

January 01, 2010

## Three essays on buyer power theory, dominant HMOs and technology transfer

Megan Gay  
Northeastern University

---

### Recommended Citation

Gay, Megan, "Three essays on buyer power theory, dominant HMOs and technology transfer" (2010). *Economics Dissertations*. Paper 2.  
<http://hdl.handle.net/2047/d20000287>

This work is available open access, hosted by Northeastern University.

**THREE ESSAYS ON BUYER POWER THEORY, DOMINANT Firms AND  
TECHNOLOGY TRANSFER**

A dissertation presented

by

Megan Gay

to

The Department of Economics

In partial fulfillment of requirements for the degree of  
Doctor of Philosophy

in the field of

Economics

Northeastern University  
Boston, Massachusetts  
June, 2010

**THREE ESSAYS ON BUYER POWER THEORY, DOMINANT Firms AND  
TECHNOLOGY TRANSFER**

by

Megan Gay

**ABSTRACT OF DISSERTATION**

Submitted in partial fulfillment of the requirements  
For the degree of Doctor of Philosophy in Economics  
In the Graduate School of Arts and Sciences of  
Northeastern University, June 2010

## **Abstract of Dissertation**

The following are abstracts of the three chapters of my doctoral dissertation entitled “Three Essays on Buyer Power Theory, Dominant HMOs, and Technology Transfer.”

The first chapter of my dissertation is an investigation into technological transfer efficacy, with success defined at specific levels culminating in revenue generation via licensing or a university-based start-up. Licensing revenue and new venture spin-offs as driven through U.S. university technology transfer offices have been a predominant goal for funded research and development over the last twenty-five years. However, as opposed to patent generation, investigation into the translation of research into viable revenue generation is somewhat sparse. The data used in the analysis is from 400 technology transfer disclosures filed over a ten-year period at a large U.S. research university. We estimate both ordered logit and ordered probit models which allow for our non-continuous, ordinal dependent variable. The results indicate that the significant factors in technology transfer success are the level of experience of the faculty member and participation in an industry sponsored research agreement. Aspects such as team size and academic department/school have no significant impact on technology transfer outcomes. The paper concludes with policy recommendations and directions for future research.

The second chapter of my dissertation examines Health Maintenance Organizations’ (HMO) entry decisions in local markets in Florida from 2001 to 2005. Unlike prior research, I analyze HMOs’ entry decisions at the firm-level using a discrete-choice approach. I estimate the probability that an HMO will enter a market (HMO entry) as a function of firm characteristics, market characteristics and firm-market characteristics. The results indicate that both firm and market heterogeneity play a significant role in explaining HMO entry in local markets. Specifically, entry decisions in the Florida HMO Market vary substantially across individual

HMOs. The geographic location of a HMO's existing operations, distance from a firm's headquarters and the type of firms already operating in a local market significantly impact HMOs' entry decisions. The importance of firm characteristics and firm-market characteristics suggests that some HMOs are better suited to a particular market than others. Thus it appears that HMOs are capitalizing upon the unique features of their organization or product when choosing which markets to enter in Florida.

The third chapter of my dissertation examines the effects of Health Maintenance Organization (HMO) buyer power on both the price and utilization of hospital inpatient services by HMO enrollees. Currently, there are three conflicting theories regarding the effects of HMO buyer power: Monopsony Theory, Welfare-Increasing Theory, and the All-or-None Theory.<sup>1</sup> I empirically test these theories using data from all general acute-care hospitals in Florida from 2001-2005. Unlike prior research, I control for HMO buyer power, measured as the market share of the largest HMO (Dominant HMO) or the level of HMO concentration (HMO HHI) in a given geographic region, in addition to HMO penetration, the share of a given market that is enrolled in HMOs. I estimate a reduced form model of the impact of HMO buyer power and HMO penetration on the price and quantity of hospital medical procedures and other supply and demand controls. I use instrumental variables to control for potential endogeneity of HMO penetration and HMO buyer power. I find that HMO buyer power has a significant negative effect on the price of inpatient hospital services for HMO enrollees and no impact on the number of hospital admissions or inpatient days per HMO enrollee. These results are only consistent with the All-or-None Theory of HMO buyer power.

---

<sup>1</sup> A classic Monopsony Theory of the effect of HMO buyer power is advanced by Pauly (1998). Conversely, Feldman and Wholey (2001) argue that HMO buyer power actually has a monopoly-busting effect which I refer to as a Welfare-Increasing Theory. Finally, Herndon (2002) claims the effects of HMO buyer power will be consistent with the All-or-None Theory.

## **Acknowledgements**

I would like to express my gratitude and deep appreciation to my advisor, Professor James Dana, for his excellent guidance, suggestions, and encouragement throughout my study. Professor Dana has the attitude and substance of a genius; he exemplifies the high quality of scholarship to which I aspire. This dissertation would not have been possible without his supervision and persistent help.

I would like to thank the other members of my committee, Professor Kamran Dadkhah and Professor John Kwoka, for their timely and instructive comments and insights at every stage of the dissertation process. I have been privileged to benefit from their insights and expertise that guided and challenged my thinking, substantially improving the finished product. In addition, I am grateful to Dr. Serdar Dalkir for his practical advice and recommendations that helped me sort out the technical details of my work.

I am also indebted to many of the other faculty and staff of the Department of Economics who assisted and encouraged me in various ways during the course of my studies. I would like to thank all of them for their support.

In addition to the technical and instrumental assistance I would like to thank my friends and family, in particular my mother, Sharon, for their endless love and support. From an early age, my mother instilled in me the desire and skills necessary to obtain this Ph.D.

Finally, I can not thank my husband, Marcus, enough for his unlimited patience, understanding and encouragement. His support and care helped me overcome setbacks and stay focused on my graduate study.

## TABLE OF CONTENTS

	Page
ABSTRACT	2
ACKNOWLEDGEMENTS	5
TABLE OF CONTENTS	6
CHAPTER-1	8
I. Introduction	9
II. Literature Review and Conceptual Foundation	11
III. Research Method	23
IV. Results	36
V. Discussion and Policy Implications	40
VI. Limitations and Future Research	47
References	48
Appendix	51
CHAPTER-2	53
I. Introduction	54
II. Florida HMO Market	55
III. Review of the Literature and Research Goals	62
IV. Data	65
V. Theoretical Model	68
VI. Research Method and Empirical Model	71
VII. Results and Discussion	89
VIII. Conclusions and Further Research	100
References	102

## TABLE OF CONTENTS (Cont'd)

	Page
CHAPTER-3	106
I. Introduction	107
II. US Market for Hospital Services and HMO Buyer Power	109
III. Review of the Literature	114
IV. Research Goals and Hypotheses	118
V. Research Method and Empirical Model	124
VI. Results and Discussion	150
VII. Discussion and Policy Implications	161
VIII. Conclusions and Further Research	165
References	168
Appendix	172

## **CHAPTER 1**

### **Levels of Success in Technology Transfer at a Large Research University<sup>1</sup>**

---

<sup>1</sup> This chapter is based on an article that has been coauthored with Tucker J. Marion and John H. Friar of The School of Technological Entrepreneurship at Northeastern University.

## **I. Introduction**

Technology transfer is a complex area of study (Bozeman 2000), and the definition of technology transfer differs among different industries (Zhao and Reisman 1992). In this study, we focus on university research that leads to the development and eventual commercialization of innovative technologies. Historically, the university's role was one of educator and provider of public domain research (Bozeman 2000). This began to change during and after World War II, as major industries were created as a result of the development of transformational technologies. Examples include the electronic computer developed at the University of Pennsylvania, the 1960s launch of fiber optics at MIT that stimulated telecommunications, the 1970s investigations in DNA at Stanford and UC Berkeley that provided the basis for the biotechnology industry, and 1980s supercomputing research at the University of Illinois that advanced the development of the Internet (Libecap 2005).

This leads us to the current state of university technology transfer. Bozeman (2000) termed the government role in fostering research and technology development at universities as the market failure paradigm. He argued that although free markets will lead to technology proliferation and economic growth, there is a need for high-level research that is not grounded by clear market need but has future commercial viability. As such, universities are increasingly being viewed by policy makers as engines of economic growth via the commercialization of intellectual property through technology transfer into the private sector (Siegel and Phan 2005). A series of U.S. government legislation in the 1980s fostered this growth. The main legislative technology transfer initiative was the passing of the Bayh-Dole Act of 1980, which permitted universities to obtain title to inventions funded by the federal government in order to seek licensing agreements. This led to the creation of technology transfer offices (TTOs) whose

primary mission is fostering the successful commercialization of university-developed technology.

In fiscal year (FY) 2006, U.S. research universities received approximately \$45 Billion in research and development (R&D) funding, corresponding to record staff levels at TTOs (AUTM Report 2006). In the FY2006 report, U.S. university TTOs received 18,874 new invention disclosures, filed 15,908 patent applications, saw 3,255 U.S. patents issued, and signed 4,963 new licensing agreements. It was also reported that 697 new products were introduced into the market in 2006, and 553 new start-ups were formed. Since the Bayh-Dole Act was passed in 1980, approximately 5,700 university-based start-ups have been formed. At first glance, these are impressive statistics for the success of technology transfer policy, but we need to better define success in order to evaluate the efficacy of the technology transfer paradigm.

Literature on technology transfer efficacy has been primarily focused on the generation of patents and licensing (Siegel and Phan 2005), and not the development of sustainable new ventures. We argue the creation of university spin-outs is also an important statistic of success for R&D/technology transfer as entrepreneurial activity - through the creation of new ventures, has been shown to be one of the strongest contributors to innovative activities, competition, economic growth and job creation (Carree and Thurik 2003). According to a 2004 Venture Impact Study, 10% of the U.S. Gross Domestic Product (GDP) is directly related to new venture creation (Global Insight 2004). The translation of technology into high-growth new stand-alone businesses or business units is paramount to sustaining economic growth and standard of living. The U.S. has tried to foster this translational growth by annual investment into universities via governmental agencies such as the National Institutes of Health (NIH) and National Science Foundation (NSF). Since 1997, U.S. research institutions have received approximately \$330

Billion dollars in funding – substantially more than venture capital investment during the same period (National Venture Capital Association 2008).

Unfortunately, high-levels of R&D funding have not translated into associated levels of licensing revenue generation or new venture creation. The cumulative gross revenue generated via technology transfer initiatives in the years between 2004 and 2006 was approximately \$3.5 Billion (AUTM 2006). With hundreds of billions of dollars invested and thousands of patents issued, the result is a low return on investment. Can that be considered success given the focus and funds allocated to university research and technology transfer? We argue that it is not, and as academics, we need to investigate the parameters behind this regrettable reality. This article seeks to understand the conversion of academic research into levels of success or research productivity (as defined by the number of disclosures, patent applications, patents received, licenses received, and revenue generated) at the university level. In order to accomplish this task, we worked with the TTO at a large U.S. research institution and evaluated 400 invention disclosures received over a ten-year period. In Section 2, we review pertinent literature and development of hypotheses. In Section 3, we outline our model and variables. In Section 4, we discuss the results. In Section 5, we explore the implications of our research and outline policy suggestions. Finally, we conclude with research limitations and directions for further study.

## **II. Literature Review and Conceptual Foundation**

Since the 1980s, research universities have functioned as creators and consumers of new knowledge, and their societal role in value creation has become an important policy issue (Markman et al. 2005). Given the level of funding and expectation of universities to act as pistons in the engine of technology-based economic growth, we first must define levels of

success in order to evaluate the current state of affairs. In FY2006, \$45 Billion was funneled to U.S. research universities which resulted in a large number of invention disclosures, a substantial number of patent applications, fewer granted patents, an even smaller number of licensing agreements, and a limited number of revenue generating licensing agreements and university spin-outs (AUTM 2006). We will use these five categories as defining levels of success in technology transfer throughout the article, with the highest-level of success being revenue generation via licensing or a university-based new venture. Success levels and associated literature are reviewed in the next sub sections.

#### **A. Success Level 1: Invention Disclosures**

With the passing of the Bayh-Dole Act, universities for the first time had a vehicle to claim ownership over research. These patent policies seek to encourage innovation by granting exclusive rights to inventors and their sponsoring universities (Markman et al. 2005). In order to accomplish this task, universities created technology transfer offices (TTOs). The Bayh-Dole Act stipulates that faculty members working under federal research grants are required to disclose their inventions to the TTO (Siegel and Phan 2005). Faculty members will approach the TTO and fill out a disclosure form, explaining the invention, its uniqueness and commercial viability. This is in essence the beginning stage of the march towards technology transfer success.

However, studies have been performed that argue many faculty members are not disclosing inventions to the TTO, instead seeking their own path towards commercialization (Thursby and Kemp 2002; Thursby and Thursby 2002). Owen-Smith and Powell (2001) argue that convincing faculty to disclose inventions is a crucial first step. In their study of 68 faculty

members at research one (R-1) institutions, they found that faculty decides to patent because of beliefs in the positive nature of IP protection. However, ambivalent faculty members may become frustrated with TTOs and decide that the effort and cost of the process is not worth the potential upside, especially given a lack of impact on the track to tenure. To ameliorate this issue, incentives for university departments to disclose discoveries can provide a positive impetus to the process of innovation (Markman et al. 2005). Once the disclosure is filed, the TTO attempts to evaluate the commercial potential of the invention (Siegel and Phan 2005). If there is sufficient evidence or third-party interest, the TTO will decide whether to move forward with a patent application.

### **B. Success Level 2: Conversion of Disclosure to Patent Applications**

The filing of new U.S. patent applications most frequently corresponds with a decision to seek patent protection of a single invention disclosure, though sometimes two or more invention disclosures are combined into a single new U.S. patent application (AUTM 2006). Given the high cost of filing, maintaining and protecting patents, some institutions are reluctant to file for a patent if there is little interest expressed by industry in the technology (Siegel and Phan 2005). Unfortunately, in looking at industry interest and the importance of university research on applied technological innovation, the impact of university invention is arguably not significant. Cohen et al. (2002) indicated that in most industries, university research plays a minor role in triggering new industrial R&D projects: instead, the stimuli originate with customers or from manufacturing operations. Yet, it can be argued that biotechnology and pharmaceuticals are an exception (Mowery 2005). If most university research is not compelling to industry, passing the gate from disclosure to patent application is telling. However, the growth of TTOs and

associated staff are increasing the conversion rate to patent applications, and by association, the number of patents granted.

### **C. Success Level 3: Granted Patents**

In technology transfer literature, quantitative work in the area has focused particularly on patents as a measure of university “output” (Jaffe 1989; Henderson et al. 1998). This is a clear metric to gauge, as historically this has been a primary tenet on which to highlight the success of technology transfer policy. University patents as a share of all patents with U.S. domestic assignees have grown dramatically since the 1940s. In 1948, the share of university patents as a percentage of total assignees was less than 0.005. By 1996, this had grown to well over 0.035 – a 700% increase (Mowery 2005). Recently however, the growth in granted patents has remained stagnant, averaging approximately 3,500 annually since 2001 (AUTM 2006). In a study of faculty at MIT over a 15-year period, Agrawal and Henderson (2002) found that on average, only 10–20% of the faculty patent in any given year, and nearly half of the faculty in the sample never filed a patent during the study period. This can be attributable to a variety of factors, from quality of the TTO office to university patent incentives.

When academic and commercial rewards are linked, incentives to patent are enhanced (Owen-Smith and Powell 2001). In this setting, frustrations with the patent process may be overcome by the general positive reputation of multiple benefits of IP protection - even ambivalent inventors may begin to disclose (Owen-Smith and Powell 2001). Regardless of inventor orientation and incentives to patent, the ability to patent quickly and comprehensively can shield a discovery from the destroying effects of imitation and work-around solutions

(Shapiro 2001). Intellectual property is a key step – not the key to success – on the road to successful technology transfer.

#### **D. Success Level 4: License or Option Received**

As a fourth level of success, licenses are the most common document that transfer rights acquired for a specific technology to another organization. Licensing or optioning research has been a main goal of TTOs for the last two decades. While TTOs participate and engage in many other kinds of agreements and transactions, licenses are the most frequent kind of transaction that a technology transfer office has sole responsibility for in a given institution (AUTM 2006). Licenses confer access to technology at the point of discovery and may increase the potential for the development of newer products (George et al. 2002). To increase licensing opportunities, TTOs actively recruit licensing representatives with experience in an industry to which they are trying to license (Owen-Smith and Powell 2001). Markman et al. (2005) found that licensing complexity increases commercialization time whereas TTO competency reduces commercialization time. Given the focus on technology transfer effectiveness, staffing at TTOs has increased dramatically over the past decade (AUTM 2006). TTO competency and staffing levels may increase lower levels of success, but arguably do not transfer into the higher levels of success of licensing and starting new firms. In fact, Thursby and Thursby (2002) found that growth in disclosures and patent applications has been greater than the corresponding growth in licenses executed. While reaching the point of an executed licensing agreement is a formidable accomplishment, it is not the final step in technology transfer success.

### **E. Success Level 5: Revenue Generation via Licensing and Start-ups**

We define the highest level of success in technology transfer as the positive generation of revenue from a license or university spin-out. Research has shown that royalties and the number of start-ups resulting from licensed technology vary significantly across universities (Markman et al. 2005). A university's academic eminence, equity involvement in their start-ups, and royalty rewards to faculty may explain some of the variation in technology licensing outcomes (Di Gregorio and Shane 2003). Licensing university developed technology is a two-fold driver, one being the paradigm of government investment to promote economic growth (e.g. the market failure paradigm as explained by Bozeman 2000), and the other being university revenue growth.

For new ventures, licensing rather than internal R&D can be a more efficient way to mine and harvest a new technology; licenses can shortcut the process of discovery, reduce technology risk, and compress innovation time (ATUM 2006). The 2001 and 2002 AUTM reports noted that 14 – 16% of university licenses in these years were to start-ups specifically created to exploit the licensed inventions. This is only slightly higher than the research of Di Gregorio and Shane (2003), who found that only 12% of university-assigned inventions are transferred to private new ventures. It should be noted that licenses to start-ups are only a small fraction of the absolute numbers of licenses to large firms (Mowery 2005). In 2006, out of 4,192 executed licensing options, only 698 went to start-ups (AUTM 2006).

University-based start-ups have the greatest potential to affect the greater economy and realize the hopes of government R&D policy makers. New ventures and entrepreneurial activity have been shown to contribute to competition, economic growth and job creation, and account for a large portion of GDP (Carree and Thurik 2003; Global Insight 2004). As mentioned, Di Gregorio and Shane (2003) found that only about 12% of university-assigned inventions are

transferred to private new ventures. If the purpose of government funded R&D is to accelerate the yield from research assets by reducing commercialization cycle time, empirical research on this issue should receive greater attention (Markman et al. 2005). Shane and Stuart (2002) suggest that start-ups based on university technology (such as Genentech, Cirrus Logic, and Lycos) tend to survive longer and are more likely to achieve Initial Public Offering (IPO) status. These examples point to the continuing importance of incubation within the university setting (Clarysse et al. 2005). In their study, Di Gregorio and Shane (2003) found that there is substantial evidence that a university's intellectual eminence and licensing policies have a significant impact on start-up activity. They argue that this is due to two points: 1) that researchers from more prestigious universities are better researchers and thus are more likely to create firms to capture the rents to their rare and valuable intellectual property (Zucker et al. 1998); and 2) that inventors from more prestigious universities may be better able to obtain the necessary capital to start their own firms. However, these two points disregard issues such as organizational characteristics of the university (O-Shea et al. 2005), level of funding, age of the TTO, and internal/external resource factors (Powers and McDougall 2005). What is clear though, is that given the amount of federal funding being funneled into universities, the output in terms of licensing revenue and viable new ventures is small.

In the next sub section, we outline five characteristics that can influence the level of success for university funded research and inventions.

## **F. Generation of Hypotheses**

The translation of funded research into greater levels of research success as defined by invention disclosure, patent application, patents granted, licenses received, and revenue

generation via licensing or university-based start-ups is not well understood in terms of empirical studies. As such, our research goal is to identify some of the factors that determine an academic inventor's ability to transfer their technology or invention outside the university into a secured license or start-up. Numerous elements could potentially influence the success of an academic inventor's research productivity. Bozeman (2000) highlighted the role of human capital and training in the effectiveness of technology transfer where human capital was made up of: formal education, skills, know-how, and R&D experience. Conversely, O'Shea et al. (2005) found that the amount of government funding had a positive impact on the amount of new spin-off companies generated by a university. Dietz and Bozeman (2005) found that the amount of industry experience of an academic researcher had a positive effect of patent productivity. On the other hand, Powers and McDougall (2005) established that faculty quality (measured by the number of citations) had a positive effect on the number of start-up companies formed and new IPOs. We have identified five different factors that we believe affect research productivity and success: (1) academic position; (2) participation in an industry sponsored research agreement; (3) research funding source; (4) school/college affiliation; and (5) research team size. These five factors in relation to outcomes are outlined in the next sub section.

### ***Academic Position***

One would assume that academic inventors with more experience (indicated by a higher job title) would be more likely to have their invention or technology successfully transferred outside the university than academic inventors with less experience (indicated by a lower job title). A number of previous studies have looked at the effect of faculty quality and experience on technology transfer and research productivity (O'Shea et al. 2005; Powers and McDougall

2005; Dietz and Bozeman 2005; Renault 2006). Previous researchers have argued that higher-quality faculty members are more interested in the commercialization of their results (Renault 2006). In fact, Renault (2006) found that faculty quality was the most important predictor of technology transfer participation. Similarly, O'Shea et al. (2005) found that human capital, specifically faculty quality as measured by the number of postdoctoral staff and faculty, had a positive impact on the number of new spin-off companies generated by a university. This is due to the fact that higher-quality faculty members have greater access to expert knowledge, skills and talent, and accordingly realize a higher degree of success in their development of cutting-edge technology (O'Shea et al. 2005) and technology transfer efforts (Powers and McDougall 2005). Finally, it has been shown that human capital and experience are a vital element in technological innovation and scientific discovery (Dietz and Bozeman 2005). Thus if one equates an academic inventor's position within a university as a measure of faculty quality, we expect there will be a positive effect of this variable on research productivity success. Stated formally:

**Hypothesis One (H1):** *An academic inventor's position within the university will impact their research success level.*

### ***Industry Sponsored Research***

When an academic inventor's research is funded by an outside industrial partner, the invention or technology that is based upon this research is considered to be part of a sponsored research agreement. Due to the larger amount of resources, human capital, experience, and guidance that participants in a sponsored research agreement have access to versus non-participants; one would assume that participants would be more likely to have their technology

or knowledge translated into a marketable product than non-participants. The idea that academics who partner with industry gain access to a valuable set of resources and insider knowledge that they can exploit during the technology development and transfer process is not novel. O'Shea et al. (2005) found that increased university-industry ties and partnerships result in greater levels of commercialization. Similarly, Blumenthal et al. (1996) found that industry funded faculty members were more commercially productive than those without industry funding. Along these lines, Dietz and Bozeman (2005) found that researchers with a higher degree of industry experience and more relationships with industry professionals developed a unique set of network communication and social capital, which enabled them to realize a distinct advantage in the innovation process. Similarly, industry participation and funding during the research process has been found to stimulate considerable technology transfer activity. Specifically, Powers and McDougall (2005) found that universities with closer ties to industry generated a greater number of start-ups. Thus we hypothesize there will be a positive effect of an academic inventor's participation in a sponsored research agreement (inventions or technologies that were created as part of an industry sponsored research agreement) on research productivity success. Stated formally:

**Hypothesis Two (H2):** *There is a positive effect of an academic inventor's participation in an industry sponsored research agreement (SRA) on research success level.*

### ***Government Funding***

Due to the fact that academic inventors with government or university funding have access to a larger amount of resources than those without funding; one would assume that academic inventors with funding would be more likely to have their invention or technology

translated into a marketable product or knowledge than those without funding – in-line with those receiving sponsored research agreements. It has long been argued that financial resources are one of the necessary components to successful technology transfer. O’Shea et al. (2005) found that the amount and size of government funding (funding from sources such as the National Science Foundation (NSF) or National Institutes of Health (NIH)) increased university spin-off activity at a variety of different academic institutions. Similarly, Landry et al. (1996) found that collaboration between universities and government increased research productivity. Thus, we expect there will be a positive effect of funding source (academic inventors whose inventions or technologies were funded with either government funding or private/university funding) on an academic inventor’s research productivity success. Stated formally:

**Hypothesis Three (H3):** *The funding source of an academic inventor’s underlying invention or technology will impact research success level.*

### ***School/College Affiliation***

One would predict that inventions or technologies that originate from academic inventors in certain disciplines (e.g., engineering or arts & science) would be more likely to be transferred into marketable knowledge or products than those from other disciplines. Numerous studies have explored the idea that entrepreneurial participation, research productivity, and commercialization success varies by academic discipline. A variety of studies have found that engineering, computer science and biology are departments that have experienced the greatest success in their patenting experience (Agrawal and Henderson 2002). Along these lines, Renault (2006) looked at the difference between life sciences and engineering faculty and their degree of technology transfer participation. Similarly, O’Shea et al. (2005) illustrated that research that

originated in science or engineering was more likely to generate spin-off companies. Owen-Smith and Powell (2001) found that faculty decisions regarding disclosure differed between faculty affiliated with life and physical sciences. Thus, there should be a positive effect of an academic inventor's school affiliation, specifically engineering or arts & sciences, on research productivity success. Stated formally:

**Hypothesis Four (H4):** *An academic inventor's school/college affiliation will affect their research success level.*

### ***Research Team Size***

Due to the larger amount of resources, human capital, and experience at their disposal, one would assume that an invention or technology that was discovered by a larger research team would be more likely to be translated into a product or new venture than those with smaller research teams. Greater resources will enable academic inventors to take the necessary steps to seek licenses or form new ventures. This idea has been previously explored by various authors including Markman et al. (2005) who looked at research originating from collaborative work of multiple scientists and its association with innovation speed. They hypothesized that collaborative work would enjoy positive spillover effects that would increase the degree of commercialization. Similarly, Dietz and Bozeman (2005) found that larger research teams have access to a greater degree of human capital, which in turn impacts research productivity and success. Thus, there should be a positive effect of research team size on an academic inventor's research productivity success. Stated formally:

**Hypothesis Five (H5):** *The size of the academic inventor's research team responsible for discovering an invention or technology will impact research success level.*

In the next section, we review the research method, including the sample, variables, and statistical models.

### **III. Research Method**

#### **A. Sample/Data**

The data used in our analysis was compiled from all invention disclosure (IDs) forms that were filed by academic inventors with Northeastern University's (NU) Technology Transfer Office (TTO) – a large research (R-1 or R-E) University in Boston, MA<sup>2</sup> - during a ten year period (all IDs filed from the inception of the NU technology transfer office – fiscal year 1999 to fiscal year 2008). One of the main reasons for filing an invention disclosure form is that it allows an academic inventor to record a specific invention or technology with Northeastern University's TTO, and begins the formal process towards commercialization – and is defined in this study as the lowest level of success. Once a technology or invention is disclosed, the TTO Staff can determine its potential patentability and commercial possibilities.<sup>3</sup> Thus completing an invention disclosure form is one of the necessary steps in order for an academic inventor's invention or technology to receive a patent, license, or license option. After eliminating invention disclosure forms with missing or incomplete data, the sample consists of four hundred observations - each corresponding to a different technology or invention submitted by an

---

<sup>2</sup> Founded in 1898, Northeastern University is a private research university located in Boston, and is a leader in interdisciplinary research, urban engagement, and the integration of classroom learning with real-world experience.

<sup>3</sup> There is a broad spectrum of the types of inventions for which invention disclosure forms should or can be filed including new and improved devices, systems, and compounds; new biological materials; diagnostics, therapeutics, and new uses of known articles and substances; new methods of producing or manufacturing an article or substance; algorithms; and software.

academic inventor on a unique disclosure form.<sup>4</sup> A complete breakdown of the filing dates of the sample is available in Table 1, which contains all of the descriptive statistics of the sample.

## **B. Variables**

The dependent variable in our research is a measure of an academic inventor's technology transfer success or research productivity, which serves as a proxy for technology transfer efficacy. The traditional measure of an academic's research success has been publication rate. However, over the past several decades, scholars have come to recognize that there is more than one-way for knowledge to be disseminated from academics to the outside world (Dietz and Bozeman 2005). Along these lines, in our study, research productivity is a measure of how well, or to what degree, an academic inventor's technology or invention is translated into a marketable product or knowledge, culminating in revenue generation via licensing or a university-based start-up. A large number of previous studies, including Owen-Smith and Powell (2001) and Renault (2006), have focused on what factors affect or influence a faculty member's decision to disclose their research or file an invention disclosure.

In our study, we are more interested in determining what affects an academic inventor's ability to successfully transfer their technology or invention outside the university into a viable license or start-up. Our measure of research productivity is broken down into five potential

---

<sup>4</sup> We believe that our sample accurately represents the population of university invention disclosures because we were unable to identify any characteristics of Northeastern University's TTO or faculty that would distinguish them from faculty or TTOs at other research universities. While there is still a self-selection issue, since faculty choose whether or not to disclose their research, there is no reason to suspect that the factors that influence Northeastern faculty decision to disclose are different from those that influence faculty at other universities. Thus while we recognize our sample comprises only a portion of the research coming out of this university, it is adequate for use in our initial attempt to evaluate technology transfer efficacy at the university level. We address ways in which a larger sample from a variety of universities could help alleviate these selection issues in our concluding remarks. Additionally, to reduce any further risk of sample selection bias we have included all invention disclosures filed with Northeastern University's TTO since its creation regardless of the identity of the academic inventor, the quality of the disclosure information, or any other arbitrary grounds.

outcomes: (1) the invention or technology is disclosed to the university's TTO (i.e. an invention disclosure form is filed); (2) a non-provisional patent application is filed for the invention or technology;<sup>5</sup> (3) the invention or technology receives a patent; (4) the invention or technology receives a licensing agreement or option; and (5) the invention or technology generates revenue through the licensing option or formation of a university spin-out. Therefore, our measure of research productivity attempts to address the issue that there are multiple ways that academic knowledge and innovation can be successfully transferred from the university to the outside world cumulating with the creation of a sustainable university-based new venture.<sup>6</sup> Table 1 is a complete list of descriptive statistics of the sample.

---

<sup>5</sup> There are a wide variety of patents which can be applied for including provisional and non-provisional patents. We take a more restrictive approach towards what qualifies as a patent application, and thus we only include patent applications for non-provisional patents.

<sup>6</sup> Previous studies, such as Agrawal and Henderson (2002), have recognized that patenting is only one way that knowledge can be transferred from a university.

**Table 1: Descriptive Statistics of the Sample**

<b>Variable Name</b>	<b>Frequency</b>	<b>Percentage of Sample</b>
Professor	269	67.25%
Assistant/Associate Professor	76	19.00%
Student	15	3.75%
Other	40	10.00%
Sponsored Research Agreement	22	5.50%
Government Funding	103	25.75%
Northeastern Funding	21	5.25%
No Funding	114	28.50%
Arts & Science	122	30.50%
Health Sciences	66	16.50%
Computer & Information Science	4	1.00%
Engineering	204	51.00%
Old ID (FY1999-FY2003)	137	34.25%
FY1999	20	5.00%
FY2000	26	6.50%
FY2001	39	9.75%
FY2002	29	7.25%
FY2003	23	5.75%
New ID (FY2004-FY2008)	263	65.75%
FY2004	47	11.75%
FY2005	43	10.75%
FY2006	52	13.00%
FY2007	56	14.00%
FY2008	65	16.25%

<b>Variable Name</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Median</b>	<b>Minimum</b>	<b>Maximum</b>
Outcome	1.46	0.949	1	1	5
Team Size	2.69	1.496	2	1	9

When filing an invention disclosure form, the discovery or invention is assigned to a primary inventor. Thus, when our independent variables pertain to the characteristics of the academic inventor, we use the primary inventor indicated on the invention disclosure form. The first category of independent variables applies to the current position or job title of the academic

inventor. In this manner, academic inventors are separated into four groups depending upon their degree of academic experience: Professor, Assistant or Associate Professor, Student (which encompasses undergraduate and graduate students, lecturers, and post-doctoral researchers), and Other (which encompasses Deans, technical or research specialists, and non-academic professionals). The position of approximately 67 percent of the academic inventors included in our sample is listed as Professor. This category of independent variables is used to evaluate Hypothesis 1.

The second category of independent variables deals with whether the academic inventor discovered their invention or technology while participating in an industry sponsored research agreement (SRA). For approximately six percent of the inventions or technologies included in our sample, the academic inventors discovered their underlying invention or technology as part of a sponsored research agreement. This independent variable is used to evaluate Hypothesis 2.

The third category of independent variables pertains to the funding source of the academic inventor's underlying research that was used to discover their invention or technology. In this manner, academic inventors are separated into three groups depending upon the funding source of their research: government funding, Northeastern or private funding, and no funding.<sup>7</sup> For approximately 26 percent of the academic inventors included in our sample, their underlying research or technology was created using some type of government funding. This category of independent variables is used to evaluate Hypothesis 3.

The fourth category of independent variables has to do with the academic inventor's college affiliation within Northeastern University. Along these lines, academic inventors are divided according to the colleges within Northeastern University in which they are affiliated: the

---

<sup>7</sup> For a limited number of invention disclosures the funding source was unavailable. In order to preserve the sample size, the funding source for these invention disclosures is identified simply as unknown.

College of Arts & Sciences (Arts & Science), the Bouve College of Health Sciences (Health Science), the College of Computer and Information Science (Computer Science), and the College of Engineering (Engineering). Approximately 51 percent of the inventions or technologies included in our sample were filed by academic inventors associated with the College of Engineering. This category of independent variables is used to evaluate Hypothesis 4.

The final and fifth category of independent variables has to do with the size of the research team used by the academic inventor to discover their invention or technology. The research teams in our sample ranged from one to nine individuals with an average team size of 2.69. This independent variable is used to evaluate Hypothesis 5.

### **C. Controls**

Due to the lengthy nature of the patenting, licensing and start-up processes, one would assume that inventions or technologies embodied on invention disclosure forms that were filed more than five years ago would be more likely to be successfully transferred outside the university than those contained on invention disclosures filed in the past five years. Previous studies have found that the average length of time to license a university-based technology or transform it into a new venture is over four years (Markman et al. 2005). Likewise, previous researchers have found that the average time it takes for a disclosed invention to receive a patent is over six years (Thursby and Thursby 2002). Therefore, since older disclosures have a propensity to be farther along the technology transfer process, we must control for disclosure age. We used the fiscal year in which the academic inventor filed their invention disclosure form with Northeastern University's TTO to control for disclosure age. Academic inventors that filed invention disclosure forms (ID) in Fiscal Years 1999, 2000, 2001, 2002, and 2003 are grouped

together (Old ID) whereas academic inventors that submitted invention disclosure forms in Fiscal Years 2004, 2005, 2006, 2007 and 2008 are grouped together (New ID). Approximately 34 percent of the academic inventors included in our sample filed invention disclosure forms between fiscal years 1999 and 2003.

#### **D. Data Limitations**

There are a number of data limitations due to the limited size of our sample and the large number of potential independent variables. Including a large number of independent variables in a model can make it difficult to find significant results.<sup>8</sup> Thus, prior to estimating our model, we eliminated all unnecessary independent variables. Independent variables that are good candidates for elimination are those that do not have much (or any) predictive or explanatory power with the dependent variable. To determine whether an independent variable explains any of the variation in the dependent variable one can run a Pearson's Chi-Square Test.<sup>9</sup> If the two variables are independent, there may not be any reason to include the independent variable in the model. The complete results of the Pearson's Chi-Square test are listed in Table 2.

---

<sup>8</sup> This is due to the fact that each independent variable included in a model takes up a degree of freedom, thereby increasing the necessary threshold for finding significant results.

<sup>9</sup> The Null Hypothesis in a Pearson's Chi-Square Test is that the two variables are independent. A high p-value (above 0.10) is evidence for accepting the Null Hypothesis, thus the two variables are independent. On the other hand, a low p-value (below 0.05) is evidence for rejecting the Null Hypothesis, thus the two variables are not independent. If one accepts the Null Hypothesis, then one variable (the independent variable) does not explain any of the variation in the other variable (the dependent variable).

**Table 2: Pearson’s Chi-Square Test Results**

<b>Independent Variable</b>	<b>Relative Hypothesis</b>	<b>P-Value</b>	<b>Pearson’s Test Results</b>
Professor	Hypothesis 1	0.003	Reject Null Hypothesis
Assistant/Associate Professor	Hypothesis 1	0.051	Accept Null Hypothesis
Student	Hypothesis 1	0.779	Accept Null Hypothesis
Other	Hypothesis 1	0.563	Accept Null Hypothesis
Sponsored Research Agreement (SRA)	Hypothesis 2	0.000	Reject Null Hypothesis
Government Funding	Hypothesis 3	0.000	Reject Null Hypothesis
Northeastern Funding	Hypothesis 3	0.704	Accept Null Hypothesis
No Funding	Hypothesis 3	0.412	Accept Null Hypothesis
Arts & Science	Hypothesis 4	0.015	Reject Null Hypothesis
Health Sciences	Hypothesis 4	0.175	Accept Null Hypothesis
Engineering	Hypothesis 4	0.237	Accept Null Hypothesis
Computer Science	Hypothesis 4	0.850	Accept Null Hypothesis
Research Team Size	Hypothesis 5	0.049	Reject Null Hypothesis

Many of the potential independent variables in the same variable category were highly correlated. Specifically, some of the variables pertaining to an academic inventor’s school/college affiliation (engineering and arts & science), an academic inventor’s job position (Professor and Assistant or Associate Professor), and the funding source of the academic inventor’s underlying research (government funding and no funding) were highly correlated. When the independent variables in a model are highly correlated, it can result in biased estimators or results. Thus, we had to restrict the independent variables included in our model to ensure that our model did not suffer from multicollinearity. Therefore, via our tests for independence and correlation, we were able to narrow our potential independent variables down to only one variable for each of the hypotheses we wanted to test.

Below is a list of the five hypotheses and corresponding independent variables included in the model to measure their effect on research productivity. All of the independent variables

listed below are binary variables. The predicted sign of the coefficient is listed after each variable.<sup>10</sup>

Hypothesis One (H1): Professor (predicted sign – positive)

Hypothesis Two (H2): Sponsored Research Agreement (predicted sign – positive)

Hypothesis Three (H3): Government Funding (predicted sign – positive)

Hypothesis Four (H4): Engineering (predicted sign – positive)

Hypothesis Five (H5): Team Size (predicted sign – positive)

## **E. Model**

Due to the nature of the data collected from the invention disclosure forms, the variable measuring the degree of an academic inventor’s research productivity success is an ordinal variable.<sup>11,12</sup> The degree of research productivity success assigned to an academic inventor depends upon how well their research or technology has been translated into a marketable product or knowledge (or how well the knowledge or technology associated with it has been transferred outside the university). Our measure of research productivity success reflects the fact that we consider revenue generation via licensing or a university spin-out as the highest level of

---

<sup>10</sup> As a precaution, we also estimated an alternate version of our model where we used different independent variables to test for Hypothesis 3 and Hypothesis 4. In the alternate version of our model, we included “No Funding” to test for Hypothesis 3 and “Arts & Science” to test for Hypothesis 4. The expected signs of these two alternate independent variables were negative for “No Funding” and positive for “Arts & Science.”

<sup>11</sup> An ordinal variable is a categorical variable, with two or more categories, where the categories have a clear ordering or ranking (i.e. lowest to highest).

<sup>12</sup> Due to the fact the variable of interest in our study is an ordinal variable, it is not appropriate to use either a Tobit or Heckman Model in our analysis (Wooldridge 2002). Furthermore, in order to use either of these models, the dependent variable must be continuous which beyond some point is unobserved or censored and its value is replaced by zero or some other limit (Wooldridge 2002; Gourierouz 1991). In our model, the dependent variable is not continuous but instead is categorical and is fully observed (thus there are no observations in our data set which are assigned a zero value due to censoring). These facts preclude us from needing to use either a Tobit or Heckman Model to address potential censoring issues in our variable of interest.

success. The ranking assigned to each academic inventor corresponds to the highest outcome their invention or technology obtained where there are five possible outcomes: (1) disclosure; (2) non-provisional patent application filed; (3) patent received; (4) license or option received; and (5) revenue generation via licensing or a start-up.<sup>13</sup> For discussion purposes, in the model we do not separate revenue generation and the formation of a start-up. Thus our approach varies from previous work in the area of technology transfer, which has up until this point simply examined each type of outcome as unique; thereby, forcing researchers to estimate a separate model for each outcome.<sup>14</sup>

There are a number of different econometric models that can be used to estimate regressions with ordinal dependent variables. In many cases, researchers simply use a simple linear regression model. However, unless the dependent variable has a sufficient number of categories, typically assumed to be more than five, this type of regression can produce biased or unreliable results. Some researchers argue that if the dependent variable only has a small number of categories (between three and five), one must estimate either an ordered logit or ordered probit model to ensure the accuracy of the results (Agresti 2002). For our research, we estimated all three models: a simple linear regression, also referred to as an ordinary least squares model, (Model 1 – OLS Model), an ordered logit model (Model 2), and an ordered probit model (Model 3).<sup>15</sup>

---

<sup>13</sup> Our sample can be broken down as follows: 299 inventions or technologies are classified as category 1; 57 inventions or technologies are classified as category 2; 13 inventions or technologies are classified as category 3; 23 inventions or technologies are classified as category 4; and 8 inventions or technologies are classified as category 5.

<sup>14</sup> We estimated a Brant Test of Parallel Regression Assumptions (“Brant Test”) to ensure that the ordered logit model was the appropriate model for our analysis. In the Brant Test, the null hypothesis is that the parallel regression assumption necessary for using an ordered logit model holds. If one rejects the null hypothesis, than a multinomial model is deemed the appropriate model rather than the ordered logit model. (Scott and Freese 2006; Park 2005) The results of the Brant Test indicated that an ordinal model was the correct model.

<sup>15</sup> We estimated a simple linear model merely as an exploratory analysis and as an additional robustness check for our results.

Both the ordered logit and ordered probit models are types of ordered-response models. They are used to estimate or determine the probability that the  $i$ th observation is in the  $j$ th or higher category. In both models, the underlying observation's research outcome is estimated as a linear function of the independent variables and a set of cut points or threshold levels (McKelvey and Zavonia 1975). For the most part, it does not matter if one uses an ordered logit or ordered probit model. In order to choose between these two models one must make an assumption about the distribution of the residuals (the random error terms) and which function to use when calculating the probabilities that an academic inventor will obtain each of the five levels of research productivity success.<sup>16</sup> Typically, researchers will estimate both types of models and see which model fits the data better (i.e. has more predictive power). Our discussion below focuses on our primary model, the ordered logit model.

In the ordered logit model, there is an observed ordinal variable,  $Y$ , that is a function of another variable,  $Y^*$ , that is not observed. In our research, the observed ordinal variable is the academic inventor's research outcome. The unmeasured variable,  $Y^*$ , is called a latent variable, it is a continuous variable whose value determines what value the observed ordinal variable  $Y$  will take on/equal (i.e. what category the observation will be in). In our research, an academic inventor's research productivity or ability to successfully transfer their knowledge outside the university is the unobserved latent variable. The continuous latent variable  $Y^*$  has various thresholds points or cut-offs. What category an academic inventor's research will be in depends on whether or not the latent variable associated with the observation has crossed a particular threshold (Boorah 2002). In our model there are five categories of research outcomes, thus there are four cut-offs or thresholds that determine the value of the observed variable  $Y$ .

---

<sup>16</sup> The ordered logit model assumes a logistic distribution of errors or cumulative distribution function (cdf), while the ordered probit model assumes a standard normal distribution of errors or a probit distribution function (pdf).

$Y_i = 1$  (ID Filed) if  $Y_i^* \leq \delta_1$  (if research productivity is less than or equal to the 1<sup>st</sup> cut-off)

$Y_i = 2$  (Patent Filed) if  $\delta_1 < Y_i^* \leq \delta_2$  (if research productivity is between 1<sup>st</sup> and 2<sup>nd</sup> cut-offs)

$Y_i = 3$  (Patent Received) if  $\delta_2 < Y_i^* \leq \delta_3$  (if research productivity is between 2<sup>nd</sup> and 3<sup>rd</sup> cutoffs)

$Y_i = 4$  (License Received) if  $\delta_3 < Y_i^* \leq \delta_4$  (if research productivity is between 3<sup>rd</sup> and 4<sup>th</sup> cut-offs)

$Y_i = 5$  (Revenue Generated) if  $Y_i^* > \delta_4$  (if research productivity is greater than the 4<sup>th</sup> cut-off)

Where the value of research productivity, the continuous latent variable  $Y^*$ , is equal to

$$Y^* = \sum \beta_k X_{ki} + \varepsilon_i = Z_i + \varepsilon_i \quad \text{for } k= 1, \dots, K$$

The random disturbance term,  $\varepsilon_i$ , has a logistic distribution and reflects the fact that some relevant variables may be left out of the model and/or that some of the variables included in the model may not be perfectly measured.<sup>17</sup> The ordered logit model estimates part of the above equation,  $Z_i$ ,

$$Z_i = \sum \beta_k X_{ki} = E(Y_i^*) \quad \text{for } k= 1, \dots, K$$

Where  $X$  is a vector of explanatory or independent variables that affect research productivity and  $\beta$  is the vector of parameters or coefficients to be estimated by the model. Similar to a regular logit model, the coefficients on the independent variables,  $\beta$ 's, in an ordered logit model, are estimated using maximum likelihood estimation. This method produces the best set of coefficients, or the coefficients that maximize the likelihood of drawing a particular sample. One interprets the coefficient on a specific independent variable as representing the effect of a one unit increase of that variable on the probability of the dependent variable taking on a higher value (being in a higher category) (Agresti 2002). In an ordered logit model, a (significant) positive coefficient indicates that a one unit increase in the independent variable increases the

---

<sup>17</sup> In an ordered probit model the disturbance term has a normal distribution.

likelihood that an academic inventor will achieve a higher degree of research productivity success. On the other hand, a (significant) negative coefficient indicates that a one unit increase in the independent variable increases the likelihood that an academic inventor will be less successful in the technology transfer of their research. Therefore, the direction of the effect of a specific independent variable on research productivity is given by the sign of its coefficient. Similarly, the size of the effect of a particular independent variable (the coefficient of the independent variable) is assumed to be constant for all categories. The only aspect that varies for each of the categories is the intercept (or constant) which increases over the categories.

In an ordered logit model there are no intercept terms. Instead, this model uses cut-off terms to estimate the probability that the dependent variable will take on a particular value. In a model where the dependent variable has five categories, the model will estimate four cut-offs. Whether our observed variable  $Y$  falls into one of the five categories depends upon that probability that the unobserved variable  $Y^*$  plus the error term falls within the various threshold limits. In the ordered logit model the probabilities of an academic inventor achieving the five types of research outcomes are determined using the natural log of the cumulative distribution and are as follows (Boorah 2002)<sup>18</sup>:

$$P(Y = 1 \text{ (ID Filed)}) = 1 / (1 + \exp(Z_i - \delta_1))$$

$$P(Y = 2 \text{ (Patent Filed)}) = 1 / (1 + \exp(Z_i - \delta_2)) - 1 / (1 + \exp(Z_i - \delta_1))$$

$$P(Y = 3 \text{ (Patent Received)}) = 1 / (1 + \exp(Z_i - \delta_3)) - 1 / (1 + \exp(Z_i - \delta_2))$$

$$P(Y = 4 \text{ (License Received)}) = 1 / (1 + \exp(Z_i - \delta_4)) - 1 / (1 + \exp(Z_i - \delta_3))$$

$$P(Y = 5 \text{ (Revenue Generated)}) = 1 - 1 / (1 + \exp(Z_i - \delta_4))$$

---

<sup>18</sup> On the other hand, in the ordered probit model the probability of being in a particular category is determined using the inverse of the standard normal cumulative distribution function (Kockelman 2002).

In order to determine the probability that a specific observation falls in each of the five categories, one must evaluate the probability with the appropriate variable values and threshold estimates (Cameron and Trivedi 2005). In the next section, we describe the results of the three models.

#### **IV. Results**

The results of the three models are summarized in Table 3. As a precaution, robust standard errors were calculated for the linear regression model (OLS Model).<sup>19</sup> Thus the OLS results listed in Table 3 are conservative. The pseudo R-squares associated with ordered logit and probit models are not a good measure of the predictive power of ordered response models. Two of the common criteria used to evaluate the effectiveness of these types of models are the chi-squared value and the log likelihood ratio.<sup>20</sup> These two “goodness of fit” measures are used to test how well the model fits the data on which it was estimated. The pseudo R-square, chi-square value (LR Chi-Sq), and the log likelihood ratio (LR Stat) are included for each of the models listed in Table 3 where applicable.

---

<sup>19</sup> There is not much difference between the regular and robust standard errors in our OLS model. Thus our model does not appear to suffer from heteroskedasticity or misspecification of the error structure.

<sup>20</sup> Log likelihoods are always negative numbers.

**Table 3: OLS, Ordered Logit and Ordered Probit Model Results**

<b>Variables</b>	<b>OLS Model (Model 1) (R<sup>2</sup>= 0.1105)  (N= 400)</b>	<b>Ordered Logit Model (Model 2) (Pseudo R<sup>2</sup>= 0.0751) (LR Stat = -314.114) (LR Chi-Sq = 50.98)  (N= 400)</b>	<b>Ordered Probit Model (Model 3) (Pseudo R<sup>2</sup>= 0.067) (LR Stat = -316.735) (LR Chi-Sq = 45.74)  (N= 400)</b>
Professor	0.286*** (0.094)	0.921*** (0.312)	0.517*** (0.167)
SRA	0.714*** (0.249)	1.514*** (0.406)	0.804*** (0.246)
Government Funding	0.400*** (0.117)	0.969*** (0.250)	0.511*** (0.145)
Engineering	0.045 (0.102)	0.027 (0.255)	0.055 (0.143)
Team Size	0.023 (0.033)	0.077 (0.082)	0.040 (0.046)
Old ID	0.170* (0.099)	0.483* (0.249)	0.218 (0.141)
<b>Thresholds</b>			
$\delta_1$		<b>2.568</b>	<b>1.460</b>
$\delta_2$		<b>3.711</b>	<b>2.087</b>
$\delta_3$		<b>4.141</b>	<b>2.305</b>
$\delta_4$		<b>5.643</b>	<b>2.978</b>

\* = 10% significance level ( $p < 0.10$ ), \*\* = 5% significance level ( $p < 0.05$ ), \*\*\* = 1% significance level ( $p < 0.01$ )

In all three models, all of the independent variables have the expected or predicted signs. Note that positive coefficients indicate the likelihood of a higher degree of research productivity success. The results of the three models are similar, variables that are statistically significant in one model are statistically significant in the other two models (except for Old ID which is statistically significant in the OLS model and the ordered logit model but not in the ordered probit model).<sup>21, 22</sup> We use the results of the ordered logit model in our discussion below.

<sup>21</sup> The results of the alternate model are consistent with these findings, except that neither of the alternate variables included testing for Hypotheses 3 and 4 are statistically significant.

After controlling for disclosure age, we found support for Hypotheses 1 through 3 in our three models. Thus, an academic inventor's research productivity is significantly related to a number of different factors. The results of the three models indicate that an academic inventor's position within the university does impact their research productivity success. Academic inventors whose job titles were listed as Professor realize a higher degree of research productivity and thus were more successful in transferring their technology or knowledge outside the university than academic inventors with lower job titles. This effect is statistically significant at the 1% level in all three models. Thus, there is support for Hypothesis 1 in all three versions of the model.

Similarly, the results of the three models also indicate that an academic inventor's participation in an industry sponsored research agreement affects their degree of research productivity success. Academic inventors who had inventions or technologies that were discovered as part of an industry sponsored research agreement were more likely to have their invention or technology be translated into a marketable product, license, or revenue generating license or spin-out than those who were not part of a sponsored research project. The effect of participation in a sponsored research agreement is statistically significant at the 1% level in all three models. Thus, there is support for Hypothesis 2 in all three models.

Finally, the results of the three models indicate that the funding source of the underlying invention or technology impacts its ability to be successfully transferred outside the university.

---

<sup>22</sup> In response to a comment by a referee questioning the clear ordering of the dependent variable, we also ran the full model using the multinomial logit model. The results of this model were consistent with those of the ordered logit model as are the predicted probabilities calculated using the results from the multinomial logit model. Thus these results appear to confirm the results presented in this paper. However, the results of both the Hausman Test of Independence of Irrelevant Alternatives (IIA) Assumption and a Small-Hsiao Test of IIA Assumption indicate that our model does not meet the IIA Assumption required for the multinomial logit model. This combined with the results of the Brant Test of Parallel Regression Assumption discussed in Section 3, indicates that the multinomial logit model is not the appropriate model for this analysis and furthermore confirms our choice of the ordered logit model. The results of the multinomial model and the predicted probabilities are available upon request.

Academic inventors whose inventions or technologies were discovered using some type of government funding obtained a higher degree of research productivity success than those without government funding. The effect of government funding is statistically significant at the 1% level in all three models. Thus, there is support for Hypothesis 3 in all three models.

While the coefficients on engineering and team size have the predicted signs, their effects on research productivity are not statistically significant.<sup>23</sup> The results indicate that neither an academic inventor's school/college affiliation within Northeastern University nor the size of the research team responsible for discovering the invention or technology appears to affect the degree of research productivity success. The result regarding school/college affiliation may be unique to academic inventors affiliated with Northeastern University and therefore may not be true for academic inventors at other universities. Therefore, there is no support for Hypothesis 4 and Hypothesis 5 in any of our models. The results also confirm our assumption that disclosure age positively affects the ability of an invention or technology to be transferred outside the university.

Furthermore, we ran an alternate version of the analysis using a subset of our data set only— using just inventions or technologies on invention disclosure forms that were filed more than five years ago (Old IDs Only). We did this in order to address any potential concerns regarding censoring or truncation issues based upon the age of the invention disclosure. As stated previously, inventions or technologies embodied on invention disclosures forms filed more than five years ago would be more likely to be successfully transferred outside the university due to the lengthy nature of the patenting and licensing processes. The results of these analyses are consistent for the most part with the results using the full sample, thus censoring due to age of

---

<sup>23</sup> Despite the fact these two variables are not each independently significant, the results of a joint significance test support the inclusion of these variables in our model.

the disclosure does not appear to be an issue.<sup>24</sup> We therefore use our regression results using the full sample in our discussion below.

## **V. Discussion and Policy Implications**

There are several implications of our findings. We will begin by individually looking at each factor that has shown influence on the degree of research productivity success and then continue with the broader ramifications of our findings. The results listed in Table 3 indicate that there is support for Hypothesis 1: an academic inventor's position within the university will impact their research success level. Accordingly, holding all other independent variables constant, an academic inventor who has a higher, tenured position in the university (i.e. whose job title is Professor) has a higher probability of obtaining a greater degree of research productivity and thereby having their invention or technology translated into a marketable product, license, or start-up. A Professor is more than twice as likely than a non-professor to have a patent application filed for their invention or technology, to have their invention or technology receive a patent, to have their invention or technology receive a license or license option, and to have their work generate revenue through a licensing option or the formation of a university-based start-up company.<sup>25</sup> See Table 4 for a detailed list of the predicted probabilities

---

<sup>24</sup> Using just a sub-sample of the entire data set containing only inventions disclosures filed more than five years ago (Old IDs Only), there is support for Hypothesis Two and Three in both the ordered logit and ordered probit models. While the coefficients on professor and engineering have the predicted signs, their effects on research productivity are not statistically significant. The coefficient on team size does not have the predicted sign nor is it statistically significant. This could be due to the fact that as research teams get larger, communication costs increase. A complete listing of these results is contained in Table 5 located in the Appendix.

<sup>25</sup> Non-professors have a 5.7% probability of having a patent application filed for their invention or technology, a 1% probability that it will receive a patent, a 1.5% probability that it will receive a license or license option, and less than a 1% probability that it will generate revenue. On the other hand, professors have a 12.1% probability of having a patent application filed for their invention or technology, a 2.3% probability that it will receive a patent, a 3.6% probability that it will receive a license or license option, and greater than a 1% probability that it will generate revenue.

from the ordered logit model.<sup>26</sup> Our result is consistent with the earlier research regarding the effect of faculty quality and experience (Dietz and Bozeman 2005; O’Shea et al. 2005; Powers and McDougall 2005; Renault 2006). This result is expected as seasoned academic inventors have more mature research, and their funded research may be of higher quality than junior faculty members. Additionally, senior faculty members are not encumbered by the pressure of tenure, and thus are free to explore alternate avenues for research other than proposal writing and publication.

One of the policies that can be utilized to ensure that universities obtain and retain high quality faculty is to create and promote an entrepreneurial culture on their campuses. Accordingly, universities should promote awareness of the technology transfer process and the benefits of entrepreneurial activity among their faculty. An option to explore is adjusting promotion and tenure policies to account for measures of research success other than publishing such as inventing, patenting, licensing, and creating spin-offs. By making these modifications, universities may minimize the siphoning of faculty members with entrepreneurial tendencies and qualifications to the private sector.

---

<sup>26</sup> See Table 6 in the Appendix for the predicted probabilities from the ordered logit model using a sub-sample of the data just invention disclosures that were filed more than five years ago (Old IDs Only).

**Table 4: Predicted Probabilities from the Ordered Logit Model**

<b>Variable Combination</b>	<b>Invention Disclosure Filed P (Y = 1)</b>	<b>Patent Application Filed P (Y = 2)</b>	<b>Patent Received P (Y = 3)</b>	<b>License or Option Received P (Y = 4)</b>	<b>Revenue Generated P (Y = 5)</b>
Base Observation*	0.914	0.057	0.010	0.015	0.004
Professor	0.809	0.121	0.023	0.036	0.011
Sponsored Research Agreement (SRA)	0.700	0.180	0.039	0.062	0.019
Government Funding	0.801	0.126	0.024	0.038	0.011
College of Engineering	0.912	0.058	0.010	0.015	0.005
All 4 Effects (Professor, SRA, Government Funding, and Engineering)**	0.255	0.263	0.105	0.258	0.119

\*Where the base observation is a non-professor, who filed an ID in the last 5 years (New ID), did not participate in a SRA, received no government funding, is not affiliated with the College of Engineering, and has an average research team size.

\*\* Where the 4 effects observation is a professor, who filed an ID in the last 5 years (New ID), participated in a SRA, received government funding, is affiliated with the College of Engineering, and has an average research team size.

Our research also denotes that there is support for Hypothesis 2: there is an effect of an academic inventor’s participation in an industry sponsored research agreement on their research success level. The results of our model demonstrate that an academic inventor who participated in a sponsored research agreement was more than three times as likely as a non-participant to have a patent application filed for their invention or technology and to receive a patent.

Similarly, an academic inventor who participated in a sponsored research agreement was more than four times as likely than a non-participant to have their research receive a license and to have their work generate revenue through a licensing option or the formation of a new venture.<sup>27</sup>

This finding is consistent with the findings of previous research regarding the effect of industry

<sup>27</sup> Non-participants have a 5.7% probability of having a patent application filed for their invention or technology, a 1% probability that it will receive a patent, a 1.5% probability that it will receive a license or license option, and less than a 1% probability that it will generate revenue. On the other hand, participants have an 18% probability of having a patent application filed for their invention or technology, a 3.9% probability that it will receive a patent, a 6.2% probability that it will receive a license or license option, and slightly less than a 2% probability that it will generate revenue.

influence and support on different aspects of the technology transfer process (Dietz and Bozeman 2005; O'Shea et al. 2005; Powers and McDougall 2005). This result could be attributed to access to a larger amount of resources, human capital and experience than non-participants in a sponsored research agreement. Likewise, this result could be due to the fact that inventions or technologies that were funded by industry may have been created to fill a specific need or purpose, applied research as opposed to basic. Accordingly, basic research may not be commercially viable for many years, while applied research, in response to a directed need from an industrial partner, may be marketable immediately. For example, in looking deeply at the invention disclosures in our sample, a successful technology transfer initiative resulting in the formation of a start-up was funded jointly by industry and the NIH. Their technology was an applied cancer therapy and diagnosis technique. Another success was completely corporate funded, on the treatment of pancreatic and other forms of cancer, also applied research. While these success stories may be contextual to the sample, we argue that universities must maintain and expand their ties with the private sector via such policies as increased collaboration with industry, expanded incubator programs, and heightened relationships with faculty and graduates within the private sector. More study is needed, but there appears to be a clear link between industry sponsored research and successful revenue generating outcomes.

Finally, our study indicates that there is support for Hypothesis 3: the funding source of an academic inventor's underlying invention or technology impacts their research success level. An academic inventor who received some type of government funding (NIH, NSF, etc.) was more than twice as likely to have a patent application filed for their invention or technology, to have their invention or technology receive a patent, to have their invention or technology receive a license or license option, and to have their work generate revenue through a licensing option or

university-based spin-out than academic inventors without government funding.<sup>28</sup> For example, in looking deeply at the invention disclosures in our sample, one of the most successful license options was applied research funded by the NIH to develop a specific drug compound. Other examples were similar, including DARPA contracts from the College of Engineering. Again, this result could be due to the fact that inventions or technologies that are discovered using government funding (such as the NSF) may have access to a larger amount of resources and/or a pre-existing commercial market than those without funding.

Our result is consistent with the findings of previous studies that have looked at the effect of government support and financial resources on research productivity (Landry et al. 1996; O’Shea et al. 2005). Subsequently, universities need to attempt to increase the amount of government funding their faculty receives. They can contribute to this goal by increasing awareness of the wide-breadth of areas for which government financial resources are available and increase support for grant writing and application efforts among their faculty. However, it should be noted that the likelihood of successfully commercializing industry sponsored research via licenses or start-up formation is approximately twice as likely as government sponsored research. This result can have important ramifications for university direction and policy on future funding initiatives. TTOs would be well served to foster combined research agreements between government, faculty, and industry partners – which can be accomplished through government activities such as the NSF Small Business Innovative Research (SBIR), Small Business Technology Transfer (STTR) program, and GOALI.<sup>29</sup>

---

<sup>28</sup> Academic inventors with no government funding have a 5.7% probability of having a patent application filed for their invention or technology, a 1% probability that it will receive a patent, a 1.5% probability that it will receive a license or license option, and less than a 1% probability that it will generate revenue. Individuals with some type of government funding have a 12.6% probability of having a patent application filed for their invention or technology, a 2.4% probability that it will receive a patent, a 3.8% probability that it will receive a license or license option, and greater than a 1% probability that it will generate revenue.

<sup>29</sup> <http://www.nsf.gov/eng/iip/sbir/index.jsp>

While the effect of each independent variable alone does not greatly increase the probability that an academic inventor will enjoy a higher degree of research productivity success, when taken in combination they do have a very sizable effect on the ability to successfully transfer technology outside the university. According to our results, an academic inventor who is a non-professor with an average-size research team, who disclosed their invention or technology in the past five years, who was unaffiliated with the College of Engineering, with no research funding, and who did not participate in a sponsored research agreement, would have almost no probability of their invention or technology receiving a patent, license, license option or having their research generate revenue. Academic inventors such as these would have a 91 percent probability that their research would at best be disclosed and only a 6 percent probability that a patent application would be filed for their invention or technology. Therefore, it would not be very likely that an academic inventor with these characteristics would have their invention or technology be translated into a marketable product via licensing or a university-based spin-off.

On the other hand, an academic inventor who is an experienced professor with an average-size research team, who disclosed their invention or technology less than five years ago, was affiliated with the College of Engineering, had government funding, and who participated in a sponsored research agreement would have a 26 percent probability of having a patent application filed based upon their research, an 11 percent probability of having their invention or technology receive a patent, a 26 percent probability of having their invention or technology receive a license or license option, and a 12 percent probability that it would generate revenue through a licensing option or the formation of a start-up company.<sup>30</sup> Thus, it is much more likely

---

<sup>30</sup> If one increases the age of the disclosure (to filed more than five years ago, (Old ID)), the probability of an experienced academic having a patent application filed for their invention or technology decreases to 22 percent while the probability that it will receive a license or license option increases to 32 percent and the probability that it will generate revenue through a licensing option or formation of a start-up increases to 18 percent.

that an academic inventor with these observed characteristics would have their invention or technology translated into a marketable product or knowledge. As TTOs and government agencies develop policies for fostering technology transfer efficacy, it is important to heed these results. In evaluating proposals and invention disclosures, TTOs and funding agencies should actively pursue the latter example starting at the proposal funding stage. If a young faculty member proposes research, funding should be granted to teams that have experienced faculty on board, which can help shepherd the idea forward. TTOs should be conscious of the limited probability of success of the new academic inventor, and seek to increase ties to more experienced faculty members who might mentor. Given these statistics, faculty members and TTOs would be well-served to interface during proposal writing, in order to architect the research to position it for the best possible outcome.

Given the amount of funds spent on technology research, success through technology transfer has not been overwhelmingly favorable. As a first step in diagnosing the issues at hand, we have undertaken an empirical study at a large research institution. Instead of focusing on patents, we have tried to define research productivity success. We have defined success at several levels, beginning with invention disclosure and culminating with positive revenue generation. This research has found several significant factors that determine technology transfer success. These include faculty academic position and funding type. An experienced faculty member, with a sponsored research agreement or government funding, and an affiliation with the College of Engineering has a substantially greater probability of success than those that do not have these characteristics. This has important implications not only for funding agencies, but also for university faculty, policy makers and TTOs.

## **VI. Limitations and Future Research**

This is one of first empirical studies to investigate technology transfer efficacy. As such, we have defined levels of success, with the highest level of success being revenue generation via licensing or a university-based new venture. In order to accomplish this task, we have engaged the TTO at a large research university and studied all disclosures received since inception of the office. There are several limitations within the research. First, the study takes place at one university, and as noted in (Markman et al. 2005), technology transfer effectiveness can vary between institutions. In our sample, the revenue generation was universally generated through the formation of university spin-outs. This is an interesting finding, and more research will be needed to quantify the result. Are university spin-outs more desirable than licensing options? What qualities are specific to universities that have greater number of start-ups versus licensing options? In future research, we plan to engage a number of universities to increase sample size and eliminate cross-campus variability and investigate whether our findings are pervasive. Second, the invention disclosures – while rich with information – do not capture all variables that can impact technology transfer success. Entrepreneurial inclination, experience, and motivation can play an important role on whether a research initiative is commercially successful. In future studies, we plan on investigating these areas and correlating them to invention disclosure data.

## References

- Agrawal, A. and R. Henderson. 2002. "Putting Patents in Context: Exploring Knowledge Transfer from MIT." *Management Science*, 48 (1): 44-60.
- Agresti, A. 2002. *Categorical Data Analysis*. New York: Wiley & Sons.
- AUTM. 2006. [http://www.autm.net/events/file/AUTM\\_06\\_US%20LSS\\_FNL.pdf](http://www.autm.net/events/file/AUTM_06_US%20LSS_FNL.pdf) (accessed October 23, 2008).
- Blumenthal, D., E. G. Campbell, N. Causino, and K.S. Louis. 1996. "Participation of Life-Science Faculty in Research Relationships with Industry." *New England Journal of Medicine*, 335 (23): 1734-1739.
- Boorah, V.K. 2002. *Logit and Probit: Ordered and Multinomial Models*. California: Sage Publications Inc.
- Bozeman, B. 2000. "Technology Transfer and Public Policy: A Review of Research and Theory." *Research Policy*, 29: 627-655.
- Cameron, A. and P. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge, MA: Cambridge University Press.
- Carree, M.A. and A. R. Thurik. 2003. "The Impact of Entrepreneurship on Economic Growth." In *Handbook of Entrepreneurship Research*, ed. D.B. Audretsch and Z.J. Acs, 437-471. Boston: Kluwer Academic Publishers.
- Clarysse, B., M. Wright, A. Lockett, E.V. de Velde, and A. Vohora. 2005. "Spinning out New Ventures: A Typology of Incubation Strategies from European Research Institutions." *Journal of Business Venturing*, 20: 183-216.
- Cohen, W.M., R.R. Nelson, and J.P. Walsh. 2002. "Links and Impacts: The Influence of Public Research on Industrial R&D." *Management Science*, 48: 1-23.
- Dietz, J.S., and B. Bozeman. 2005. "Academic Careers, Patents, and Productivity: Industry Experience as Scientific and Technical Human Capital." *Research Policy*, 34: 349-367.
- Di Gregorio, D. and S. Shane. 2003. "Why Do Some Universities Generate More Start-Ups Than Others?" *Research Policy*, 32: 209-227.
- George, G., S. Zahra, and D.R. Wood. 2002. "The Effects of Business-University Alliances on Innovative Output and Financial Performance: A Study of Publicly-Traded Biotechnology Firms." *Journal of Business Venturing*, 17: 577-609.
- Global Insight. 2004. "Venture Impact 2004: Venture Capital Benefits to the U.S. Economy." White Paper prepared for National Venture Capital Association.

Gourierouz, C. 1991. *Econometrics of Qualitative Dependent Variables*. Cambridge, England: Cambridge University Press.

Henderson, R., A. Jaffe, and M. Trajtenberg. 1998. "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965–1988." *Review Economic Statistics*, 80: 119–127.

Jaffe, A. 1989. "Real Effects of Academic Research." *American Economics Review*, 79: 957–970.

Kockelman, K.M. 2002. "Driver Injury Severity: An Application of Ordered Probit Models." *Accident Analysis and Prevention*, 34 (3): 313-321.

Landry, R., N. Traore, and B. Godin. 1996. "An Econometric Analysis of the Effect of Collaboration on Academic Research Productivity." *Higher Education*, 32: 283-301.

Leopold, G. 2008. "U.S. Patent Chief: Applications Up, Quality Down." *EE Times*.

Libecap, G.D. 2005. *University Entrepreneurship and Technology Transfer: Process, Design, and Intellectual Property*. San Diego, CA: Elsevier, Ltd.

Markman, G.D., P.T. Gianiodis, P.H. Phan, and D.B. Balkin. 2005. "Innovation Speed: Transferring University Technology to Market." *Research Policy*, 34: 1058-1075.

McKelvey, R. and W. Zavonia. 1975. "A Statistical Model for the Analysis of Ordinal Level Dependent Variables." *Journal of Mathematical Sociology*, 4: 103-120.

Mowery, D.C. 2005. "The Bayh-Dole Act and High Technology Entrepreneurship in U.S. Universities: Chicken, Egg, or Something Else?" In *Advances in the Study of Entrepreneurship, Innovation and Economic Growth*, Vol. 16, ed. G. Libecap, 39-68. Bingley, England: Emerald Group Publishing Limited.

National Venture Capital Association. 2008. Archives. <http://www.nvca.org/> (accessed November 7, 2008).

Owen-Smith, J. and W.W. Powell. 2001. "To Patent or Not: Faculty Decisions and Institutional Success at Technology Transfer." *Journal of Technology Transfer*, 26: 99-114.

O'Shea, R. P, T. Allen, A. Chevalier, and F. Roche. 2005. "Entrepreneurial Orientation, Technology Transfer and Spinoff Performance of U.S. Universities." *Research Policy*, 34: 994-1009.

Park, H.M. 2005. "Categorical Dependent Variable Regression Models Using Stata, SAS, and SPSS." <http://www.indiana.edu/~statmath>, (accessed September 9, 2009).

Powers, J.B., and P.P. McDougall. 2005. "University Start-Up Formation and Technology Licensing with Firms that go Public: A Resource-based View of Academic Entrepreneurship." *Journal of Business Venturing*, 20: 291-311.

Renault, C.S. 2006. "Academic Capitalism and University Incentives for Faculty Entrepreneurship." *Journal of Technology Transfer*, 31: 227-239.

Scott, J. and J. Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*. 2<sup>nd</sup> ed. College Station, Texas: Stata Press.

Siegel, D.S. and P.H. Phan. 2005 "Analyzing the Effectiveness of University Technology Transfer: Implications for Entrepreneurship Education." In *Advances in the Study of Entrepreneurship, Innovation and Economic Growth*, Vol. 16, ed. G. Libecap, 1-38. Bingley, England: Emerald Group Publishing Limited.

Shane, S., and T. Stuart. 2002. "Organizational Endowments and the Performance of University Start-Ups." *Management Science*, 48: 154-170.

Shapiro, C. 2001. "Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting." In *Innovation Policy and the Economy*, ed. A. Jaffe, J. Lerner, and S. Stern, 1190-1150. Cambridge, MA: MIT Press.

Thursby, J. and S. Kemp. 2002. "Growth and Productivity Efficiency of University Intellectual Property Licensing." *Research Policy*, 31: 109-124.

Thursby, J.G. and M.C. Thursby. 2002. "Who is Selling the Ivory Tower? Sources of Growth in University Licensing." *Management Science*, 48 (1): 90-104.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Zhao, L.M. and A. Reisman. 1992. "Toward Meta Research on Technology-Transfer." *IEEE Transactions on Engineering Management*, 39(1): 13-21.

Zucker, L.G., M.R. Darby, and M.B. Brewer. 1998. "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises." *American Economic Review*, 88(1): 290-306.

## Appendix

In response to potential concerns regarding censoring and truncation, we ran an alternate version of the analysis using a subset of our data set only– using just inventions or technologies on invention disclosure forms that were filed more than five years ago (Old IDs Only). The results of the alternate version of the analyses are consistent for the most part with the results using the full sample, thus censoring due to age of the disclosure does not appear to be an issue. Table 5 contains the results of the OLS Model (Model 1), Ordered Logit Model (Model 2), and Ordered Probit Model (Model 3) using a sub-sample of the data set containing only inventions and technologies contained on invention disclosures that were filed more than five years ago (Old IDs Only).

**Table 5: OLS, Ordered Logit and Ordered Probit model results (Old IDs Only)**

<b>Variables</b>	<b>OLS Model (Model 1) (R<sup>2</sup> = 0.2150)  (N= 137)</b>	<b>Ordered Logit Model (Model 2) (Pseudo R<sup>2</sup> = 0.1277) (LR Stat = -121.078) (LR Chi-Sq = 35.45)  (N= 137)</b>	<b>Ordered Probit Model (Model 3) (Pseudo R<sup>2</sup> = 0.1130) (LR Stat = -123.118) (LR Chi-Sq = 31.37)  (N= 137)</b>
Professor	0.199 (0.207)	0.594 (0.590)	0.414 (0.322)
SRA	0.883** (0.344)	1.825*** (0.689)	0.875** (0.412)
Government Funding	0.928*** (0.183)	1.991*** (0.423)	1.076*** (0.241)
Engineering	0.162 (0.168)	0.320 (0.426)	0.226 (0.239)
Team Size	-0.006 (0.061)	-0.036 (0.160)	-0.008 (0.091)
<b>Thresholds</b>			
$\delta_1$		<b>2.014</b>	<b>1.266</b>
$\delta_2$		<b>2.977</b>	<b>1.809</b>
$\delta_3$		<b>4.070</b>	<b>2.385</b>
$\delta_4$		<b>6.212</b>	<b>3.291</b>

Table 6 contains a detailed list of the predicted probabilities from the ordered logit model using a sub-set of the data which contains only invention disclosures that were filed more than five years ago (Old IDs Only). The predicted probabilities using a sub-sample of the entire data set are comparable to those using the entire sample. As expected, the probabilities are higher for an invention or technology contained on an invention disclosure filed more than five years ago compared to the entire data in regards to a patent application being filed (outcome 2), a patent being received (outcome 3), and a license or option being received (outcome 4). These results are consistent with the widely acknowledged lengthy nature of patenting and licensing processes.

**Table 6: Predicted Probabilities from the Ordered Logit model (Old IDs Only)**

<b>Variable Combination</b>	<b>Invention Disclosure Filed P (Y = 1)</b>	<b>Patent Application Filed P (Y = 2)</b>	<b>Patent Received P (Y = 3)</b>	<b>License or Option Received P (Y = 4)</b>	<b>Revenue Generated P (Y = 5)</b>
Base Observation*	0.891	0.064	0.029	0.014	0.002
Professor	0.759	0.133	0.069	0.034	0.005
Sponsored Research Agreement (SRA)	0.570	0.207	0.136	0.077	0.011
Government Funding	0.529	0.217	0.151	0.089	0.013
College of Engineering	0.856	0.083	0.039	0.019	0.003
All 4 Effects (Professor, SRA, Government Funding, and Engineering)**	0.048	0.069	0.166	0.488	0.230

\*Where the base observation is a non-professor, did not participate in a SRA, received no government funding, is not affiliated with the College of Engineering, and has an average research team size.

\*\* Where the 4 effects observation is a professor, participated in a SRA, received government funding, is affiliated with the College of Engineering, and has an average research team size.

## **CHAPTER 2**

### **The Determinants of HMO Entry**

## **I. Introduction**

Why do firms enter some local markets and not others? This is a question which businessmen, local lawmakers and economists have contemplated for decades. One market where these issues may be of particular importance is the US healthcare market. Over the past two decades, the cost of healthcare in the US has skyrocketed to \$2.5 trillion dollars in 2009 or 17.6% of the nation's gross domestic product in that year (Centers of Medicare and Medicaid Services 2010). Healthcare experts argue that Health Maintenance Organizations (HMOs) may be able to lower healthcare costs by preventing excessive or wasteful care via strict patient utilization review, lower administrative costs, and promoting competition within the healthcare system. The goal of my research is to determine what motivates a HMO to enter a local market. There is a wide range of factors which could motivate a firm's entry decision into a local market; I focus on the characteristics of the local market, the characteristics of the HMOs operating in these markets, and firm-market characteristics.

A number of previous studies have examined the role of entry in the HMO market. However, these studies analyzed HMO entry at the market-level and focused almost exclusively on the role of market characteristics in determining the establishment of an HMO and the number of firms in a given geographic market. As such, prior research in this area assumed that the HMO market was made up of homogenous firms. I expand upon the earlier research in this area by examining entry in the Florida HMO Market at the firm-level. By doing so, I introduce firm heterogeneity into my model which allows me to analyze the role of firm characteristics and firm-market characteristics on an individual HMO's entry decision. The results of my research indicate that firm-characteristics and firm-market characteristics play an equal, if not more significant, role in a firm's entry decision than market characteristics. Specifically, firm type,

product offerings, network size and quality all have a statistically significant effect on a HMO's entry decision in local markets. Likewise, firm-market characteristics pertaining to the geographic location of a firm's existing operations, distance from the firm's headquarters and the type of firm already operating in a local market have a significant impact on HMO entry decisions. Thus the results of my research indicate that entry decisions in the Florida HMO Market are dictated at the firm-level and vary substantially across individual HMOs. The combined aspects of firm and market heterogeneity which characterize the Florida HMO Market entail that some firms are better suited to a particular market than others. Thus it appears that HMOs are capitalizing upon the unique features of their organizations and products when choosing which local markets in Florida to enter.

The remainder of this paper will be presented in the following order: Section 2 discusses the HMO Market in Florida; Section 3 reviews the previous research in this area and my research goals; Section 4 identifies the data sources and data limitations; Section 5 discusses my theoretical model; Section 6 outlines the empirical model and variables; Section 7 contains the results of my analysis and discussion; and Section 8 includes concluding remarks and areas for future research.

## **II. Florida HMO Market**

The market for health insurance in Florida is made up of a number of different types of providers including Health Maintenance Organization (HMOs), Preferred Provider Organizations (PPOs), other commercial providers (including POS plans and EPO provider groups), and government sponsored plans such as Medicare and Medicaid. Each type of provider offers a unique insurance plan which varies from the plans offered by other types of

providers based upon a number of dimensions including: access to care; service utilization review; the size and quality of their provider network; and consumer's out-of-pocket expenses or costs. In this market, individual consumers of medical services purchase health insurance from local providers where multiple consumers can select the same insurance provider.<sup>1</sup> In my current analysis, I will assume that each type of health insurance product constitutes its own unique market. As such, I will focus on the sale of health insurance product by HMOs to consumers in Florida.

One can base this assumption on the degree to which consumers for health insurance regard the different types of insurance products or plans as substitutes (Gaynor and Haas-Wilson 1999).<sup>2</sup> If one assumes that individuals do not view insurance products as substitutes for one another (i.e. consumers do not view PPO plans as substitutes for HMO plans), then each plan or product type will constitute a separate market. On the other hand, if one assumes that the HMO product is part of a broader market for health insurance; then not controlling for the market structure of the other types of providers may produce biased results. However, by assuming that different types of insurance products are not substitutes relaxes this need to control for the market structure of other providers. A number of other studies in this area including Welch et al. (1984); McLaughlin (1988); Baker & Corts (1996); Pauly et al. (2002); and Bates and Santerre (2008) have assumed that the HMO insurance product is a separate markets due to the fact either employers, employees or both groups perceive HMOs and PPOs to be different products that meet different needs and appeal to different types of enrollees. Similarly, the switching behavior

---

<sup>1</sup> This can include any agent (i.e. employers) who purchases health insurance on behalf of individual consumers (i.e. its employees) and is assumed to act in the best interests of the individual consumers.

<sup>2</sup> In some cases, there are restrictions that limit which individuals can select certain providers such as with government restrictions regarding Medicare and Medicaid eligibility. Also, there are some consumers who do not select insurance providers (self-pay and uninsured). Thus I will limit my discussion to only other commercial health insurance providers, such as PPOs.

of consumers in the market for health insurance supports this assumption whereby the majority of individuals who change health plans stay within the same plan type (Cunningham and Kohn 2000). Finally, the US government recognized that the HMO product constituted its own unique market in *US v. Aetna* (1999).

The market for the HMO insurance product (“HMO Market”) is not static, but instead has undergone a number of changes over the past two decades. The changes the HMO Market underwent in the 1990s and early 2000s can be broken-down into three main periods. One of these changes was the rapid consolidation of the HMO Market in the early 1990s, commonly referred to as the “Consolidation Period,” due to numerous mergers and acquisitions among existing HMOs both on the national and local level (Gabel 1997; Gaynor and Haas-Wilson 1999). This initial period of increased market concentration was followed by a period of rapid growth in the mid-1990s, often referred to as the “Expansion Period.” During the Expansion Period, the number of local HMOs increased substantially and the overall level of HMO enrollment grew at the national level and in many local markets (Feldman et al. 1999; Shen et al. 2008). However, during the late-1990s and continuing through 2005, the HMO industry underwent another period of change referred to by Shen et al. (2008) as the “HMO Backlash Period.” During this period, overall HMO enrollment decreased as a larger share of the national population began to obtain their health insurance from alternate sources (i.e. types of providers). Also during the HMO Backlash Period, the level of concentration in the HMO Market increased via a new wave of mergers and local firms exiting the industry. In my current research, I will

focus on the final of these three periods, the HMO Backlash Period, specifically the HMO market in Florida from 2001 to 2005.<sup>3</sup>

Many of the market forces that occurred in the HMO Backlash Period at the national-level were evident on the state-level in the HMO Market in Florida (“Florida HMO Market”). Between 2001 and 2005 the total number of individuals enrolled in HMOs decreased by over 18.5 percent. In 2001, 4,753,568 individuals in Florida were enrolled in HMOs; by 2005, this number had shrunk to 3,866,617. Similarly, between 2001 and 2005, the share of the state population enroll in HMOs (which I refer to as HMO penetration) decreased from 29.11 percent in 2001 to 21.58 percent in 2005. At the same time, the HMO market in Florida underwent a period of increased merger activity. Between 2001 and 2003, five mergers occurred in the Florida HMO Market. Three of these mergers involved the acquisition of a local or independent HMO by a larger national HMO; whereas the 2002 acquisitions of Beacon Health Plans and Healthplan Southeast by Vista Healthplan created one of the largest managed care providers in Florida (Business Wire 2002).<sup>4</sup> Table 1 contains a detailed breakdown of the changing dynamics of the Florida HMO Market on a state-level

**Table 1: Florida HMO Market – Annual State-Level Breakdown**

<b>Year</b>	<b>Total HMO Enrollment</b>	<b>Total HMO Penetration</b>	<b>Total Number of HMOs</b>	<b>Average HMO HHI</b>
<b>2001</b>	<b>4,753,568</b>	<b>29.11%</b>	<b>27</b>	<b>0.105</b>
<b>2002</b>	<b>4,424,081</b>	<b>26.53%</b>	<b>24</b>	<b>0.097</b>
<b>2003</b>	<b>4,264,925</b>	<b>24.98%</b>	<b>25</b>	<b>0.091</b>
<b>2004</b>	<b>4,044,451</b>	<b>23.09%</b>	<b>26</b>	<b>0.090</b>
<b>2005</b>	<b>3,866,617</b>	<b>21.58%</b>	<b>32</b>	<b>0.085</b>

<sup>3</sup> Previous studies on entry found that entry rates vary over time within the same industry (Geroski 1995). Therefore, limiting my study on firm entry decisions in the HMO Market to just a single period could entail that the findings of my research may not be consistent with entry patterns in this market in other time periods.

<sup>4</sup> The following five mergers occurred in the Florida HMO Market between 2001 and 2003: (1) Prudential Health Care Plan, Inc. was acquired by Aetna in 2001; (2) Beacon Health Plan, Inc. was acquired by Vista Healthplan, Inc. in 2002; (3) Healthplan Southeast, Inc. was acquired by Vista Healthplan, Inc. in 2002; (4) Physicians Health Care Plans, Inc. was acquired by Amerigroup Florida, Inc. in 2003; and (5) American Medical Healthcare, Inc. was acquired by Health Options (a part of the Blue Cross Blue Shield network) in 2003.

Unlike on the national-level, between 2001 and 2005, the Florida HMO Market underwent two distinct periods of increased entry activity. Between 2001 and 2003, four new firms entered the HMO market in Florida while only a single existing local HMO exited the Florida Market.<sup>5</sup> Also between 2004 and 2005, seven new firms entered the Florida HMO Market; all of the firms that entered the Florida HMO Market during this period, excluding one, were independent or local HMOs that were not affiliated with any National HMO plans.<sup>6</sup> The combined effect of these mergers and the entry and exit activity in the Florida HMO Market caused both the number of firms and industry concentration on a state-level to fluctuate during the “HMO Backlash Period.” As illustrated in Table 1, the number of HMOs in Florida changed slightly between 2001 and 2004 from 24 to 27 firms before rapidly increasing to 32 firms in 2005. Also the overall level of concentration in the Florida HMO Market, depicted by the Herfindahl-Hirschman Index (HHI) of the HMO Market, steadily decreased during the period. The lower level of concentration in the HMO Market on a state-level was contrary to what was occurring in the HMO Market on a national-level during the period. This is likely due to the positive net effect of the entry and exit activity that occurred in the Florida HMO Market during the period. The increase in the number of local HMOs in the Florida HMO Market is consistent with the results illustrated in Feldman et al. (1999). In their study, the authors found that concentration levels fell in local HMO markets despite the increase in concentration in the top

---

<sup>5</sup> Between 2001 and 2003, four new firms entered the HMO market in Florida – (1) Amerigroup Florida, Inc., which is part of the Amerigroup Corporation, entered in 2002; (2) Preferred care Partners, Inc., an independent Florida-based HMO, in early 2002; (3) Quality Health Plans, a local Florida HMO, entered in 2003; and (4) Universal Health Care, Inc., an independent Florida HMO, entered in 2003. During this time period, only a single existing local HMO exited the Florida Market (Mayo Health Plan, Inc.) which exited in 2002.

<sup>6</sup> Seven new firms entered the Florida HMO Market between 2004 and 2005: (1) Citrus Health Care, Inc. entered in 2004; (2) Doctorcare, Inc. entered in 2005; (3) Freedom Health, Inc. entered in 2005; (4) Healthsun Health Plans, Inc. entered in 2005; (5) Leon Medical Centers Health Plans, Inc. entered in 2005; (6) Medica Healthcare Plans, Inc. entered in 2005; and (7) Metcare Health Plans, Inc. entered in 2005.

national HMOs. Thus one can see that entry has played an important role in the Florida HMO Market during the HMO Backlash Period.

The changing dynamics of the Florida HMO Market can also be seen if we focus our attention on the local-market level, such as the county-level. Florida is made up of 67 counties which vary substantially in geographic size, population, wealth and costs of living. Similar to the state-level, both the average number of enrollees and the average level of HMO Penetration per county have steadily decreased during the HMO Backlash Period. The average number of HMO enrollees per county has decreased from 70,650 in 2001 to 57,711 in 2005. Similarly, the share of each county enrolled in HMOs has decreased from 18.40 percent in 2001 to 13.50 percent in 2005. On the other hand, the average number of firms in each county has remained fairly constant during the period ranging between 6.70 and 7.79 firms. Finally, the level of concentration in the HMO Market on the local level has only slightly decreased during the HMO Backlash period from 0.463 to 0.431. These concentration levels indicated that, at the local-level, the market for the HMO insurance product is highly concentrated. Table 2 contains a detailed breakdown of the changing dynamics of the Florida HMO Market on the local-market or county-level.

**Table 2: Florida HMO Market – Annual County-Level Breakdown**

<b>Year</b>	<b>Average Number of HMO Enrollees per County</b>	<b>Average County-Level HMO Penetration</b>	<b>Average Number of HMOs per County</b>	<b>Average County-Level HMO HHI</b>
<b>2001</b>	<b>70,650</b>	<b>18.40%</b>	<b>7.79</b>	<b>0.463</b>
<b>2002</b>	<b>66,031</b>	<b>16.97%</b>	<b>6.70</b>	<b>0.428</b>
<b>2003</b>	<b>63,656</b>	<b>15.55%</b>	<b>7.60</b>	<b>0.416</b>
<b>2004</b>	<b>60,365</b>	<b>14.61%</b>	<b>6.72</b>	<b>0.442</b>
<b>2005</b>	<b>57,711</b>	<b>13.50%</b>	<b>7.30</b>	<b>0.431</b>

Finally, it is also possible to examine the Florida HMO Market on an even more detailed level: the firm-level. Despite the increase in the number of firms in the HMO Market on the

state-level, the average number of counties or local markets each HMO was active in Florida decreased from 19.33 markets in 2001 to 15.28 markets in 2005. This illustrates that although more firms were successfully entering the Florida HMO Market; individual firms were choosing to enter fewer local markets than they did previously. Table 3 contains a detailed breakdown of the changing dynamics of the Florida HMO Market on the firm-level. In fact, entry decisions varied greatly across HMOs in Florida from 2001 to 2005 with firms choosing to enter anywhere from 1.5% to 95.8% of all potential local-markets. Some of this variation can be attributed to differences in entry strategies based upon the type of HMO such as independent HMOs versus National HMOs (i.e. Aetna, Cigna, Humana and United). However, even within HMO type entry percentages have varied greatly. On average, independent HMOs entered 15.25% of all local-markets with HMOs of this type choosing to enter anywhere from 1.49% to 47.46% of all local-markets. Conversely, National HMOs on average entered 41.23% of all potential local-markets with this type choosing to enter anywhere from 4.48% to 95.80% of all potential local-markets. The wide variation in these entry percentages, even within HMO type, indicates that HMOs in the Florida HMO Market utilized a variety of different entry strategies during the HMO Backlash Period.

**Table 3: Florida HMO Market – Annual Firm-Level Breakdown**

<b>Year</b>	<b>Average Number of Markets with Members</b>	<b>Average Number of Members per Market (Active Firms Only)</b>	<b>Average Market Share (Active Firms Only)</b>
<b>2001</b>	<b>19.33</b>	<b>9,068</b>	<b>12.6%</b>
<b>2002</b>	<b>18.71</b>	<b>9,853</b>	<b>14.9%</b>
<b>2003</b>	<b>20.36</b>	<b>8,379</b>	<b>13.2%</b>
<b>2004</b>	<b>17.31</b>	<b>8,988</b>	<b>14.9%</b>
<b>2005</b>	<b>15.28</b>	<b>7,907</b>	<b>13.7%</b>

Furthermore, it is also possible to examine the market structure of the Florida HMO Market on a variety of different levels. On a state-level, the top three providers with the most

enrollees in Florida throughout the HMO Backlash Period have consistently been National HMOs.<sup>7</sup> However, if one uses a more detailed level to examine HMO market structure in Florida, such as the firm-level, it is possible to observe a wide variety of experiences in post-entry experiences during the HMO Backlash Period. On average, firms that successfully entered local market (Active Firms) had fewer members per market in 2005 than they did in 2001. This is likely due to the lower levels of HMO Penetration that were characteristic of the period. However, the drop in the number of firms in each market caused the average market share of all firms in a given market or county to increase slightly from 12.6% in 2001 to 13.7% in 2005. These results indicate that despite the decrease in the number of members per market, firms that choose to enter each market were reaping the benefits by obtaining a larger share of the total number of HMO enrollees per market. Thus it appears that entry has a significant effect on the Florida HMO Market on both the local-market level and firm-level.

### **III. Review of the Literature and Research Goals**

There are a large number of studies that examine the topics of entry in product markets ranging from pharmaceuticals to banking. Bresnahan (1989), Siegfried and Evans (1994), Geroski (1995), and Berry and Reiss (2007) summarize a number of the empirical studies and models which have been used to analyze the topics of entry in the IO literature.

Correspondingly, the study of entry has extended to the health insurance market. As such, there have been a number of previous studies which have focused exclusively on HMO entry (McNeil and Schlenker 1975; Berki and Ashcraft 1980; McLaughlin 1988; Dranove, Gron and Mazzeo

---

<sup>7</sup> The following are the top three HMOs with the largest membership at the state-level in Florida (firms are listed in order of the number of members from largest to smallest): in 2001, United, Health Options and Aetna; in 2002, Health Options, United and Aetna; in 2003, United, Health Options and Aetna; in 2004, Health Options, Aetna and United; and in 2005, Aetna, Humana, and United.

2003).<sup>8</sup> In these studies, the authors focused on the effect of market characteristics (including market size, income, population demographics, and hospital expenses) and regulation differences on the formation of new HMOs and the number of HMOs operating in a market in a given time period. These studies were all conducted at the market-level where HMOs were assumed to be homogenous firms. To date, there has only been one previous study, Dranove, Gron and Mazzeo (2003), which has allowed for firm heterogeneity and looked at the effect of firm-level variables on HMO entry decisions and market structure. The authors argued that the plans offered by HMOs are not homogenous but instead are differentiated products based upon geographic scope (national or local) of the individual HMO. The authors found that product differentiation, specifically the type of HMO, affected both HMO entry decisions, the number of HMOs operating in the market, and the level of competition in the market where there was a high-level of competition within HMO type but little across type. Thus there has been limited research regarding the effect of the firm characteristics or firm-market characteristics on entry in the HMO market.

In areas outside of the HMO industry, a number of previous studies have examined the effect of forces other than market characteristics on entry. Berry (1992) estimated the effect of market characteristics and firm characteristics on a firm's entry decision and post-entry profits in the airline industry. The author argued that potential entrants in this market were heterogeneous

---

<sup>8</sup> The study by McNeil and Schlenker (1975) looked at the relative importance of market, legal and policy conditions in influencing the number of HMOs across geographic areas. The authors found that population size and hospital expenses were positively related to HMO entry and new HMO formation. They also found that prior HMO presence was a positive predictor of new HMO formation. Similarly, Berki and Ashcraft (1980) found that HMOs are often found in areas with high population mobility. A study by McLaughlin (1988) examined how HMO entry decisions were influenced by political, economic, and demographic characteristics of providers and consumers and the level of hospital expenses – all of which affect the supply or demand for hospital services. The author found that the probability a geographic area has an HMO in a given year is determined by population size, number of doctors in the geographic area, and if a HMO was in the area in the previous year/period. She also found that the demand for the HMO product is influenced by socioeconomic factors including the percentage of the population that graduate high-school, percentage of families with children, percentage of new population in the area (population mobility) and area income.

due to observed and unobserved variation in firm costs and demand. The author found that firm characteristics, such as airport output share and city presence, had a statistically significant effect on a firm's entry decision and post-entry profits. Similarly, Scott Morton (1999) examined the effect of firm characteristics and firm-market interactions in the entry choices of generic pharmaceutical firms. The author argued that a firm's entry decision was a function of characteristics of the market pertaining to market size, firm characteristics and firm-market interactions that predict the firm's fixed cost of entry. The author found that entry decisions varied greatly across firms where firms were more likely to enter drug and therapy markets with which they already had experience. Likewise, Kyle (2006) looked at the effect of firm and market characteristics and firm-market interactions on the launch of new pharmaceutical products in G7 markets. The author used firm-market interactions to examine how language similarities, geographic proximity, and common regulations affected a firm's entry decision. The author found that similarities between a firm's home market and target market in regards to language, location and regulations increased the probability of entry where firms tended to enter markets that were similar to those where they already competed. Finally, Felici and Pagnini (2008) used firm characteristics and firm-market interactions to examine the role of firm heterogeneity in entry choices in the local banking markets in Italy. The results indicate bank heterogeneity affects entry choices where both geographic distance and economic distance have a negative effect on a firm's entry decision. Thus the authors found evidence of a spatial pattern of entry in local banking markets. The results of these studies outside the HMO industry indicate that firm characteristics and firm-market characteristics are useful in predicting entry of heterogeneous potential entrants into market with different characteristics.

The goal of my research is to examine the effect of market characteristics, firm characteristics and firm-market characteristics on a HMO's entry decision into local markets in Florida.<sup>9</sup> As discussed above, to date, there have been few studies which have tried analyzed entry decisions in the HMO product market on an individual firm-level. In all of the previous entry studies in this area, the authors have focused their analysis around the number of HMOs operating in a market in a given time period. As a result, these authors have assumed that firms operating in the HMO market are homogenous. This is due to the fact that they have been forced to conduct their entry analysis at the market-level rather than the firm-level due to data limitations. Furthermore, these studies have primarily focused on the effect of market forces and regulation differences in their entry analysis. Thus there has been limited research into the effect of the firm characteristics or firm-market characteristics on entry decisions in the HMO market. However, the results of studies in other fields, such as the pharmaceutical industry and banking industry, indicate that allowing for firm heterogeneity improves the predictive ability of a model and is useful in analyzing entry into markets with different characteristics (Berry 1992; Scott Morton 1999; Kyle 2006; Felici and Pagnini 2008). Therefore, I improve upon the previous literature in this area by using firm characteristics and firm-market characteristics to explore the effects of firm and market heterogeneity on HMO entry decisions into local markets.

#### **IV. Data**

##### **A. Sample and Data Sources**

The data used in my analysis is made up of 8,645 observations and is a pooled cross section of five years of data on all Health Maintenance Organizations (HMOs) operating in

---

<sup>9</sup> Due to the fact I restrict my analysis to a single state, I do not look at the effect of government policies and regulations since these do not vary on the local-level but rather the state-level.

Florida. The data used in the regressions are from 2001 to 2005 and was compiled from a number of different sources. Each observation in my analysis represents a specific firm-local market combination ( $x_{ij}$ ); where  $i$  is a firm or HMO operating in at least one local geographic market in Florida and  $j$  is the local-market. A number of other studies which have analyzed entry decisions on a firm-level with pooled cross-section data have used similar units of observations in their analysis including Berry (1992), Scott Morton (1999), Kyle (2006), and Felici and Pagnini (2008). The relevant local geographic market is a county which accounts for the localized nature of health insurance entry decisions and HMO enrollment concentration. County has been used as the relevant geographic market in a number of previous studies in this area including those by Baker and Corts (1996); Dranove, Gron and Mazzeo (2003); Felici and Pagnini (2008), and Schneider et al. (2008).<sup>10</sup> Since there are 65 local-markets in Florida, there are 65 potential firm-local market combinations, or local-market opportunities for entry, for a specific HMO operating in Florida in a single year.<sup>11</sup>

---

<sup>10</sup> One can define the relevant geographic market using a variety of different techniques (Schneider et al. 2008). It can be defined empirically using the Elzinga-Hogerty test which is based upon patient flows or using some existing geopolitical boundary such as counties or metropolitan statistical areas (MSAs). Due to lack of data on HMO enrollee flows from health insurers, I use an existing geographic boundary to define my relevant geographic market. I argue that the market for health insurance entry and enrollment concentration will be relatively localized. In her study, (McLaughlin 1987), the author found that HMO enrollment varied widely within a single state or larger geographic location. She argued that it was inaccurate to simply divide state enrollment number by total area population to reflect HMO Concentration since it would not reflect the localized nature of HMO enrollment. Counties, as a relevant geographic market area, are superior to MSAs because there are relatively few (20) MSAs in the state of Florida. Also, only 39 of Florida's 67 counties are assigned to a MSA (the counties not assigned to MSAs are rural and located in similar geographic regions). Thus using MSA as the relevant geographic market would exclude many areas from analysis and result in the loss of a large portion of the data. Furthermore, using counties as the geographic market lets me account for the fact that there are a number of HMOs in the state which only have members in a few counties. The number of enrollees in these HMOs may be small in comparison to the total number of HMO enrollees in the state but may actually account for the bulk of the total HMO enrollees in the local area. Some drawbacks of using county as the relevant geographic market are that it does not account for firm competition on the state or national level.

<sup>11</sup> While there are 67 counties in Florida, there are two counties in Florida, Gulf County and Washington County, where total HMO enrollment was always less than 30 enrollees and zero in many of the years. Thus I did not include local-markets in my analysis where there were zero HMOs in most years. This decision reduced my original sample of 8,911 firm-local market combinations by 266 observations.

My primary data source for firm characteristics or HMO data is the Florida Office of Insurance Regulation (FLOIR). FLOIR gathers yearly Financial Data and Annual Enrollment Data from all HMOs operating in Florida. From the FLOIR Annual HMO Enrollment Data, I obtain data on the number of HMOs per county, total HMO enrollment per county, breakdown of total county HMO enrollment by individual HMO, HMO product offerings, and the number and identity of the geographic areas where an HMO operates. I also obtain data on a number of other HMO characteristics from the FLOIR Financial Data including HMO net income, headquarters location, and national HMO affiliation. Some additional data used in my analysis are from the following sources: US Department for Health and Human Services' Centers for Medicare and Medicaid Services (hospital wage index); US Department of Labor, Bureau of Labor Statistics (average annual pay by county); the Florida Legislature Office of Economic and Demographic Research (total county population and population demographics); and the Florida Agency for Health Care Administration (AHCA) Hospital Financial Data (number of hospitals; hospital type – general, specialty, or teaching; and all the insurance providers with whom a hospital has contracts which is used to construct a provider's hospital network).

## **B. Data Limitations**

There are a number of data limitations due to the nature of the data I use to construct my sample. First, as previously discussed I assume that each type of health insurance product constitutes its own unique market. Thus, in my current analysis I do not have data on different types of providers such as PPOs or government sponsored plans (Medicare and Medicaid). However, if one assumes that all providers combine to form one large market for health insurance than not controlling for the market structure of other provider may produce biased

results. Therefore, the data would be more complete if I had market share data for other providers than HMOs. Next, in order to analyze a HMO's entry decision into local markets at the firm-level, I need variables which are unique to each firm-market combination. However, my data only contains a few variables that vary both for the same firm by market (or conversely same market by firm). Instead, many of the firm characteristics, obtained from the FLOIR HMO Financial Data, do not vary for the same firm by market. Thus each HMO will have the same firm characteristics for all of its potential firm-market combinations in a single time period. Likewise, the market characteristics obtained from the sources outlined above do not vary for the same market by firm. I use firm-market interactions terms to supplement the limited number of firm-market characteristics I have in my dataset. These interaction terms are unique to the firm-market combination and enable me to more accurately exploit variation in a firm's entry decision that occurs due to both firm and market heterogeneity. Another one of the limitations of my data is the unbalanced nature of the dependent variable used in my analysis which pertains to a firm's entry decision. The bulk of the observations for this variable are zero. Thus there is a mass point on zero for this dependent variable. This data limitation could result in my model lacking sensitivity and not fitting the data well. I discuss the second and third of these data limitations and their potential effects in further detail in the next sections.

## **V. Theoretical Model**

In order to achieve my research goal, I estimate an entry model that builds upon the entry models used in areas outside the HMO industry. In my model, individual firms (HMOs) make entry decisions where a firm's entry decision is based upon its expected post-entry profits. I assume that a firm will chose to enter a market as long as its expected post-entry profits are

positive; otherwise, it will chose not to enter a market and earn zero profits. The firm's entry decision rule utilized in my analysis is similar to the ones used in Berry (1992), Scott Morton (1999), and Kyle (2006). I also assume that a firm's entry decision in a given market is independent of its entry decisions in other markets since a HMO has the ability to solicit potential enrollees in multiple geographic markets at the same time. Furthermore, a decision by an HMO to obtain members in one market does not preclude it from seeking members in another market in the same time period. I assume that the costs of entry are fixed and sunk because a firm cannot transfer the costs it incurs trying to gain entry into one market to another market. Scott Morton (1999), Kyle (2006), and Felici and Pagnini (2008) also assume that the costs associated with entry are fixed, sunk and non-transferable between markets. Finally, I assume that costs of entry will vary across markets and firms. Thus costs of entry vary with individual firm and market characteristics and firm-market characteristics for reasons discussed below.

In the Florida HMO Market, the set of potential entrants is known. This is an advantage over a number of the previous firm-level entry studies, including Scott Morton (1999), where the set of potential entrants was unknown or not clear. In these cases, researchers were forced to use a variety of econometric and statistical techniques to overcome this data limitation. In order to provide an HMO insurance product in Florida, an insurance provider must obtain approval and a license (for each insurance product line – Commercial, Medicare, Medicaid, etc.) from the Florida Office of Insurance Regulation (FLOIR). Once, a HMO obtains a license from FLOIR it has the ability to provide its insurance product in all of the counties within the state since the FLOIR license is not specific to the local geographic market (i.e. one single FLOIR license allows an HMO to offer its insurance product in all counties in Florida). Thus the set of potential entrants includes all licensed HMOs operating in Florida in a given time period. Similar to Berry

(1992), I assume that the set of entrants also includes firms that were incumbents in a market at the beginning of the period and decide to remain in the same market at the end of the same period. As a result of these assumptions, the set of potential entrants is clear and I am able to overcome the data limitations of some of the other researchers in this area.

Next, I assume that firms make their entry decisions simultaneously due to the fact numerous HMOs can be actively pursuing potential enrollees in the same market during the single time period. This differs from Berry (1992) who assumed that firms' entry decisions were sequential and thereby determined partly by the entry decisions of other firms. As a result, Berry (1992) was forced to estimate the entry equation at the market-level using an equilibrium entry model. By allowing for simultaneous entry decisions, I can model a firm's entry decision using a discrete-choice approach as applied to individual firm behavior. Similar approaches are used by Scott Morton (1999), Kyle (2006), and Felici and Pagnini (2008) when analyzing entry. Thus I estimate my analysis at the firm-level which is important because it enables me to incorporate firm heterogeneity into my model. Due to the fact I assume that a firm's entry decision varies over time, I treat each year for the same firm-market combination as a separate observation. However, because firm entry decisions are clearly correlated over time, I plan to correct for correlation in the errors in the future. In my current analysis, I control for local-market fixed effects which will pick up some of the correlation in the errors, but not all; thus, the standard errors reported here are potentially biased downwards.<sup>12</sup>

The Florida HMO Market is not made up of identical homogeneous firms but instead a wide variety of differentiated firms. Correspondingly, I assume that potential entrants are

---

<sup>12</sup> As an initial attempt to correct for the correlation in errors, I estimate my analysis using a single year of data. While a single year is not the ideal specification, the regressions estimated using pure cross sections suggest what might change when I correct for the bias in my standard errors. I briefly discuss the results of my regressions estimated using a single year of data, a pure cross section, in the conclusion.

heterogeneous which stems from differences in observed and unobserved variables that affect firm costs and demand. As a result, some firms will be better suited to a particular market than others. Furthermore, the products or plans offered by all firms in a market are not identical. Instead, HMO products are heterogeneous.<sup>13</sup> The specific plans offered by a number of HMOs in the same market can be differentiated based upon the following dimensions: access to care, the size and quality of their provider network, and consumer's out-of-pocket expenses. This product heterogeneity can result in different entry costs, operating costs (fixed costs and variable costs), and demand for a given firm in a given market. As discussed in the next section, I use firm characteristics and firm-market characteristics in my empirical model to control for both firm and product heterogeneity of potential entrants.

## **VI. Research Method and Empirical Model**

### **A. Empirical Model**

I use both the logit model and probit model with local-market (county) fixed effects to examine a HMO's entry decision into local markets in Florida. Both Scott Morton (1999) and Kyle (2006) use local-market fixed effects to control for unobserved differences across markets, such as differences in local market growth rates, that are important to a firm's entry decision.<sup>14,15</sup> My empirical model choice is motivated due to the fact that the dependent variable I use to represent a HMO's entry decision is binary. Both the logit and probit models are types of binary

---

<sup>13</sup> This assumption varies from Scott Morton (1999) who assumed that the products offered by all generic pharmaceutical firms were identical or homogenous.

<sup>14</sup> I estimate alternate versions of my analysis using local-market fixed effects and time fixed effects which is similar to the research method used in Felici and Pagnini (2008). My results are consistent using either type of fixed effects illustrating the robust nature of my findings.

<sup>15</sup> Difference in local market growth rates have been shown to effect entry in other industries (Siegfried and Evans 1994). While local-market fixed effects will control for differences in market growth rates, I cannot identify the direction of this effect on HMO entry decisions because I do not include a separate variable for market growth rates in my empirical model.

response models (commonly referred to as discrete choice models). In these models the dependent variable or outcome is a binary variable that can only take on the values of 0 and 1, and is used to indicate whether or not a certain event has occurred. Typically a 1 is indicative of a “success” or the event occurring and a 0 is associated with a “failure” or the event not occurring. It is often problematic to use a linear probability model with binary dependent variables because this type of model will commonly predict outcomes outside the unit interval (the 0, 1 range). This occurs because the linear probability model assumes constant marginal effects of the independent variables (i.e. that a *ceteris paribus* unit increase in an independent variable,  $x$ , always changes  $P(y = 1|x)$  by the same amount, regardless of the initial value of  $x$ ) (Wooldridge 2002). On the other hand, the logit and probit models imply diminishing marginal magnitudes of the partial effects of the independent variables. This ensures the predicted probabilities remain within the unit interval. Thus studies that involve the analysis of discrete outcomes are good candidates for discrete choice models. The general form of a discrete-choice model is:

$$P_i = P(y_i = 1) = F(x_i^*, \theta) \quad \text{for } i= 1, 2, \dots, n$$

In a binary response model, researchers predict the probability an event will occur (i.e. the probability that the dependent variable,  $y$ , will equal 1). The probability of the dependent variable depends on a vectors of independent variables,  $x^*$ , and a vector of unknown parameters,  $\theta$ . Thus, I predict the probability that a firm will enter a given market where  $P \geq 0.5$  indicates a firm will enter a given market. Typically, the probit model is best suited to processes that are inherently discrete, whereas the logit model is designed for a zero-one outcome of a decision process that is not inherently discrete. Since a firm’s entry decision is a purely discrete choice, the probit model may be the preferred model. However for the most part, it does not matter if

one uses the probit model or the logit model, except in cases where data are heavily concentrated in the tails (Greene 1990). In order to choose between these types of models one must make an assumption about the probability of the residuals. The logit model assumes a logistic distribution of errors (cdf) while the probit model assumes a normal distribution of errors (pdf). Typically, researchers will estimate both types of models and see which fits the data better (i.e. has more predictive power).

In discrete choice models, the coefficients of the independent variables are estimated using the maximum likelihood method. This method produces coefficients that maximize the likelihood or probability of drawing this particular sample. The primary interest in these models is the response probability: the effect of a change in one of the independent variables on the probability of the outcome  $[P(y = 1|x)]$ . One interprets the coefficient on a specific independent variable as representing the change in the mean of the probability distribution of the dependent variable. Therefore the sign of the effect of a specific independent variable is given by the sign of the coefficient on that variable. Thus a (significant) positive coefficient means that an increase in that independent variable increase the probability or likelihood of the outcome  $[P(y = 1)]$ ; while a (significant) negative coefficient means that the independent variable decrease the probability or likelihood of the outcome occurring (Long 1997). Similarly, a large (significant) regression coefficient means that the independent variable strongly influences the probability of the outcome, whereas a near-zero or insignificant coefficient means that the independent variable has little or no influence on the likelihood of the outcome. However, in order to determine the exact magnitude of the partial effect of a specific independent variable, one must evaluate the entire likelihood function holding all the other independent variables fixed (typically at their mean values) (Wooldridge 2002).

I assume a firm's entry decision is a function of market characteristics, firm characteristics and firm-market characteristics which affect the costs of entry, operating costs, the level of competition, and demand for an HMO's product in a given local market. The basic empirical model used to estimate a firm's probability of entry is:

$$\Pr_{ij}(\text{entry}) = \Pr(y_{ij} = 1) = f(\beta_0 + X_i B_1 + Z_j B_2 + \Psi_{ij} B_3 + \delta_j B_4 + \varepsilon_{ij})$$

As stated above, the firm's entry decision rule is that a firm will chose to enter a local-market ( $y_{ij} = 1$ ) as long as its expected post-entry profits are positive; otherwise, it will chose not to enter a local-market ( $y_{ij} = 0$ ) and earn zero profits where  $i = \text{firm or HMO}$ ,  $j = \text{local-market}$ , and  $\delta = \text{unobserved local-market fixed-effects that affect a firm's entry decision}$ . Thus my empirical model builds upon the firm-level entry research conducted by Scott Morton (1999) and Kyle (2006) in the field of pharmaceuticals and Felici and Pagnini (2008) in the filed of banking.

All local markets are not identical. As such, the state of Florida is not made up of identical homogeneous local markets but instead a wide variety of markets. Market characteristics, vector  $Z$ , determine the size of the HMO market or overall demand for the HMO product and the level of competition in the market and therefore affect a firm's expected post-entry profits in a given local market. Thus all the market characteristics included in my model will be demand-side variables. It is possible to divide these demand-side variables into two categories: variables that increase the demand for either the overall HMO product (i.e. increase the demand for all HMOs in a market collectively) or variables that increase the demand for the insurance product offered by a particular HMO or type of HMO. Similarly, firm characteristics, vector  $X$ , allow me to account for the heterogeneity among the individual HMOs based upon their different entry costs, costs of providing their insurance product, and the share of the overall demand for the HMO insurance product in a given market that applies to their individual plan.

Thus the firm characteristics included in my model will be either supply-side variables which lower the costs of entry or post-entry costs of operation or demand-side variables which increase the demand for the product offered by a particular type of HMO or specific HMO. Finally, as previously discussed the products or plans offered by all HMOs are not identical. The use of firm-market characteristics, vector  $\Psi$ , allows the demand-side market characteristics that affect an individual HMO's post-entry profits to vary by firm-type or specific firm. Thus these characteristics determine the share of overall market demand for the HMO product which pertains to a unique type of HMO or specific HMO. I discuss the specific variables included in each of the three vectors below.

## **B. Dependent Variable**

The dependent variable I use in my analysis is discrete and can therefore only take on either 0 or 1 values. In discrete choice models, dependent variables must meet the following three criteria: (1) the set of choices or classifications must be finite; (2) the set of choices or classifications must be mutually exclusive; and (3) the set of choices or classifications must be collectively exhaustive (Wooldridge 2002). The dependent variable used in my analysis meets the above three criteria. First, a HMO can either enter or not enter a given market. There are only two possible outcomes, thus the set of classifications is both finite and collectively exhaustive. Likewise, a HMO can only be classified as either entering or not entering a given market. A HMO can only obtain a single outcome to the entry question in a single time period. Therefore, the set of classifications is mutually exclusive.

In order to analyze a firm's entry-decision, I need a variable that indicates whether or not a HMO has entered a given market. In any given year, a HMO can have members in sixty-five

local markets each corresponding to a local geographic area in Florida (a county).<sup>16</sup> I assume that if a HMO has at least one hundred members in a market than the HMO has successfully entered the market.<sup>17</sup> Thus, first I create a variable indicating the number of members each HMO has in each of the sixty-five local markets which I refer to as HMO Members per Market. To construct this variable, I use data from the Florida Office of Insurance Regulation (FLOIR) regarding the total number of enrollees that a HMO has in all of the geographic areas where it is active. FLOIR then offers a breakdown for each individual HMO of their enrollees by geographic market (county). The annual values of HMO Members per Market in my sample range from 0 to 228,308, with a mean of 2,376 members.

Next, I use the data from HMO Members per Market to create a binary variable indicating whether a HMO has entered a given market which I refer to as Entry. Thus an observation where Entry equals 1, ( $y_{ij} = 1$ ), indicates that a HMO has successfully entered a specific market (i.e. HMO Members per Market is greater than or equal to 100 members) while an observation where Entry equals 0, ( $y_{ij} = 0$ ), indicates that a HMO has failed to enter a given market (i.e. HMO Members per Market is less than 100). HMOs have successfully entered the market in approximately 20.10% of the total 8,645 sample firm-local market combinations. If I restrict my sample to only the firm-local market combinations where HMOs are active; the annual values of HMO Members per Market in my sub-sample range from 100 to 228,308, with a mean of 12,168 members.

---

<sup>16</sup> Again, I do not include observations from two local-markets in Florida where there were zero HMOs in most years. Since one of my data limitations is the unbalanced nature of the dependent variable, I do not include the observations from these local-markets in an effort to improve the sensitivity of my model. When I include the observations from these local markets in my model there is no significant effect on my results other than all of the models have lower sensitivity. This is due to the fact that when I include these observations, I increase the number of observations with a non-entry or zero outcome by 266 while holding the number of observations with an entry or one outcome constant.

<sup>17</sup> I estimate my analysis using alternate thresholds for entry including 25 and 50 members per market. The results of my analysis are consistent when I use these alternate entry thresholds illustrating the robustness of my findings.

One of the limitations of my data is the unbalanced nature (or skewed distribution) of the dependent variable used in my analysis. As stated above, my dependent variable is binary; thus, this type of variable does not have a normal distribution but instead has a binomial distribution. However, the distribution of my dependent variable is not symmetric which would only occur if there was an equal (or close to equal) number of both zeros and ones. Instead, there is a mass point on zero since a HMO does not choose to enter all potential markets or conversely all HMOs do not enter a single market.<sup>18</sup> This data limitation could result in models which lack sensitivity and do not fit the data well.<sup>19</sup> When a dataset with a binary dependent variable contains mostly observations where the dependent variable is either 0 or 1, discrete choice models can lack either sensitivity or specificity in predicting certain outcomes. When the dataset contains mostly unsuccessful outcomes or zeros, the probability of an event is very small. As a result, both the coefficients and predicted probabilities will be biased downwards (Wooldridge 2002).<sup>20</sup> Thus the model will be more likely to predict that an event will not occur than we may actually see in the observed outcomes. As a result, the model will lack sensitivity in predicting successful outcomes or ones. This is extremely problematic since I am interested in determining what factors increase the probability that a HMO will enter a market. However, the results of a Hosmer and Lemeshow Goodness of Fit test indicate that using the entire sample to examine a firm's entry decision, the model is not a poor fit (i.e. I reject the null that the model is a poor fit).

---

<sup>18</sup> This is evident by the fact that in only 20 percent of my potential firm-market combinations do the firms actually choose to enter the market (i.e. entry occurs in only 1,738 of the 8,645 unique firm-market observations).

<sup>19</sup> Sensitivity and specificity are two common statistical measures of performance for discrete choice models. In cases such as these, it will not be possible to use a standard "goodness-of-fit" test to assess the validity of the model or the ability of the model to fit the data. This is due to the fact that that model will be lacking in the ability to predict positive outcomes (i.e. lacking in sensitivity) but will be very good at predicting negative outcomes (i.e. profuse in specificity). However, the "goodness-of-fit" of the model is based on a combination of the sensitivity and specificity of the model. Due to the unbalanced nature of the dataset, the net effect of these two measures will result in the model correctly classifying the bulk of the observations since it will be more likely to predict unsuccessful outcomes (i.e. zeros) and the probability of the event is very small.

<sup>20</sup> In this case, a downward bias on positive coefficients will entail that that the coefficient will be closer to zero whereas negative coefficients will be larger in absolute terms. Conversely, a downward bias on predicted probabilities will entail that the probabilities predicted by the model are closer to zero.

Furthermore, due to the fact the critical mass on zero in my dependent variables is not the result of censoring, it is not appropriate to use either a Tobit or Heckman Model (Wooldridge 2002).<sup>21</sup> Thus it is not necessary to use an alternate method when examining the entry question. I include both the sensitivity and specificity of the model in the results section which illustrate that my empirical model is doing an appropriate job of correctly predicting both types of entry outcomes.

### **C. Explanatory Variables**

The explanatory variables used to explain variation in a HMO's entry decision can be divided into three categories: explanatory variables controlling for market characteristics (Vector Z in the empirical model), explanatory variables controlling for firm characteristic (Vector X in the empirical model), and explanatory variables controlling for firm-market interactions (Vector  $\Psi$  in the empirical model). All of the explanatory variables controlling for firm characteristics are HMO specific whereas all of the explanatory variables controlling for market characteristics are assigned to each HMO based upon the geographic market the HMO is debating entering into or where it already operates. I calculate annual values for 2001 to 2005 for each of the explanatory variables in my sample. Table 4 contains a complete list of descriptive statistics of the sample.

---

<sup>21</sup> Furthermore, in order to use either of these models, the dependent variable must be continuous which beyond some point is unobserved or censored and its value is replaced by zero or some other limit (Wooldridge 2002; Gourierouz 1991). In my analysis, the dependent variable is not continuous but instead binary and is fully observed (i.e. my data is not unbalanced due to missing values). Thus there are no observations in my data set which are assigned a zero value due to censoring. These facts preclude me from needing to use either a Tobit or Heckman model to address potential censoring issues.

### **i. Market Characteristics**

As previously stated, all local markets in Florida are not identical. There is a wide range of market characteristics one could use to differentiate local market; however, many of these characteristics are highly correlated. Thus, I can only include a limited number of market characteristics in a single model. The variables controlling for market characteristics are demand-side variables that account for local market heterogeneity based upon the size of the HMO market, the overall demand for the HMO product, the level of competition in the market, and population demographics. These market characteristics are easily observed and quantified by a HMO and are therefore likely to play a role in a HMO's entry decision. Similar market variables were used by McNeil and Schlenker (1975), Morrissey and Ashby (1982), McLaughlin (1988), and Balla (1999) during their analyses of HMO entry. It is important to note that these variables will be the same for all firms operating in the same local market.

*Income* controls for variations in market wealth and is measured by the average annual pay of the market (in 1,000s). According to theory, this variable should have a negative effect on a firm's entry decision. Previous studies by Berki and Ashcraft (1980) and Morrissey and Ashby (1982) found that markets with higher incomes were associated with lower levels of HMO Entry and HMO Penetration. This is due to the fact that HMOs offer more restrictive health insurance products in terms of provider selection and access to care; both of which are normal goods. Thus, in areas with higher income consumers are less likely to enroll in HMOs which can be viewed as offering an inferior insurance product. As a result, local markets with higher average incomes will be less attractive to HMOs when making their entry decisions. *Population* accounts for variations in market size and is measured by the total population of the market (in 10,000s). According to theory, this variable should have a positive effect on a firm's entry

decision. Berry (1992) and Kyle (2006) both found that, *ceteris paribus*, firms were more likely to enter larger markets. Similarly, McLaughlin (1988), Balla (1999), and Dranove et al. (1998) all found a positive relationship between market size and the number of HMOs in a market. Thus larger markets should represent an increase in overall demand for the HMO product offered collectively by all HMOs in a market. However, this effect typically diminishes which is evident by a negative second partial derivative. Thus, *Population Squared* should have a negative effect on HMO entry.

Numerous previous studies of HMO entry found that the presence of an HMO in the previous period increased the number of HMOs in the market in the following period (McNeil and Schlenker 1975; McLaughlin 1988). This positive relationship conflicts with the finding in other industries where competition was typically found to have a negative effect on entry (Siegfried and Evans 1994). However, McNeil and Schlenker (1975) argue that additional HMOs are likely to enter a market where other HMOs already operate because the conditions which attracted earlier HMOs will also appeal to later entrants. Along this line, the presence of firms in a market may be evidence of existing demand for the HMO product in the local market. Thus both *National HMOs<sub>t-1</sub>*, which indicates for the number of National HMOs in the market in the previous year, and *Independent HMOs<sub>t-1</sub>*, which indicates the number of independent HMOs in the market in the previous year, should have positive effects on HMO entry. It is important to differentiate based upon the type of firm already operating in a market since this may be indicative of the potential demand for the insurance product offered by a specific type of HMO. On the other hand, *Elderly* accounts for the share of the market population that is above 65 years old or elderly. This portion of the market is not eligible for the products offered by most HMOs. Berki and Ashcraft (1980), Welch et al. (1984), and Baker and Corts (1996) all

found the younger individuals and healthier individuals were more likely to join HMOs. Thus according to theory, this variable should have a negative effect on a HMO's entry decision. Finally, *Hospital Wage* accounts for geographic difference in local medical market costs and is measured by the local hospital wage index. Goldberg and Greenberg (1981) and McNeil and Schlenker (1975) both found that higher hospital costs and expenses increased the likelihood of HMO entry and the share of the area population enrolled in HMOs. On the other hand, Balla (1999) found that higher hospital expenses were correlated with lower numbers of HMOs and share of the population enrolled in HMOs. Thus according to theory, this variable will have an ambiguous effect on a firm's entry decision.

## **ii. Firm Characteristics**

One of the main goals of my present research is to look at the effect of firm heterogeneity on HMO entry decisions. I use firm characteristics to differentiate all of the HMOs operating in Florida HMO Market. It is important to note that these variables will be the same for all local markets for a given firm in the same year. There are a plethora of firm characteristics one could use to divide HMOs into different types. However, many of these characteristics are highly correlated; thus, I can only include a limited number in a single model. The explanatory variables controlling for firm characteristics allow me to account for the heterogeneity among the individual HMOs based upon their different entry costs, costs of providing their insurance product, and the share of the overall demand for the HMO insurance product that applies to their individual plan. *National HMO* is a binary variable which indicates whether a firm is part of or affiliated with a National HMO. According to theory, this variable will have a positive effect on a HMO's entry decision. Dranove, Gron and Mazzeo (2003) found that it was possible to

differentiate HMOs based upon their scope of operations where HMOs can either be independent firms or part of a larger firm (affiliated with a National HMO). The authors argued that HMOs which are affiliated with a National firm will have lower entry costs than independent firms due to economies of scale and savings on administrative and advertising costs. Similarly, Scott Morton (1999) and Jia (2006) both found that large firms have lower costs of entry due to savings on advertising costs, customer service costs, and R&D costs. *HMO Income* indicates a HMO's net income for the entire state of Florida (in 100,000s). Many health care experts claim that HMOs use a variety of tactics to lower health care costs including strict patient utilization review to prevent excessive or wasteful care, lower administrative costs, and volume discounts.<sup>22</sup> In turn, these tactics can be transformed into higher profits for the firm. Firm's can use these higher profits to expand the geographic scope of their operations by expanding into new markets. Thus this variable will have a positive effect on a HMO's entry decision. Furthermore, Felici and Pagnini (2008) found a positive relationship between a firm's profitability and entry in the banking industry.

HMOs have the option of offering only a single product or multiple product types. Accordingly, HMOs can offer either a narrow or broad range of health insurance products. There are three main types of HMO products: a commercial HMO product - which is available primarily to employees (and their families) of small and large firms and self-employed individuals; a Medicaid HMO product – which is available to only low-income and disabled individuals (both elderly and non-elderly); and a Medicare HMO product - which is only available to elderly individuals who are eligible for Medicare. *Medicare Product* is a binary variable which indicates if the firm offers a Medicare Product and has any Medicare Enrollees in

---

<sup>22</sup> The following is a sample of the studies which have found evidence that HMOs can help to lower US healthcare costs: Luft (1978, 1980); Robinson (1991, 1996); Feldman and Wholey (2001); and Miller and Luft (2002).

the state. Similarly, *Medicaid Product* is a binary variable which indicates if the firm offers a Medicaid Product and has any Medicaid Enrollees in the state. According to theory, firms that offer multiple products or a broad product line are more likely to enter markets. Thus both *Medicare Product* and *Medicaid Product* should have positive effects on a firm's entry decision. Firms that offer more than a single product type could realize a higher level of demand for their product because they have access to multiple segments of consumers (i.e. elderly, low-income, etc.). As a result, a HMO that offers either a Medicaid or Medicare product may find it profitable to enter markets that a HMO which only offer a commercial product would not. Similarly, firms that offer multiple product lines may enjoy cost savings when compared to firms with a single product line due to economies of scope and savings on administrative costs (Frech and Ginsburg 1988; Kyle 2006). These firms may also be able to obtain more favorable contract terms and/or rates with area hospital and providers for their enrollees further lowering their costs of operation.

Finally, firms can be differentiated based upon their hospital network. As previously stated, an HMO is a type of health insurance where an individual HMO offers its members the ability to access a select network of providers at a reduced cost. Thus one can separate HMOs into different types based upon the size and/or quality of the hospital network to which their members have access. I define a HMO's network to include all of the hospitals in Florida with whom the HMO has a contract. A study by Hogan (2008) found that the distance consumers are willing to travel to receive medical services depended upon their severity of illness. Thus consumers may be willing to travel outside of their local market to receive medical services. *Network Size* indicates the number of hospitals in Florida, regardless of type, which are part of the HMO's hospital network. *Network Quality* is a binary variable which indicates if the firm

has a high quality hospital network. I measure the quality of a HMO's hospital network based upon the number of elite teaching hospitals in Florida it has in its network. Firms which have more than the median number of teaching hospitals (two) in their network are classified as having a high quality network while those who have less than or equal to the median number of teaching hospitals are classified as having a low quality hospital network. According to theory, both *Network Size* and *Network Quality* should have a positive effect on a firm's entry decision. A study by Grefer et al. (2009) found that consumer were more likely to join HMOs with larger networks and those that offered access to superior services or providers. Furthermore, having more hospitals, especially multiple elite providers, in their networks will increase a firm's operating costs due to the fact HMOs must pay higher reimbursement rates to elite providers that offer more complex medical procedures (Ho 2009). HMOs may be able to mitigate these higher operational costs by offering their insurance product to individuals in multiple geographic locations. Thus the potential of large economies of scale will lower a firm's entry costs, thereby, increasing the likelihood of entry.

### **iii. Firm-Market Characteristics**

Another one of the limitations of my data is the lack of variables which are unique to each firm-market combination. Each HMO has the same firm characteristics for all of its potential firm-market combinations in a single time period. Similarly, all of the market characteristics included in my models are the same for all of the firms operating or debating entry in a given market. This is problematic because firm entry behavior is likely to vary by local market. Thus, currently my empirical models do not fully capitalize on the unique effects firm characteristics and market characteristics are likely to have on different firm-market

combinations. This data limitation will make it difficult for me to use the current data to achieve my research goal. In order to overcome this data limitation, I use firm-market interactions terms to supplement the limited number of firm-market characteristics I have in my dataset. These interaction terms are unique to each of firm-market combination and allow for the effect of market characteristics to vary by either the type of firm or the specific firm. (Or conversely, to see if the effects of firm characteristics vary based upon either the type of market or specific market.) Thus the use of firm-market interactions enables me to more accurately control for the effect firm and market heterogeneity on firm entry decisions.

As previously discussed the products or plans offered by all HMOs are not identical. The use of firm-market characteristics allows the demand-side market characteristics that affect an individual HMO's post-entry profits to vary by firm-type or specific firm. Thus these explanatory variables determine the share of overall market demand for the HMO product which pertains to a unique type of HMO or specific HMO. HMOs can be differentiated based upon the number of markets they have members in and the geographic locations of these markets. As such, HMOs can have members in the any of the surrounding or adjacent markets to the ones it may debate entering into. *Adjacent Markets* indicates the number of surrounding or adjacent local geographic markets where a firm has members. According to theory, this variable will have a positive effect on a firm's entry decision. A firm with members in surrounding local markets will have lower entry costs due to economies of scale and cost savings via over-lapping advertising costs, common distributional channels, and use of existing agents in surrounding areas (Nakeo 1993; Kyle 2006). In fact, Felici and Pagnini (2008) found a spatial pattern of entry while Kyle (2006) found that a common border increased the likelihood of entry. However, the magnitude of these positive effects is likely to decrease with each additional

surrounding market in which a firm has members. Thus *Adjacent Markets Squared* will have a negative effect on a firm's entry decision. Finally, *Adjacent Market Share* indicates the share of the surrounding or adjacent local markets where a firm has members. Since not all local-markets in Florida have the same amount of surrounding markets, it is important to control for more than just the number of adjacent markets where a firm has members. Again, according to theory this variable will have a positive effect on a firm's entry decision for the reasons discussed above.

Next, it is possible to differentiate firms based upon the location of their headquarters (Wholey et al. 1997). *HQ Distance* indicates the distance (in miles) from the local market where a firm's Florida headquarters is located to each target market, or the local market which the firm is debating entering. According to theory, this variable will have a negative effect on a HMO's entry-decision. The location where a firm establishes its headquarters is likely to be geographically close to the bulk of its operations in an effort to decrease its operating costs via savings on administrative costs and overhead. Thus firms are likely to initially establish and focus their operations in the same geographic location as their local headquarters. Furthermore, an HMO is likely to remain active in the local markets that are closer to the market where its headquarters is located because firms have superior marketing ability and lower entry costs which increase the likelihood of entry (Kyle 2006).<sup>23</sup>

To supplement the firm-market characteristics listed above, I create two firm-market interaction terms, *National HMO\* National HMOs<sub>t-1</sub>* and *National HMO\*Independent HMOs<sub>t-1</sub>* which are based upon the interaction of the firm characteristic *National HMO* and the difference between the number of *National HMOs<sub>t-1</sub>* (*Independent HMOs<sub>t-1</sub>*) operating in a given market

---

<sup>23</sup> I ran an alternate version of my analysis using a binary variable to control for the location of a firm's Florida headquarters which I referred to simply as *HQ in Market*. This variable indicated whether the firm's headquarters was located in the given local market and theoretically should have a positive effect on a HMO's entry decision. The results of the alternate version indicate that *HQ in Market* had a positive statistically significant effect on a HMO's entry decisions; thus, my analysis using this binary variable is consistent with the results reported here.

and the average number of *National HMOs*<sub>t-1</sub> (*Independent HMOs*<sub>t-1</sub>) in all local markets. A previous study by Dranove, Gron and Mazzeo (2003) found that the type of HMO affected HMO entry decisions. Thus the use of these two firm-market interaction terms will allow me to see if the effect of prior HMO presence on a firm's entry decision varies based upon not only the type of HMO already operating in a market but also the type of firm making the entry decision. As previously discussed, the presence of firms of the same type in a market may be indicative of existing demand for the insurance product offered by other HMOs of that type. On the other hand, the presence of firms of a different type may not provide this same indication of existing demand in the local market. Instead non-type firms are simply additional competitors a HMO will have to compete against for prospective members. Therefore, I expect the probability a firm will enter a given market will be positively affected by the presence of firms of the same type and negatively affected by the presence of firms of a different type. Thus *National HMO\*National HMOs*<sub>t-1</sub> should have a positive effect on a firm's entry decision while *National HMO\*Independent HMOs*<sub>t-1</sub> should have a negative effect on the probability of entry.<sup>24</sup>

I also use firm-market interactions to see how the effect of the size and quality of a HMO's hospital network on a firm's entry decision varies based upon market size and wealth. I create four firm-market interaction terms: *Network Size \*Population*; *Network Size\*Income*; *Network Quality\* Population*; and *Network Quality\*Income*. For both market characteristics, I look at the difference between the *Population (Income)* in a given local market and the average *Population (Income)* in all local markets. One would assume that firms with larger hospital networks would be more likely to enter more urban markets so as to further capitalize on their

---

<sup>24</sup> Furthermore, when I include these two firm-market interactions in my model, *National HMOs*<sub>t-1</sub>, and *Independent HMOs*<sub>t-1</sub>, indicate how independent or local HMOs' entry decisions vary based upon the type of firm already operating in a local market. According to the theory discussed above, *National HMOs*<sub>t-1</sub> should have a negative effect on independent HMOs entry decisions whereas *Independent HMOs*<sub>t-1</sub> should have a positive effect on independent HMOs entry decisions.

economies of scale and spread their operating costs over a larger member base. As a result, *Network Size \* Population* should have a positive effect on a firm's entry decision because it is likely to increase a firm's expected post-entry profits. However, *Network Quality \* Population* should have a negative effect on a firm's entry decision. This is due to the fact that HMOs negotiate less favorable rates with elite teaching hospitals when compared to other hospitals. As a result, they make less profit when their members utilize elite teaching hospitals rather than regular hospitals to obtain standard hospital services. Due to the fact that most elite teaching hospitals in Florida are located in urban areas and consumers are more likely to receive medical services from local providers (Hogan 2008); *Network Quality \* Population* may decrease a firm's expected post-entry profits thereby making entry into these local markets less likely. It is also possible to use either the number of hospital or the type of hospitals in a firm's network as a measure of product quality. If consumers perceive providers with larger hospital networks or more elite teaching hospitals in their network as an indication of a higher quality HMO insurance product; then firms with these types of hospital networks may find it profitable to enter wealthier markets. If this is the case, then both *Network Size \* Income* and *Network Quality \* Income* should have a positive effect on a firm's entry decision because they will increase a firm's expected post-entry profits; thereby, making entry into these local markets more likely.

**Table 4: Descriptive Statistics of the Sample**

Variable Name	Mean	Standard Deviation	Median	Minimum	Maximum
<b>Dependent Variable</b>					
Entry	20.10			0	1
<b>Market Characteristics</b>					
Income	28.625	4.284	27.966	20.837	40.599
Population	26.253	41.923	12.047	0.7057	242.208
Population Squared	2,441.347	7,960.167	145.133	0.498	58,664.48
National HMOs $t_{-1}$	5.265	2.555	5	0	13
Independent HMOs $t_{-1}$	1.480	1.787	1	0	10
Elderly	0.176	0.068	0.152	0.073	0.343
Hospital Wage	0.914	0.043	0.893	0.836	1.071
<b>Firm Characteristics</b>					
National HMO	0.440			0	1
HMO Income	147.897	367.261	22.785	-402.284	1,648.613
Medicare Product	0.627			0	1
Medicaid Product	0.463			0	1
Network Size	59.396	50.428	38	4	169
Network Quality	0.493			0	1
<b>Firm-Market Characteristics</b>					
Adjacent Markets	1.291	1.916	0	0	10
Adjacent Markets Squared	5.337	11.418	0	0	100
Adjacent Market Share	0.272	0.372	0	0	1
HQ Distance	199.333	124.777	171	0	551
National HMO* National HMOs $t_{-1}$	2.348	3.155	0	0	13
National HMO* Independent HMOs $t_{-1}$	0.605	1.316	0	0	10
Network Size*Population	1,561.663	3,521.426	369.370	2.823	40,933.07
Network Size*Income	1,704.908	1,486.43	1,109.028	83.348	6,861.231
Network Quality*Population	12.890	32.099	0	0	242.208
Network Quality*Income	14.027	14.544	0	0	40.599

## VII. Results and Discussion

In my analysis, I look at the effect of market characteristics, firm characteristics, and firm-market characteristics on a HMO's entry decision. When analyzing the effect of these characteristics on a HMO's entry decision, I estimate my empirical models using both logit and probit models with local-market fixed effects. As an added precaution, I also estimate all of my

empirical models using local-market fixed effects and time fixed effects. The results of the entry regressions are summarized in Table 5 (Entry Probit Model Results) and Table 6 (Entry Logit Model Results). To prevent confusion the type of fixed effects used in each model are clearly labeled in both Table 5 and Table 6. I initially estimate my entry regressions using only the market characteristics, firm characteristics, and firm-market characteristics obtained from my data. The results of these initial entry regressions are provided in Model 1 and Model 2. In these initial models I do not include any of the firm-market interactions I use to supplement my firm-market characteristics. I then re-estimate my entry equations using the additional firm-market interaction terms. The results of these full entry equations are provided in Model 3 and Model 4.

One common criterion used to evaluate the effectiveness of discrete choice models is the percentage of correctly predicted observations compared to the observed/actual data. This performance measure or “goodness of fit” is used to test how well the model fits the data on which it was estimated. According to this criterion, a perfect model would correctly predict the outcome for 100% of the cases, whereas a failed model would do no better than predicting 50% of the cases. Thus the percentage of correctly predicted cases between 50 and 100 provides a crude measure of the predictive accuracy of the model. Furthermore, in order to address any concerns regarding the unbalanced nature of my dataset. I also include the sensitivity, the percent of correctly predicted positive outcomes, and the specificity, the percent of correctly predicted negative outcomes, for each of my models.<sup>25</sup> Finally, I report the Pseudo R-Squared values for all of the models.

---

<sup>25</sup> My use of an entry threshold of 100 members decreases the sensitivity of all my models. If I use an entry threshold of a single member, the average sensitivity of my model increases to approximately 85%. Similarly, if I use an entry threshold of 50, the average sensitivity of my model is approximately 77%.

**Table 5: Entry Probit Model Results (Entry Threshold of 100)**

Variable	Model 1 Market Fixed Effects	Model 2 Market and Time Fixed Effects	Model 3 Market Fixed Effects	Model 4 Market and Time Fixed Effects
Income	-0.031 (0.022)	-0.035 (0.034)	-0.042* (0.025)	-0.003 (0.035)
Population	0.032 (0.040)	0.027 (0.042)	0.005 (0.043)	0.017 (0.046)
Population Squared	-0.00004 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
National HMOs $t_{-1}$	0.002 (0.035)	0.064 (0.039)	-0.082** (0.038)	-0.026* (0.041)
Independent HMOs $t_{-1}$	0.026 (0.025)	0.035 (0.037)	0.032 (0.029)	0.041 (0.040)
Elderly	3.474 (6.363)	1.742 (7.165)	5.538 (6.422)	0.763 (7.300)
Hospital Wage	0.167 (1.794)	0.176 (1.905)	0.106 (1.842)	0.462 (1.960)
National HMO	0.111* (0.065)	0.111* (0.065)	0.059 (0.069)	0.059 (0.070)
HMO Income	0.0002*** (0.0001)	0.0003** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)
Medicare Product	0.301*** (0.057)	0.296*** (0.058)	0.375*** (0.061)	0.368*** (0.061)
Medicaid Product	0.294*** (0.050)	0.297*** (0.050)	0.287*** (0.052)	0.291*** (0.052)
Network Size	0.001* (0.001)	0.001 (0.001)	0.002*** (0.001)	0.002** (0.001)
Network Quality	0.119* (0.071)	0.140* (0.073)	0.083 (0.075)	0.119 (0.077)
Adjacent Markets	0.634*** (0.089)	0.631*** (0.089)	0.555*** (0.089)	0.551*** (0.090)
Adjacent Markets Squared	-0.056*** (0.007)	-0.056*** (0.007)	-0.051*** (0.007)	-0.051*** (0.007)
Adjacent Market Share	1.334*** (0.260)	1.348*** (0.261)	1.458*** (0.263)	1.482*** (0.264)
HQ Distance	-0.003*** (0.0003)	-0.003*** (0.0003)	-0.003*** (0.0003)	-0.003*** (0.003)
National HMO*National HMOs $t_{-1}$			0.173*** (0.024)	0.175*** (0.024)
National HMO* Independent HMOs $t_{-1}$			-0.0003 (0.032)	-0.003 (0.033)
Network Size*Population			0.0002*** (0.00003)	0.0002*** (0.00003)
Network Size*Income			-0.001*** (0.0002)	-0.001*** (0.0002)
Network Quality* Population			-0.005*** (0.002)	-0.005** (0.002)
Network Quality*Income			0.062*** (0.021)	0.064*** (0.021)
N(observations)	8645	8645	8645	8645
Pseudo R <sup>2</sup>	0.5784	0.6022	0.6014	0.6035
Percent Correctly Classified	90.38%	90.42%	91.08%	91.16%
Sensitivity	74.63%	74.45%	74.05%	74.51%
Specificity	94.34%	94.44%	95.37%	95.35%

**Table 6: Entry Logit Model Results (Entry Threshold of 100)**

Variable	Model 1 Market Fixed Effects	Model 2 Market and Time Fixed Effects	Model 3 Market Fixed Effects	Model 4 Market and Time Fixed Effects
Income	-0.060 (0.041)	-0.066 (0.062)	-0.082* (0.046)	-0.004 (0.064)
Population	0.060 (0.073)	0.056 (0.078)	0.005 (0.079)	0.028 (0.084)
Population Squared	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
National HMOs $t-1$	0.0004 (0.063)	0.114 (0.071)	-0.164** (0.069)	-0.057* (0.076)
Independent HMOs $t-1$	0.045 (0.045)	0.065 (0.065)	0.037 (0.054)	0.057 (0.074)
Elderly	6.671 (11.473)	2.417 (12.910)	10.589 (11.638)	1.543 (13.228)
Hospital Wage	0.510 (3.288)	0.544 (3.471)	0.246 (3.434)	1.010 (3.640)
National HMO	0.196* (0.119)	0.192 (0.119)	0.124 (0.127)	0.131 (0.128)
HMO Income	0.0004*** (0.0001)	0.0005*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
Medicare Product	0.580*** (0.104)	0.571*** (0.105)	0.723*** (0.112)	0.713*** (0.114)
Medicaid Product	0.523*** (0.091)	0.526*** (0.091)	0.517*** (0.095)	0.522*** (0.096)
Network Size	0.003* (0.002)	0.002 (0.002)	0.005*** (0.002)	0.004** (0.002)
Network Quality	0.222* (0.131)	0.256* (0.135)	0.132 (0.002)	0.201 (0.145)
Adjacent Markets	1.238*** (0.167)	1.235*** (0.167)	1.113*** (0.169)	1.106*** (0.170)
Adjacent Markets Squared	-0.109*** (0.013)	-0.109*** (0.013)	-0.102*** (0.014)	-0.102*** (0.014)
Adjacent Market Share	2.145*** (0.488)	2.162*** (0.490)	2.402*** (0.497)	2.447*** (0.500)
HQ Distance	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
National HMO*National HMOs $t-1$			0.321*** (0.045)	0.329*** (0.045)
National HMO* Independent HMOs $t-1$			-0.042 (0.062)	-0.035 (0.062)
Network Size*Population			0.0004*** (0.0001)	0.0004*** (0.0001)
Network Size*Income			-0.002*** (0.0004)	-0.002*** (0.0004)
Network Quality* Population			-0.009** (0.004)	-0.009** (0.004)
Network Quality*Income			0.122*** (0.040)	0.125*** (0.040)
N(observations)	8645	8645	8645	8645
Pseudo R <sup>2</sup>	0.5746	0.5991	0.5981	0.6006
Percent Correctly Classified	90.47%	90.61%	91.05%	91.36%
Sensitivity	74.63%	74.45%	74.11%	75.14%
Specificity	94.45%	94.67%	95.31%	95.44%

The results depicted in Table 5 and Table 6 illustrate that firm and market heterogeneity play a significant role in HMO's entry decisions in local market in Florida. The results are consistent regardless of the type of fixed effects. I will limit my discussion to the models where I control for local-market fixed effects only (Model 1 and Model 3). Similarly, the results of the entry regressions estimated using the probit models (Table 5) are the same as the results obtained using logit models (Table 6).<sup>26</sup> I will begin by discussing the effect of market characteristics on HMO entry decisions. As predicted, *Population* and *Hospital Wage* both have positive effects on the probability a firm will enter a local market. However, neither of these effects is statistically significant. The direction of the effect of *Hospital Wage* indicates that HMOs are more likely to enter markets with higher local medical costs which could potentially increase their expected post-entry profits. The only market characteristic whose effect is contrary to theory is *Elderly* which has a positive but not statistically significant effect on HMO entry. The unexpected direction of this effect may be due to the fact that elderly individuals live in local markets with unobserved characteristics, such as higher prior healthcare utilization, which are likely to increase HMO enrollment (Baker and Corts 1996).

On the other hand, *Income* and *Population Squared* both have the expected negative effects on a firm's entry decision. The first of these effects indicate that HMOs are less likely to enter wealthy local markets. This effect provides support for claims by other researchers that consumers value choice indicating that both provider selection and access to care are normal goods. Due to the fact the HMO insurance product is relatively more restrictive in terms of both provider selection and access to care, it is not surprising that that HMO's are less likely to enter markets where wealthy consumers are less likely to enroll in HMO plans. However, it is

---

<sup>26</sup> The only variation in the results estimated using either different types of fixed effects or different models (logit or probit) is in regards to statistical significance of the effects.

important to note that the negative effect of *Income* is only statistically significant when controlling for local-market fixed effects. Next, the combined positive effects of *Population* and negative coefficient on *Population Squared* indicate that market size has the predicted positive but diminishing effect on the probability of HMO entry. Thus, ceteris paribus, HMOs are more likely to enter larger markets that contain more potential enrollees. In fact, there is a strong positive correlation between the number of HMOs in a market and market size.

Turning our attention to effect of the effect of *National HMOs*  $t-1$ , and *Independent HMOs*  $t-1$ , we see that in the initial entry regression estimated without any of the additional firm-market interaction terms (Model 1), both variables have a positive effect on the probability a firm will enter a local market. However, neither of these effects is statistically significant. These results illustrate that prior HMO presence increases a firm's probability of entry which is consistent with previous research by McNeil and Schlenker (1975) and McLaughlin (1988). In these initial regressions, while I do differentiate based upon the type of firm already operating in the market I do not distinguish which type of firm is making the entry decision. However, when I re-estimate my entry equations using the additional firm-market interaction terms it is possible for me to see how the type of HMO already operating in a market affects both National HMO entry decisions and independent HMO entry decisions. I will discuss how both National HMOs and independent HMOs entry decisions vary based upon the type of firm already operating in the market below.

As predicted, all of the firm characteristics have positive effects on a HMO's entry decision. These effects are consistent with the theory discussed in Section 6. Thus, it appears that National HMOs enjoy economies of scale and other operating costs savings which lower their costs of entry and make it profitable for this type of firm to engage in a more aggressive

entry strategy than independent HMOs. However, this effect is not statistically significant in all models; *National HMO* is only statistically significant in the restricted models that do not include the additional firm-market interaction terms. Similarly, the results indicate that HMOs with larger net incomes are using their positive financial positions to expand the geographic scope of their operations by entering into additional local markets. The positive effect of *HMO Income* on a firm's entry decision is statistically significant in all of the models. Next, both *Medicare Product* and *Medicaid Product* have the expected positive effects on a firm's entry decision. Thus, HMOs that have more expansive product lines are more likely to enter local markets since they have access to additional segments of potential consumers than firms that offer only a single insurance product. The positive effects of both *Medicare Product* and *Medicaid Product* are statistically significant in all models.

Furthermore, firms with larger hospital networks or a large number of teaching hospitals in their networks are also more likely to enter local markets. The positive statistically significant effect of *Network Size* is likely due to the lower costs of entry faced by firms with expansive hospital networks. HMOs with large hospital networks likely already have contracts with hospitals in multiple geographic locations. Thus it is unnecessary for them to increase the size of their hospital network when they enter into additional local markets. These contract savings lower the firm's entry costs thereby increasing their expected post-entry profits and the probability of entry. *Network Quality* also has a positive effect on entry but it is only statistically significant in the restricted models that do not include the additional firm-market interaction terms. The positive effect of *Network Quality* indicates that HMOs with more elite teaching hospitals in their hospital networks are more likely to enter an additional local market so as to be able to spread their operating costs over a larger patient base. A study by Hogan (2008) found

that the distance patients are willing to travel to receive hospital medical treatments increases with their severity of illness. Thus, HMOs with higher quality hospital networks do not need to increase the number of elite teaching hospitals in their network when they expand into new markets, thereby lowering their costs of entry. Overall, the effect of most of the firm characteristics included in the model are statistically significant indicating that firm heterogeneity affects entry choices. Thus analyzing entry at the firm-level is critical to accurately predicting HMO entry decisions.

Correspondingly, the effect of almost all of the firm-market characteristics, included in the empirical models, have statistically significant effects on a HMO's entry decision. As predicted, both *Adjacent Markets* and *Adjacent Market Share* have positive effects on HMO entry. Thus firms are more likely to enter local markets that are geographically closer to the markets where they currently operate. This result goes along with the entry patterns found by Kyle (2006) in large pharmaceutical markets. Furthermore, HMOs with members in adjacent markets likely have lower costs of entry than firms who do not have members in the surrounding areas; thereby, making it profitable for them to enter local markets. However, the negative sign on *Adjacent Markets Squared* indicate that these costs savings decrease with each additional adjacent market that a HMO has members. Similarly, HMOs are more likely to enter and remain active in local markets that are geographically closer to where their headquarters are located. The negative effect of *HQ Distance* is statistically significant in all of the models providing support for the argument made by Kyle (2006) that firms have superior marketing ability and lower operating costs in the market where the bulk of their administrative operations occur. This result is also consistent with the spatial pattern of entry found by Felici and Pagnini (2008) in the banking industry.

As previously stated, when I estimate my entry equations using *National HMO\*National HMOs<sub>t-1</sub>* and *National HMO\*Independent HMOs<sub>t-1</sub>* it is possible for me to see how the type of HMO already operating in a market affects National HMO entry decisions and independent HMO entry decision separately. In Model 3, *National HMOs<sub>t-1</sub>*, and *Independent HMOs<sub>t-1</sub>*, indicate how independent or local HMOs' entry decisions vary based upon the type of firm already operating in a local market. On the other hand, *National HMO\*National HMOs<sub>t-1</sub>* and *National HMO\*Independent HMOs<sub>t-1</sub>* indicate how National HMOs' entry decisions vary based upon the type of firm already operating in a local market. While *National HMOs<sub>t-1</sub>* has a negative effect on independent HMOs entry decisions, *Independent HMOs<sub>t-1</sub>* has a positive effect on independent HMOs entry decisions. However, only the effect of *National HMOs<sub>t-1</sub>* is statistically significant. Independent HMOs are more likely to enter markets where there are already a large number of other independent HMOs operating whereas they are less likely to enter markets where a large number of National HMOs have members. The second of these two effects indicate that independent HMOs avoid entering local markets where they will likely face a higher degree of competition from National HMOs for potential enrollees. This effect is consistent with the findings of Siegfried and Evans (1994) where competition had a negative effect on entry in other industries.

Conversely, *National HMO\*National HMOs<sub>t-1</sub>* has the predicted positive effect on National HMOs' entry decisions whereas *National HMO\*Independent HMOs<sub>t-1</sub>* has the predicted negative effect the probability of National HMO entry. The effect of *National HMO\*National HMOs<sub>t-1</sub>* is highly significant in all models indicating that firm type plays a significant role in National HMO entry decisions. National HMOs are more likely to enter local markets where a large number of other National HMOs already operate whereas they are less

likely to enter markets where a large number of independent or local HMOs have members. These results offer additional support for the findings made by Dranove, Gron and Mazzeo (2003) that the products offered by all HMOs are not homogenous. It appears that National HMOs regard the presence of other National HMOs as evidence of existing demand in a given local market for the insurance products offered by their type. This may be due to the fact that National HMOs are likely to operate in local markets where large companies which are part of national chains are located. These types of consumers may be more likely to obtain their health insurance from National providers due to cost savings obtained from having the same insurance provider for all their employees. On the other hand, the presence of HMOs of different type does not appear to offer this same expectation of higher demand for their insurance product. Furthermore, the effect of *National HMO\*Independent HMOs<sub>t-1</sub>* is not statistically significant in any of the models indicating that the presence of non-type firms in the market does not have a significant impact on National HMO entry decisions. Overall, it appears that HMOs tend to enter local markets where the same type of firm already operates relying upon the similarities between their insurance products to produce higher post-entry profits.

Finally, HMO entry decisions vary based upon the size and quality of a firm's hospital network. Both *Network Size\*Population* and *Network Quality\*Population* have the expected effects on HMO entry decisions. The results indicate that HMOs with larger hospital networks are more likely to enter large urban markets, whereas HMOs that offer high quality networks are less likely to enter these same markets. These two effects are statistically significant in all models. HMOs with large hospital networks are more likely to enter large local markets since they will be able to spread existing operating and hospital contracting costs over a larger member base. On the other hand, HMOs with high quality networks are less likely to enter these same

markets fearing that increased membership will disproportionately increase their operating costs lowering their expected post-entry profits. Conversely, *Network Size\*Income* has a negative effect on HMO Entry while *Network Quality\*Income* have positive effects on the probability a HMO will enter a local market. Both of these effects are statistically significant in all models; however, only the second is consistent with the theoretical predictions. The combination of these two effects indicates that HMOs are aware of the negative reputation their type of insurance product has regarding provider selection and access to care. However, firms with more elite teaching hospitals in their networks may be relying upon this feature to make wealthier consumers more likely to enroll in their plans; thereby, making it profitable to enter local markets where a firm with a lower quality product would not. On the other hand, firms with larger hospital networks are less likely to enter wealthy markets. The unexpected direction of *Network Size\*Income* on HMO Entry may be due to the fact that having a large hospital network, in comparison to other HMOs in the market, does not increase a member's provider selection and access to care enough so that wealthy consumers will enroll in their plans. Thus, entry into wealthy local markets remains unprofitable regardless of the size of a provider's hospital network. Overall, the results indicate that entry decisions in the Florida HMO Market vary substantially across individual HMO. Furthermore, the inclusion of firm characteristics and firm-market characteristics in the empirical model is useful when analyzing the entry decisions of heterogeneous potential entrants into local markets with different characteristics.

## **VIII. Conclusions and Further Research**

In my research, I examine the effect of firm characteristics, market characteristics, and firm-market characteristics on HMO entry decisions in the Florida HMO Market. I analyze entry at the firm-level thereby allowing me to control for both firm and market heterogeneity in my empirical models. Thus I expand upon the earlier research on HMO entry that was conducted primarily at the market-level. The results depicted in Table 5 and Table 6 indicate that firm and market heterogeneity play a significant role in HMO's entry decisions in local market in Florida. Specifically, there are a number of firm characteristics, including firm type, scope of operations and hospital network size and quality, that increase the probability a HMO will enter a local market in Florida. Likewise, firm-market characteristics pertaining to the geographic location of a firm's existing operations, distance from the firm's headquarters, and the type of firm already operating in a local market have a significant impact on HMO entry decisions. My results indicate that HMOs tend to enter local markets where the same type of firm already operates relying upon the similarities between their insurance products to produce higher post-entry profits. Furthermore, the results of my entry analysis collaborate with the findings by Scott Morton (1999) and Kyle (2006) in the pharmaceutical industry which demonstrated that potential entrant heterogeneity was useful in predicting entry into markets with different characteristics. Finally, the combined aspects of firm and market heterogeneity which characterize the Florida HMO Market entail that some firms are better suited to a particular market than others. Thus it appears that HMOs are capitalizing upon the unique features of their organization and product when choosing which local markets in Florida to enter.

One of the limitations of my current research is that I lack data on other types of providers than HMOs, such as PPOs or government sponsored plans (i.e. Medicare and

Medicaid). Currently, I overcome this data limitation by assuming that each type of health insurance product constitutes its own unique market. In my future research, I would like to incorporate market share data for other providers than HMOs to see if entry behavior varies by type of provider or based upon the presence of other types of providers in the local market. Another limitation of my research is that firm entry decisions are clearly correlated over time which will cause correlation in the errors. As a result, the standard errors reports here may be biased because I do not completely control for the correlation in the errors. As a first attempt at addressing this issue, I estimate my entry analysis using a single year of data. For the most part, the cross-sectional results are consistent with the finding using a pooled cross-section; however, the standard errors of all of my independent variables increase.<sup>27</sup> These results indicate that failure to correct for the correlation in the errors is producing a downward bias on the standard errors reported here. Finally I use data from only a single state to estimate the effect of firm characteristics and firm-market characteristics on HMO entry decisions. It would be interesting to see if the results reported here hold when one uses data from states other than Florida. Similarly, the data used in my analysis is from the HMO Backlash Period. However, Geroski (1995) found that entry rates vary over time within the same industry. Thus, I would like to expand my study on firm entry decisions in the HMO Market to years outside the HMO Backlash Period to see if the findings of my research are consistent with entry patterns in this market in other time periods.

---

<sup>27</sup> Accordingly, when I estimate my entry analysis using a single year of data the effects of many of the firm and market characteristics included in the model are no longer statistically significant. However, the effects of most of the firm-market characteristics and firm-market interaction remain statistically significant. For the most part, the directions of the effects of all of the independent variables remain unchanged.

## References

- Baker, L. and K. Corts. 1996. "HMO Penetration and the Cost of Health Care: Market Discipline or Market Segmentation?" *American Economic Review*, 86(2): 389-394.
- Balla, S. 1999. "Markets, Governments, and HMO Development in the 1990s." *Journal of Health Politics, Policy and Law*, 24(2): 215-238.
- Balla, S. 1999. "Markets, Government, and HMO Development in the 1990s." *Journal of Health Politics, Policy and Law*, 24(2): 215-238.
- Bates, L., and R. Santerre. 2008. "Do Health Insurers Possess Monopsony Power in the Hospital Service Industry?" *International Journal of Health Care Finance and Economics*, 8: 1-11.
- Berki S. and M. Ashcraft. 1980 "HMO Enrollment: Who Joins What and Why: A Review of the Literature." *Health and Society*, 58(4): 588-632.
- Berry, S. 1992. "Estimation of a Model of Entry in the Airline Industry." *Econometrica*, 60(4): 889-917.
- Berry, S. and P. Reiss. 2007. "Empirical Models of Entry and Market Structure." In *Handbook of Industrial Economics*, Volume 3, ed. M. Armstrong and R. Porter, 1845-1886. Amsterdam, The Netherlands: North Holland.
- Bresnahan, T. 1989. "Empirical Studies of Industries with Market Power." *Handbook of Industrial Economics*, Volume 2, ed. R. Schmalensee and R.D. Willig, 1011-1057. Amsterdam, The Netherlands: Elsevier Science Publishers B.V.
- Business Wire. December 20, 2002. "Vista Healthplan Announces Merger and Name Change." <http://www.allbusiness.com/health-care/managed-care-organizations/6015031-1.html>.
- Centers of Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group. January 2010. *National Health Care Expenditures Data*. [http://www.kff.org/insurance/upload/7692\\_02.pdf](http://www.kff.org/insurance/upload/7692_02.pdf).
- Cunningham, P. and L. Kohn. 2000. "Health Plan Switching: Choice of Circumstance?" *Health Affairs*, 19(3): 158-164.
- Dranove, D., A. Gron, and M. Mazzeo. 2003. "Differentiation and Competition in HMO Markets." *The Journal of Industrial Economics*, 51(4): 433-454.
- Dranove, D., C. Simon and W. White. 1998. "Determinants of Managed Care Penetration." *Journal of Health Economics*, 17: 729-745.
- Feldman, W., and D. Wholey. 2001. "Do HMOs Have Monopsony Power?" *International Journal of Health Care Finance and Economics*, 1: 7-22.
- Feldman, R., D. Wholey, and J. Christianson. 1999. "HMO Consolidations: How National Mergers Affect Local Markets." *Health Affairs*, 18(4): 96-104.

- Felici, R. and M. Pagnini. 2008. "Distance, Bank Heterogeneity and Entry in Local Banking Markets." *The Journal of Industrial Economics*, 56(3): 500-534.
- Frech III, G. and P. Ginsberg. 1988. "Competition Among Health Insurers, Revisited." *Journal of Health Politics*, 13(2): 279-291.
- Gabel, J. 1997. "Ten Ways HMOs Have Changed During the 1990s." *Health Affairs*, 16(3): 134-145.
- Gaynor, M. and D. Haas-Wilson. 1999. "Change, Consolidation, and Competition in Health Care Markets." *Journal of Economic Perspectives*, 13(1): 141-164.
- Geroski, P.A. 1995. "What Do We Know About Entry?" *International Journal of Industrial Organization*, 13: 421-440.
- Goldberg, L. and W. Greenberg. 1981. "The Determinants of HMO Enrollment and Growth." *Health Services Research*, 16(4): 421-438.
- Gourierouz, C. 1991. *Econometrics of Qualitative Dependent Variables*. Cambridge, UK: Cambridge University Press.
- Greene, W. 1990. *Econometric Analysis*. New York, NY: MacMillian Publishing Company.
- Grefer, J., L. Mobley, and H.E. Frech III, 2009. "Where do HMOs and PPOs Locate? Debunking an Urban Myth." Research Triangle Park, NC: RTI Press.
- Ho, K. 2009. "Insurer-Provider Networks in the Medical Care Market." *American Economic Review*, 99(1): 393-430.
- Hogan, C. 2008. "Patterns of Travel for Rural Individuals Hospitalized in New York State: Relationships between Distance, Destination, and Case Mix." *The Journal of Rural Health*, 4(2): 29-41.
- Jia, P. 2006. "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry." <http://econ-www.mit.edu/files/1090>
- Kyle, M. 2006. "The Role of Firm Characteristics in Pharmaceutical Product Launches." *RAND Journal of Economics*, 37(3): 602-618.
- Long, S. J. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: SAGE Publications, Inc.
- Luft, H. 1978. "How do Health-Maintenance Organizations Achieve Their 'Savings'?" *The New England Journal of Medicine*, 298(24): 1336-1343.
- Luft, H. 1980. "Trends in Medical Care Costs: Do HMOs Lower the Rate of Growth?" *Medical Care*, 18(1): 1-16.
- McLaughlin, C. 1987. "HMO Growth and Hospital Expenses and Use: A Simultaneous-Equation Approach." *Health Services Research*, 22(2): 183-205.

- McLaughlin, C. 1988. "The Effect of HMOs on Overall Hospital Expenses: Is Anything Left after Correcting for Simultaneity and Selectivity?" *Health Services Research*, 23(3): 421-441.
- McNeil R. and R. Schlenker. 1975. "HMOs, Competition, and Government." *Health and Society*, Spring: 195-224.
- Miller, R. and H. Luft. 2002. "HMO Plan Performance Update: An Analysis of the Literature, 1997-2001." *Health Affairs*, 21(4): 63-86.
- Morrisey, M. 2001. "Competition in Hospital and Health Insurance Markets: A Review and Research Agenda." *Health Services Research*, 36 (1): 191-221.
- Morrisey, M. and C. Ashby. 1982. "An Empirical Analysis of HMO Market Share." *Inquiry*, 19(Summer): 136-149.
- Nakao, T. 1993. "Market Share, Advertising, R&D, and Profitability: An Empirical Analysis of Leading Industrial Firms in Japan." *Review of Industrial Organization*, 8: 315-328.
- Pauly, M., A. Hillman, M. Kim, and D. Brown. 2002. "Competitive Behavior in the HMO Marketplace." *Health Affairs*, 21(1): 194-202.
- Robinson, J. 1991. "HMO Market Penetration and Hospital Cost Inflation in California." *The Journal of the American Medical Association*, 266(19): 2719-2723.
- Robinson, J. 1996. "Decline in Hospital Utilization and Cost Inflation Under managed Care in California." *The Journal of the American Medical Association*, 276(13): 1060-1064.
- Schneider, J., P. Li, D. Klepser, N. Peterson, T. Brown, and R. Scheffler. 2008. "The Effect of Physician and Health Plan Market Concentration on Prices in Commercial Health Insurance Markets." *International Journal of Health Care Finance and Economics*, 8: 13-26.
- Scott Morton, F. M. 1999. "Entry Decisions in the Generic Pharmaceutical Industry." *RAND Journal of Economics*, 30(3): 421-440.
- Shen, Y., V. Wu, and G. Melnick. 2008. "The Changing Effect of HMO Market Structure: An Analysis of Penetration, Concentration, and Ownership Between 1994-2005." NBER Working Paper #13775.
- Siegfried, J. and L. Evans. 1994. "Empirical Studies of Entry and Exit: A Survey of the Evidence." *Review of Industrial Organization*, 9: 121-155.
- United States v. Aetna. 1999. No.: 3-99CV1398-H (N.D. Texas) Revised Competitive Impact Statement filed August 3.
- Welch, W., R. Frank, and P. Diehr. 1984. "Health Care Costs in Health Maintenance Organizations: Correcting for Self-Selection." *Health Economics and Health Services Research*, Vol. 5, 95-128. New York, NY: JAI Press Inc.
- Wholey, D., J. Christianson, J. Engberg, and C. Bryce. 1997. "HMO Market Structure and Performance: 1985-1995." *Health Affairs*, 16(6): 75-84.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: the MIT Press.

## **CHAPTER 3**

### **Buyer Power Theory and the Effect of Dominant HMOs in the Market for Hospital Inpatient Services**

## I. Introduction

Since the early 1980's, Health Maintenance Organizations (HMOs) have been one of the main buyers in the market for medical services. Initially, many health care experts maintained that HMOs were one potential way to control the increasing costs of healthcare in the United States.<sup>1</sup> These experts claim that HMOs can help to contain health care costs in a number of different ways. Some researchers argue that HMOs are able to lower health care costs by preventing excessive or wasteful care via strict patient utilization review, lower administrative costs, and promoting competition within the health care system.<sup>2</sup> Others take a more pragmatic view and insist that HMOs are able to negotiate low rates with area hospitals and physicians for their members via such tactics as selective contracting, strategic behavior, and volume discounts.<sup>3</sup> If the later explanation is correct, then the cost savings achieved by HMOs may simply be a byproduct of HMOs dominant position in the market for hospital inpatient services.

As one of the main buyers in the market for hospital inpatient services, an HMO with a large market share will have buyer power which they can use to influence the price and quantity in the market. Currently, there are three conflicting theories regarding the effects of HMO buyer power: Monopsony Theory, Welfare-Increasing Theory, and the All-or-None Theory.<sup>4</sup>

According to all of these theories, an increase in HMO buyer power should have a negative effect on the price in the market. However, these theories have contrasting predictions on the impact of HMO buyer power on the utilization or quantity of inpatient hospital services. The

---

<sup>1</sup> See Baker and Brown (1999); Baker and McClellan (2001); and Luft (1980).

<sup>2</sup> See Frech and Ginsburg (1978); Luft (1978, 1980); Miller and Luft (2002); Feldman and Wholey (2001); Robinson (1991, 1996); Bradford and Krumholz (2003); McLaughlin et al. (1984); and Goldberg and Greenberg (1981).

<sup>3</sup> See Frank and Welch (1985); Feldman and Wholey (2001); Dranove et al. (1993); and Gaynor and Haas-Wilson (1999).

<sup>4</sup> A classic Monopsony Theory of the effect of HMO Buyer power is advanced by Pauly (1998). Conversely, Feldman and Wholey (2001) argue that HMO buyer power actually has a monopoly-busting effect which I refer to as a Welfare-Increasing Theory. Finally, Herndon (2002) claims the effects of HMO buyer power will be consistent with the All-or-None Theory.

goal of my research is to examine the effects of HMO buyer power on both the price and quantity of hospital inpatient services in Florida and to determine which of the theories of buyer power is consistent with reality of this market. As such, my research is the first study to empirically test the All-or-None Theory of HMO buyer power.

A number of previous studies have analyzed the effects of HMO buyer power in the market for hospital services. However, in many of these studies the measure of buyer power was HMO penetration, the share of a given market that is enrolled in HMOs, not an individual HMO's market share. I attempt to correct for the flaws of the earlier research in this area by controlling for multiple aspects of HMO market structure in my model: HMO penetration and HMO buyer power. By doing so, I am able to more accurately gauge the impact of HMO buyer power on price and quantity. In my analysis, I use two variables to control for HMO buyer power: the market share of the largest HMO (Dominant HMO Market Share) and the level of HMO concentration (HMO HHI) in a given geographic market. The results of my research indicate that HMO buyer power has a significant negative effect on the price of inpatient hospital services for HMO enrollees in my sample. Specifically, a one percent increase in either the Dominant HMO Market Share or HMO HHI will lower HMO price per admission and inpatient day by approximately 1.6 to 2.0 percent. On the other hand, HMO buyer power appears to have no impact on either the number of hospital admissions or inpatient days per HMO enrollee. These two effects are only consistent with the All-or-None Theory of HMO buyer power. Thus it appears that HMOs are able to use their dominant position in the market to obtain more favorable rates for their enrollees without any impact on the utilization of inpatient hospital services. This effect is likely due to hospitals' economic dependence on the dominant insurer in

the market which prevents them from not entering into contracts with this HMO even when confronted with lower reimbursement rates.

The remainder of the paper will be presented in the following order: Section 2 outlines the US market for hospital services and establishes the sources of HMO buyer power; Section 3 discusses the previous research performed in this area; Section 4 examines my research goals and generation of my hypotheses; Section 5 discusses the research method, empirical model, data sources, data limitations, and variables; Section 6 outlines the results of the analysis; Section 7 highlights the broader policy implications of my findings; and Section 8 includes concluding remarks and areas for further research.

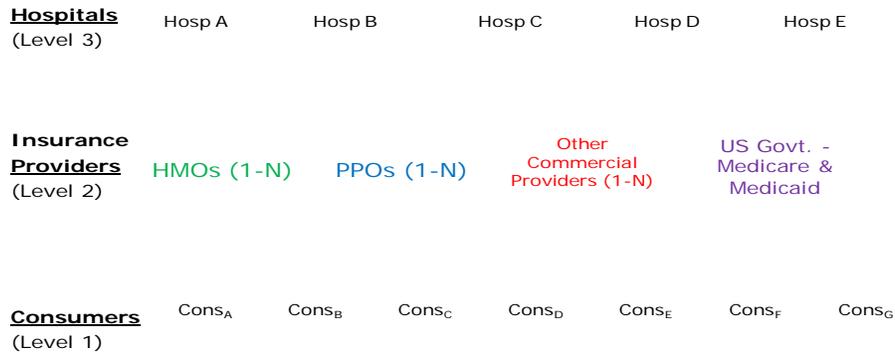
## **II. US Market for Hospital Services and HMO Buyer Power**

The market for hospital inpatient services in the US is rather unique and can be broken down into three levels based upon the parties involved in the transaction. As depicted in Figure 1, the first level is comprised of the individual consumers of medical services;<sup>5</sup> the second level is made up of health insurance providers or payers including HMOs, PPOs, Other Commercial Providers (like EPOs), Medicare, Medicaid, etc.; and the third level consists of the hospitals that actually supply or provide medical services.

---

<sup>5</sup> The first level can include any agent (i.e. employers) who purchase health insurance on behalf of individual consumers (i.e. its employees) and is assumed to act in the best interests of the individual consumer.

**Figure 1: US Market for Hospital Medical Services**



The first step in this transaction is that individual consumers select health insurance providers where multiple consumers can select the same insurance provider.<sup>6</sup> As a result, health insurers, such as HMOs, can represent a large number of enrollees or members. In the second step, health insurance providers negotiate contracts with local area hospitals to provide medical services to their enrollees or members.<sup>7</sup> In this manner, health insurance providers create networks of hospitals from which their members or enrollees can receive inpatient medical services at discounted rates. Thus in this market, individual consumers do not directly negotiate with hospitals for the price of the medical services they ultimately receive (unless they do not have health insurance). Thereby, health insurance providers are the buyers in the market for hospital medical services. Due to the fact that these health insurance providers represent a large number of consumers during the negotiation process with hospitals, they can obtain market

<sup>6</sup> In some cases, there are restrictions that limit which individuals can select certain providers such as with government restrictions regarding Medicare and Medicaid eligibility. Also, there are some consumers who do not select insurance providers (self-pay and uninsured). In the case of an HMO, the provider assumes a contractual responsibility to assure the delivery of hospital services to its voluntarily enrolled population in exchange for a fixed premium. This premium is the HMO's major source of revenue (Luft 1978).

<sup>7</sup> By entering into this contract, the hospital accepts contractual responsibility for the delivery of a stated range of health services for the provider's entire enrolled population (Goldberg and Greenberg 1980).

power in the market for hospital inpatient services. Furthermore, health insurers, such as HMOs, can engage in strategic behavior during the negotiation process including selective contracting and playing hospitals off against each other to obtain better rates for their members. As such, health insurance providers, such as HMOs, can use their market power to negotiate more favorable contract terms and/or rates with hospitals for their enrollees.

A number of previous studies that have looked at the effect of HMO market share on a variety of dependent variables relating to healthcare including: hospital expenditures, costs, premiums, utilization, length-of-stay, and spending.<sup>8</sup> These studies have found that increased market share of HMOs can have both welfare increasing and anticompetitive effects on the healthcare system. However with the consolidation of the health insurance industry beginning in the late 1990's, the work in this field began to reflect the idea of a dominant buyer in the market for medical services sold by hospitals to health insurers.<sup>9</sup> A monopsony is a market in which there is only a single buyer and multiple sellers for a product. As a result of this market structure, the buyer has significant market power which it can use to drive the price in the market down below the competitive level by using less than the competitive amount of the product. One

---

<sup>8</sup> Bradford and Krumholz (2003) examined the effect of HMO market power, measured as the number of HMOs in the MSA and the share of the total MSA population enrolled in HMOs, on costs and spending per patient. The authors found that an increase in HMO market share lead to lower costs per admission, and that a larger number of HMOs was associated with more spending per patient. Robinson (1996) looked at the effect of HMO market power, measured as the percentage of total admissions to competing hospitals that were from HMO enrollees, on hospital utilization, service mix and expenditure. His results indicate that increased HMO market power was associated with lower inpatient hospital utilization by HMO enrollees and expenditures per patient. Baker and Brown (1999) assessed the effect of HMO market share, measured as the ratio of HMO enrollees to total county population, on average costs per facility and the number and size of facilities that made up a health care system. Their results indicated that an increase in HMO market share was associated with a reduction in average costs and the number of facilities in a geographic area and an increase in patient volume at the remaining sites. McLaughlin (1987) explored the effect of HMO market power, measured as the share of the SMSA population enrolled in HMOs, on hospital utilization rates and length-of-stay for HMO enrollees. Her results illustrate that an increase in HMO market share lead to lower hospital utilization and shorter length-of-stay for HMO members. These results are consistent with McLaughlin (1988) and McLaughlin et al. (1984).

<sup>9</sup> See Gaynor and Haas-Wilson (1999); Pauly (1998); and Shen et al. (2008). In a study released in 2006, the American Medical Association (AMA) reported there have been over 400 mergers between health insurance providers in the last ten years. In the Florida health insurance market, Vista Healthplan merged with Beacon Health Plans and Healthplan Southeast in 2002 creating one of the largest managed care plans in Florida.

of the requirements for monopsony power to arise in a market is that the long-run supply curve for the product must be upward sloping (i.e. the market level supply curve cannot be perfectly or highly elastic) (Pauly 1998; Robinson 1933; Feldman and Wholey 2001). If the supply curve is very elastic, then sellers in this market would be extremely sensitive to changes in price; thereby limiting a buyer's ability to use its market power to lower market price. Therefore despite a lack of competition, a dominant buyer cannot obtain monopsony power unless it has the ability to use this power to influence the price and quantity in the market.

However, there has been some debate on whether or not the market for hospital inpatient services actually fits the textbook case of monopsony for a number of reasons including: (1) the lack of a single dominant buyer, or type of buyer, in the market for hospital medical services (i.e. HMOs, PPOs, EPOs, Medicare and Medicaid, etc.); (2) the mobility of medical service providers to move to other markets without a dominant buyer; (3) the relatively elastic supply for hospital services due to excess hospital capacity; and (4) the lack of a single price in the input market due to the wide distribution of reimbursement rates and contract terms between health insurance providers and hospitals (McCarthy 2003).

As stated above, there are many buyers in the market for hospital inpatient services. The US government via Medicare and Medicaid is one of the largest buyers in this market. However, there are restrictions in place by the US government regarding consumer eligibility for these two health insurance products. Thus, many consumers cannot select this type of health insurance. In addition, the lack of a formal price negotiation process between Medicare/Medicaid and hospitals regarding reimbursement rates may preclude one from considering them to be true "buyers" of hospital medical services.<sup>10</sup> Thus we can limit our focus to only commercial health

---

<sup>10</sup> Schneider et al. (2008) discusses how prices for Medicare and Medicaid are established by those agencies rather than negotiated. Therefore, the prices paid by Medicare and Medicaid are not sensitive to market structure.

insurance providers. HMOs are a type of commercial health insurance provider in the market for hospital inpatient services. Due to the fact HMOs represent a large volume of patients during the negotiation process with hospitals, one can argue that size confers bargaining power and thereby the potential for dominant buyers in this market (Sorensen 2003). Likewise, the recent wave of consolidations in the health insurance market has reinforced the existence of dominant buyers in this market. Furthermore, Pauly (1998) argues that the market for hospital inpatient services may be more consistent with a partial monopsony (or an oligopsony) rather than a complete monopsony. In a partial monopsony more than one buyer exists in the market, and one or more of those buyers can have sufficient market share to influence the price in the market.<sup>11</sup> Thus the lack of a single dominant buyer in the market for hospital services does not preclude monopsony theory from applying to it.

Similarly, state certificate-of-need (CON) laws, make it impossible for hospitals to relocate in response to changing or unfavorable demand conditions (Feldman and Wholey 2001).<sup>12</sup> Thus, the mobility of medical service providers does not apply to hospitals. In fact, it is the existence of these barriers to mobility that ensure the long-run supply curve for hospital medical services is upward sloping (i.e. not perfectly elastic). Similarly, the supply curve for hospital services will be less than perfectly elastic as long as there are specialized inputs in the service's production. Thereby, the existence of excess hospital capacity does not create an economic condition which would preclude a dominant buyer from exploiting its monopsony power. Furthermore, the amount of excess hospital capacity in the US was sharply reduced with the "wave" of hospital mergers in the 1980's and 1990's and the continued consolidation of the

---

<sup>11</sup> Bates and Santerre (2008) reference the annual reports of the American Medical Association (2003-2006) which find that the health insurance industry is characterized by a few dominant health insurance providers which the AMA argues may engage in monopsony behavior.

<sup>12</sup> Similarly, hospital care is not geographically transferable because hospitals require specially trained labor (Pauly 1998).

hospital industry during the early twenty-first century.<sup>13</sup> Finally, hospitals offer a wide range of medical services for which there exist many different prices. As such, health insurance providers must negotiate complex contracts and reimbursement rates for the provision of these numerous medical services to their enrollees. The terms of these contracts and the rates obtained by health insurance providers can vary greatly (Sorensen 2003). In general, we find that payers which represent larger volumes of patients are able to extract greater price concessions from hospitals (Sorensen 2003; Pauly 1998). Thus it is the ability of health insurance providers to use their market power to obtain more favorable rates that creates the basis for monopsony power in this market. Therefore while the market for hospital services may not be identical to the textbook case, it does not mean that a dominant buyer in this market may not obtain monopsony power.

### **III. Review of the Literature**

Currently, there are three theories regarding the effects of a dominant buyer in the market for hospital inpatient services. The first of these theories was introduced by Pauly (1998) and is an extension of classic monopsony theory to the hospital inpatient service market. I refer to this theory simply as “Monopsony Theory.” Under this theory, a dominant buyer can arise in the market for inpatient medical services where hospitals interact with health insurance providers. The author argues that managed care providers, specifically HMOs, can use their dominant market position to force the price and quantity in this market below their competitive levels thereby resulting in anticompetitive effects.<sup>14</sup> Accordingly, HMOs will be able to use their buyer

---

<sup>13</sup> Vogt and Town (2006) estimate that there were more than 900 hospital mergers and acquisitions during the 1990s. Similarly, according to Irving Levin Associates (2006) there were approximately 375 hospital mergers and acquisitions between 2000 and 2005 involving over 730 hospitals.

<sup>14</sup> The underlying market structure where this will occur is one in which there is a single (or dominant) buyer and multiple competitive sellers. The initial price and quantity in the market are at their competitive levels. In this market, the single buyer will use its dominant position in the market to obtain lower input prices by choosing to buy

power to obtain more favorable rates for their members which may be translated into lower prices for hospital medical services for their enrollees. However if this price reduction is accompanied by an even larger reduction in the quantity of hospital services received by their enrollees, than their members will be harmed via the disproportionate reduction in medical service utilization.<sup>15</sup> One of the main contributions of this work to the literature was that it established an efficiency test for monopsony based upon the relative magnitudes of the reduction in price and quantity of hospital medical services as buyer power increases.<sup>16</sup>

The second theory regarding the effects of monopsony power in the market for hospital services is an extension of Pauly's work by Feldman and Wholey (2001). I refer to this theory simply as "Welfare-Increasing Theory." The authors claim that buyer power may actually increase welfare and efficiency in the market for hospital inpatient services. This will occur if an increase in buyer power, specifically HMOs buyer power, is accompanied by a decrease in price and an increase in quantity from their initial levels. The authors claim that these two effects will occur because HMOs will use their buyer power to the break-up or reduce hospital monopoly power (monopoly-busting effects), thereby increasing welfare and/or efficiency in the healthcare market.<sup>17</sup> Thus the authors develop their own efficiency test for buyer power based upon the

---

less of the input. Thus in this model, both the price and quantity of the input will be below their competitive equilibrium levels as a result of increased buyer power. (Pauly 1998; Robinson 1933) However, as discussed in the All-or-None Theory and Discussion section, the ability of the dominant HMOs to achieve lower input prices via reduced quantity of hospital services may be limited since it could ultimately result in them losing profits if they lose too many enrollees.

<sup>15</sup> If this is the case, then consumers (where an insurance provider's enrollees are the consumers in this market) may be harmed by the existence of a dominant buyer if the decrease in consumer welfare due to lower quantity exceeds the increase in consumer welfare due to the reduction in price. However as long as the dominant HMO faces a downward-sloping demand curve from the consumers, it will find it profit-maximizing to pass-through (at least in part) the reduction in hospital prices to the consumers in the form of lower premiums.

<sup>16</sup> One can still apply this quantity test even if there is more than one buyer in the market. This is due to the fact that a dominant firm will use its market power to obtain larger discounts (thereby lower prices) from hospitals than the other (smaller) firms.

<sup>17</sup> The underlying market structure where this will occur is one in which there is a single buyer (monopsony) and a single seller (monopoly) commonly referred to as a "bilateral monopoly" or "bilateral monopoly-monopsony." The initial price and quantity in the market are at the monopoly levels. In this market, the single buyer will use its

direction of the effect of HMO buyer power on hospital prices and utilization of inpatient and ambulatory hospital services by HMO enrollees. Accordingly, the existence of health insurer buyer power will only be inefficient if the buyer uses its dominant market position to restrict the quantity of hospital medical services below the optimal or competitive level.

The final theory regarding the effects of monopsony power in the market for hospital services is the All-or-None Model by Herndon (2002). I refer to this simply as the “All-or-None Theory.” In her research, the author claims that the traditional monopsony model does not apply to the market for hospital medical services.<sup>18</sup> Instead, when health insurance providers negotiate contract terms with hospitals they face an all-or-none decision regarding quantity. If a hospital enters into a contract with a health insurer, it gains the opportunity to treat all of the provider’s potential enrollees at the agreed upon rate(s). On the other hand, if it does not enter into a contract it loses out on the opportunity to treat any of the provider’s enrollees.<sup>19</sup> Therefore, the hospital’s decision to contract with an HMO boils down to an all-or-none decision for the hospital because it cannot restrict the quantity of services it provides in response to a lower

---

dominant position to lower prices from the monopoly level while at the same time increasing the quantity above its initial monopoly level. Thus in this model, price will decrease and quantity will increase from the initial monopoly levels as a result of increased buyer power. (Cicchetti and Makhol 1988; Pauly 1998) Accordingly, a bilateral monopoly-monopsony will improve welfare in the market over the simple monopoly case; however, market efficiency will still be less than it would be if price and quantity were at their competitive levels (Gaynor and Vogt 2007).

<sup>18</sup> This is due to the fact that a lower quantity in this market translates into a reduction in the amount of hospital medical services available to health insurance provider’s enrollees. In turn, this would lower the value of the insurance product to an enrollee; thereby decreasing the number of enrollees and having a negative impact on a health insurer’s profits. This corresponds to a downward movement on the supply curve for hospital services, whereby a lower price (imposed by the dominant health insurer) reduces the quantity supplied. By monopsonizing (partially or wholly) the market for hospital services, a dominant health insurer realizes two opposing effects: (1) an increase in the buyer’s share of the total surplus through the reduction in the price it pays to the hospitals, and (2) a reduction in the total (buyer plus seller) surplus in the market through the reduction in quantity. Clearly a dominant buyer would prefer to pay the lower price without a resulting reduction in quantity; that is, it would prefer to appropriate a larger share of the total surplus without reducing its size. To effectuate this, a dominant health insurer would offer hospitals a contract which preserves a higher level (ideally, the competitive level) of hospital services at the lower (“monopsony”) price, thereby enabling itself to maintain the attractiveness of its insurance product for its members and obtain more profit.

<sup>19</sup> In this model, a provider does not need to specify the exact quantity, both parties just need to know that is it different from zero (the no contract option).

price.<sup>20</sup> Thus in the All-or-None model, only price (and not quantity) will deviate from the competitive level due to the fact the dominant health insurer can extract price concessions from hospitals without suffering a decline in quantity. According to this theory, an increase in HMO buyer power will result in a reduction in the price of hospital services but no change in the quantity of medical services received or utilized by its members.

Table 1 is a summary of the three theories regarding the effects that an increase in insurer (HMO) buyer power will have on the price and quantity of hospital inpatient services.

**Table 1: Summary of HMO Buyer Power Theories**

<b>Theory Name (Author)</b>	<b>Effect of an increase in HMO buyer power on price for hospital services:</b>	<b>Effect of an increase in HMO buyer power on quantity of hospital services per enrollee:</b>
Monopsony Theory (Pauly)	Price of Hospital Services ↓	Quantity of Hospital Services per Enrollee ↓
Welfare-Increasing Theory (Feldman and Wholey)	Price of Hospital Services ↓	Quantity of Hospital Services per Enrollee ↑
All-or-None Theory (Herndon)	Price of Hospital Services ↓	No change in Quantity of Hospital Services per Enrollee

To date, there have been no studies which have empirically tested the All-or-None Theory. However, there have been a number of previous studies that examine whether the effects of HMO buyer power are more consistent with Monopsony Theory or Welfare-Increasing Theory. In their study, Feldman and Wholey (2001), attempted to determine whether the effect of HMO buyer power, measured as the percentage of hospital days purchased by an HMO, on price and utilization was consistent with either Pauly’s Monopsony Theory or their Welfare-Increasing Theory. Their results indicate that an increase in HMO buyer power lead to lower hospital prices (which is consistent with both theories) and higher hospital utilization as

---

<sup>20</sup> As such, the supplier will be forced from their regular supply curve onto their All-or-None supply curve which lies below their regular supply curve. The All-or-None Supply curve indicates the maximum quantity of a good that will be supplied at a specific price given that the alternate is to supply zero (Herndon 2002).

measured by inpatient hospital days per HMO enrollee (which is consistent only with their Welfare-Increasing Theory). Similarly, Bates and Santerre (2008) looked at the effect of level of market concentration in the HMO market (HMO HHI) and PPO market (PPO HHI) in the markets for inpatient hospital services and outpatient visits. The authors found limited support for the Welfare-Increasing Theory where an increase in the HMO HHI lead to an increase in inpatient hospital days and an increase in PPO HHI lead to an increase in outpatient visits. However, the authors lacked the data necessary to examine the effects of HMO HHI or PPO HHI on the prices of either inpatient or outpatient hospital services. Finally, Schneider et al. (2008) looked at the effect of health plan concentration (HHI of all health plans) on physician prices for outpatient services. The authors found limited support for the Welfare-Increasing Theory whereby health plan HHI had no significant effect on physician prices for outpatient services.

#### **IV. Research Goal and Hypotheses**

The goal of my research is to examine the effects of HMO buyer power on the price and quantity of inpatient hospital services received by HMO enrollees. In doing so, I will empirically test the three theories of buyer power outlined above. To date, there have been no studies that have tried to empirically test the All-or-None Theory nor have any studies found any empirical support for Monopsony Theory. This may be due to the fact that in a number of these previous studies, the variables used to control for HMO buyer power were actually measures of HMO penetration (the percentage of an area population enrolled in HMOs or the number of HMOs). Morrissey (2001) claims that one of the major flaws of the current research on managed care is that it tends to measure managed care penetration and equate it with competition. Accordingly, the variables used in these previous studies to control for HMO buyer power did

not accurately reflect the market structure of the HMO market.<sup>21</sup> The variables that were used to measure HMO market share included the number of HMOs in a given geographic area (state, city, SMSA, etc.), the number of HMO enrollees as a percentage of total population of the given geographic area,<sup>22</sup> or a combination of the two (Hay and Leahy 1984; Gaskin and Hadley 1997; Bradford and Krumholz 2003). Thus as a result of data limitations, these studies were actually looking at the effect of HMO penetration, rather than HMO buyer power, on the variables of interest in their studies. My research attempts to build upon these previous studies by controlling for multiple aspects of the HMO market thereby obtaining a more accurate gauge of the market structure in this market.

In my study, I control for the effect of both HMO penetration (the share of the total area population enrolled in HMOs) and HMO buyer power (which I refer to simply as HMO Concentration) using separate variables for each effect. Therefore by controlling for both HMO penetration and HMO Concentration, I will be able to isolate the effects of HMO buyer power and more accurately gauge its influence on HMO inpatient hospital prices and the quantity of services received by each HMO enrollee. There is only one other study, Shen et al. (2008), that has included controls for both HMO penetration and the level of concentration in the HMO Market in the same model. Their results indicate that an increase in HMO penetration (share of the total MSA population enrolled in HMOs) had a modest negative effect on hospital net

---

<sup>21</sup> Previous studies which used HMO penetration to measure the effect of HMO buyer power would only be accurate if HMOs collectively bargain with hospitals for contract terms whereby the share of the total population (i.e. a hospital's total potential patient base) enrolled in HMOs would represent HMO market share and buyer power. However, HMOs do not collectively bargain with hospitals, instead they independently bargain with hospitals in an attempt to obtain more favorable rates for their enrollees not all HMO enrollees as a whole. Thus, the portion of the total population enrolled in HMOs does not reflect an individual HMO's buyer power but rather just the amount of HMO penetration or another aspect of the HMO market structure. Furthermore, to the extent that an individual HMO's buyer power is a function of its actual buyer share rather than the buyer share of the average HMO in the market, the number of HMOs is at best a poor measure of HMO buyer power.

<sup>22</sup> See Feldman and Wholey (2001); Goldberg and Greenberg (1980); Baker and Corts (1996); Morrisey and Ashby (1982); McLaughlin et al. (1984); McLaughlin (1987, 1988); and Baker and Brown (1999).

inpatient revenue; whereas, the level of concentration in the HMO market (HHI of all HMOs in the MSA) had no impact on either cost or revenue growth after controlling for HMO penetration. However, one of the main limitations of their research was the lack of instruments for both HMO penetration and HMO HHI despite their acknowledged endogeneity.<sup>23</sup> Furthermore, the authors only looked at the effect of these variables on the rate of hospital cost and revenue growth since they lacked data on the quantity of hospital services. As discussed below, I am able to overcome both of these limitations in my research.

#### **A. Step # 1: Identify the Effect of HMO Concentration on the Price of Hospital Inpatient Services**

The first step of my analysis is to isolate the effect of HMO Concentration on various measures of HMO inpatient hospital prices. In order to do so, I will need to control for multiple aspects of the HMO market structure: the effect of both HMO penetration in a given geographic market and HMO Concentration in that same area. I will use the same variable to control for the effect of HMO penetration in a given geographic area (county) as used in many previous studies: the share of the county population enrolled in HMOs. I will assign this value to all the hospitals in my sample based upon the geographic location of the hospital (i.e. which county the hospital is located in). Furthermore, in order to measure the effect of HMO Concentration on HMO inpatient hospital prices I will use either the market share of the largest HMO (Dominant HMO Market Share) in the county in which a hospital is located or the level of HMO concentration in the county (HMO HHI) in which a hospital is located.<sup>24</sup>

---

<sup>23</sup> Rather than using instrumental variables to correct for the endogeneity of HMO Penetration and HMO HHI, the authors used the fixed effects model.

<sup>24</sup> Bates and Santerre (2008) use HMO HHI as one of their measures of HMO buyer power in their research. Similarly, Schneider et al. (2008) use health plan HHI as a measure of market concentration. Finally, Shen et al. (2008) use HMO HHI as a measure of HMO buyer power in their model.

One can argue that there should be an effect of HMO Concentration independent of the penetration of HMOs in a given geographic market for a variety of reasons. First, HMOs engage in selective contracting and patient steering during their negotiations with local area hospitals (Dranove et al. 1998; Feldman and Wholey 2001; Baker and Brown 1999). These tactics enable HMOs to play hospitals off against each other in order to obtain more favorable contract terms (i.e. higher discount rates, lower per diems, etc.) and increase their power during the negotiation process. These favorable contract terms will result in hospitals receiving lower net revenue per patient (lower price per admission and inpatient day) due to the effects of increased HMO buyer power. Similarly, HMOs are able to lower their enrollees' health care expenses by eliminating unnecessary procedures via strict utilization review practices, lower administrative costs, shorter lengths of stay, and economies of scale (Dranove et al. 2003; McLaughlin 1987, 1988; Feldman and Wholey 2001). Thus I predict there will be a negative impact of HMO Concentration on a hospital's average HMO net inpatient revenue per admission and inpatient day (HMO inpatient price). The negative effect of HMO Concentration on HMO inpatient price is consistent with all three theories of the effects of increased HMO buyer power.

**Hypothesis One: HMO Concentration is negatively correlated with a hospital's HMO inpatient price per admission and inpatient day.**

**B. Step 2: Identify the Effect of HMO Concentration on the Quantity of Hospital Inpatient Services**

The second step of my analysis will be to identify the effect of HMO Concentration on the quantity of hospital inpatient services per HMO enrollee. In order to achieve this goal, I will have to look at the effect of HMO Concentration on a number of different variables relating to

the utilization of inpatient hospital services by HMO enrollees including the number of hospital admissions and inpatient days. Depending upon whether HMO Concentration has an effect or not on the utilization of inpatient hospital services and the direction of this effect will determine which theory regarding HMO buyer power is consistent with the reality of this market.

According to Monopsony Theory, an increase in HMO buyer power should result in a decrease in the quantity of inpatient hospital services below the competitive level. As previously stated, HMOs engage in strict utilization review whereby they are able to generate large cost savings by shifting patients with less-severe conditions from inpatient to outpatient procedures (Baker and Brown 1999; Robinson 1996; Bradford and Krumholz 2003). Similarly, another way in which HMOs are able to reduce the health care costs for their enrollees is by limiting their length-of-stay (LOS) when receiving inpatient hospital procedures.<sup>25</sup> Thus a negative effect of HMO Concentration on inpatient hospital utilization by HMO enrollees would be evidence in support of the Monopsony Theory of the effects of HMO buyer power.

**Hypothesis Two: According to Monopsony Theory, there is a negative effect of HMO Concentration on utilization of hospital inpatient services by HMO enrollees.**

On the other hand, according to the Welfare-Increasing Theory, an increase in HMO buyer power should result in an increase in the quantity of inpatient hospital services above the competitive level. HMOs can use their buyer power to engage in patient steering and other types of strategic behavior which could result in increased utilization of inpatient hospital services by their enrollees from area hospitals from whom they obtain more favorable rates (Dranove et al.

---

<sup>25</sup> Along these lines, HMOs are able to use their buyer power to put pressure on local hospitals to develop critical pathways which encourage earlier discharge or shorter length-of-stays (Bradford and Krumholz 2003). HMOs also can use other tactics to increase cost-savings such as payment incentives for providers, administrative controls and management programs to reduce hospital length-of-stays for their members (Robinson 1996)

1998). As a result, an increase in HMO buyer power may actually have a beneficial impact on their enrollees and increase efficiency in the provision of inpatient hospital services (Feldman and Wholey 2001; McLaughlin 1987, 1988). Thus a positive effect of HMO Concentration on inpatient hospital utilization by HMO enrollees would be evidence in support of the Welfare-Increasing Theory of the effects of HMO buyer power.

**Hypothesis Three: According to Welfare-Increasing Theory, there is a positive effect of HMO Concentration on utilization of hospital inpatient services by HMO enrollees.**

Finally, according to the All-or-None Theory, an increase in HMO buyer power should have no impact on the quantity of inpatient hospital services received by HMO enrollees. This is due to the particulars of the contract negotiation process between hospitals and health insurance providers. As a result, hospitals are unable to restrict and/or deny inpatient hospital services to the enrollees of the providers they have contracts with regardless of changing contract terms and/or rates. Furthermore, hospitals are economically dependent on dominant providers due to the sheer volume of their enrollees. As a result, they are forced to enter into contracts with dominant providers regardless of their unfavorable terms (as long as revenues exceed variable costs) or risk losing a large portion of their patient base.<sup>26</sup> Thus the lack of an effect of HMO Concentration on inpatient hospital utilization by HMO enrollees would be evidence in support of the All-or-None Theory of the effects of HMO buyer power.

**Hypothesis Four: According to the All-or-None Theory, HMO Concentration has no effect on utilization of hospital inpatient services by HMO enrollees.**

---

<sup>26</sup> Herndon (2002) asserts that what really matters in the hospital-insurer negotiation process is the percentage of patient revenue that a particular insurer accounts for and the difficulty the hospital will have in replacing those lost patients should it not enter into a contract.

## **V. Research Method and Empirical Model**

### **A. Sample and Data Sources**

The data used in my analysis is made up of 731 observations and is a five-year panel data set which was compiled from a number of different sources. Each observation in my analysis represents a general acute care hospital in Florida.<sup>27</sup> Thus the level of observation in my analysis is the hospital level. A number of other previous studies have also utilized hospital level analysis including: Shen et al. (2008); Robinson (1991, 1996); Gaskin and Hadley (1997); Feldman et al. (1990); and Dranove et al. (1993). The relevant product market was determined to be all acute care inpatient services received by HMO patients.<sup>28</sup> Firms that sell in this product market are acute general hospitals in Florida. Specialty hospitals such as behavioral, rehabilitation, veterans and children's hospitals are not included in this product market because they do not serve the entire population of HMO enrollees (Abraham et al. 2003). The relevant geographic market used in my analysis is county which was the smallest level most data was available on and has been used as the relevant geographic market in previous studies by Baker and Corts (1996); Dranove et al. (2003); and Schneider et al. (2008).<sup>29</sup>

---

<sup>27</sup> I use data from Florida in my analysis for a number of reasons including the superior inpatient hospital data collected and made available to me via the Florida Agency for Health Care Administration (AHCA) and the Florida Office of Insurance Regulation.

<sup>28</sup> Bates and Santerre (2008); Shen et al. (2008); Morrisey et al. (1988); and Vogt and Town (2006) all use inpatient services as the relevant product market.

<sup>29</sup> One can define the relevant geographic market using a variety of different techniques (Schneider et al. 2008). It can be defined empirically using the Elzinga-Hogerty test which is based upon patient flows or using some existing geopolitical boundary such as counties or metropolitan statistical areas (MSAs). Due to lack of data on HMO enrollee flows from health insurers, I use an existing geographic boundary to define my relevant geographic market. I argue that the market for hospital inpatient services will be relatively localized. Thus patients may be willing to travel outside their town or city of origin to receive inpatient services but only to a limited degree and depending upon their severity of illness (Hogan 2008). Using county as the relevant geographic market accounts for the localized nature of patients seeking inpatient hospital services. Counties, as a relevant geographic market area, are superior to MSAs because there are relatively few (20) MSAs in the state of Florida. Also, only 39 of Florida's 67 counties are assigned to a MSA (the counties not assigned to MSAs are rural and located in similar geographic regions). Thus using MSA as the relevant geographic market would exclude many areas from analysis and result in the loss of a large portion of the data. Furthermore, using counties as the geographic market lets me account for the fact that there are a number of HMOs in the state which only have members in a few counties. The number of enrollees in these HMOs may be small in comparison to the total number of HMO enrollees in the state but may

The hospital data used in the regressions are from 2001 to 2005 and were accumulated by the Florida Agency for Health Care Administration (AHCA). AHCA gathers yearly financial and patient level discharge data (time-series data) from all hospitals in Florida and uses it to generate two separate data sets: Hospital Financial Data and Patient Discharge Data. After eliminating specialty hospitals and hospitals with missing or incomplete data, the sample includes annual data from 163 general acute care hospitals. These hospitals have patient level discharge data for approximately 1.4 million HMO patients (inpatient admissions) and over 5 million HMO inpatient hospital days during the five-year sample period (see Table 2).

**Table 2: HMO Hospital Admissions and Inpatient Hospital Days (in sample)**

<b>Year</b>	<b>Total HMO Admissions</b>	<b>Total HMO Inpatient Days</b>
<b>2001</b>	<b>299,546</b>	<b>1,122,474</b>
<b>2002</b>	<b>293,067</b>	<b>1,094,362</b>
<b>2003</b>	<b>270,445</b>	<b>1,012,364</b>
<b>2004</b>	<b>269,997</b>	<b>990,067</b>
<b>2005</b>	<b>261,050</b>	<b>976,261</b>
<b>TOTAL</b>	<b>1,394,105</b>	<b>5,195,528</b>

Similarly, as depicted in Table 3, the HMOs included in my sample represent the bulk of the total HMO enrollees in the state of Florida during the sample period.

**Table 3: Size of HMO Market in Florida**

<b>Year</b>	<b>HMO Enrollees in Florida</b>	<b>HMO Enrollees in Sample</b>	<b>Percent Rep. by Sample</b>
<b>2001</b>	<b>4,753,568</b>	<b>4,689,620</b>	<b>98.65%</b>
<b>2002</b>	<b>4,424,081</b>	<b>4,356,549</b>	<b>98.47%</b>
<b>2003</b>	<b>4,264,825</b>	<b>4,198,329</b>	<b>98.44%</b>
<b>2004</b>	<b>4,044,451</b>	<b>3,979,618</b>	<b>98.40%</b>
<b>2005</b>	<b>3,866,617</b>	<b>3,800,403</b>	<b>98.29%</b>
<b>TOTAL</b>	<b>21,353,542</b>	<b>21,024,519</b>	<b>98.46%</b>

---

actually account for the bulk of the total HMO enrollees in the local area. Some drawbacks of using county as the relevant geographic market is that it does not account for individuals who seek medical care from hospitals outside their local area and hospitals that contract with HMOs operating outside the county they are located in.

I obtain data on a number of hospital characteristics from the AHCA Financial Data set including: number of hospital beds, hospital network status, ownership status (non-profit verses for-profit), teaching status, and geographic location (county the hospital is located in). I acquire data on a number of patient characteristics from the AHCA Patient Discharge Data including patient orientation location (which is used to calculate hospital HHI), severity of illness and DRG code (which is used to calculate a patient's case-mix-index). I then use this patient level data to create an individual average value for each hospital in my data set using the methods described in the Appendix.

Some additional data used in my analysis are from the following sources: US Department for Health and Human Services' Centers for Medicare and Medicaid Services (CMS) (hospital wage index, DRG weights which are used to calculate CMI, and number of individuals who are eligible to enroll in Medicare in each county in Florida); US Department of Labor, Bureau of Labor Statistics (average annual pay by county and county unemployment rate); Florida Office of Insurance Regulation (number of HMOs per county, total HMO enrollment per county, and the breakdown of total county HMO enrollment by individual HMO); and the Florida Legislature Office of Economic and Demographic Research (total county population and population demographics including race, age, and gender).

## **B. Data Limitations**

There are a number of data limitations due to the nature of the AHCA Patient Discharge Data and Financial Data I use to construct my sample. First, in order to test the four hypotheses listed above, ideally I would need to have hospital specific values of HMO Concentration. However, due to the makeup of the AHCA Patient Level Data I can identify the type of each

patient (HMO, PPO, Medicare, etc.) treated at a given hospital (by year) but I cannot distinguish which specific HMO in Florida an HMO patient is enrolled in. Thus I cannot calculate unique values of HMO Concentration for each hospital in my sample. Instead I am forced to calculate my measures of HMO Concentration using county level data. Thus, I assign the variables used to control for HMO Concentration to all the hospitals in my sample based upon the geographic location of the hospital. This data limitation could result in measurement error in the variables of interest in my model. I discuss this data limitation and its potential effects in further detail in the next section.

Second, in my analysis I am interested in examining the effect of buyer power in the market for inpatient hospital services. As stated previously, HMOs are only one of the buyers in the market for inpatient hospital services. Other buyers in this market include PPOs, EPOs, Medicare, Medicaid, etc. Another limitation with my data is that while I am able to calculate a measure of buyer power for HMOs (the market shares of all HMOs in a given geographic area), I am unable to do the same for other payer groups. Thus I am only able to observe the market structure of some of the buyers in the market for inpatient hospital services. In order to deal with this data limitation, I assume that the sale of hospital services to HMOs constitute a separate market from sales of hospital services to other insurers. I discuss this data limitation and the necessary assumption in further detail in the next section.

Third, in the first stage of my analysis, I want to look at the effect of HMO Concentration on the price of inpatient hospital services received by HMO enrollees. Ideally, I would want to use the transaction price (net price) rather than the list price as my measure of price.<sup>30</sup> However, due to the attributes of the AHCA Patient Data, I do not have transaction prices for each of the

---

<sup>30</sup> Net price is the preferred measure in most hospital research because gross charges or list prices do not accurately reflect the final transaction prices paid by most patients due to discounting by commercial insurance companies.

HMO patients treated at my sample hospitals. Instead, I am able to calculate a measure of the net revenue (gross charges or revenue minus discount-off-charges) that a hospital receives for treating an HMO enrollee and use this as a measure of HMO inpatient transaction price. As a result, my dependent variable in the first stage of my analysis may be subject to measurement error. Furthermore, in order to calculate a hospital's net revenue per discharge (inpatient day) I need to calculate the appropriate discount rate. Ideally, I would want to calculate a different discount rate for each HMO a specific hospital has a contract with. However, due to the makeup of the AHCA Financial Data, I am only able to calculate a single HMO discount rate for each hospital in my sample which is an average of all the HMO discount rates. The effect of using a single average HMO discount rate for each hospital is that the dependent variable I use in the first step of my analysis will suffer from measurement error. I discuss this data limitation and its potential effects in further detail in the next section.

### **C. HMO Concentration**

The goal of my analysis is to determine whether the effect of HMO Concentration is consistent with a variety of theories regarding buyer power. Thus the variable of interest in all of my analyses is HMO Concentration. I use two alternate variables to capture the effect of HMO Concentration in my analysis: either the market share of the largest HMO (Dominant HMO Market Share) or the level of HMO concentration of all the HMOs in the county (HMO HHI).<sup>31</sup> As stated above, there are a number of data limitations due to the makeup of the AHCA Patient Discharge Data and Financial Data which I use to construct my sample. First, due to the nature of the AHCA Patient Level Data I can identify the type of each patient (HMO, PPO, Medicare,

---

<sup>31</sup> Shen et al. (2008) and Bates and Santerre (2008) control for HMO buyer power using HMO HHI. Similarly, Schneider et al. (2008) control for health plan concentration using HHI.

etc.) treated at a given hospital (by year). Thus I can use this information to determine the share of a given hospital's total patients that belong to each payer group. However I do not know which specific HMO in Florida an HMO patient is enrolled in. Thus I can not calculate unique values of HMO Concentration for each hospital in my sample. Instead I am forced to calculate my two alternate measures of HMO Concentration using county level data. Thus, I assign the variables used to control for HMO Concentration to all the hospitals in my sample based upon the geographic location of the hospital (i.e. which county the hospital is located in). In this manner, hospitals in the same county are assigned the same values for Dominant HMO Market Share and HMO HHI.

This data limitation could result in measurement error in the variables of interest in my model.<sup>32</sup> Measurement error typically occurs because one is using an imprecise measure of an economic variable in the model. Some of the effects measurement error in an explanatory variable can have on results include biased coefficients and standard errors.<sup>33</sup> Since standard errors of inaccurately measured explanatory variables are typically larger, this can make it more difficult to find significant results because t-statistics for these variables will be lower. One potential method that can be used to correct for measurement error in an explanatory variable is to use instrumental variables (IVs) for the variable(s) that may suffer from this problem (Cohen and Cohen 2003). The use of IVs will produce more accurate coefficients, however, standard errors and significance tests may still not be completely accurate. Thus even with the use of IVs it may still be difficult to find significant results. As discussed in the next section, I have identified a number of potential IVs for either measure of HMO Concentration used in my

---

<sup>32</sup> Measurement error occurs when the values observed in the sample of either the dependent variable or independent variable vary from the true level of the variable seen in the population.

<sup>33</sup> If measurement error is random, then coefficients will be accurate but standard errors will be larger and variances will be biased. On the other hand, if measurement error is non-random than coefficients, standard errors, and variances will all be biased.

analysis in order to correct for potential endogeneity issues. Therefore the use of IVs and a two-stage-least squares model should enable me to correct for measurement error in my explanatory variables of interest.

In order to construct the market share of the Dominant HMO in a given geographic market, I use data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county. From this data source I am also able to determine the number of HMO enrollees for each individual HMO that has members in this county. To calculate the market share of the Dominant HMO, I simply divide the total number of enrollees from the Dominant HMO in a given county by the total number of HMO enrollees in that county. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate Dominant HMO Market Share for their county for each year.

$$\text{Dominant HMO Market Share}_{jt} = \frac{\text{\# of HMO enrollees for Dominant HMO}_{ct}}{\text{Total Number of HMO Enrollees}_{ct}}$$

Where  $j$  = hospital,  $t$ =year,  $c$ =county

The annual values of Dominant HMO Market Share in the sample range from 0.12 to 0.998, with a mean of 0.349. (See Table 6 and Table 7 for a complete list of Descriptive Statistics of the Sample). The mean value of this measure of HMO Concentration is close to the 40% market share threshold established by Motta (2004) and reiterated by Tardiff and Weisman (2009) for when a firm can be considered a dominant firm. In fact for 236 observations in the sample, the Dominant HMO Market Share is greater than 40%. Thus a large portion of the hospitals in my sample are operating in markets where a dominant firm exists and may be in the position to leverage its market power to obtain better rates for their enrollees.

In order to construct the level of HMO concentration (HMO HHI) within a given geographic market I use data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county. From this data source I am also able to identify the number of HMO enrollees for each individual HMO that has members in this county. I first calculate the market share of all the individual HMOs in a given county simply by dividing the total number of enrollees for a given HMO in the county by the total number of HMO enrollees in that county. The level of HMO concentration is calculated by squaring and then summing all of the market shares of all competing HMOs in a particular county. Thus each county is assigned a unique HMO HHI between 0 and 1. Counties with very competitive HMO markets have low HMO HHI values, and counties with little or no HMO competition have higher values. Finally, the AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate HMO HHI for their county for each year.

$$\text{HMO HHI}_{jt} = \sum ((\text{HMO Market Share}_{1ct})^2, \dots (\text{HMO Market Share}_{mct})^2)$$

**Where j= hospital, t=year, c=county, m=number of HMOs in a market**

The annual values of HMO HHI in the sample range from 0.075 to 0.997, with a mean of 0.248. The mean value of this measure of HMO Concentration is above the threshold established by the Federal Trade Commission and Department of Justice in the Horizontal Merger Guidelines for what constitutes a highly concentrated market.<sup>34</sup> In fact for 337 observations in the sample, the HMO HHI is greater than 1800. Thus a large portion of the hospitals in my sample are operating in highly concentrated HMO markets. Table 4 provides a breakdown of the two variables used to control for HMO Concentration on an annual basis.

---

<sup>34</sup> According to §1.51 in the Horizontal Merger Guidelines (1997), a market in which the HHI is in excess of 1800 points is considered to be highly concentrated.

**Table 4: HMO Concentration – by Year**

<b>Year</b>	<b>Average Dominant HMO Market Share</b>	<b>Average HMO HHI</b>
<b>2001</b>	<b>0.377</b>	<b>0.267</b>
<b>2002</b>	<b>0.334</b>	<b>0.234</b>
<b>2003</b>	<b>0.338</b>	<b>0.244</b>
<b>2004</b>	<b>0.349</b>	<b>0.254</b>
<b>2005</b>	<b>0.344</b>	<b>0.241</b>

By looking at the average annual values of the market share of the Dominant HMO and HMO HHI, one can see that the HMO market in Florida has been highly concentrated throughout the sample period.

Another limitation with my data is that while I am able to calculate a measure of the market shares of all HMOs in a given geographic area, I am unable to do the same for other payer groups.<sup>35</sup> HMOs are only one of the buyers in the market for inpatient hospital services. Other buyers in this market include PPOs, EPOs, Medicare, Medicaid, etc. Thus I am only able to observe the market structure of some of the buyers in the market for inpatient hospital services. This inability is especially problematic in terms of the other major type of commercial managed care in the health care market – Preferred Provider Organizations (PPOs). While I am able to measure changes in HMO market structure over time in a geographic area and see how changes in this directly affect HMO patients, I am unable to control for the effects of changes in PPO market structure in the same geographic area.

In order to deal with this data limitation one must make some assumption regarding the nature of these two different types of managed care, HMOs and PPOs, and whether or not they constitute separate markets or one combine market for health insurance.<sup>36</sup> This will depend upon

---

<sup>35</sup> A number of other studies that look at the effects of HMO market structure also suffer from this data limitation including Shen et al. (2008) and Feldman and Wholey (2001).

<sup>36</sup> There are two potential frameworks one can use to address this question: (1) whether HMOs and PPOs are separate products in the sale of insurance to consumers, or (2) whether the sale of hospital services to HMOs is a separate product from the sale of hospital services to PPOs. As discussed earlier, HMOs and PPOs are buyers in the

the degree to which consumers for health insurance regard the two goods as substitutes (Gaynor and Haas-Wilson 1999). If one assumes that individuals do not view HMOs and PPOs as substitutes for one another, then each constitutes a separate market.<sup>37</sup> However if one assumes that HMOs and PPOs are both part of a broader managed care market, then together they combine to form one large market for health insurance. If the two products are part of one large market, then not controlling for PPO market structure may produce biased results. However, by assuming that the two goods are not substitutes relaxes this need to control for PPO market structure. Furthermore, one could assume that HMOs and PPOs are “separate but equal” products where what enrollees really care about is the name of the insurer.<sup>38</sup> This assumption also eliminates the need to control for PPO market structure. In my analysis, I will assume that HMOs and PPOs constitute separate markets, thus not controlling for PPO market structure, or changes in PPO concentration, will not cause the coefficient of HMO Concentration to be biased.<sup>39, 40</sup> The switching behavior of consumers in the market for health insurance supports

---

market for hospital services whereas these two groups are sellers in the market for health insurance. The goal of this paper is to examine the effect of HMO buyer power, thus at issue here is the sale of hospital services to HMOs not the sale of health insurance to potential enrollees (consumers). However, it follows that as long as consumers view HMOs and PPOs as separate health insurance products then the sale of hospital services to HMOs will constitute a separate product market. Thus, the subsequent discussion focuses on the degree to which consumers view HMO and PPO products to be separate health insurance products.

<sup>37</sup> In their study, Bates and Santerre (2008) - citing *US v. Aetna*, 1999 - outline a number of reasons why HMOs and PPOs are distinctively different health insurance products and thereby constitute two separate markets including: differences in benefit design, costs, and low price elasticity of demand between the two products.

<sup>38</sup> In this set-up, if HMO market structure and PPO market structure are perfectly correlated then HMO buyer power serves as a perfect instrument for PPO buyer power. Conversely, if one assumes that within an insurer that the HMO-PPO split is random then HMO and PPO buyer power are not correlated at all. In either case, excluding PPO market structure will not bias the coefficient of HMO Concentration.

<sup>39</sup> It is possible to partially validate this assumption by looking at the effect of the Dominant HMO market share on hospital prices. If one assumes that the sale of hospital services to HMOs does not constitute a separate market but is rather part of a larger health insurer market, then Dominant HMO market share and/or HMO HHI should not have a significant effect on hospital prices. Thus, any evidence of a significant effect of Dominant HMO market share on hospital price will support the assumption that the sale of hospital services to HMOs constitutes a separate market from sales of hospital services to other insurers. One caveat to this is if HMO dominance is correlated with PPO dominance (i.e. the largest HMO is also the largest PPO). If this is the case, then the effect of Dominant HMO share on price may actually be indicative of the effect of HMO plus PPO share on hospital price. However, even if this is the case the significant effect of Dominant HMO market share can still provide support for an empirical assumption that HMO dominance is not significantly correlated with other types of insurer dominance.

this assumption whereby the majority of individuals who change health plans stay within the same plan type (Cunningham and Kohn 2000; Bates and Santerre 2008). A number of other studies in this area including Bates and Santerre (2008) have also assumed that the HMO and PPO health insurance products are separate markets due to the fact both employers and employees perceive HMOs and PPOs to be different products that meet different needs and appeal to different types of enrollees. Similarly, the US government recognized that the HMO product constituted its own unique market in *US v. Aetna* (1999).

### **i. HMO Concentration Independent of HMO Penetration**

As stated above, I am primarily interested in examining the effect of HMO Concentration independent of HMO penetration, so as to correct for the flaws of previous work in this area.<sup>40</sup> Therefore I need to control for both HMO Concentration and HMO penetration in all of my models. I will use the same variable to control for the effect of HMO penetration in a given geographic area (county) as used in the previous studies: the share of the county population enrolled in HMOs. Again, I will assign this to all the hospitals in my sample based upon the geographic location of the hospital (i.e. which county the hospital is located in). In order to identify the share of the county population enrolled in HMOs, I use data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county. I then combined this with data regarding the total county population generated by the Florida Legislature Office of Economic and Demographic Research. To calculate the share of the

---

<sup>40</sup> As an added precaution, I estimated versions of two my price models using the share of total hospital patients which are PPO patients (PPO Share) as a proxy for PPO market share. The results indicate that PPO Share does not have a significant effect on either the price per hospital admission or inpatient day of HMO enrollees which substantiates my assumption that the sale of hospital services to HMOs is a separate product from the sale of hospital services to PPOs.

<sup>41</sup> By controlling for both HMO Concentration and HMO Penetration, I will also be able to simultaneously examine the effects of multiple aspects of the HMO market in a single model.

county population enrolled in HMOs, I simply divide the total number of HMO enrollees in a given county by the total county population for that county. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate share of the county population enrolled in HMOs (HMO Share) for their county for each year.

$$\text{HMO Share}_{jt} = \frac{\text{Number of HMO enrollees}_{ct}}{\text{Total Population}_{ct}}$$

Where **j** = hospital, **t**=year, **c**=county

The annual values of HMO Share in the sample range from 0.001 to 0.448, with a mean of 0.247. Thus when HMOs engage in negotiations with local area hospitals to obtain rates for their enrollees, they are representing a large portion of the area population. Table 5 offers a breakdown of HMO penetration on an annual basis.

**Table 5: HMO Penetration – by Year**

<b>Year</b>	<b>Average HMO Share</b>
<b>2001</b>	<b>0.284</b>
<b>2002</b>	<b>0.271</b>
<b>2003</b>	<b>0.248</b>
<b>2004</b>	<b>0.224</b>
<b>2005</b>	<b>0.210</b>

By looking at the average annual values of the share of the area population enrolled in HMOs, we can see that HMO penetration in Florida has decreased between 2001 and 2005. This is consistent with the consolidation of HMOs that was occurring nationwide during the period. Shen et al. (2008) refer to this as the “HMO Backlash Period” which they estimate began around 1999 and continued beyond 2005. Two common characteristics of this period were the wave of consumers leaving HMOs and the reduction in the number of HMOs in a given market via mergers among health plans and existing firms exiting markets. Prior to the HMO Backlash

period, throughout the 1990s, HMO enrollment has been increasing and a number of new HMOs entered the market.<sup>42</sup>

#### **D. The Empirical Model**

When examining the effect of HMO Concentration on HMO inpatient hospital prices and quantity of services, one can not use an ordinary least squares regression model (OLS Model). Using an OLS model to estimate the effect of HMO Concentration on HMO inpatient hospital prices or quantity of services is a naïve approach because this model suffers from endogeneity in the variables measuring the effect of HMO Concentration and the explanatory variable used to control for HMO penetration.<sup>43</sup>

The variables used to control for HMO market structure are endogenous for a number of reasons. First, HMO Concentration and the dependent variables measuring hospital inpatient price and utilization are correlated. Along these lines, HMO entry decisions into a given geographic market may be affected by hospital costs and price whereby HMOs tend to locate in high-cost (price) markets in order to increase their profits.<sup>44</sup> As a result, there may be a dual-causality issue. Second, HMO Concentration is endogenous due to the simultaneity between HMO Concentration and hospital expenditure and utilization where an increase in HMO Concentration is a positive function of hospital expenditure per capita.<sup>45</sup> Third, the two variables

---

<sup>42</sup> Shen et al. (2008); Miller and Luft (2002); Dranove et al. (1998); Bradford and Krumholz (2003); and Baker and Brown (1999) all reference the increase in HMO penetration which immediately preceded the HMO Backlash Period.

<sup>43</sup> Shen et al. (2008) acknowledge that both HMO Penetration and HMO HHI are endogenous and identify their inability to overcome this issue as one of the main limitations of their research.

<sup>44</sup> Gaskin and Hadley (1997) refer to this the “location effect.” McLaughlin (1987) and Bradford and Krumholz (2003) found that HMO enrollment was a function of hospital costs and therefore suffered from dual causality. Hay and Leahy (1984) argued that it was impossible to determine whether health plans react to local market conditions or influence market conditions via market share pressure.

<sup>45</sup> Frank and Welch (1985); McLaughlin (1987, 1988); and Feldman and Wholey (2001) found that HMO enrollment was a function of hospital expenditures and utilization and therefore suffered from dual causality.

used to measure the effect of HMO Concentration may be correlated with unobserved market and hospital characteristics that influence hospital price and quantity of service – specifically unobserved cost characteristics. As a result, the variables controlling for HMO Concentration will be correlated with the error term and are therefore endogenous.

Similarly, the variable used to control for HMO penetration may also be endogenous for many of the same reasons including a dual-causality between HMO penetration and the dependent variables measuring inpatient hospital prices and quantity of service.<sup>46</sup> Furthermore, HMO penetration may also be correlated with unobserved characteristics that influence the demand for healthcare services.<sup>47</sup> As a result, there is non-random selection of individuals into HMOs (McLaughlin 1987, 1988; McLaughlin et al. 1984). Thus lower health care costs associated with HMO may actually be the result of a selection bias where lower-risk individuals (i.e. younger and/or healthier individuals) enroll in HMOs. Since the OLS model ignores these relationships and assumes that the variables controlling for both HMO Concentration and HMO penetration are exogenous, biased results will be produced (Bradford and Krumholz 2003).

It is possible to correct for these endogeneity problems using a simultaneous equation regressions method such as two-stage least squares (2SLS).<sup>48</sup> Due to the fact the 2SLS model enables an individual to account for the endogeneity of HMO Concentration and HMO Penetration, it produces unbiased estimators and results.<sup>49</sup> After determining the correct model for my analysis, I applied a Hausman test to determine whether a fixed effects or random effects

---

<sup>46</sup> Bradford and Krumholz (2003); McLaughlin (1987); and Shen et al. (2008) argue that HMO plans may selectively enter high-cost provider markets.

<sup>47</sup> McLaughlin (1988) argued that the HMO penetration rate may be influenced by political, economic and demographic characteristics of consumers which affect the demand for hospital services.

<sup>48</sup> Previous studies looking at the effect of HMO market power that used a 2SLS model include: Frank and Welch (1985); Baker and Corts (1996); Feldman and Wholey (2001); Bates and Santerre (2008); Robinson (1996); Baker and Brown (1999); Bradford and Krumholz (2003); McLaughlin (1987, 1988); and McLaughlin et al. (1984).

<sup>49</sup> The results of both a Hausman Endogeneity Test and a Davison-Mackinnon Test for Endogeneity confirm the variables measuring HMO Penetration and HMO Concentration are endogenous. Accordingly, 2SLS is the superior model for estimating my reduced-form price and quantity regressions.

was the correct approach. The results of the Hausman test indicated that a reduced-form 2SLS with fixed effects was the correct model for use in my analysis.<sup>50</sup> The use of fixed effects will help to remove any bias that might result from time-invariant unobserved heterogeneity across hospitals and counties (Shen et al. 2008).

The general form of this model is:

$$Y_{jt} = B_0 + B_1 \text{HMO Concentration}_{jt} + B_2 \text{HMO Penetration}_{jt} + B_3 X_{jt} + B_4 Z_{ct} + \lambda_{jc} + \varepsilon_{jt}$$

**Where:**

**X = vector of hospital characteristic variables**

**Z = vector of market characteristic variables,**

**$\lambda$  = hospital and county fixed effects,**

**j = hospital**

**c = county**

**t = time period**

### **i. Instrumental Variables**

In order to use a 2SLS model one must first identify possible instrumental variables (IVs) for the two endogenous variables in the model - HMO Concentration and HMO Penetration.

One of the main self-acknowledged limitations of Shen et al. (2008) was the authors' inability to identify valid instruments for either of these variables. A good instrument for HMO

Concentration should be correlated with HMO Concentration but not correlated with cost or an HMO's profit or price margins. Similarly, a good instrument for HMO Concentration must be correlated with the variables used to measure its effect (Dominant HMO Market Share and HMO HHI) but not correlated with any of the unobserved market or hospital characteristics that influence hospital prices and quantities.<sup>51</sup> It is possible to use either demand side IVs or supply

side IVs to instrument for HMO Concentration and/or HMO Penetration (Dranove et al. 1998;

---

<sup>50</sup> The main differences when I estimate my models using random effects rather than fixed effects are quantitative – the direction of the effect of HMO Concentration remains the same, however, both the magnitude and statistical significance are weakened.

<sup>51</sup> In Wooldridge (2002) the two necessary conditions for an instrument (z) are that it must be correlated with the independent variable it is serving as an instrument for ( $\text{cov}(z, x) \neq 0$ ) and it must be uncorrelated with the error term ( $\text{cov}(z, u) = 0$ ).

Baker and Brown 1999). Demand side IVs are factors that are associated with insurance preference, demand for the HMO product/ healthcare, and socioeconomic status (Dranove et al. 1998). In general, these variables reflect the population demographics in the geographic markets and influence the demand for an HMO product. Thus they are good candidates for IVs for HMO Penetration. On the other hand, Supply side IVs are factors that affect local medical care market conditions. These variables reflect the market structure in the surrounding area and are good candidates for IVs for HMO Concentration (Bradford and Krumholz 2003; Dranove et al. 1998).

There are two potential supply side IVs for HMO Concentration: the average market share of the Dominant HMO in the surrounding geographic areas and the average HMO HHI in the surrounding geographic regions. (See the Appendix for a detailed description of how each of these variables is constructed) A number of studies in other fields have used a firm's market share in one market as an instrument for its market share in another market.<sup>52</sup> One of the strengths of this choice of instrument is that a firm's market share in one market will typically be correlated with its market shares in surrounding areas. In fact, there is a strong positive correlation between Dominant HMO Market Share and both IVs (where the correlation coefficients are both over 0.54) and between HMO HHI and the two IVs (where the correlation coefficients are both over 0.56). On the other hand, one potential weakness of this choice of instruments is that they will also be endogenous if the same unobserved factors that influence a HMO's market share in one geographic area also influence its market share in the surrounding areas (i.e. there are common unobserved variables across geographic regions) . However, the unobserved market and hospital characteristics that influence hospital price and quantity of service (specifically unobserved cost characteristics) in one geographic region or market should

---

<sup>52</sup> Bilotkach and Pai (2009) use an airline's market share across all routes generating from the same airport as an instrument for an airline's market share on a specific route. Heckman and Learner (2007) discuss the use of price and non-price variables in one market as instruments for the same variable in other markets.

have no impact on the prices and quantity of services provided by hospitals in other regions. Thus by assuming that the Dominant HMOs Market Share and HMO HHI in surrounding counties are independent of the errors in other geographic regions or counties (Heckman and Learner 2007), these variables are valid instruments. Furthermore, the F-statistic of the first-stage regressions for the variables used to control for HMO Concentration both exceed the weak instrument threshold of 10, established by Staiger and Stock (1997) and Bound et al. (1995), indicating that my model does not suffer from a weak instrument problem.<sup>53</sup>

Similarly, there are four potential demand side IVs for HMO Penetration which reflect the population demographics in the geographic market including: (1) the share of the county population that is over 65 and therefore not potential HMO enrollees; (2) the share of the county population that is female; (3) the share of the county population that is white; and (4) the unemployment rate of the county. All four of these demand side IVs were used by McLaughlin (1987) and the first three IVs were used by Bradford and Krumholz (2003) to instruments for their respective measures of HMO Penetration. Furthermore, these variables are consistent with the theory of demand factors that influence managed care penetration discussed in McLaughlin (1987) and Dranove et al. (1998).<sup>54</sup> (See the Appendix for a detailed description of how each of these variables is constructed). Additionally, these four demand side variables are highly correlated with the variable which measures the effect of HMO Penetration – HMO Share. There is also no reason to suspect that county demographics should impact the price and quantity of hospital services. The F-statistic of the first-stage regression for the variable used to control

---

<sup>53</sup> The F-statistic of the first-stage regression for the Dominant HMO Market Share is 44.47 and the F-statistic of the first-stage regression for HMO HHI is 22.60. According to theory, models with weak instruments can suffer from severe finite-sample bias and large variances of the instrument variables which can make it difficult to find significant results.

<sup>54</sup> McLaughlin (1987) and Dranove et al. (1998) both discuss which segments of the population are traditionally more likely to enroll in an HMO product.

for HMO Penetration easily exceeds the weak instrument threshold.<sup>55</sup> Thus my ability to identify valid instruments for the variables measuring both HMO Concentration and HMO Penetration enables me to overcome one of the main limitations of the only other study to date, Shen et al. (2008), that has attempted to include both of these variables in the same model.

## ii. Dependent Variables

In the first stage of my analysis, I look at the effect of HMO Concentration on the price of inpatient hospital services received by HMO enrollees.<sup>56</sup>

**Step # 1:  $\log(\text{HMO price per Admission})_{jt}$  or  $\log(\text{HMO price per Inpatient Day})_{jt}$**

**Where  $j$  = hospital and  $t$  = year**

Ideally, I would want to use the transaction price (net price) rather than the list price as my measure of price. Net price is the preferred measure in most hospital research because gross charges or list prices do not accurately reflect the final transaction prices paid by most patients due to discounting by commercial insurance companies. Thus measured prices will be subject to measurement error if list prices are used in regressions (Abraham et al. 2003). However, due to the limitations of the AHCA Patient Data, I do not have transaction prices for each of the HMO patients treated at my sample hospitals. Instead, I am able to calculate a measure of the net revenue (gross revenue minus discount-off-charges) that a hospital receives for treating an HMO enrollee and use this as a measure of HMO inpatient transaction price.<sup>57</sup> Thus the dependent variables in the first step of my analysis are the log of average inpatient net revenue per

---

<sup>55</sup> The F-statistic of the first-stage regression for HMO share is 35.26.

<sup>56</sup> Previous studies that have used hospital price or expenditure as a dependant variable include: Feldman and Wholey (2001); Shen et al. (2008); Bradford and Krumholz (2003); McLaughlin et al. (1984); Hay and Leahy (1984); and Robinson (1996).

<sup>57</sup> There are a number of other studies in this field that have used net revenue as a measure of transaction price including Dranove et al. (1991, 1993), Bradford and Krumholz (2003), Sorensen (2003), and Shen et al. (2008).

admission (patient discharge) or inpatient day by hospital. Since HMOs negotiate significant discounts, there is a wedge between the list and net inpatient prices (Dranove et al. 1991).

Inpatient net revenue per HMO admission was calculated by multiplying the total gross charges per HMO patient by one minus the corresponding hospital HMO discount percentage or rate depending upon each patient's hospital of origin (Vogt and Town 2005). The hospital HMO discount rate was generated by dividing each hospital's total annual net HMO inpatient revenue by their total annual HMO inpatient revenue and then subtracting this quotient (or ratio) from one.

$$\text{HMO Discount Rate}_{jt} = 1 - \frac{\text{Total Annual Net HMO Inpatient Revenue}_{jt}}{\text{Total Annual HMO Inpatient Revenue}_{jt}}$$

Where  $j$  = hospital the patient was treated at, and  $t$  = year

Due to the nature of the AHCA Financial Data, I am able to determine the total inpatient revenue, total inpatient deductions, and total net inpatient revenue for each payer category (HMO, PPO, Medicare, etc.). I use this information to calculate an annual HMO discount rate for each hospital in my sample. However, in any given year, a specific hospital will have contracts with multiple HMOs. The terms of these contracts will vary greatly by individual HMO, thus there is a wide variation among the discount rates that different HMOs receive from the same hospital.<sup>58</sup> However, I am only able to calculate a single HMO discount rate for each hospital in my sample which is an average of all of the different HMO discount rates that a hospital contracts with. Thus despite the fact that each hospital in my sample has different contracts with multiple HMOs in a given year and the terms of these contracts are not identical; due to data limitations, I am forced to assume that the discount rate is the same for all HMO patients that are treated at a given hospital. The effect of using a single HMO discount rate for

---

<sup>58</sup> Sorensen (2003) found evidence that hospital reimbursement rates vary substantially across payers of the same type where the largest discounts were nearly five times larger than the smallest discount in the same hospital.

each hospital is that the dependent variable I use in the first step of my analysis (average hospital HMO net inpatient price) will suffer from measurement error.

While measurement error in the dependent variable can still have negative consequences, the effects of it are less serious than measurement error in an explanatory variable. When there is measurement error in the dependent variable both standard errors and significant tests will remain valid. However, the standard errors will tend to be slightly larger than if there had been no measurement error due to the fact that the population variances of the coefficients are larger. For the most part, as long as the measurement error in the dependent variable is non-systematic, the results will remain valid. I must therefore assume that the methods used by AHCA to collect its financial data from all Florida hospitals (specifically the net revenue, total deductions, and total revenue by payer) do not have a systematic difference on different hospitals included in my sample. Since AHCA uses the same forms and methods to collect data from all the hospitals in my sample regardless of hospital type, size, or geographic location; I can conclude that the measurement error in my dependent variable is not-systematic.

Finally, inpatient net revenue per HMO admission was calculated by multiplying the total gross charges per HMO patient by one minus the corresponding hospital HMO discount rate depending upon each patient's hospital of origin.

**Net Inpatient Revenue per HMO Admission  $_{ijt} = \text{List Charge}_{ij} * (1 - \text{HMO Discount Rate}_{jt})$**

**Where  $i$  = HMO patient,  $j$  = hospital the patient was treated at, and  $t$  = year**

In order to have just a single (annual) price value per admission for each of my hospital observations, I calculate an average price for each hospital admission by summing all HMO net inpatients revenue per admissions (for a given hospital in a single year) and dividing it by the

total number of HMO patients treated at that hospital in the given year. I refer to this value simply as HMO price per admission.

$$\text{HMO Price per Admission}_{jt} = \frac{\Sigma (\text{HMO Inpatient Net Revenue}_i)_{jt}}{\Sigma (\text{HMO Admissions})_{jt}}$$

Where **j = hospital, t = time period**

Similarly, I calculate an average price for each HMO inpatient hospital day (inpatient net revenue per HMO day), for a given hospital in a single year, by dividing total inpatient net revenue for all HMO hospital inpatients by the corresponding total number of HMO inpatient days. I refer to this value simply as HMO price per inpatient day

$$\text{HMO Price per Inpatient Day}_{jt} = \frac{\Sigma (\text{HMO Inpatient Net Revenue})_{jt}}{\Sigma (\text{HMO Inpatient Days})_{jt}}$$

Where **j = hospital, t = time period**

Finally, I define my dependent variable as the logarithm of HMO price per admission and HMO price per inpatient day because both HMO price per admission and HMO price per inpatient day are highly skewed to the right.<sup>59</sup> By converting my price variables into a “log form,” I am able to transform HMO price per admission and HMO price per inpatient day into variables with normal distributions. Therefore, I have two measures of HMO net inpatient price for each of the hospitals (observations) in my sample. The annual values of log HMO price per admission in the sample range from 5.824 to 11.116, with a mean of 9.294. The annual values of log HMO price per inpatient day in the sample range from 5.412 to 10.017, with a mean of 8.059.

---

<sup>59</sup> A number of previous studies have also used the log of their price variables because the distribution of price is highly skewed to the right including: Feldman and Wholey (2001); Shen et al. (2008); Gaskin and Hadley (1997); and Robinson (1996).

Thus the general formula for of the 2SLS model in step #1 is:

$$\text{Log (HMO price)}_{jt} = B_0 + B_1 \text{ Concentration}_{jt} + B_2 \text{ Penetration}_{jt} + B_3 X_{jt} + B_4 Z_{ct} + \lambda_{jc} + \varepsilon_{jt}$$

Where **j = hospital, t = time period, c = county**

In the second step of my analysis (step # 2), I use two dependent variables to examine the effect of HMO Concentration on inpatient hospital utilization by HMO enrollees including hospital admissions per 100 HMO enrollees and inpatient hospital days per 100 HMO enrollees.

**Step # 2: Hospital Admissions per HMO Enrollee  $_{jt}$  or Inpatient Days per HMO Enrollee  $_{jt}$**

Where **j = hospital and t = year**

These two measures of quantity are similar to the measures of hospital utilization used by Feldman and Wholey (2001).<sup>60</sup> In order to calculate my two measures of inpatient hospital utilization, I use the AHCA Patient Discharge Data to determine the total number of HMO hospital admissions (inpatient hospital days) treated at a given hospital in a year. Next, I use the AHCA Financial Data to identify which county in Florida each hospital in the sample is located in. I combine this with data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county (in which a hospital is located in). I then divide the total number of HMO hospital admissions (inpatient hospital days) by the total number of HMO enrollees per county, and multiply it all by one hundred. Thus each hospital in the sample was assigned the appropriate annual values for Hospital Admissions (Inpatient Days) per 100 HMO Enrollees for each year.

---

<sup>60</sup> In their study, Feldman and Wholey (2001) look at the effect of HMO buyer power on both inpatient and outpatient hospital utilization per 1000 HMO enrollees. In my study, I only look at the effect of HMO Concentration on inpatient hospital utilization – thus I do not have any dependent variables which reflect the use of outpatient hospital services.

$$\text{Hospital Admissions per HMO Enrollee}_{jt} = \frac{\sum (\text{HMO Inpatient Hospital Admissions}_{jt}) * 100}{\text{Total Number of HMO Enrollees}_{ct}}$$

$$\text{Inpatient Days per HMO Enrollee}_{jt} = \frac{\sum (\text{HMO Inpatient Hospital Days}_{jt}) * 100}{\text{Total Number of HMO Enrollees}_{ct}}$$

Where **j** = hospital, **t** = year, **c** = county

The annual values of hospital admissions per 100 HMO enrollees in the sample range from 0.001 to 17.123, with a mean of 1.500. The annual values of inpatient days per 100 HMO enrollees in the sample range from 0.001 to 93.561, with a mean of 5.311. (See Table 6 and Table 7 for a complete list of Descriptive Statistics of the Sample).

Thus the general formula for of the 2SLS model in step #2 is:

$$\text{Admissions (Inpatient Days) per 100 HMO Enrollees}_{jt} = B_0 + B_1 \text{Concentration}_{jt} + B_2 \text{Penetration}_{jt} + B_3 X_{jt} + B_4 Z_{ct} + \lambda_{jc} + \varepsilon_{jt}$$

Where **j** = hospital, **t** = year, **c** = county

### iii. Other Explanatory Variables

The other explanatory variables used to explain the variation in the dependent variables of my analysis can be divided into two main categories: explanatory variables controlling for hospital characteristics (Vector X – in my empirical models) and explanatory variables controlling for market characteristics (Vector Z – in my empirical models).<sup>61, 62</sup> The explanatory variables controlling for hospital characteristics include: (1) Average HMO Case Mix Index -

<sup>61</sup> I use the same explanatory variables to explain variation in the dependent variables in step # 2 (utilization analysis) of my analysis as in step # 1 (price analysis) except I don't include controls for Network affiliation, Ownership status or Total County Population. There is no impact on my results when I estimate the quantity models with these additional explanatory variables, except a number of the explanatory variables which are significant in the results are no longer significant.

<sup>62</sup> All of the explanatory variables controlling for hospital characteristics are hospital specific whereas all of the explanatory variables controlling for market characteristics are assigned to each hospital based upon the geographic location of the hospital (i.e. which county the hospital is located in) except for hospital HHI which is hospital specific.

which is used as a measure of severity of illness of patients treated at the hospital. According to theory, this should have a positive effect on price and quantity because patients with more severe illnesses should received more/longer treatments; (2) Number of hospital beds - which is used to control for the size of the hospital. There is no clear theoretical prediction regarding the direction of this effect on price; however, an increase in the size of hospitals should have a positive impact on the quantity of inpatient services received; (3) Network affiliation, where hospitals are either part of a hospital network or independent/standalone hospitals. According to theory, hospitals that are part of networks should be able to obtain more favorable rates from HMOs thereby increasing their revenue (Ho 2009). Thus this variable should have a positive impact on price; (4) Ownership status, specifically non-profit and for-profit. Theory predicts that this should have a negative impact on price since non-profit hospitals are viewed as maximizing social welfare rather than profit; and (5) Teaching status – which is used to control for the quality or caliber of the hospital. Teaching hospitals are typically assumed to be “higher quality” hospitals that provide more complex medical procedures. According to theory, this variable should have a positive effect on price and a negative effect on quantity (Ho 2009). I calculate an annual value for each of these hospital explanatory variables for all of the hospitals in my sample. Table 6 and Table 7 contain a complete list of Descriptive Statistics of the Sample.<sup>63</sup>

The explanatory variables controlling for market characteristics include: (1) Hospital wage index - which is used as a measure of hospital’s labor costs and controls for variation in hospital input costs which could affect a hospital’s net revenue per discharge. There is no clear theoretical prediction regarding the direction of this effect on quantity of service, however, this variable should have a positive effect on price; (2) Hospital market structure (hospital HHI), where hospital HHI reflects the level of market concentration and the corresponding level of

---

<sup>63</sup> See the Appendix for a detailed description of how each of the explanatory variables is calculated.

competition that each hospital faces when choosing its optimal pricing strategy. According to theory, this variable should have a positive effect on price, however, there is no clear theoretical prediction regarding the direction of this effect on quantity; (3) County Income - which controls for the average annual pay of the county where each hospital is located. According to theory, this variable should have a positive effect on both price and quantity of inpatient services received; (4) Total County Population - which controls for the size of the potential market where each hospital is located in. There is no clear theoretical prediction regarding the direction of this effect on price; and (5) Medicare Share - which represents the share of the County population that is eligible for Medicare and may impact an HMO's strength during contract negotiations with local area hospitals. According to theory, this variable should have a negative impact on both price and quantity of inpatient services received. I calculate an annual value for each of these market explanatory variables for all of the hospitals in my sample.

**Table 6: Descriptive Statistic of the Sample**

<b>Variable Name</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Median</b>	<b>Minimum</b>	<b>Maximum</b>
Dominant HMO Market Share	0.349	0.199	0.272	0.120	0.998
HMO HHI	0.248	0.190	0.166	0.075	0.997
Log HMO Price per Admission	9.294	0.652	9.374	5.824	11.116
Log HMO Price per Inpatient Day	8.059	0.584	8.124	5.412	10.017
Hospital Admissions per 100 HMO enrollees	1.500	2.099	0.718	0.001	17.123
Inpatient Days per 100 HMO enrollees	5.311	8.518	2.466	0.001	93.561
HMO Share	0.247	0.116	0.262	0.001	0.448
Average HMO Case Mix Index	1.085	0.284	1.035	0.475	3.622
Beds	315.878	257.859	249	15	1745
Hospital Wage Index	0.950	0.053	0.950	0.836	1.071
County Income (in thousands)	32.939	4.595	33.721	20.837	40.599
County Population (in ten thousands)	92.080	75.439	82.628	1.886	242.208
Medicare Eligible Share	0.182	0.052	0.168	0.092	0.328
Hospital HHI (75% PSA)	0.066	0.069	0.040	0.003	0.403
<b>IVs for HMO Concentration</b>					
Surrounding Area Avg. HMO HHI	0.358	0.130	0.342	0.137	0.831
Surrounding Area Avg. Dominant HMO Market Share	0.468	0.132	0.464	0.188	0.892
<b>IVs for HMO Penetration</b>					
Unemployment Rate (County)	4.840	0.891	4.800	2.700	8.200
Share of Pop that is white (County)	0.822	0.081	0.822	0.585	0.962
Share of Pop that is female (County)	0.511	0.013	0.515	0.432	0.526
Share of Pop that is 65+ (County)	0.179	0.061	0.159	0.082	0.343

**Table 7: Descriptive Statistics of the Sample**

Variable Name	Frequency	Percentage of Sample
Non-Profit	300	41.04%
Teaching	24	3.28%
Network	483	66.07%

## **VI. Results and Discussion**

In the first step of my analysis, I use both log-linear ordinary least squares (OLS) and two-stage least squares (2SLS) models with fixed effects to look at the effect of HMO Concentration on two measures of price of inpatient hospital services - log HMO price per admission (Models 1 and 2) and log HMO price per inpatient day (Models 3 and 4).<sup>64</sup> In all of the models, I compute robust standard errors to correct for potential heteroskedasticity. I estimate two alternate versions of these models one where my measure of HMO Concentration is the Dominant HMO Market Share (Model 1 and Model 3) and another where my measure of HMO Concentration is HMO HHI (Model 2 and Model 4). I also control for HMO penetration in each model using the share of the total county population that is enrolled in HMOs. Thus in each of my models, I am able to isolate the effect of HMO Concentration on the price variables from the effect of HMO penetration. The results of the price regressions are summarized in Table 8 and Table 9.<sup>65</sup>

---

<sup>64</sup> Despite the acknowledged endogeneity of HMO Concentration and HMO Penetration, I estimate OLS versions of all the models just to ensure that when I correct for this error it has the anticipated effect on the coefficients of each of these variables. As previously discussed, large HMOs are more likely to form in areas with low prices – thus the OLS coefficient should be biased downwards when compared to the 2SLS coefficient. According to Baker and Brown (1999), since the theory predicts HMO buyer power should have a negative effect on hospital inpatient prices, a downward bias on the OLS coefficient will entail that the OLS coefficient will be closer to zero (be of lower magnitude in absolute terms) when compared to the 2SLS coefficient.

<sup>65</sup> The R-Squared values reported in Table 8 and Table 9 for both OLS and 2SLS are Within R-Squared. When estimating a 2SLS model with fixed effect, the model is aimed at maximizing the within variation (variation within the same hospital over time) whereas an OLS model attempts to maximize overall R-Squared. Thus With-in R-

**Table 8: OLS and Two Stage Least Squares (2SLS) Models with Fixed Effects Results (Robust SEs)**

(Dependent variable is the log average net HMO inpatient revenue per admission)  
 (Variable of Interest in Model 1 is HMO Concentration – measured by Dominant HMO Market Share)  
 (Variable of Interest in Model 2 is HMO Concentration – measured by HMO HHI)

Variable	Model 1 OLS	Model 1 2SLS		Model 2 OLS	Model 2 2SLS
Dominant HMO Market Share	-0.517** (0.211)	-1.596** (0.696)			
HMO HHI				-0.171 (0.318)	-2.116** (0.959)
HMO Case Mix Index	0.757*** (0.109)	0.764*** (0.109)		0.766*** (0.118)	0.763*** (0.109)
Number of Beds	-0.0004 (0.001)	-0.0003 (0.001)		-0.001 (0.001)	-0.0003 (0.001)
Network Status	0.035 (0.061)	0.025 (0.060)		0.033 (0.060)	0.024 (0.059)
Ownership Status (Nonprofit)	-0.113 (0.087)	-0.103 (0.092)		-0.110 (0.087)	-0.105 (0.092)
Teaching Status	0.029 (0.030)	0.074* (0.042)		0.022 (0.029)	0.073* (0.041)
Hospital Wage Index	0.762 (0.562)	0.962* (0.511)		0.683 (0.554)	0.904* (0.511)
Hospital HHI	-0.193 (0.923)	-0.126 (0.964)		-0.227 (0.926)	-0.159 (0.961)
County Income	0.081*** (0.012)	0.088*** (0.012)		0.077*** (0.012)	0.087*** (0.012)
County Population	-0.002 (0.007)	-0.008 (0.009)		0.001 (0.007)	-0.007 (0.008)
Medicare Share	1.748 (2.865)	0.975 (2.869)		1.275 (2.914)	0.793 (2.869)
Share of HMO enrollees	0.067 (0.239)	0.486 (0.775)		-0.060 (0.267)	0.535 (0.766)
N (hospitals)	163	163		163	163
T (years)	5	5		5	5
Total (observations)	731	731		731	731
R <sup>2</sup>	0.4071	0.4107		0.4013	0.4105

Square is a more accurate measure of the goodness-of-fit for 2SLS models (Wooldridge 2009; Verbeek 2000). In order to make comparisons across the OLS and 2SLS models easier, I report the Within R-Squared for all models.

**Table 9: OLS and Two Stage Least Squares (2SLS) Models with Fixed Effects Results (Robust SEs)**

(Dependent variable is log average net HMO inpatient revenue per inpatient day)  
 (Variable of Interest in Model 3 is HMO Concentration – measured by Dominant HMO Market Share)  
 (Variable of Interest in Model 4 is HMO Concentration – measured by HMO HHI)

Variable	Model 3 OLS	Model 3 2SLS		Model 4 OLS	Model 4 2SLS
Dominant HMO Market Share	-0.408** (0.175)	-1.589** (0.774)			
HMO HHI				-0.096 (0.213)	-1.951* (1.000)
HMO Case Mix Index	0.354 (0.248)	0.360 (0.247)		0.364 (0.256)	0.358 (0.247)
Number of Beds	-0.0004 (0.001)	-0.0003 (0.001)		-0.001 (0.001)	-0.0003 (0.001)
Network Status	0.012 (0.058)	0.002 (0.055)		0.010 (0.057)	0.002 (0.055)
Ownership Status (Nonprofit)	-0.073 (0.084)	-0.063 (0.084)		-0.071 (0.084)	-0.065 (0.084)
Teaching Status	0.103*** (0.037)	0.148*** (0.048)		0.098*** (0.037)	0.143*** (0.047)
Hospital Wage Index	1.161* (0.693)	1.348** (0.653)		1.091 (0.694)	1.287** (0.651)
Hospital HHI	-1.469* (0.815)	-1.412* (0.820)		-1.496* (0.827)	-1.446* (0.827)
County Income	0.072*** (0.012)	0.081*** (0.013)		0.069*** (0.012)	0.080*** (0.013)
County Population	0.005 (0.008)	-0.007 (0.009)		0.008 (0.007)	0.001 (0.009)
Medicare Share	1.676 (2.766)	0.707 (2.804)		1.239 (2.750)	0.472 (2.792)
Share of HMO enrollees	0.125 (0.211)	0.861 (0.781)		0.006 (0.222)	0.957 (0.776)
N (hospitals)	163	163		163	163
T (years)	5	5		5	5
Total (observations)	731	731		731	731
R <sup>2</sup>	0.3279	0.3362		0.3240	0.3348

The results depicted in Table 8 and Table 9 illustrate that HMO Concentration has the predicted negative effect on HMO price per admission and HMO price per inpatient day. This result is the same regardless of which measure of HMO Concentration is used indicating that this

effect is robust. In all of the 2SLS Models, the effect of HMO Concentration is statistically significant and in most models at the 5% significance level.<sup>66</sup> As predicted, once I correct for dual-causality and the other sources of endogeneity in my models the coefficients on the HMO Concentration variables become larger in magnitude (in absolute terms).<sup>67</sup> Thus when one compares the coefficients on HMO Concentration between the OLS and 2SLS models, the coefficient in the 2SLS should be larger in absolute terms.<sup>68</sup> Additionally, the results indicate that HMO Concentration has the predicted negative effect on HMO prices per admission and per inpatient day even after controlling for other aspects of the HMO market structure (i.e. HMO penetration).<sup>69, 70</sup> The results indicate that the effect of HMO Concentration is slightly larger

---

<sup>66</sup> The effect of HMO Concentration is statistically significant at the 10% level in the 2SLS versions of Model 4.

<sup>67</sup> Therefore the effect of including instruments in my price models appears to be mostly quantitative in terms of both HMO Concentration and HMO Penetration since it only changes the magnitudes, not the directions, of each effect (except for in Model 2 where using instruments for HMO Penetration causes the sign of the variable measuring HMO penetration to change from negative to positive).

<sup>68</sup> In the OLS versions of both Model 2 and Model 4, HMO HHI does not have a statistically significant effect on HMO price per admission or inpatient day after controlling for HMO Penetration. This result is similar to those of Shen et al. (2008) whereby HMO HHI had no impact on hospital costs and revenue after controlling for HMO penetration. However, once I correct for the acknowledged endogeneity of HMO HHI via instruments the effect of this variable becomes statistically significant. Thus it appears the inability of Shen et al. (2008) to find significant effects of HMO HHI may be a product of the acknowledged limitations of their model.

<sup>69</sup> I estimate additional versions of each price regressions using alternate controls for HMO penetration such as the number of HMOs or both HMO Share and the number of HMOs. In all of these regressions, HMO Concentration has a statistically significant negative effect on both price measures regardless of which variable(s) is used to control for HMO penetration indicating this result is robust. The magnitudes of the effects of HMO Concentration are approximately the same as the ones reported in Table 8 and Table 9. The number of HMOs has a statistically significant negative effect on HMO price per admission and HMO price per inpatient day. This result is consistent with the findings from previous studies by Feldman and Wholey (2001), Gaskin and Hadley (1997), and Bradford and Krumholz (2003).

<sup>70</sup> I estimate an alternate version of my price models using a non-linear specification of my measures of HMO Concentration. In these models, I interact my measures of HMO Concentration and HMO Penetration. According to all the theories on HMO buyer power, this interaction term should have a negative effect on the price of inpatient hospital services (both per admission and inpatient day) received by HMO enrollees. This is due to the fact that in markets where there is a larger share of the area population enrolled in HMOs and the HMO market is more highly concentrated; a Dominant HMO should have more power in contract negotiations with area hospitals because they represent a larger number of enrollees or the hospital's patient base. However, in all of my price models, the interaction term has a positive statistically significant effect on HMO price per admission and inpatient day. This effect is contrary to the theoretical predictions and is something I plan to investigate further in my future work. Nevertheless, even when I include the interaction term, all of my measures of HMO Concentration continue to have a negative statistically significant effect on the price of inpatient hospital services received by HMO enrollees. Overall, the combined effect of HMO Concentration, HMO Penetration and the interaction term is still negative in all of my price models when using the mean values of HMO Concentration and HMO Penetration. However, the magnitude of this negative effect is smaller (closer to zero) when I include the interaction term in the price models.

when it is measured as HMO HHI rather than the market share of the Dominant HMO. Table 8 lists the results of Model 1 which indicate that HMO price per admission would be 1.6% lower as a result of a one-percent increase in the market share of the Dominant HMO in the market.<sup>71</sup> Similarly, Model 2 illustrates that HMO price per admission would be 2.1% lower as a result of a 0.01 increase in HMO HHI. Model 3 (results listed in Table 9) indicates that HMO price per inpatient day would be 1.6% lower as a result of a one-percent increase in the market share of the Dominant HMO. Likewise, Model 4 (results listed in Table 9) illustrates that HMO price per inpatient day would be 2.0% lower as a result of a 0.01 increase in HMO HHI. Thus the results of the price analysis indicate that HMOs are able to utilize their buyer power in negotiations with hospitals in order to obtain more favorable reimbursement rates which can be translated into lower inpatient hospital prices for their enrollees. Therefore there is support for Hypothesis One in Models 1 through 4 which are consistent with all three theories of HMO buyer power.<sup>72</sup>

Table 8 and Table 9 illustrate that the variable I include in my model to control for HMO penetration, HMO Share or the share of the total county population enrolled in HMOs, has a positive but not statistically significant effect on both HMO price per hospital admission and inpatient day. The other explanatory variables in the price models have the expected signs for the most part. As predicted, case-mix-index, teaching status and county income all have positive and statistically-significant effects on HMO price per admission (see Table 8). Other variables with a consistently positive effect on HMO price per admission include network status and hospital wage index. The direction of these effects is as predicted; however, they are not statistically significant. Some of the other explanatory variables in model including number of

---

<sup>71</sup> This result is of similar magnitude to those of Feldman and Wholey (2001) who found that a one-percent increase in HMO buyer power would reduce hospital price per diem by 2.3 percent.

<sup>72</sup> Furthermore, the statistically significant effect of Dominant HMO Market Share on hospital prices is evidence in support of the assumption that the sale of hospital services to HMOs constitutes a separate market from the sale of hospital services to other types of insurers.

beds, nonprofit status, hospital HHI and county population all have a negative effect on HMO price per admission however they are not statistically significant. The only variable whose effect is contrary to theory predictions is the share of the population that is eligible for Medicare (Medicare Share) which has a positive though statistically insignificant effect on HMO price per admission. Due to the fact that many of these explanatory variables are not statistically significant I re-estimated Models 1 and 2 just including the variables that were significant in the full models. The results of the simplified models were consistent with the results of the full models whereby an increase in HMO Concentration has a statistically significant negative effect on HMO price per admission, thus, for completeness I report the results of the full models in Table 8.

Similarly, teaching status and county income both have the predicted positive and statistically-significant effects on HMO price per inpatient day (see Table 9). Other variables with a consistently positive effect on HMO price per inpatient day include HMO case-mix-index, network status, hospital wage index, and county population. The direction of these effects is as consistent with the theory; however, they are not statistically significant. Some of the other explanatory variables in model including number of beds, nonprofit status, and hospital HHI all have a negative effect on HMO price per inpatient day; however, only hospital HHI is statistically significant. The only variable whose effect is contrary to theory predictions is Medicare Share which has a positive though statistically insignificant effect on HMO price per inpatient day. Due to the fact that many of these explanatory variables are not statistically significant I re-estimated Models 3 and 4 including only the variables that were significant in the full models. The results of the simplified models were consistent with the results of the full models whereby an increase in HMO Concentration had a statistically significant negative effect

on HMO price per inpatient day, thus, for consistency I report the results of the full models in Table 9.<sup>73</sup>

In the second step of my analysis I use ordinary least squares (OLS) and two-stage least squares (2SLS) models with fixed effects to look at the effect of HMO Concentration on two measures of utilization of inpatient hospital services - hospital admissions per 100 HMO enrollees (Models 5 and 6) and inpatient days per 100 HMO enrollees (Models 7 and 8).<sup>74</sup> In all of the models I compute robust standard errors to correct for potential heteroskedasticity. Again, I estimate two alternate versions of these models one where my measure of HMO Concentration is the Dominant HMO Market Share (Model 5 and Model 7) and another where my measure is HMO HHI (Model 6 and Model 8). I also control for HMO penetration in each model using the share of the total county population that is enrolled in HMOs. Thus in each of my models I am able to isolate the effect of HMO Concentration on the measures of inpatient hospital utilization from the effect of HMO penetration. The results of the utilization regressions are summarized in Table 10 and Table 11.

---

<sup>73</sup> In addition to the models listed in Table 8 and Tables 9, I also estimate alternate versions of all my price models including controls for HMO patient demographics treated at a hospital in a given year including average age, female patient share, and white patient share. The results of these alternate models are consistent with the results of the original models listed in Table 8 and Table 9 whereby HMO Concentration has a statistically significant negative effect on both price per admission and inpatient day. However, of the variables I use to control for HMO patient demographics only gender (female) has a statistically significant (positive) effect on price per inpatient day, thus, I report the models excluding these controls in Table 8 and Table 9.

<sup>74</sup> Despite the acknowledged endogeneity of HMO Concentration and HMO Penetration, I estimate OLS versions of all the models just to ensure that when I correct for this error it has the anticipated effect on the coefficients of each of these variables.

**Table 10: OLS and 2SLS Models with Fixed Effects Results (Robust SEs)**

(Dependent variable is the number of hospital admissions per 100 HMO enrollees)  
 (Variable of Interest in Model 5 is HMO Concentration – measured by Dominant HMO Market Share)  
 (Variable of Interest in Model 6 is HMO Concentration – measured by HMO HHI)

<b>Variable</b>	<b>Model 5 OLS</b>	<b>Model 5 2SLS</b>		<b>Model 6 OLS</b>	<b>Model 6 2SLS</b>
Dominant HMO Market Share	-1.705 (2.515)	0.651 (1.998)			
HMO HHI				-2.131 (2.484)	-0.655 (2.822)
HMO Case Mix Index	-0.266 (0.309)	-0.354 (0.323)		-0.358 (0.333)	-0.335 (0.321)
Medicare Share	-1.975 (1.426)	-2.121 (1.389)		-1.861 (1.409)	-2.071 (1.385)
County Income	-0.005 (0.038)	0.043 (0.058)		0.002 (0.037)	0.036 (0.057)
Hospital Wage Index	-1.051* (0.577)	-0.851 (0.580)		-1.026* (0.569)	-0.859 (0.582)
Teaching Status	0.013 (0.133)	-0.021 (0.167)		0.021 (0.133)	0.003 (0.164)
Number of Beds	0.003** (0.001)	0.003** (0.001)		0.003** (0.001)	0.003*** (0.001)
Hospital HHI	-1.141 (3.435)	-1.135 (3.468)		-1.416 (3.562)	-1.120 (3.469)
Share of HMO enrollees	-2.450*** (0.826)	0.644 (3.423)		-2.096* (1.103)	0.234 (3.415)
N (hospitals)	163	163		163	163
T (years)	5	5		5	5
Total (observations)	731	731		731	731
R <sup>2</sup>	0.0743	0.0403		0.0750	0.0402

**Table 11: OLS and 2SLS Models with Fixed Effects Results (Robust SEs)**

(Dependent variable is the number of inpatient days per 100 HMO enrollees)  
 (Variable of Interest in Model 7 is HMO Concentration – measured by Dominant HMO Market Share)  
 (Variable of Interest in Model 8 is HMO Concentration – measured by HMO HHI)

Variable	Model 7 OLS	Model 7 2SLS		Model 8 OLS	Model 8 2SLS
Dominant HMO Market Share	-0.463 (0.887)	0.509 (0.760)			
HMO HHI				-0.572 (0.865)	0.096 (1.073)
HMO Case Mix Index	0.775 (1.209)	0.382 (1.168)		0.529 (1.347)	0.462 (1.176)
Medicare Share	-4.982 (4.814)	-5.245 (4.799)		-4.683 (4.733)	-5.024 (4.800)
County Income	0.035 (0.145)	0.216 (0.213)		0.052 (0.143)	0.190 (0.211)
Hospital Wage Index	-4.111* (2.217)	-3.358 (2.197)		-4.045* (2.191)	-3.379 (2.205)
Teaching Status	-0.274 (0.537)	-0.455 (0.670)		-0.251 (0.540)	-0.362 (0.662)
Number of Beds	0.015** (0.007)	0.015** (0.007)		0.015** (0.007)	0.015** (0.007)
Hospital HHI	-0.560 (1.159)	-0.570 (1.168)		-0.639 (1.207)	-0.561 (1.167)
Share of HMO enrollees	-0.988*** (0.313)	0.132 (1.122)		-0.895** (0.410)	0.030 (1.126)
N (hospitals)	163	163		163	163
T (years)	5	5		5	5
Total (observations)	731	731		731	731
R <sup>2</sup>	0.0805	0.0726		0.0808	0.0705

The results illustrate that HMO Concentration has no effect on hospital admissions or inpatient days per HMO enrollee. This result is the same regardless of which measure of HMO Concentration is used indicating that this effect is robust. The utilization results indicate that there is no support for either Hypothesis Two (Monopsony Theory) or Hypothesis Three (Welfare-Increasing Theory) due to the fact HMO Concentration does not have either a statistically-significant positive or negative effect on the utilization of inpatient hospital services

by HMO enrollees. Conversely, there is support for Hypothesis Four (All-or-None Theory) in Models 5 through 8 whereby HMO Concentration has no effect on the quantity of inpatient hospital services utilized by HMO enrollees despite its negative effect on the price of inpatient hospital services.<sup>75</sup> Similarly, the results of the 2SLS models listed in Table 10 and Table 11 illustrate that the variable I include in my model to control for HMO penetration, the share of the total population enrolled in HMOs, has positive but insignificant effect on both the number of hospital admissions and inpatient days per HMO enrollee.<sup>76</sup> This result is consistent with Feldman and Wholey (2001) where the authors found that an increase in the percentage of community days in the HSA (health service area) purchased by an HMO had a positive effect on inpatient hospital utilization per HMO enrollee. However, in their analysis the authors were using the percentage of community days purchased by HMO to represent HMO buyer power which is actually a measure of HMO penetration rather than HMO buyer power. Thereby, it appears the authors may have inaccurately found support for the Welfare-Increasing Theory due to the fact they were actually looking at the effect of HMO penetration rather than HMO buyer power on inpatient hospital utilization.

The other explanatory variables in the quantity models have the expected signs for the most part. Both county income and number of hospital beds have positive effects on the number of hospital admissions per HMO enrollee (Table 10). However, only the effect of the number of

---

<sup>75</sup> To further ensure that my quantity results were not specific to the selection of the dependent variable used in the quantity regressions, I estimated additional models where I used a variety of other variables to control for inpatient hospital service utilization including: the log of total HMO inpatient days, the log of total HMO hospital admissions, HMO inpatient days as a share of total hospital inpatient days, and HMO hospital admissions as a share of total hospital admissions. The reason I selected the log of total inpatient days and admissions were that these were the same measures used by Bates and Santerre (2008) in their analysis. I find no support for either Monopsony Theory or Welfare-Increasing Theory in any of these models. In all of these models, I find additional overwhelming support for Hypothesis Four (All-or-None Theory): HMO Concentration has no effect on these additional measures of utilization of inpatient hospital services by HMO enrollees.

<sup>76</sup> I estimate additional versions of each quantity regressions using alternate controls for HMO penetration such as the number of HMOs or both HMO Share and the number of HMOs. In all of these regressions, HMO Concentration does not have a statistically significant effect on either utilization measures regardless of which variable(s) is used to control for HMO penetration indicating this result is robust.

hospital beds is statistically-significant. All of the other explanatory variables in model including case-mix-index, Medicare share, hospital wage, teaching status, and hospital HHI have negative effects on number of hospital admissions per HMO enrollee. Although none of these effects are statistically significant. Similarly, case-mix index, county income and number of hospital beds have positive effects on the number of inpatient days per HMO enrollee (Table 11) of which only the effect of the number of hospital beds is statistically-significant. All of the other explanatory variables in model including Medicare share, hospital wage, teaching status, and hospital HHI have negative effects on number of inpatient days per HMO enrollee; although these effects are not statistically significant. Due to the fact that many of the explanatory variables are not statistically significant in any of the utilization regressions, I re-estimated Model 5 through Model 8 just including the variables that were significant in the full models. The results of the simplified models were consistent with the results of the full models whereby HMO Concentration did not have a statistically significant effect on the number of hospital admissions and inpatient days per 100 HMO enrollees, thus, for completeness I report the full model results in Table 10 and Table 11.<sup>77, 78</sup>

---

<sup>77</sup> In addition to the models listed in Table 10 and Table 11, I also estimate alternate versions of all my quantity models including controls for HMO patient demographics treated at a hospital in a given year including average age, female patient share, and white patient share. The results of these alternate models are consistent with the results of the original models listed in Table 10 and Table 11 whereby HMO Concentration does not have a statistically significant effect on either the number of hospital admissions or inpatient days per 100 HMO enrollees. However, of the variables I use to control for HMO patient demographics only race (white) had a statistically significant (negative) effect on the number of hospital admissions per 100 HMO enrollees; thus, I report the models excluding these controls in Table 10 and Table 11.

<sup>78</sup> The R-squares values for Models 6 to 8 are all rather low (less than 0.10), thus it appears that neither hospital nor market characteristics explains much of the variation in utilization of inpatient hospital services by HMO enrollees. Furthermore, even when I add controls for patient demographics the R-squares remain low. Thus, there are some unobserved factors (other than market, hospital or patient demographics) which play a large part in determining both the number of hospital admissions and inpatient days utilized by HMO enrollees.

## VII. Discussion and Policy Implications

The results of my analysis indicate that the effects of HMO Concentration are consistent with the All-or-None Theory. According to this theory, an increase in a HMO buyer power will have a negative effect on the price an HMO pays for inpatient hospital services but no impact on the quantity of hospital services utilized by its members. Thus it appears that HMOs are able to leverage their dominant position in the market for hospital inpatient services to obtain more favorable contract terms and rates for their enrollees from local hospitals. Correspondingly, hospitals are forced to agree to these contract terms, which ultimately reduce their net revenue per admission and inpatient day, so as to remain in the provider's network. In exchange, the hospital obtains the opportunity to provide medical services to the provider's members or enrollees. If the hospital were to opt not to agree to these terms then it would no longer be in the provider's network and would lose out on the opportunity to treat their enrollees. As such, the most important factors in the contract negotiation process are the percentage of potential patient revenue that a particular insurer accounts for and the difficulty the hospital will have replacing the lost patients.<sup>79</sup> Therefore, hospitals have to agree to the dominant firm's contract demands because they are economically dependent upon the firm's enrollees.

This all-or-none choice faced by hospitals when negotiating with a dominant HMO forces the hospital from its regular supply curve onto its All-or-None supply curve which lies below the regular supply curve.<sup>80</sup> In Figure 2, when the market is competitive the price and quantity are determined by the intersection of the regular supply and demand curve. Thus P (E) is the efficient price and Q (E) is the efficient quantity in this market (i.e. the price and quantity in the

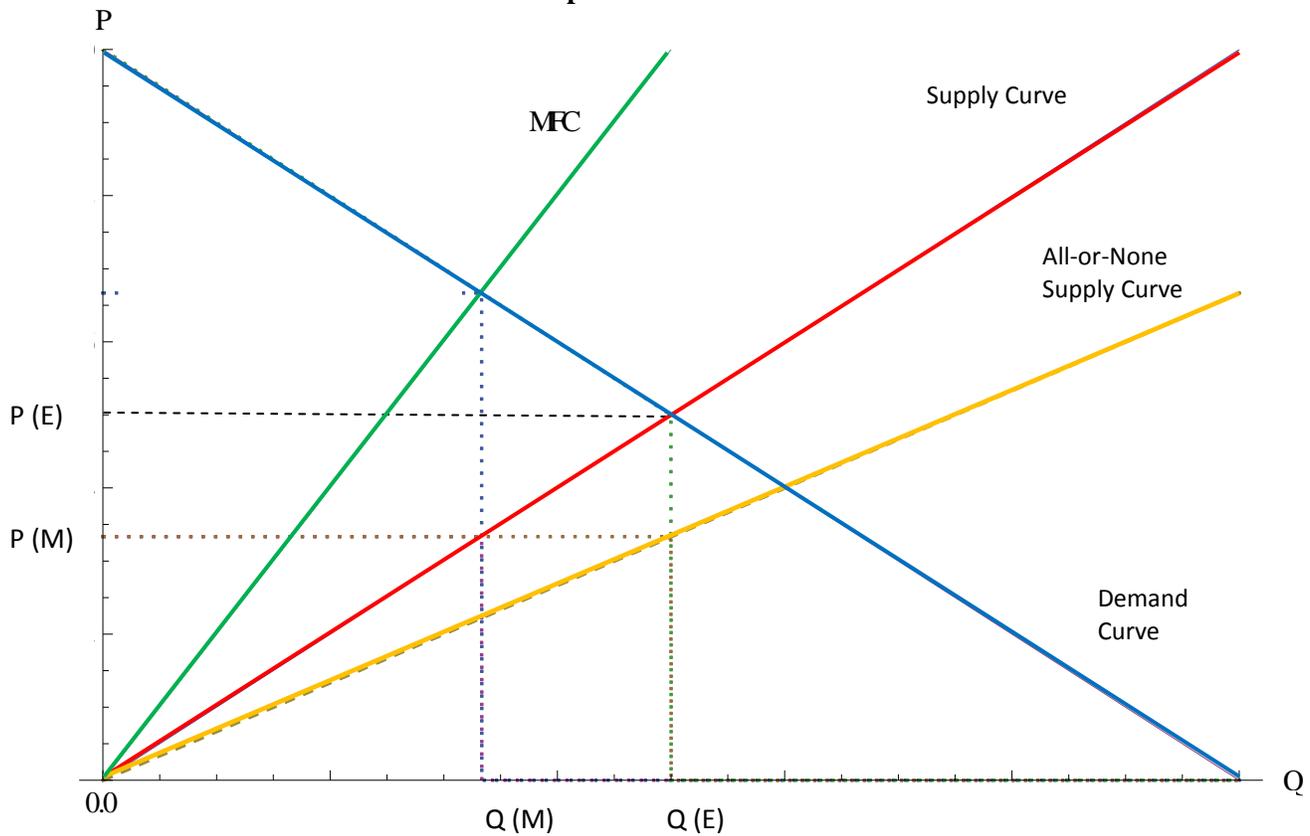
---

<sup>79</sup> For some of the hospitals included in my sample, HMO patients make up over half of their total admissions and approximately half of their inpatient hospital days in a given year.

<sup>80</sup> According to (Herndon 2002) the All-or-None Supply curve indicates the maximum quantity of a good that will be supplied at a specific price given that the alternate is to supply zero.

market when the market is competitive). Once a hospital is on its All-or-None supply curve, Figure 2 illustrates how the dominant firm in this case can obtain the same amount of output [Q (E)] at the lower price [P (M)] compared to when the hospital is on its regular supply curve [P (E)]. Thus the only difference between the All-or-None outcome and the efficient outcome is that the price in the input market is lower. On the other hand, in the classical monopsony setting (when the seller is on its regular supply curve), if a dominant buyer wanted to obtain the output at a lower price [P (M)] it would only be able to do so by restricting the quantity it buys below the efficient level to Q (M). Therefore, it is the existence of the All-or-None supply curve which makes it possible for the dominant HMO to obtain the input (inpatient hospital services) at the lower input price [P (M)] without having to restrict quantity as is typically the case in the traditional monopsony setting.

**Figure 2: Regular Supply Curve Verses All-or-None Supply Curve –  
Impact on Market Outcomes**



Similarly according to classic monopsony theory, when a dominant firm uses its buyer power to obtain a lower price from sellers, sellers can react by reducing the amount of output in the market. Thus an increase in buyer power is accompanied by both a decrease in price and quantity in the market below their competitive levels. However this is not what we observe in the market for hospital inpatient services. This is due to the fact that once a contract has been signed between a hospital and a health insurance provider a hospital cannot refuse to treat any of the provider's enrollees.<sup>81</sup> Thereby, the hospital cannot respond in the traditional manner that we typically observe in the case of buyer power in other markets: it cannot reduce quantity

<sup>81</sup> Herndon (2002) discusses both the contract provisions that limit a hospital's ability to adjust quantity of medical services it provides in response to lower reimbursement rates and a number of factors that deter providers from renegeing on their contractual obligations.

of medical services it provides.<sup>82</sup> Thus a dominant HMO in this market is able to obtain the same amount of inpatient hospital services for their enrollees at a lower price.

There are a number of welfare effects of the All-or-None Model of buyer power in the market for inpatient hospital services. I will begin by discussing the short-run effects in this market. First, there is a transfer of profits from hospitals to HMOs (the dominant health insurance provider). This occurs due to the fact HMOs are able to obtain the same quantity of medical services for their enrollees at a lower price.<sup>83</sup> By doing so, an HMO is able to maintain the attractiveness of its health insurance product to both current and potential enrollees. Next, since the dominant HMO's enrollees are still able to obtain the same quantity and quality of medical services, they are not negatively impacted by the existence of a dominant buyer in this market. In fact, depending upon if the dominant HMO passes any of their savings onto their enrollees in the form of lower premiums or co-payments, then their enrollees may actually be better off.<sup>84</sup> However, there is nothing forcing HMOs from passing their savings onto their enrollees, nor do I analyze the impact of HMO buyer power on the premiums they charge enrollees and their employers in this study. In order to determine the welfare effects that HMO buyer power has on consumers of health insurance (a HMO's enrollees) one must combine my research with research that looks at the effects of HMO buyer power on employee and employer premiums. Thus, I am unable to conclude the impact that changes in HMO buyer power will have on the consumers of medical service (a HMO's enrollees) in the short-run.

---

<sup>82</sup> However, this does not mean that a hospital cannot respond to the lower input price in the long-run by trying to limit or reduce the number of medical services covered under the contract. It is possible that a hospital could retaliate by shifting medical services from inpatient services to outpatient treatments (Robinson 1996).

<sup>83</sup> This boils down to a simple transfer of producer surplus to consumer surplus. In the market for inpatient hospital services, hospitals are the sellers and health insurance providers (HMOs) are the buyers.

<sup>84</sup> According to theory, as long as the dominant HMO faces a downward sloping demand curve from the consumers, it will find it profit-maximizing to pass-through (at least in part) the reduction in hospital prices to consumers in the form of lower premiums.

While in the short-run the effects of the All-or-None Model are purely distributional, this is not the case in the long-run. In the long-run, hospitals (producers) may be forced to exit the market if the input price offered by the dominant HMO is below their costs of production.<sup>85</sup> In fact, there have been a number of lawsuits brought by medical providers against health insurers involving their monopsonistic pricing strategies which fit the All-or-None model (Blair and Harrison 2009).<sup>86</sup> If hospitals are forced to exit the market, then the consumers of medical services (a HMO's enrollees) will be worse-off. However, a dominant insurer does not want this exit to occur, as it would reduce the supply and thereby alter the All-or-None price and quantity. Similarly, if hospitals were to exit the market this would negatively impact the value of a health insurer's insurance product to potential and current enrollees. Therefore, the dominant provider will try to keep these hospitals in the market in other ways (i.e. make lumpy cash handouts in the form of low-interest loans or grants). Thus a long-run characteristic of All-or-None Model in the market for inpatient hospital services is that some hospitals will be forced to exit the market and a "dependency relationship" (in the form of periodic lumpy payments) may arise between the remaining hospitals in the market and the dominant buyer.

## **VIII. Conclusions and Further Research**

In my research I examine the effect of HMO buyer power on both the price and quantity of inpatient hospital services received by HMO enrollees. I control for HMO buyer power using

---

<sup>85</sup> From the hospitals' point of view, a monopsony is bad (low price and low quantity), but an all-or-none supply contract is worse (zero or very little surplus left to the hospital/seller).

<sup>86</sup> In Blair and Harrison (2009), the authors claim that the following cases in the health care market appear to fit the All-or-None Model: *Kartell v. Blue Shied of Massachusetts* (1984), *Med. Arts Pharmacy of Stamford, Inc. v. Blue Shield of Connecticut* (1982), *Travelers Insurance Company v. Blue Cross of Connecticut, Inc.* (1973), and *Pa. Dentist Association v. Medical Services Association of Pa.* (1983). Furthermore, Herndon (2002) also discusses in her article how the particulars of *Kartell v. Blue Shield of Massachusetts* appear to be similar to the All-or-None Model.

two different measures: the market share of the Dominant HMO and HMO HHI. At the same, I control for another aspect of the HMO market structure which I refer to as HMO penetration. By doing so, I am able to obtain a more precise measure of the effect of HMO buyer power in the market for inpatient hospital services. The results listed in Table 8 and Table 9 indicate that an increase in HMO buyer power will have a negative impact on both HMO price per admission and HMO price per inpatient day. This effect is consistent with the three theories of health insurance provider buyer power in the market for hospital inpatient services: Monopsony Theory, Welfare-Increasing Theory, and All-or-None Theory. The results in Table 10 and Table 11 depict that HMO buyer power has no impact on the utilization of inpatient hospital services by HMO enrollees. Thereby, an increase in HMO buyer power has no effect on either the number of hospital admissions per HMO enrollee or inpatient days per HMO enrollee. This result is only consistent with the All-or-None Theory of HMO buyer power. To date, this is the only study that has empirically tested the All-or-None Theory. Due to the extensive number of individuals who are enrolled in HMOs in the US, the results identified in this paper will likely have a significant impact on a large percentage of the population.

The ultimate short-run effect of buyer power in the All-or-None Model is that a dominant health insurance provider gains increased profits at the expense of the hospitals they contract with. This is consistent with what Feldman and Wholey (2001) describe as the “monopoly-busting” effect of HMO buyer power whereby an increase in HMO buying power will lead to the break-up of hospital monopoly power. Whether or not increased HMO buyer power will help to control healthcare costs in the US or ultimately increase consumer (i.e. health insurance enrollees) surplus will depend upon if the price savings HMOs obtain are dissipated to consumers, in the form of lower premiums, or merely redistributed from hospitals to health

insurance providers. The long-run effects of the All-or-None Model will depend upon the degree to which hospitals exit the market.

There are a number of limitations of this study due to a lack of available data in this market. First, at present I do not control for the market structure or share of any of the other buyers of hospital inpatient services. This is especially problematic if one assumes health insurance is one giant market rather than just made up of a number of smaller markets based upon the specific insurance product. It would be interesting to see if the results continue to hold when one controls for the market share and market structure of other buyers in the market for hospital services. Second, in my current analysis I am unable to calculate hospital specific values of HMO buyer power. Instead I am forced to assign these values to hospitals based upon their geographic location. As such, hospitals in the same geographic region are assigned the same values of HMO HHI and Dominant HMO Market Share. Third, presently I am using data from only a single state to estimate the effect of the HMO buyer power on the price and quantity of inpatient services for HMO enrollees. It would be interesting to see if the effects of HMO buyer power are consistent to the results of the present analysis when one uses data from states other than Florida. Finally, my research is limited to the effects of HMO buyer power on the market for inpatient hospital services. It is naïve to assume that HMO buyer power could have an impact on inpatient hospital services without at the same time having an impact on outpatient services. There are a number of studies that have found evidence of HMOs shifting inpatient services to outpatient procedures.<sup>87</sup> Future research on this topic may want to consider all of these issues.

---

<sup>87</sup> In Robinson (1996), the author found that HMOs gain most of their cost savings by shifting inpatient services to outpatient procedures via payment incentive to medical service providers and administrative controls.

## References

- Abraham, J., M. Gaynor and W. Vogt. 2003. "Entry and Competition in Local Hospital Markets" CMPO Working Paper Series No. 03/088.
- Baker, L. and M. Brown. 1999. "Managed Care, Consolidation among Health Care Providers, and Health Care: Evidence from Mammography." *RAND Journal of Economics*, 30(2): 351-374.
- Baker, L. and K. Corts. 1996. "HMO Penetration and the Cost of Health Care: Market Discipline or Market Segmentation?" *American Economic Review*, 86(2): 389-394.
- Baker, L. and M. McClellan. 2001. "Managed Care, Health Care Quality and Regulation." *Journal of Legal Studies*, 30(2): 715-742.
- Bates, L., and R. Santerre. 2008. "Do Health Insurers Possess Monopsony Power in the Hospital Service Industry?" *International Journal of Health Care Finance and Economics*, 8: 1-11.
- Bilotkach, V. and V. Pai. 2009. "Hubs Versus Airport Dominance." [http://www.socsci.uci.edu/~vbilotka/Bilotkach\\_Pai\\_February09%20v2.pdf](http://www.socsci.uci.edu/~vbilotka/Bilotkach_Pai_February09%20v2.pdf).
- Blair, R. and J. Harrison. 2009. "The Antitrust Response to Monopsony and Collusive Monopsony." In *Monopsony in Law and Economics*, New York: Cambridge University Press.
- Bound, J., D. Jaeger and R. Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak." *Journal of American Statistical Association*, 90(43): 443-450.
- Bradford, W. and H. Krumholz. 2003. "The Effect of Managed Care Penetration on the Treatment of AMI in the Fee-For-Service Medicare Population." *International Journal of Health Care Finance and Economics*, 2: 265-283.
- Cicchetti, C. and J. Makhholm. 1988. "Pareto Optimality Through Non-Collusive Bilateral Monopoly with Cost-of-Service Regulation." NBER Working Paper.
- J. Cohen and P. Cohen. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*. 3rd ed. Mahwah, New Jersey: Lawrence Erlbaum Associates, Inc.
- Cunningham, P. and L. Kohn. 2000. "Health Plan Switching: Choice of Circumstance?" *Health Affairs*, 19(3): 158-164.
- Dranove, D., A. Gron, and M. Mazzeo. 2003. "Differentiation and Competition in HMO Markets." *The Journal of Industrial Economics*, 51(4): 433-454.
- Dranove, D., M. Shanely, and W. White. 1991. "How Fast Are Hospital Prices Really Rising?" *Medical Care*, 29(8): 690-696.
- Dranove, D., M. Shanely, and W. White. 1993. "Price and Concentration in Hospital Markets: the Switch from patient-Driven to Payer-Driven Competition" *Journal of Law & Economics*, 36: 179-204.

- Dranove, D., C. Simon and W. White. 1998. "Determinants of Managed Care Penetration." *Journal of Health Economics*, 17: 729-745.
- Feldman, R., H. Chan, J. Kralewski, B. Dowd, and J. Shapiro. 1990. "Effects of HMOs on the Creation of Competitive Markets for Hospital Services." *Journal of Health Economics*, 9: 207-222.
- Feldman, W., and D. Wholey. 2001. "Do HMOs Have Monopsony Power?" *International Journal of Health Care Finance and Economics*, 1: 7-22.
- Frank, G. and W. Welch. 1985. "The Competitive Effects of HMOs: A Review of the Evidence." *Inquiry*, 22(Summer): 148-161.
- Frech H. and P. Ginsberg. 1978. "Competition Among Health Insurers." In *Competition in the Health Sector: Past, Present, and Future*, ed. Warren Greenberg, 167-188. Germantown, Maryland: Aspen Systems.
- Gaskin, D. and J. Hadley. 1997. "The Impact of HMO Penetration on the Rate of Hospital Cost Inflation, 1985-1993." *Inquiry*, 34(Fall): 205-216.
- Gaynor, M. and D. Haas-Wilson. 1999. "Change, Consolidation, and Competition in Health Care Markets." *Journal of Economic Perspectives*, 13(1): 141-164.
- Gaynor, M. and W.B. Vogt. 2007. "Antitrust and Competition in Health Care Markets." In *Handbook on Health Economics*. Vol. 1B, ed. A. Culyer and J. Newhouse, 1405-1488. Oxford, England: North Holland.
- Goldberg, L. and W. Greenberg. 1980. "The Competitive Response of Blue Cross to the Health Maintenance Organization." *Economic Inquiry*, 18: 55-68.
- Goldberg, L. and W. Greenberg. 1981. "The Determinants of HMO Enrollment and Growth." *Health Services Research*, 16(4): 421-438.
- Hay, J. and M. Leahy. 1984. "Competition among Health Plans: Some Preliminary Evidence." *Southern Economic Journal*, 50(3): 831-846.
- Heckman, J. and E. Learner. 2007. *Handbook of Econometrics*. Vol. 6A, Oxford, England: North Holland Press.
- Herndon, J. 2002. "Health Insurer Monopsony Power: the All-or-None Model." *Journal of Health Economics*, 21: 197-206.
- Ho, K. 2009. "Insurer-Provider Networks in the Medical Care Market." *American Economic Review*, 99(1): 393-430.
- Hogan, C. 2008. "Patterns of Travel for Rural Individuals Hospitalized in New York State: Relationships between Distance, Destination, and Case Mix." *The Journal of Rural Health*, 4(2): 29-41.
- Irving Levin Associates. 2006. *The Health Care Acquisition Report*, 12th ed. Canann, Connecticut: Irving Levin Associates, Inc.

- Luft, H. 1978. "How do Health-Maintenance Organizations Achieve Their 'Savings'?" *The New England Journal of Medicine*, 298(24): 1336-1343.
- Luft, H. 1980. "Trends in Medical Care Costs: Do HMOs Lower the Rate of Growth?" *Medical Care*, 18(1): 1-16.
- McCarthy, T. 2003. "Health Insurance Monopsony Issues: Product Market Definition." <http://www.nera.com/image/6018.pdf>.
- McLaughlin, C. 1987. "HMO Growth and Hospital Expenses and Use: A Simultaneous-Equation Approach." *Health Services Research*, 22(2): 183-205.
- McLaughlin, C. 1988. "The Effect of HMOs on Overall Hospital Expenses: Is Anything Left after Correcting for Simultaneity and Selectivity?" *Health Services Research*, 23(3): 421-441.
- McLaughlin, C., J. Merrill and A. Freed. 1984. "The Impact of HMO Growth on Hospital Costs and Utilization." In *Advances in Health Economics and Health Services Research*, Vol. 5, ed. R. M. Scheffler and L.F. Rossiter, 57-93. Greenwich, CY: JAI Press Inc.
- Miller, R. and H. Luft. 2002. "HMO Plan Performance Update: An Analysis of the Literature, 1997-2001." *Health Affairs*, 21(4): 63-86.
- Morrisey, M. 2001. "Competition in Hospital and Health Insurance Markets: A Review and Research Agenda." *Health Services Research*, 36(1): 191-221.
- Morrisey, M. and C. Ashby. 1982. "An Empirical Analysis of HMO Market Share." *Inquiry*, 19(Summer): 136-149.
- Morrisey, M., F. Sloan and J. Valvona. 1988. "Defining Geographic Markets for Hospital Care." *Law and Contemporary Problems*, 51(2): 165-194.
- Motta, M. 2004. *Competition Policy: Theory and Practice*. New York: Cambridge University Press.
- Pauly, M. 1998. "Managed Care, Market Power, and Monopsony." *Health Services Research*, 33(5): 1439-1460.
- Robinson, J. 1933. *The Economics of Imperfect Competition*. London: Macmillan.
- Robinson, J. 1991. "HMO Market Penetration and Hospital Cost Inflation in California." *The Journal of the American Medical Association*, 266(19): 2719-2723.
- Robinson, J. 1996. "Decline in Hospital Utilization and Cost Inflation Under managed Care in California." *The Journal of the American Medical Association*, 276(13): 1060-1064.
- Schneider, J., P. Li, D. Klepser, N. Peterson, T. Brown, and R. Scheffler. 2008. "The Effect of Physician and Health Plan Market Concentration on Prices in Commercial Health Insurance Markets." *International Journal of Health Care Finance and Economics*, 8: 13-26.

- Shen, Y., V. Wu, and G. Melnick. 2008. "The Changing Effect of HMO Market Structure: An Analysis of Penetration, Concentration, and Ownership Between 1994-2005." NBER Working Paper #13775.
- Sorensen, A. 2003. "Insurer-Hospital Bargaining: Negotiated Discounts in Post-Deregulation Connecticut." *The Journal of Industrial Economics*, 51(4): 469-490.
- Staiger, D. and J. Stock. 1997. "Instrumental Variables Regression with Weak Instruments" *Econometrica*, 65(3): 557-586.
- Tariff, T. and D. Weisman. 2009. "The Dominant Firm Revisited." *Journal of Competition Law and Economics*, 5(3): 517-536.
- United States Department of Justice and Federal Trade Commission. 1997. *Horizontal Merger Guidelines*, Revised April 8, 1997.
- United States v. Aetna. 1999. No.: 3-99CV1398-H (N.D. Texas) Revised Competitive Impact Statement filed August 3.
- Verbeek, M. 2000. *A Guide to Modern Econometrics*. West Sussex, England: John Wiley and Sons Ltd.
- Vogt, W. and R. Town. 2006. "How has Hospital Consolidation Affected the Price and Quality of Hospital Care?" Robert Wood Johnson Foundation Research Synthesis Report 9.
- Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: the MIT Press.
- Wooldridge, J. 2009. *Introductory Econometrics: A Modern Approach*, 4th ed. Mason, Ohio: South-Western Cengage Learning.

## **Appendix**

### **I. Explanatory Variables**

The following are detailed descriptions of how all of the explanatory variables used in my price and quantity analyses were constructed.

In order to calculate case mix index (CMI), one uses the primary diagnostic code (DRG) assigned to each patient by their hospital of origin (the hospital where they receive their medical treatment). All hospitals in Florida use the same DRGs for each illness. Once a patient's DRG is identified, to determine case mix index one must use the DRG weights assigned by CMS to each specific DRG. The DRG codes are constant across all years (aside from the addition of new inpatient hospital services); however the DRG weight for a particular DRG can change from year to year. In this manner, CMS determines the relative "weight" or severity of each hospital service (for a given year) and assigns a corresponding reimbursement amount to it. Thus more severe cases or services are assigned higher DRG weights because it is assumed hospitals will have to use a greater amount of resources to treat these cases. Thus using the DRG codes from the AHCA Patient Discharge Data and the DRG weight information for the appropriate year from CMS one is able to calculate each HMO patient's case mix index. A single annual HMO CMI is calculated for each hospital in my sample. In order to have just a single (annual) HMO CMI for each of my hospital observations, I calculate an average HMO CMI for each hospital by summing all HMO patient case-mix-index (for a given hospital in a single year) and dividing it by the total number of HMO patients treated at that hospital in the given year. The values of average hospital HMO case mix index in the sample range from 0.475 to 3.622, with a mean value of 1.085.

Number of hospital beds, ownership status, teaching status and network status are determined on the hospital level using the AHCA Hospital Financial Data. The values of hospital beds in the sample range from 15 to 1745, with a mean value of 315.878. Ownership status, teaching status, and network status are all binary variables where a value of 1 was assigned to hospitals that were nonprofit hospitals, teaching hospitals, or part of a larger hospital network (respectively) and all for-profit hospitals, non-teaching hospitals, and standalone hospitals were assigned a value of 0 (respectively). Approximately 41% of the sample hospitals are nonprofit hospitals. In addition, approximately 3% of the sample hospitals are teaching hospitals. Approximately 66% of the sample hospitals are part of larger hospital networks.

To determine the wage index of each hospital in my sample, one must use the hospital county wage index generated by CMS. This index is used to account for differences in labor and input costs between hospitals depending upon where they are geographically located. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate wage index for their county for each year. The annual values of hospital wage index in the sample range from 0.836 to 1.071, with a mean of 0.950.

To calculate the hospital market concentration (hospital HHI) one must first determine the primary service area for each hospital in the sample. According to the Elzinga-Hogerty 75% Rule, a hospital's primary service area (PSA) is the geographic location from which they received 75% of their total patients (Vogt and Town 2005; Morrissey, Sloan and Valvona 1988). To generate each hospital's PSA, the zip code of origin that is listed for each patient in the AHCA Patient Discharge Data can be used.<sup>88</sup> Thus each hospital's PSA is the group of zip codes

---

<sup>88</sup> For this matter, patients with missing or incomplete zip code information were also excluded from the sample because they could not be used to determine the size of each hospital's PSA.

from which they receive 75% of their total patients (Morrisey, Sloan and Valvona 1988). The zip codes included in a given hospital's PSA can vary year from year depending upon the origin of their patients. Thus I calculated a different PSA for each hospital in my sample using each separate year of data. One must then use this PSA information to calculate each hospital's annual HHI. This is done by determining the market share of all other hospitals that receive patients from the zip codes that comprise a hospital's PSA. Finally, HHI is calculated by squaring and then summing all of the market shares of all competing hospitals in a particular hospital's PSA. Thus each hospital in the sample is assigned a unique HHI somewhere between 0 and 1. Where hospitals that are in very competitive markets (i.e. face lots of competition from other hospitals for patients) have low HHI values, and hospitals that face little or no competition have higher values. The annual values of hospital HHI included in the sample are between 0.003 and 0.403 with a mean of 0.066.<sup>89</sup>

To determine the average county income of each hospital in my sample, one must use the average annual pay data generated by the Bureau of Labor Statistics. This variable is used to account for differences in the input costs and patient bases between hospitals depending upon where they are geographically located. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate income data for their county for each year. The annual values of County Income (in thousands) in the sample range from 20.837 to 40.599, with a mean of 32.939.

---

<sup>89</sup> I also calculated each hospital's PSA using the geographic location (zip codes) where they received 85% and 90% of their total patients respectively. As expected these resulted in hospital HHI values that were slightly smaller than current values included in my analysis. The results of my analysis do not vary when I use Hospital HHI calculated using either an 85% PSA or a 90% PSA.

To determine the total county population of each hospital in my sample, one must use county population data generated by the Florida Legislature Office of Economic and Demographic Research. This variable is used to account for differences in market sizes between hospitals depending upon where they are geographically located. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate total population data for their county for each year. The annual values of County Population (in ten-thousands) in the sample range from 1.886 to 242.208, with a mean of 92.080.

To determine the share of the total county population eligible for Medicare of each hospital in my sample, one must use data on the number of individuals that are eligible for Medicare generated by CMS and the county population data generated by the Florida Legislature Office of Economic and Demographic Research.<sup>90</sup> This variable is used to account for the fact that the share of county population that is eligible for Medicare (i.e. not an HMO enrollee or potential HMO enrollee) could impact HMOs ability to negotiate more favorable contract terms with hospitals for their members. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate Medicare Eligible Share for their county for each year. The annual values of Medicare Eligible Share in the sample range from 0.092 to 0.328, with a mean of 0.182.

---

<sup>90</sup> According to CMS, an individual is considered to be eligible for Medicare if they are either currently or formerly entitled or enrolled in either part A or part B original Medicare.

## **II. IVs for HMO Concentration**

As previously discussed, there are two potential supply side IVs for HMO Concentration which reflect the local medical care market conditions: the average market share of the Dominant HMO in the surrounding geographic areas and the average HMO HHI in the surrounding geographic regions.

To determine the average Dominant HMO Market Share in the surrounding geographic areas, one must first determine what comprises the surrounding geographic area for each geographic region (county) in Florida where a county's surrounding geographic area is made up of all the other counties that border it. In order to construct the market share of the Dominant HMO in a given geographic market, I use data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county. From this data source I am also able to determine the number of HMO enrollees for each individual HMO that has members in this county. To calculate the market share of the Dominant HMO, I simply divide the total number of enrollees from the largest HMO in a given county by the total number of HMO enrollees in that county. I then take the average of the Dominant HMO Market Shares in all of the surrounding geographic areas (counties). The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate average Dominant HMO Market Share in the surrounding geographic areas for their county for each year. The annual values of Surrounding Area Average Dominant HMO Market Share range from 0.188 to 0.892, with a mean of 0.468.

To determine the average HMO HHI in the surrounding geographic areas, one must first determine what comprises the surrounding geographic area for each geographic region (county) in Florida where a county's surrounding geographic area is made up of all the other counties that

border it. In order to construct HMO HHI within a given geographic market I use data from the Florida Office of Insurance Regulation regarding the total number of HMO enrollees per county. From this data source I am also able to identify the number of HMO enrollees for each individual HMO that has members in this county. I first calculate the market share of all the individual HMOs in a given county simply by dividing the total number of enrollees for a given HMO in the county by the total number of HMO enrollees in that county. The level of HMO concentration is calculated by squaring and then summing all of the market shares of all competing HMOs in a particular county. Finally, the AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate average HMO HHI in the surrounding geographic areas for their county for each year. The annual values of Surrounding Area Average HMO HHI range from 0.137 to 0.831, with a mean of 0.358.

### **III. IVs for HMO Penetration**

As previously discussed, there are four potential demand side IVs for HMO Penetration which reflect the population demographics in the geographic market including: (1) the share of the county population that is over 65 and thereby not potential HMO enrollees; (2) the share of the county population that is female; (3) the share of the county population that is white; and (4) the unemployment rate of the county.

To determine the share of the county population that is over 65 for each hospital in my sample, one must use county population demographic data generate by the Florida Legislature Office of Economic and Demographic Research. The share of population over 65 is generated by dividing the total number of the county population that was over 65 (for a given county in a

single year) and dividing it by the county's total population in a given year. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate over 65 share of population data for their county for each year. The annual values of share of Population that is over 65 in the sample range from 0.082 to 0.343, with a mean of 0.179.

To determine the share of the county population that is female for each hospital in my sample, one must use county population demographic data generate by the Florida Legislature Office of Economic and Demographic Research. The share of population that is female was generated by dividing the total number of the county population that is female (for a given county in a single year) and dividing it by the county's total population in a given year. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate female share of population data for their county for each year. The annual values of share of Population that is female in the sample range from 0.432 to 0.526, with a mean of 0.511.

To determine the share of the county population that is white for each hospital in my sample, one must use county population demographic data generate by the Florida Legislature Office of Economic and Demographic Research. The share of population that is white was generated by dividing the total number of the county population that is white (for a given county in a single year) and dividing it by the county's total population in a given year. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate share of population that is white data for their county for each year. The annual values of share of Population that is white in the sample range from 0.585 to 0.962, with a mean of 0.822.

To determine the unemployment rate of each hospital in my sample, one must use the annual county unemployment rate data generated by the Bureau of Labor Statistics. The AHCA Financial Data was used to identify which county in Florida each hospital in the sample is located in. Therefore each hospital in the sample was assigned the appropriate unemployment rate data for their county for each year. The annual values of County Unemployment Rate in the sample range from 2.7 to 8.2, with a mean of 4.840.