</td>
<td>(0.201)</td>
</tr>
<tr>
<td>ln(beds)</td>
<td>-0.072</td>
<td>(0.148)</td>
</tr>
<tr>
<td>% Medicaid</td>
<td>0.118</td>
<td>(0.337)</td>
</tr>
<tr>
<td>intercept</td>
<td>9.145</td>
<td>(0.828)*</td>
</tr>
<tr>
<td>R²</td>
<td>0.080</td>
<td></td>
</tr>
</tbody>
</table>

Appendix Figure A 1 depicts the average price estimation figure for control and treatment hospitals over this period. Given that figure, a lack of any significant results is unsurprising. Price estimates for both groups are relatively steady over time, and there is no discernible difference between the price trends of the two groups, and certainly not enough of a difference for any significant results to be expected. The DID parameter (estimated at -0.024) is essentially zero.

Figure A 1 also reveals that control group price estimates are approximately $1,500 to $2,000 (dollars per case-mix adjusted discharge) higher than those of the treatment group throughout. This, and many other concerns, call into question how accurate this measure of prices truly is. The standard deviation in any given year across price estimates is about $2,000, while the overall mean is about $6,000. These findings were found to be consistent with Schmitt (2018), who used the same price estimation method, using data from the study. However, a standard deviation that is one-third of the mean instantly raises concern; do prices really differ so vastly across hospitals, or does this aggregated yearly data fail to capture too many key
differences between hospitals? It is also worth noting the decreased accuracy and higher standard error for price estimates caused by the relatively small sample size of 19 total hospitals.

This study found no concrete evidence of an increase (or decrease) in prices for inpatient services due to the three mergers in question, but given the concerns addressed above, any findings resulting from my estimation of prices would come with major caveats. Due to the inconsistencies, aggregation, and self-reporting nature of this public data, it cannot measure changes in prices charged to patients as effectively as private claims data can. Additionally, the price calculation itself, serving as a rough estimate of the average amount a hospital charged per inpatient in a given year, cannot provide the accuracy of private claims data.

4.2 Charge-to-cost Ratios

Table 4 displays the coefficient estimates of the model with the natural logs of cost-to-charge ratios for EKGs, CT scans, and MRIs used as independent variables in three separate regressions. Again, the natural log of total beds is used as a hospital-level control, attempting to take into account the size of each hospital. Appendix Figures A 2, A 3, and A 4 show how these charge-to-cost ratios evolved for each hospital group over time. As mentioned above, please note that in the CT scan and MRI regressions, UPMC Altoona is not included in the treatment group because of data deficiencies.
Table 4. Coefficient Estimates for Charge-to-cost Ratio Regressions

<table>
<thead>
<tr>
<th></th>
<th>EKG Charge/Cost Ratio</th>
<th>CT Scan Charge/Cost Ratio</th>
<th>MRI Charge/Cost Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Post*Trt</td>
<td>0.236 (0.094)*</td>
<td></td>
<td>0.265 (0.091)**</td>
</tr>
<tr>
<td>Post</td>
<td>0.092 (0.038)*</td>
<td></td>
<td>0.175 (0.034)**</td>
</tr>
<tr>
<td>Trt</td>
<td>-0.566 (0.277)*</td>
<td></td>
<td>0.065 (0.289)</td>
</tr>
<tr>
<td>ln(beds)</td>
<td>-0.169 (0.253)</td>
<td></td>
<td>0.248 (0.224)</td>
</tr>
<tr>
<td>intercept</td>
<td>3.492 (1.416)*</td>
<td></td>
<td>1.710 (1.235)</td>
</tr>
</tbody>
</table>

$R^2$           | 0.203                 | 0.166                     | 0.092                 |

The model finds a significant increase in EKG charge-to-cost ratios attributable to the three acquisitions, as shown by the DID parameter estimate of 0.236, significant at the $p < 0.05$ level. This can be roughly interpreted as the merged parties raising this ratio 23.6% more than the control group post-merger. Figure A 2 shows that the “common trends assumption” that is key for the DID technique holds well: Pre-acquisition, control and treatment averages appear to move in ideal unison.

CT scan charge-to-cost ratio data also results in a significant DID parameter estimate of 0.265, significant at the $p < 0.01$ level. Given Figure A 2, this finding is anticipated: Markup growth for this service in treatment hospitals was outpacing control hospitals before the mergers, but the ratios grew even more rapidly after 2013. Nothing of significance can be drawn from the MRI charge-to-cost ratio regressions, but Figure A 4 does show that treatment hospitals had higher MRI markups over the entire period, although the two groups seem to be converging towards more recent years.

In considering these results, there are a number of concerns to keep in mind. While the EKG regression found significant increases attributable to the mergers, Figure A 2 shows that the average control hospital’s margins on an EKG are consistently above those of the treatment
providers. It could be argued that the acquired entities are simply reverting to the industry’s norm. These figures are also taken from the same self-reported, publicly available HCRIS data as the price estimate components. While the values are taken directly from cost reports without the assumption-laden manipulation of my price estimations, there still could be inconsistencies due to things like reporting error and countless factors omitted by this kind of information being aggregated on a yearly level.

4.3 Quality of Care

Table 5 presents the results of three regressions with “high-box” HCAHPS survey responses as the independent variables. These are: (1) The percent of respondents rating the hospital a “9” or “10” on a scale of one to ten, (2) the percent of respondents claiming they “always” received help as soon as they wanted it, and (3) the percent of respondents claiming they would “definitely” recommend the hospital to friends and family. The natural log of beds is again used to control for hospital size. Figures A 5, A 6, and A 7 show how the percent of people responding in these ways changed from 2010 to 2016. Please note that for the regressions, these response percentages were divided by 100, so that coefficients could be directly representative of percent changes due to regressors.
Table 5. Coefficient Estimates for High-box Survey Response Regressions

<table>
<thead>
<tr>
<th></th>
<th>% Rating Highly</th>
<th></th>
<th>% Always Timely</th>
<th></th>
<th>% Definitely Recommend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Post*Trt</td>
<td>-0.059</td>
<td>(0.012)**</td>
<td>-0.041</td>
<td>(0.013)**</td>
<td>-0.042</td>
</tr>
<tr>
<td>Post</td>
<td>0.038</td>
<td>(0.004)**</td>
<td>0.028</td>
<td>(0.005)**</td>
<td>0.017</td>
</tr>
<tr>
<td>Trt</td>
<td>0.003</td>
<td>(0.038)</td>
<td>0.023</td>
<td>(0.025)</td>
<td>-0.014</td>
</tr>
<tr>
<td>ln(beds)</td>
<td>-0.066</td>
<td>(0.030)*</td>
<td>-0.116</td>
<td>(0.028)**</td>
<td>-0.026</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.066</td>
<td>(0.166)**</td>
<td>1.296</td>
<td>(0.157)**</td>
<td>0.873</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.141</td>
<td></td>
<td>0.257</td>
<td></td>
<td>0.043</td>
</tr>
</tbody>
</table>

These DID parameters, as estimated by the coefficient on the interaction variable between post-acquisition and treatment hospital dummies, provide statistically significant evidence that average patient satisfaction suffered post-acquisition for the three hospitals in question. The coefficients of interest can be interpreted to observe that the mergers resulted in 5.9% lower, 4.1% lower, and 4.2% lower “high-box” responses in overall rating, timeliness, and recommendation respectively, with all estimates significant at the \(p < 0.01\) level. Figure A 6 shows that “high-box” timeliness responses are fairly consistent with the “common trends assumption” in the pre-merger period, with the average favorable responses only falling significantly after 2013.

While these percentage losses of “high-box” responses may not seem compelling at first, it is important to keep in mind that control hospitals, according to Appendix Figures, exhibited a trend of steadily increasing patient satisfaction over the period, using HCAHPS survey results. As discussed in Chapter 1, the average American hospital also had increasingly satisfied patients from 2010-2016. So, in a period where comparable peers were moving in a positive direction, these three hospitals displayed the opposite trend. Additionally, while 4–6% losses are ostensibly small, they change a hospital’s standing among the competition considerably. For example, in
2016, only a 5% difference in “high-box” response rate for overall score separated the bottom quartile from the median, and the median from the top quartile.

Table 6 displays coefficient estimates for models using “bottom-box” responses to the same questions as independent variables. Specifically, these are: (1) The percent of respondents rating the hospital a “6” or below on a scale of one to ten, (2) the percent of respondents claiming they “sometimes” or “never” received help as soon as they wanted it, and (3) the percent of respondents claiming they would “definitely not” or “probably not” recommend the hospital to friends and family. Appendix Figures A 8, A 9, and A 10 show time-series plots of these response rates from 2010 to 2016.

**Table 6. Coefficient Estimates for Bottom-box Survey Response Regressions**

<table>
<thead>
<tr>
<th></th>
<th>% Rating Poorly</th>
<th></th>
<th>% Some/Nev Timely</th>
<th></th>
<th>% Would Not Recommend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Post*Trt</td>
<td>0.026</td>
<td>(0.006)**</td>
<td>0.032</td>
<td>(0.008)**</td>
<td>0.014</td>
</tr>
<tr>
<td>Post</td>
<td>-0.011</td>
<td>(0.002)**</td>
<td>-0.016</td>
<td>(0.003)**</td>
<td>-0.002</td>
</tr>
<tr>
<td>Trt</td>
<td>-0.003</td>
<td>(0.014)</td>
<td>-0.020</td>
<td>(0.012)</td>
<td>-0.008</td>
</tr>
<tr>
<td>ln(beds)</td>
<td>0.017</td>
<td>(0.014)</td>
<td>0.057</td>
<td>(0.015)**</td>
<td>0.018</td>
</tr>
<tr>
<td>intercept</td>
<td>-0.018</td>
<td>(0.079)</td>
<td>-0.223</td>
<td>(0.084)**</td>
<td>-0.063</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.130</td>
<td></td>
<td>0.355</td>
<td></td>
<td>0.115</td>
</tr>
</tbody>
</table>

These three positive DID parameters, all significant at the $p < 0.01$ level, build on the inferences of Table 5 and the “high-box” regressions. Not only were post-acquisition, treatment hospital patients less likely to have the most positive responses to these questions, they were more likely to have the most negative responses. Put simply, we see significantly less very satisfied inpatients, and significantly more very unsatisfied patients. According to the model, the acquisitions resulted in 2.6% more patients rating the hospitals poorly overall, 3.2% more
patients saying their doctors and nurses were sometimes or never timely, and 1.4% more patients claiming they probably or definitely would not recommend the hospital.

Again, the distribution of responses in 2016 for “bottom-box” response rates show how the tightness of the distributions mean that “small” percentage gains are significant: The middle 95% of “bottom-box” response rates for overall score and recommendation have ranges of only 12% and 11%, respectively. Figures A 8, A 9, and A 10 all support the validity of the DID parameters, as the “common trends assumption” is relatively well satisfied for all three independent variables, with spikes in negative survey responses occurring only after 2013. The Appendix Figures also show control hospitals exhibiting a steady (albeit small) decrease in “bottom-box” responses.

Overall, these findings pertaining to quality of care (as measured by inpatient satisfaction) are the most striking findings of this study. The average treatment hospital appears to exhibit a decrease in highly satisfied patients and an increase in highly unsatisfied patients. The issue most blatantly disregarded by this inference is why patient satisfaction dropped in the newly acquired entities. For example, merging and non-merging hospitals alike can run into disputes with insurance companies that cause major inconveniences for patients – an occurrence that we would expect to affect survey results. Also, the simple axiom that people are strongly averse to change could explain why any number of reasonable adjustments that mergers cause could upset some patients, especially in the short run.
Chapter 5

Conclusion and Discussion

In research concerned with the impact of mergers, prices are perhaps the most commonly examined factor because of their homogeneous interpretation and ubiquitous importance across all industries. In this study, results related to price levels are completely insignificant and based on numerous dubious assumptions about data reliability and price calculation. However, findings from charge-to-cost ratio regressions show that the acquired hospitals exhibited significantly larger increases in markups on EKGs and CT scans, compared to control group hospitals. Charge-to-cost data presents some of the same concerns as my price data; it is from the same annually aggregated and self-reported data set, although it is taken directly from the files without a complicated, assumption-laden calculation.

Results pertaining to quality of care, as measured by patient satisfaction surveys, provide statistically significant evidence suggesting that these three hospital acquisitions resulted in a decrease in very satisfied patients and an increase in very dissatisfied patients, implying a post-acquisition downturn in quality of care. This conflicts with claims made by both the acquiring and acquired parties in these transactions, presented in Chapter 1. Again, these results should be interpreted with caution because they fail to consider countless explanations for post-acquisition drops in patient satisfaction, such as people’s natural averseness to change.

All findings (and lack of findings, in the case of price regressions) should be interpreted as conjectural evidence. The DID method is ultimately an approach that attempts to simulate a controlled experiment in thoroughly uncontrolled circumstances. Circumstances affecting
hospitals and health care providers are especially complex and difficult to account for; factors such as Medicare/Medicaid, relationships/contracts with insurers, and unique patient-mixes are among those I attempt to retroactively control for. However, doing so on any level comparable to a true controlled experiment is categorically impossible. So, even in the absence of the data and methodology concerns addressed in Chapter 4, these findings should not be inflated past their most simple implications. Haas-Wilson & Vita (2011) point out that DID has become the standard approach for retrospective hospital merger studies despite its drawbacks. This may simply be the result of a lack of better options.

The conclusion of this line of thought can be a frustrating impasse for any researcher concerned with merger effects. Conclusively determining the impact of a merger before its consummation, as the FTC and DOJ attempt to, is difficult because it hinges on forecasting the future. Retrospective merger analysis with a broad scope and overarching implications is unreliable because every transaction is fundamentally different in numerous ways that cannot be controlled for. A solution lies in studies like this one (i.e. studies of this kind that are more robust) that examine at most a handful of mergers with as many similarities as possible. The Horizontal Merger Guidelines acknowledge this, citing the “effects of analogous events in similar markets” as an important type of evidence for challenging mergers (DOJ & FTC, 2010).

The findings of this study cannot be stated as anything more than conjectural evidence that for these specific hospital acquisitions, the transactions resulted in decreased quality of care and increased markups on certain procedures. Any retrospective hospital merger analysis claiming to have broader implications should be received with heightened skepticism and doubt.
Appendix

Select Figures and Tables

Figure A 1. Average Price Estimates, Control and Treatment Hospitals, 2010-2016
Figure A 2. Average EKG Charge-to-cost Ratio, Control and Treatment Hospitals, 2010-2016

Figure A 3. Average CT Scan Charge-to-cost Ratio, Control and Treatment Hospitals, 2010-2016
Figure A 4. Average MRI Charge-to-cost Ratio, Control and Treatment Hospitals, 2010-2016

Figure A 5. Average Percent of HCAHPS Respondents Rating Hospital Highly Overall, Control and Treatment Hospitals, 2010-2016
Figure A 6. Average Percent of HCAHPS Respondents Rating Hospital's Service as Always Timely, Control and Treatment Hospitals, 2010-2016

Figure A 7. Average Percent of HCAHPS Respondents who would Definitely Recommend Hospital, Control and Treatment Hospitals, 2010-2016
Figure A 8. Average Percent of HCAHPS Respondents Rating Hospital Low Overall, Control and Treatment Hospitals, 2010-2016

Figure A 9. Average Percent of HCAHPS Respondents Rating Hospital Service as Sometimes or Never Timely, Control and Treatment Hospitals, 2010-2016
Figure A 10. Average Percent of HCAHPS Respondents who would Not Recommend Hospital, Control and Treatment Hospitals, 2010-2016


ACADEMIC VITA

George A. Saleeby

Education
The Pennsylvania State University - Schreyer Honors College, Paterno Fellows Program          University Park, PA
College of the Liberal Arts - Bachelor of Science in Economics                 Class of May 2019
Smeal College of Business - Bachelor of Science in Finance
College of the Liberal Arts - Minor in French and Francophone Studies

Experience
Bates White Economic Consulting              June 2018 - August 2018
Summer Consultant                     Washington, DC
● Processed and analyzed complex databases and statistical models to support expert analysis
● Collaborated on a case study to produce reports and presentations driven by statistical modeling and regression analysis
● Produced data extracts, deliverables, and documentation memos for superiors and clients

Penn State University Department of Economics        August 2017 - May 2018
400-level Undergraduate Grader                   University Park, PA
● Graded coursework for an advanced undergraduate course covering strategic decision making and game theory
● Cooperated with course instructor and teaching assistant to equitably evaluate a class of 70 students

CoBuilders Startup Incubator and Accelerator             May 2017 - July 2017
Communications Intern                  Paris, France
● Facilitated wider appeal to prospective clients by translating multimedia content from several startups
● Created multimedia content such as PowerPoint presentations for business pitches and outreach
● Developed new ideas for the incubation/acceleration of startups by collaborating in a startup inspiration studio

The Tavern Restaurant/Adam’s Apple Bar                    May 2016 - October 2017
Server/Food Runner/Door                        State College, PA
● Prepared tables, took orders, and transported food in a timely manner to ensure customer satisfaction
● Ensured the safety of all patrons and coworkers by regulating entrance into bar

Leadership
Lion Ambassadors - The Penn State Student Alumni Corps        January 2017 - Present
Tour Guide/Committee Member                   University Park, PA
● Administered tours to prospective/accepted students as a representative of the university
● Planned and executed on-campus projects promoting education and university improvement
● Participated in and facilitated community and/or university enriching events on a volunteer basis
Schuyler Fund Allocation Committee
● Managed and reviewed organization-wide requests for funding from a $30,000+ endowment

Delta Sigma Pi Professional Business Fraternity          October 2015 - Present
Chancellor                     University Park, PA
● Facilitated and lead chapter-wide meetings for a chapter of over 100 members
● Implemented and enforced all bylaws, rules, and regulations of the organization
Vice President of Scholarships and Awards
● Coordinated study groups and textbook swaps in which members could effectively share academic resources
● Initiated and implemented a tutor pairing system that matched new members with older members in their problem areas

Skills
Languages
● French: Advanced speech, reading, and writing skills
● Arabic: Intermediate speech skills
Computer
● Competency in Microsoft Office (Excel, Word, PowerPoint)
● Stata: Intermediate proficiency, working experience
● Python: Basic proficiency, classroom experience