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Abstract of Dissertation Presented to the Graduate School
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THREE ESSAYS ON HEALTH ECONOMICS

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There are approximately 4 million babies born every year in the United States. My research investigates two distinct issues that may affect both health outcomes of newborns and mothers as well as the costs of their care. The first chapter introduces the issues of hospital competition. In the second chapter, I find that increased levels of hospital competition lead to better outcomes for some premature babies. The third chapter investigates the relationship between competition and prices. I find that increased competition leads to lower prices and this effect is greater for the lower cost, i.e., least complicated patients. The fourth chapter investigates physician decision making in response to medical malpractice lawsuits. I show that doctors respond to lawsuits by increasing the number of caesarean sections performed, a result consistent with defensive medicine.

CHAPTER 1
INTRODUCTION

With approximately 4 million babies born every year in the United States, Caesarean sections, and other obstetrics procedures, are some of the most common medical procedures performed. At the same time, obstetrics patients are rarely the focus of health economics research. Little is known about the effects of competition on procedure use or health outcomes in this patient population. Health care costs are a growing concern in America. Much academic research has investigated the causes of growing medical costs and, more recently, the benefits and determinants of procedure use. Frequently, health economists rely on Medicare data as it is readily available for all states. By construction, Medicare patients are older and this data ignores a large section of hospital admissions. My research uses data on obstetrics admissions, both mothers and babies. The vast majority of these patients are healthy and young which leads to a considerably different population to study. With this data, I study the effects of hospital regulation on health outcomes and prices. I also use this data to investigate the effects of malpractice lawsuits on physician procedure use.

Researchers have documented vast differences in procedure use among different geographic areas that lead to higher health care costs without corresponding health improvements. It is unclear whether the tendency to use Medicare data skews these conclusions. It is reasonable to assume that the underlying distribution of health outcomes differs between Medicare Patients and new mothers and babies. The cause of procedure use variation is still an open question. While it is possible that some of these differences are due to patient and physician preferences, the wide range of legal and competitive environments may be responsible. Obstetrics data sheds new light on these issues.

In my first chapter, I use the repeal of Certificate of Need (CON) regulations as a proxy for hospital competition and study the effects of this competition on newborn health outcomes. These regulations started in New York in 1965 with the intent of controlling health care costs. At the time, hospitals were paid on a cost-plus basis. That is, their costs were covered plus a given percentage as profit. Because of this regulatory structure, hospitals had no incentives to control costs since they were all but guaranteed of covering them. There was also a fear that as insurance dulled the price sensitivity of consumers, hospitals in competitive markets would engage in a “medical arms race” and supply a socially excessive amount of medical care.

Federal regulation in 1972 required hospitals to obtain state approval of capital improvements in order to receive Medicare/Medicaid payment for health care that used these improvements. In 1974, federal regulation required all states to implement a CON program by 1980. In the early 1980s the federal requirement for CON programs was repealed. In the following year, 14 states eliminated their CON laws. This framework allows me to study the relationship between changes in hospital competition and health outcomes.

I find that most babies benefit from being born in a state without Certificate of Need. It appears that the repeal of these laws does not have an immediate effect on newborn health, but outcomes shift over a period of time. In the short run, very premature babies may be harmed by the repeal. However, it is possible that this effect is due to small sample issues.

The second chapter uses detailed hospital discharge data from Pennsylvania for all new mothers and babies in the years surrounding Pennsylvania's repeal of Certificate of Need regulations. I examine hospital competition as the regulatory regime changed and determine the type of hospital most likely to be affected by the repeal.

To measure hospital competition, I calculate a hospital-specific Hirschman-Herfindahl Index (HHI). Instead of using county borders as the definition of the hospital's market, the hospital-specific HHI uses a patient's zip code as the geographic market and constructs a weighted average of these smaller geographic areas. I argue that the hospital-specific HHI is superior to the standard HHI as, it measures each hospital's competitive environment at a much finer geographic level. I find that the repeal of CON did not have a measurable effect on hospital competition although, it appears that small hospitals in more competitive areas are more likely to close. I use the changing levels of hospital competition over these years to investigate the effects of competition on the prices charged by hospitals. I also find that increased levels of competition lead to lower prices.

The third chapter uses the same Pennsylvania discharge data to explore the effect of medical malpractice lawsuits on physician behavior. While there are a number of papers that investigate the issue of litigation induced medical procedures or "defensive medicine", this chapter directly measures how doctors respond when they are sued for malpractice. This is distinct from previous research which was not able to link an individual doctor's lawsuit experience with their procedure use and therefore looked at the how changes in the legal environment might be related to changing procedure use.

Using the data from Philadelphia and Allegheny Counties, I show that doctors increase the number of caesarean sections they perform after being sued for malpractice. This is consistent with the hypothesis of defensive medicine. I also find that doctors in Allegheny County respond to a lawsuit in a more dramatic fashion relative to doctors in Philadelphia County. It is possible that the larger number of lawsuits relative to Allegheny County causes doctors in Philadelphia to be hyper-sensitive to the threat of lawsuits given.

CHAPTER 2
CERTIFICATE OF NEED REGULATIONS AND HEALTH OUTCOMES

Introduction

Certificate of need regulations affect the number of hospitals in a community as well as the number and type of services that a hospital can provide. Initially designed to control costs, these regulations may limit competition and potentially impact the quality of healthcare. While there has been much research on the impact of Certificate of Need laws (CON) on health care costs, few have looked at the effect of these laws on health outcomes. In this paper, I document a negative correlation between Certificate of Need laws and health outcomes of newborn babies. Specifically, I use data from the U.S. Department of Health and Human Services Linked Birth/Infant Death File (which includes information from almost every birth certificate matched to the corresponding death certificate), and a difference-in-difference approach to show that babies in states with CON laws are less likely to be healthy (as measured by the 5-minute Apgar score). By comparing health outcomes in states that repealed their laws at different times, I also show that the positive effects, i.e., greater probabilities of a healthy birth, of removing CON restrictions is due to those states which repealed their laws at least 10 years earlier. In addition, these positive effects, of increased hospital competition, are greater for most premature births.

Certificate-of-Need regulations started in New York in 1965 with the intent of controlling health care costs. At the time, hospitals were paid on a cost-plus basis. That is, their costs were covered plus a given percentage as profit. Because of this regulatory structure, hospitals had no incentives to control costs since they were all but guaranteed of covering them. There was also a fear that as insurance dulled the price sensitivity of consumers, hospitals in competitive markets would engage in a "medical arms race" and supply a socially excessive amount of medical care.

Certificate of need requires state approval of a hospital's large capital projects, including either the expansion of existing facilities or the introduction of new services. For example, the purpose of Missouri's CON statute "is cost containment through health cost management, assurance of community need and the prevention of unnecessary duplication of health care services. CON is based on a goal of public accountability through public review of proposed health care services, value promotion and negotiation among competing interests" (Meier, July 2001). States differ on the level of investment or changes in the level of service (regardless of changes in capital) that requires prior approval. Often a decrease in the level of services as well as an increase must go through approval process.

Federal regulation in 1972 required hospitals to obtain state approval of capital improvements in order to receive Medicare/Medicaid payment for health care that used these improvements. In 1974, federal regulation required all states to implement a CON program by 1980. The "Reagan revolution" in the early 1980s removed the federal requirement for CON programs and, subsequently, some states eliminated their CON laws. However, most did not, and some expanded their programs. Currently, 14 states do not have a CON program (Table 2-1).

There is a perception within the health care industry that CON programs protect incumbents (i.e., Stigler's capture theory of regulation). The director of government relations for the Missouri State Medical Association said, “The Certificate of Need program has outlived its usefulness. It doesn’t do anything but stifle competition and innovation. It’s extremely bureaucratic, and no one relishes having to go through it. It’s the people who have existing projects who want it to continue. It helps them keep competition out of their backyard” (Meier, July 2001).

Economic theory suggests that certificate of need regulation will lead to inefficient results in competitive markets. However, the hospital market is far from competitive. There is a mix of non-profit and profit hospitals in most geographical markets. There are also areas with only one hospital. While there has been research on competition and medical care, there is not a generally accepted theory of how competition affects prices/costs and quality. As will be discussed, others have looked at the effects of competition and prices/costs. It is hypothesized that either prices/costs will be higher than they would be in the absence of pure competition or that quality will be lower. This can occur because incumbents are protected from competition because competitors (either new entrants or existing hospitals that wish to expand) must go through the certificate of need process. This process is costly and, in many states, an existing hospital is allowed to testify against a potential entrant. As with any market barrier, it is reasonable to expect less strenuous competition and possibly less innovation. If these barriers limit competition along both the price as well as the quality dimension, then it is reasonable to expect sub-optimal health outcomes in the states with CON requirements. Previous studies have shown that prices/costs tend to be higher in states with CON requirements; this paper shows that there is also a decrease in health outcomes in those same states.

Previous Literature

The existing literature on certificate of need and hospital competition covers two distinct areas. The earliest research looked at the impact of both CON regulation and its subsequent repeal in some states, as well as general competition within the health care market, on costs. More recently, researchers have begun to investigate the effect of competition, and specifically CON programs, on the quality of health care.

Certificate of Need and Costs

Sloan (1988) provides a detailed review of the early literature. In general, the early studies find that CON has no statistically significant effect on health care costs and most agree that if there were to be an effect, it would increase costs rather than lower costs. CON proponents argued that these early studies were flawed because of their limited time horizon immediately following the introduction of these programs. It was argued that the programs needed time to "get up and running" before they could be expected to control costs.

More recent studies have looked at longer periods of time and evaluated the effects of repeal of the programs (a good survey is Morrisey, 2000). These studies suggest that, if anything, CON programs have tended to increase costs (Sloan, Morrisey and Valvona, 1988) and found that the repeal of CON had no effect on hospital costs per capita (Sherman, 1988). Conover and Sloan (1998) found that "mature" CON programs result in a slight reduction in bed supply but higher costs and higher profits.

Antel, Ohsfeldt, and Becker (1995) analyzed hospital costs allowing for interaction between regulation programs other than CON. Using state data on hospitals costs per day, per admission, and per capita, they found that CON had no statistically significant effect in any of their empirical specifications. Health care costs and prices charged both increase with the duration of the CON program. Using Medicare price and cost data from 1977–78, Noether (1988) found prices were higher relative to costs and therefore profits were higher in states with a CON program. CON proponents also argued that hospitals were different than other industries and therefore competition did not, and could not, work. However, the empirical evidence does not support this. Melnick, et al. (1992) looked at transaction prices that a large California preferred provider organization (PPO) negotiated with hospitals in 1987. While controlling for many factors, they found that the PPO paid more in the less competitive markets. This suggests that competition does work to lower prices in hospital markets.

Certificate of Need and Quality

While much research has been done on the determinants of health care quality (see Tancredi, 1988 for a review), very little work has been devoted to examining the effects of health care regulation or competition on quality. In one of the few papers, Ho and Hamilton (2000) looked at the effects of hospital consolidation on health care quality. Analyzing California hospital care before and after mergers and acquisitions between 1992 and 1995, they looked at several proxies for quality of care. They find 90-day readmission rates for heart attack patients and discharges within 48 hours for normal newborn babies increased in some cases. While mortality and readmission rates are reasonable, though imperfect, metrics for health care quality, it is unclear that an increase in “early discharges” should be considered as such. The authors equate early discharge with cost cutting measures of hospitals, but the connection with quality is not discussed. Furthermore, they find no measurable effect on inpatient mortality for heart attack and stroke patients.

A recent paper by Kessler and McClellan (2000) looks at hospital competition and Medicare beneficiaries' heart attack care from 1985 to 1994. They find the welfare effects, i.e., expenditures and treatment and patient health outcomes, of competition to be ambiguous in the 1980s. However, in the 1990s, "competition unambiguously improves social welfare".

In addition to these papers on competition and the quality of healthcare, two papers have focused on the effect of CON regulations on Coronary Artery Bypass Graft (CABG) quality. Robinson, et al. (2001) looked at outcomes in Pennsylvania for the years 1994 – 1999. The elimination of the state's CON program is found to increase the number of open-heart surgery programs by 25% without a significant increase in the number of surgeries performed. With this limited sample, quality (as measured by the mortality rate) was not impacted by this reallocation of volume. Vaughan-Sarrazin, et al. (2002) consider a larger dataset of Medicare beneficiaries who underwent CABG surgery between 1994 and 1999. The authors find higher mortality rates for CABG patients in states without CON programs (5.1% compared to 4.4%). There is one potential problem with this paper, it compares cross-sectional differences across states. The authors cite several papers that point to a negative connection between hospital volume and mortality for CABG surgery. While they do not state such a hypothesis, it would appear that there is a type of "learning by doing" in open-heart surgery. This is a reasonable hypothesis as open-heart surgery is a complicated and lengthy process in which the skills of the surgeon and the other medical professionals could have a great impact on patient outcomes.

While the previous literature looked at both CON regulation and hospital competition as determinants of health care costs, the question how CON regulations affect health care quality has only begun to be addressed. This paper will attempt to evaluate the issue of certificate of need regulation, hospital competition and the quality of care. Specifically, the effect of CON regulation on the quality of neonatal care will be investigated.

Quality of Neonatal Health

Birth certificates in the United States record many different kinds of information about the parents as well as the baby. Information about both parent's socioeconomic background, as well as factors affecting the mother and baby's health are collected. One variable recorded is the "5-minute Apgar score" for the newborn baby. I use the Apgar score as a proxy for the quality of neonatal health.

The Apgar score is a subjective measure of the infant's condition based of heart rate, respiratory effort, muscle tone, reflex irritability, and color. Each of these factors is given a score of 0, 1, or 2; the sum of these 5 values is the Apgar score, which ranges from 0 to 10. A score of 10 is optimal, and a very low score raises a flag about the subsequent health and the survival of the infant. The Apgar score was designed to be a useful measure of the need for resuscitation and a predictor of the infant's chances of surviving the first year of life. A recent paper by Casey, et al. (2001) shows that for premature infants (26 to 36 weeks of gestation), the neonatal mortality rate was 315 per 1000 births for an infant with an Apgar score of 0–3, as compared with 5 per 1000 births for an infant with an Apgar score of 7–10. Similar results are demonstrated for full term babies.

Despite the emphasis placed on low birth weight and poor health outcomes, in the popular press, there is some evidence that low birth weight is not itself the sole predictor of infant mortality. One paper concludes that the threshold weight below which mortality is significantly greater is the 3rd percentile (McIntire, et al. (1999)). A recent working paper by Almond, et al. (2002) uses twins to compare the correlation between birth weight and various health outcomes. The authors find that the heavier twin is no more likely to survive past the first year than the lighter twin. They also find that the Apgar score is more highly associated with infant mortality but is not correlated with birth weight. This is because a low Apgar score may be caused by a birth trauma not related to prematurity. For these reasons, low birth weight is not used as a health outcome.

After consultation with a labor and delivery nurse, I chose Apgar scores of 8 and above to be healthy.[1] The reasoning for this is as follows, while the Apgar score is a subjective measure based on the health care professional's opinion, there appears to be some agreement on what score denotes a healthy baby. For example, one nurse may give a baby an Apgar score of 9 while another may give a score of 8, the score is different but both professionals would agree that the baby was healthy. It is highly unlikely that one professional would score a baby a 6 and another score the same child as an 8. In addition, while the percentage of Apgar scores either 9 or 10 have changed from 1983 to 1999, the percentage of Apgar scores greater than or equal to 8 has stayed relatively stable.[2] While the break between score of 8 and 9 appears to be the "natural" break (see Table 2-2), I have chosen to be conservative and defined the break point for health to be between 7 and 8.

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[1] As a robustness check, the same models were estimated with a cutoff of 7 or 9. The conclusions do not change with the different cutoff points.

[2] One potential reason for the shift from Apgar scores of 10 to Apgar scores of 9 is the increasing use of pain medication over this time period, specifically epidurals. These medications tend to "dull" the baby's responses and therefore affect the Apgar score.

Description of Data

The data set and the description of the variables are from the National Center for Health Statistics Matched Birth/Death Certificates file for 1983 and 1999. The beginning of the sample was chosen to be 1983 because in years preceding that time the Matched Birth/Death was incomplete for many of the states for earlier years. The data for 1983 are based on the total number of births in 46 states. In 1983, California, Delaware, Oklahoma and Texas did not report Apgar scores on their birth certificate therefore these four states were excluded from the sample. Unfortunately, California and Texas are two of the 15 states without a CON program. New Mexico was also dropped from the sample because it did not record gestational age in 1983. Louisiana was excluded from the analysis because it was the only state to not implement a CON regulation while it was required by the federal government[3]. Arizona, California, Delaware, and Georgia as well as the District of Columbia only reported a 50 percent random sample of their births.

The data set is limited to those births for which all variables of interest, described in the model specification section, are available. In order to control for differences in prenatal care in other countries, an observation was also dropped if the mother was a resident of another country[4]. We are left with 2,602,155 observations in 1983 and 2,920,950 observations in 1999, for a total of 5,523,105 observations.

Model Specification

The basic model estimated is,

$$outcome = X\beta + noCON89\alpha_1 + noCON99\alpha_2 + year99\alpha_3 + u_j + \varepsilon$$

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[3] Louisiana actually started its CON regulations in 1991, after 11 states had repealed their CON laws.

[4] Most of the discarded observations are lacking an Apgar score or gestational age.

where outcome is an indicator of either a healthy birth or a neonatal death. For the models that estimate the probability of a healthy birth, the dependent variable, is a dummy variable that takes the value of one if a baby has a 5-minute Apgar score greater than or equal to 8 depending on the model. Because the 5-minute Apgar score is a measure of health at the 5-minute mark, it is an imperfect measure of hospital quality at best. It is likely that many quality related problems would occur after the 5-minute mark and would not be picked up in this data. Nonetheless, it is reasonable to believe that some quality related problems would occur before the Apgar score. Because the vast majority of problems will not be captured in the Apgar score, the estimates can be considered a lower bound. The fact that we find any results with the healthy dependent variable, suggests that these laws have an effect.

Because the Apgar score may not pick up all health problems, the same model is estimated with the dependent variable an indicator of neonatal death. That is, the variable is equal to one if the baby died in its first year of life and is zero otherwise. If CON laws have an effect, we would expect the results to have opposite signs because of the nature of the indicators. For example, if CON laws are beneficial then the estimated coefficients on the noCON indicators will be negative if the dependent variable is healthy (indicating that dropping a state's CON program reduces the probability of a healthy baby). Similarly, the estimated coefficients will be positive for the noCON indicators if the dependent variable is death (indicating that dropping a state's CON program increases the probability of a baby dying in its first year).

The variables of interest are the noCON variables; noCON89 is a dummy variable that takes the value of one if the state has dropped its Certificate of Need program by

1989 and noCON99 is an indicator that is equal to one if the state dropped its CON program between 1990 and 1999. The noCON variables are the difference in differences estimates of the effect of dropping a state's certificate of need program either in the 1980s or the 1990s relative to the states that still maintain these regulations. That is, noCON89 is the difference between 1983 and 1999 in the difference between states with a CON program and those that dropped their CON program in the 1980s (a similar interpretation holds for noCON99). As previously mentioned, of the 45 states in the sample and Washington D.C., 14 had dropped their CON programs by 1999 (11 in the 1980s and 3 in the 1990s).

The obvious question is why did only some of the states repeal their regulations in the 1980s. And then why did the second wave of repeals occur in the 1990s. On the surface, endogeneity appears to be a problem. However, it is likely to be less of a concern than is initially apparent.

Omitted variables are the most common form of endogeneity; to the extent to which the underlying factors do not change much over time, the omitted variables problem is dealt with using state level fixed effects. If there are time-varying omitted variables, we may have a reverse causality problem. That is to say, the dependent variable influences the variable of interest. In this case, health outcomes, or underlying health trends, would have to affect the repeal of a state's certificate of need regulations. This is highly unlikely, in order for this to be true one would have to argue that politicians or bureaucrats observe a downward trend in health outcomes, relative to other states, and conclude that the way to fix this problem is through the repeal of the state's CON regulation. One could argue that obvious solution from a planner's perspective would be to argue for more regulation in this case, rather than less. If this is the case, then the potential bias in this case works against finding any effect from the repeal of CON.

The mother and child characteristics contained in X are: the mother's age at the time of birth and the baby's birth weight rounded to the nearest 100 grams[5]. (See Table 2-3). Year99 is an indicator that is equal to one if the year is 1999; while, u_j represents state fixed effects and ε is a random error.

All models are estimated as a linear probability model with state fixed effects to control for unobserved state specific variation. As the certificate of need laws vary at the state level, all of the standard errors are corrected for clustering of the errors at the state level as described in Moulton (1990). State fixed effects and state level laws imply that we are estimating probabilities at the state level, i.e., the average probability of a healthy baby in a state, conditional on observed characteristics. Because the vast majority of births in the United States are healthy ones, we are trying to explain a rare event, that of an unhealthy birth or a neonatal death. The rarity of this event, combined with the limited information recorded on the birth certificate, makes one suspect that a goodness of fit measure such as R^2 is going to be poor. Indeed, this is what is found for all of these models.

Results

As mentioned in the previous section, the dependent variable (Healthy) is an indicator equal to one if the Apgar score is greater than or equal to 8, and zero otherwise.

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[5] While birth certificates record other useful information, i.e mother's education, number of prenatal visits, etc. not all states report these variables. The model was limited to mother's age and birth weight to maximize the number of states included in the data. Gestational age is used in later models.

The coefficients all have the expected sign (see Table 2-4, column 1). The variable year99 is positive and significant, which suggests that the likelihood of a healthy baby increased from 1983 to 1999, given the advances in medical technology (such as fetal monitoring), this intuitively makes sense. The coefficient on birth weight is positive and statistically significant. Babies with higher birth weight are more likely to have an Apgar score of 8 or higher, an increase of one standard deviation (600 grams or 21 ounces) leads to an increase in the probability of a healthy birth by 4 %.

The variables of interest in this paper are the noCON indicators. This variable takes the value of one if a state does not have a Certificate of Need program and zero otherwise. The noCON89 coefficient is both statistically and economically significant. A baby born in a state that removed its CON program in the 1980s is .59 % more likely to be healthy than a baby born in a state with a CON program. While this may appear economically insignificant, the estimated increase in the probability of a healthy birth only increased 1.2% from 1983 to 1999. As the vast majority of babies are born healthy, it is impossible for the effect of CON repeal to lead to a large change in the likelihood of a healthy birth. The noCON99 coefficient is negative but not statistically significant. This implies that the states which dropped their restrictions on hospital competition in the 1990s did not see an increase in the likelihood of a healthy birth. This result is not surprising, since the entire 2nd wave of CON removals occurred in the later part of the 1990s.[6] The differential impact between the early and later groups implies a time lag between the removal of competition barriers and an increase in hospital competition or the increased competition's effect on health outcomes. Given the time required to

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[6] The three states that dropped their CON regulations in the 1990s did it in either 1995 or 1996

finance and construct major capital improvements, a delayed effect on health outcomes is not surprising. The lack of an effect implies that it takes time for there to be an increase in hospital competition and for this increase to have an effect on health outcomes. Given the length of time it takes to build new a hospital, a lag in the effect of removing constraints on competition is to be expected.

Because the Apgar score is an imperfect measure of a newborn baby's health, the same basic model was estimated with an indicator of neonatal death as the dependent variable. Again, the coefficients have the expected signs. An increase in the baby's weight of 600 grams (one standard deviation) leads to a 2% reduction in the probability of death. While the coefficient on mother's age is positive, indicating increasing age increases the chance of death, it is difficult to argue that the coefficient is economically significant. The coefficient on the year99 indicator is negative, which again makes sense given the improvements in medical technology. The coefficients on both of the noCON variables are statistically and economically insignificant. This is not completely unexpected since very few babies are so sick that they are in danger of dying. However, it raises the question of the effects of CON regulation on high-risk, i.e., premature, births. Because premature births are more likely to have health problems and are more likely to die, there is the possibility of more aggressive medical interventions and hence, more quality related issues.

The Interactions of Certificate of Need regulation and Premature Births: Because CON programs may affect neonatal health by limiting Neonatal Intensive Care Units (NICUs), the same model is estimated with the inclusion of different indicators of premature birth interacted with the certificate of need indicators as before. These high-risk births are more likely than a normal birth to require the services of a NICU. While not all premature births need a NICU, the presence of a NICU indicates that the hospital staff is more prepared to handle these high-risk births.

The average length of gestation is 39 weeks, while the definition of full term pregnancy is 40 weeks. Anything less than 37 weeks is considered premature and increases the risk of medical complications for the infant and the mother. Premature births are relatively rare in the data (approximately 10% are born at less than 36 weeks in 1983 and 12% in 1999). Of these premature births, the majority of premature births are born between 36 and 32 weeks (variable P36), this represents 7% of the total number of births in 1983 and 9% in 1999. As can be seen in Table 2-5, all types of premature births have increased relative to 1983.

Babies born premature are less likely to be healthy and more likely to die. Although these babies are less healthy, their prospects have improved over the time period. For those births with a gestational age between 32 and 36 weeks, the probability of being healthy has increased from 92% to 95%, while the mortality has decreased from 2% to 1%.

To test the effect of CON regulations on premature births, an indicator of prematurity is created that equals one if the baby had a gestational age of 36 weeks or less. The first of these models estimated is[7]

$$\begin{gathered} outcome = X\beta + noCON89\alpha_1 + noCON99\alpha_2 + \\ PRE\beta_1 + PRE \times noCON89\beta_2 + PRE \times noCON99\beta_3 + year99\alpha_3 + u_j + \varepsilon \end{gathered}$$

[7] The secondary interactions are not reported but are available upon request.

where PRE is an indicator of premature birth (i.e., PRE equals 1 if gestation is less than or equal to 36 weeks). The coefficient on the interacted term can be interpreted as a “difference in difference in differences” estimate. For example, the interaction of PRE with one of the noCON indicators gives us the “difference” between these high-risk births and other births in the “difference” between states with a certificate of need program and those without a program. Given that noCON is a difference in difference estimate, the coefficient on the interaction term is the difference in difference in differences estimate.

First, the model was estimated with health as the dependent variable. As expected, being born prematurely significantly reduces the probability of being healthy (-7.7%). The coefficient on the interaction of the noCON indicators with the premature indicator is positive for both the states that dropped their CON in the 1980s and in the 1990s. Again, we see that only the interaction with noCON89 is statistically significant. The estimated impact on premature babies is 1.98% (Column 1, Table 2-6) in those states that repealed their CON programs in the 1980s. These positive coefficients indicate that removing barriers to competition results in a higher likelihood of a healthy birth. As before, the higher probability of a healthy birth in the states that removed their CON restrictions in the 1980s versus those that removed the restrictions in the 1990s is reasonable given the time needed for increased competition to have an effect on health care. Again, this may appear to be a small effect. However, when compared to the average change in the probability of being healthy over this time period, the effect of CON repeal leads to a large increase.

Next, the same model was estimated with death as the dependent variable. As would be expected, being born prematurely increases the chance of death (2.96%). The interactions of the premature indicator and the noCON indicators are not as easy to interpret as with the health regression. Premature babies born in states that removed their CON restrictions in the 1990s are slightly more likely (.23%) to die relative to those states that still maintain CON restrictions. There is no statistically significant effect on those babies born in the states that removed their CON restrictions in the 1980s. This seems to imply that there are short run costs to the removal of CON, although this effect is small from an economic significance point of view.

Because it is possible that the effect of certificate of need regulation varies with the gestational age of the baby, indicators of prematurity by specific weeks are created. The variables P28, P32, P36 are indicators of premature births (i.e., P28 indicates gestation less than or equal to 28 weeks while P32 indicates gestation greater than 28 and less than or equal to 32 weeks).

These indicators of premature birth are interacted with the noCON indicators and the following model estimated is[8]:

$$
\begin{aligned}
&outcome = X\beta + noCON89\alpha_1 + noCON99\alpha_2 + year99\alpha_3 \\
&+ P28\beta_1 + P32\beta_2 + P36\beta_3 \\
&+ P28 \times noCON89\delta_1 + P32 \times noCON89\delta_2 + P36 \times noCON89\delta_3 \\
&+ P28 \times noCON99\gamma_1 + P32 \times noCON99\gamma_2 + P36 \times noCON99\gamma_3 \\
&+ u_j + \varepsilon
\end{aligned}
$$

[8] As before, the secondary interactions are not reported.

Not surprisingly, the probability of a healthy birth is monotonically increasing in the prematurity indicators and the probability of death is monotonically decreasing (Table 2-7). The extremely premature births (P28) are much less likely to be born healthy (47%) and more likely to die (34%) than a full term birth. The births with a gestational age between 28 and 32 weeks (P32) have a better chance of a healthy birth (17%) and are less likely to die (4%) than the extremely premature births. The babies born between 32 and 36 weeks are only slightly more likely to be unhealthy (3%) or to die (.25%) than a full term birth.

For all but the oldest premature births, the removal of CON restrictions does not appear to have an effect. For the P36 births, the interactions of the noCON indicators are positive for the health outcomes regardless of when the CON restrictions were removed. As before, the effect of removing the CON restrictions is larger for the states that repealed their laws in the 1980s versus those that repealed in the 1990s. These results are also economically significant given the reduced probability of being healthy if born prematurely (Table 2-5).

Again, we see an effect in the short run when the dependent variable is death. The interaction of noCON99 and P28 is positive (3.07%); indicating the repeal of Certificate of Need in the 1990s has led to an increase in mortality for the extremely premature births. We also see a decrease in mortality for the babies born between 28 and 32 weeks. The interaction of noCON99 and p32 is -.82%. It appears that these babies benefit from the repeal. There is no effect from the repeal of CON in the 1980s.

It is possible that these contradictory results are due to the small number of very premature babies, especially in those states that dropped their laws in the 1990s, in this data set. However there is a possible economic explanation for these results. The certificate of need process was not established simply to hinder competition but also to maintain acceptable levels of quality in the hospital industry. One argument in favor of the certificate of need process is to maintain a critical volume at area hospitals, especially in services like NICUs. It is conceivable that, in the short-term, the removal of CON leads to worse outcomes for very high-risk infants by expanding the number of places where a premature baby can be born within a geographical area. Newly opened hospital facilities may not have high enough volumes of these special needs of births to allow the medical staff to maintain their skills of a more established hospital.

A baby born with less than 28 weeks of gestation is extremely small and is likely to have health problems. A baby of this size is difficult to intubate or administer an I.V. to when such steps are necessary and problems in these processes could impact the 5-minute Apgar score. These are also tasks for which there may be “learning by doing” present. If experience leads to greater medical proficiency, learning by doing could result in better health outcomes in those hospitals that perform a large number of these procedures. This hypothesis would lead us to expect that very high-risk infants would be harmed by the repeal of CON regulations, as seen in these empirical findings. In the long-run, the repeal of CON regulations allows competitor hospitals to establish NICUs and to achieve high enough volume levels to improve outcomes. It is important to remember that the vast majority of births benefit immediately from the repeal of CON regulations and given time extremely premature births benefit as well.

Conclusion

Restricting competition within the hospital market appears to negatively affect the quality of care as measured by health outcomes. Complementing the earlier findings that certificate of need regulation does not control health care costs, this paper shows that CON regulations are associated with lower Apgar scores and a slightly higher incidence of neonatal deaths. However, a small subsection of high-risk births may benefit from a CON program. More research to determine the cause of this is necessary.

As this data does not include information on costs, it is impossible to say whether or not the certificate of need process is socially efficient. Yet, given the negative impact of these laws on the overwhelming majority of births, Certificate of Need regulations may not be the optimal social policy.

Table 2-1. States without Certificate of Need (CON)

State	Year Dropped
Arizona	1985
California*	1987
Colorado	1987
Idaho	1983
Kansas	1985
Minnesota	1984
New Mexico	1983
North Dakota	1995
Ohio	1995
Pennsylvania	1996
South Dakota	1988
Texas*	1985
Utah	1984
Wyoming	1985

* does not record Apgar scores

Table 2-2. Apgar scores

	1983				1999			
Apgar	Percent of Births	Total Number	Percent Dead	Total Died	Percent of Births	Total Number	Percent Dead	Total Died
0	0.06	1,547	0.61	950	0.07	2,164	0.55	1180
1	0.21	5,543	0.77	4284	0.18	5,263	0.82	4303
2	0.14	3,629	0.55	1989	0.08	2,415	0.56	1356
3	0.14	3,752	0.36	1333	0.09	2,607	0.32	826
4	0.20	5,285	0.23	1225	0.14	4,079	0.18	739
5	0.38	9,889	0.15	1468	0.25	7,357	0.12	872
6	0.79	20,680	0.08	1754	0.59	17,184	0.08	1354
7	1.99	51,743	0.04	1821	1.51	43,961	0.04	1596
8	8.72	226,889	0.01	2618	7.06	206,303	0.01	2140
9	62.62	1,629,369	0.00	6699	82.05	2,396,692	0.00	5492
10	24.74	643,829	0.00	2102	7.97	232,925	0.00	439
Total		2,602,155	1.01	26,243		2,920,950	0.69	20,297

Table 2-3. Summary statistics (standard deviations in parentheses)

Variable	1983	1999	Total
Mom's Age	25.554	27.209	26.429
	(5.307)	(6.156)	(5.831)
Birth Weight (100s grams)	33.514	33.144	33.319
	(5.944)	(6.152)	(6.058)
Gestation (weeks)	39.405	38.772	39.070
	(2.825)	(2.620)	(2.737)
Healthy	0.961	0.971	0.966
	(0.194)	(0.168)	(0.181)
Died	0.010	0.007	0.008
	(0.100)	(0.083)	(0.091)
(P28) Gestation <= 28 weeks	0.009	0.010	0.009
	(0.093)	(0.098)	(0.096)
(P32) 28 weeks < Gestation <=32 weeks	0.014	0.016	0.015
	(0.119)	(0.127)	(0.123)
(P36) 32 weeks < Gestation <=36 weeks	0.071	0.092	0.082
	(0.256)	(0.289)	(0.274)

Table 2-4. Results of the first model

	(1)		(2)	
	Healthy		Died	
	Coefficient	Std Error	Coefficient	Std Error
noCON89	0.5808	(0.2040)	-0.0197	(0.0613)
noCON99	-0.0807	(0.2612)	0.0795	(0.0324)
Weight	0.6696	(0.0132)	-0.3350	(0.0076)
Age	-0.0226	(0.0028)	0.0091	(0.0012)
Year99	1.2182	(0.0690)	-0.4593	(0.0246)
Constant	74.2231	(0.4208)	12.0051	(0.2452)
Observations	5523105		5523105	
Number of state	45		45	
R-squared	0.05		0.05	

Table 2-5. Health outcome if premature

	1983			
Prematurity	Percentage of Births	Total Number	Percent Healthy	Percent Died
Gestation <=28 weeks	0.88	22,808	0.44	0.38
28 weeks < Gestation <=32 weeks	1.44	37,358	0.76	0.07
32 weeks < Gestation <=36 weeks	7.05	183,478	0.92	0.02
36 weeks < Gestation	90.64	2,358,511	0.97	0.01

	1999			
Prematurity	Percentage of Births	Total Number	Percent Healthy	Percent Died
Gestation <=28 weeks	0.96	28,127	0.42	0.34
28 weeks < Gestation <=32 weeks	1.65	48,076	0.83	0.04
32 weeks < Gestation <=36 weeks	9.21	269,161	0.95	0.01
36 weeks < Gestation	88.18	2,575,586	0.98	0.00

Table 2-6. Results of the second model

	(1) Healthy		(2) Died	
	Coefficient	Std Error	Coefficient	Std Error
noCON89	0.4942	(0.1535)	-0.0293	(0.0560)
noCON99	-0.0857	(0.2148)	0.0430	(0.0259)
Weight	0.5397	(0.0118)	-0.2952	(0.0074)
Age	-0.0189	(0.0028)	0.0084	(0.0012)
Year99	0.9354	(0.0593)	-0.2786	(0.0177)
Premature	-7.6778	(0.2647)	2.9625	(0.0780)
Premature x noCON89	1.9781	(0.9056)	-0.2087	(0.2041)
Premature x noCON99	0.3842	(0.6014)	0.2386	(0.0889)
Constant	79.2237	(0.3660)	10.4124	(0.2379)
Observations	5523105		5523105	
Number of state	45		45	
R-squared	0.06		0.05	

Table 2-7. Results of the third model

	(1)		(2)	
	Healthy		Died	
	Coefficient	Std Error	Coefficient	Std Error
noCON89	0.4761	(0.1507)	-0.0185	(0.0535)
noCON99	-0.1009	(0.1973)	0.0525	(0.0182)
Weight	0.3196	(0.0075)	-0.1576	(0.0043)
Age	-0.0095	(0.0024)	0.0022	(0.0010)
Year99	0.9090	(0.0547)	-0.2615	(0.0159)
P28	-47.7169	(0.8620)	34.3691	(0.8272)
P32	-17.3646	(0.5657)	4.0656	(0.1837)
P36	-3.0095	(0.2340)	0.2526	(0.0480)
P28 x noCON89	2.3086	(3.4791)	-0.5584	(3.0722)
P32 x noCON89	3.3508	(2.2495)	-0.8877	(0.5830)
P36 x noCON89	1.6457	(0.6683)	-0.1384	(0.1504)
P28 x noCON99	-3.1427	(2.3017)	3.2114	(0.8427)
P32 x noCON99	1.1753	(0.6270)	-0.8233	(0.3561)
P36 x noCON99	0.7822	(0.4249)	0.0286	(0.0559)
Constant	86.5317	(0.2382)	5.8538	(0.1431)
Observations	5523105	5523105		
Number of state	45	45		
R-squared	0.11	0.15		

CHAPTER 3
HOSPITAL COMPETITION AND PRICES

Originally mandated by the Federal government, Certificate of Need (CON) regulations were designed to control hospital competition. With the goal of limiting redundancy and tempering a "medical arms race," Certificate of Need regulations restricted hospital competition. The repeal of these laws creates new opportunities for the hospital markets; new entrants have a lower barrier to entry and existing players can expand services more easily.

To explore the relationship between the repeal of CON, hospital competition and prices charged by hospitals, I employ two techniques. First, a hospital-specific Hirschman-Herfindahl Index (HHI) is constructed to capture each hospital's competitive environment. Second, I use quantile regression to estimate the effect of changes in competition on prices. The extreme skewness of price data could unduly influence the econometrics otherwise. While prior hospital competition research focused on Medicare data, this paper uses the full sample of obstetrics patients in Pennsylvania between 1994 and 2004. These patients differ greatly in terms of both age and general health from Medicare patients providing a new perspective on the impact of hospital competition. Given the type of data, it is impossible to identify a causal relationship between the repeal of CON and hospital competition. However, I find that while the repeal of CON is not correlated with changes in competition, changes in the competitive landscape have an impact on prices. This effect is larger for the lower quantiles, implying that competition matters more for the easier/cheaper medical care.

History of Certificate of Need

Certificate of Need regulations affect the number of hospitals in a community as well as the number and type of services that a hospital can provide. Certificate of Need regulations started in New York in 1965 with the intent of controlling health care costs. At the time, hospitals were paid on a cost-plus basis. That is, their costs were covered plus a given percentage as profit. Because of this regulatory structure, hospitals had no incentives to control costs since they were all but guaranteed to cover them. There was also a fear that as insurance dulled the price sensitivity of consumers, hospitals in competitive markets would engage in a “medical arms race” and supply a socially excessive amount of medical care. These regulations are designed to limit competition and in the process, control costs.

The Certificate of Need process requires hospitals to receive state approval of large capital projects, including either the expansion of existing facilities or the introduction of new services. For example, the purpose of Missouri’s CON statute “is cost containment through health cost management, assurance of community need and the prevention of unnecessary duplication of health care services. CON is based on a goal of public accountability through public review of proposed health care services, value promotion and negotiation among competing interests” (Meier, July 2001). States differ on the level of investment or changes in the level of service (regardless of changes in capital) that requires prior approval. Often a decrease in the level of services as well as an increase must go through approval process.

Federal regulation in 1972 required hospitals to obtain state approval of capital improvements in order to receive Medicare/Medicaid payment for health care that used these improvements. In 1974, federal regulation required all states to implement a CON program by 1980. The "Reagan revolution" in the early 1980s removed the federal requirement for CON programs and, subsequently, some states eliminated their CON laws. However, most did not, and some expanded their programs. Currently, 15 states, including Pennsylvania, do not have a CON program.

There is a perception within the health care industry that CON programs protect incumbents (i.e., Stigler's capture theory of regulation). The director of government relations for the Missouri State Medical Association said, "The Certificate of Need program has outlived its usefulness. It doesn't do anything but stifle competition and innovation. It's extremely bureaucratic, and no one relishes having to go through it. It's the people who have existing projects who want it to continue. It helps them keep competition out of their backyard" (Meier, July 2001).

Economic theory suggests that Certificate of Need regulation will lead to inefficient results in competitive markets. However, the hospital market is far from competitive. There is a mix of non-profit and profit hospitals in most geographical markets. There are also areas with only one hospital. It is hypothesized that either prices/costs will be higher than they would be in the absence of pure competition or that quality will be lower. This can occur because incumbents are protected from competition because competitors (either new entrants or existing hospitals that wish to expand) must go through the Certificate of Need process. This process is costly and, in many states, an existing hospital is allowed to testify against a potential entrant. As with any market barrier, it is reasonable to expect less strenuous competition and possibly less innovation. Indeed, previous studies have shown that prices/costs tend to be higher in states with CON requirements.

Previous Literature

The existing literature on Certificate of Need and hospital competition covers two distinct areas. The earliest research looked at the impact of both CON regulation and its subsequent repeal in some states, as well as general competition within the health care market, on costs.[1] In general, the early studies find that CON has no statistically significant effect on health care costs and most agree that if there were to be an effect, it would increase costs rather than lower costs. CON proponents argued that these early studies were flawed because of their limited time horizon immediately following the introduction of these programs. It was argued that the programs needed time to "get up and running" before they could be expected to control costs.

More recent studies have looked at longer periods of time and evaluated the effects of repeal of the programs.[2] These studies suggest that, if anything, CON programs have tended to increase costs (Sloan, Morrisey and Valvona, 1988) and found that the repeal of CON had no effect on hospital costs per capita (Sherman, 1988). Conover and Sloan (1998) look at the effect of CON removal on state-level per-capita hospital spending among other things for the years 1976 to 1993. They find that CON laws had no effect on per-capita health expenditures, however CON did reduce spending on acute care by 5%. They find no effects on spending from the removal of CON laws.

Antel, Ohsfeldt, and Becker (1995) use state-level average hospital costs to investigate the affect of state regulations over the years 1968 to 1990. Specifically, they look at rate-setting regulations and Certificate of Need regulations; as well as procedure

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[1] Sloan (1988) provides a detailed review of the early literature.

[2] A good survey of the more recent work is Morrisey (2000).

controls like Peer Review Organizations and the interactions of these regulations. After controlling for state fixed effects, they find that regulations in isolation do not have an effect on costs. There are some effects from different interactions of regulations, but the magnitudes are small.

Health care costs and prices charged increase with the duration of the CON program. Using Medicare price and cost data from 1977 to 1978, Noether (1988) found prices were higher relative to costs and therefore profits were higher in states with a CON program. CON proponents also argued that hospitals were different than other industries and therefore competition did not, and could not, work. However, the empirical evidence does not support this.

A number of studies have investigated the effects of hospital competition on prices and costs. The early research tended to use a Hirschman-Herfindahl Index (HHI) as a measure of competition faced by a hospital. Because of data limitations, this index was usually calculated at the county level as finer geographic information was unavailable. There are two drawbacks to this approach. One, this assigns every hospital in a county the same measure of competition, ignoring the fact that there is frequently a dominant hospital and a couple of smaller hospitals. Two, it assumes that a patient would be willing to go to any hospital in a county or stated differently, that every hospital is on equal footing in competing for patients and that no patients cross county borders for medical care.

Because of these strong and unrealistic assumptions, a hospital-specific HHI is used in this paper.[3] A hospital specific HHI is calculated using the patient's zip code as the measure of the market. The market shares of the competing hospitals were calculated for each zip code. These market shares were then used to calculate a HHI at the zip code level. A weighted sum of these HHIs was then calculated for each hospital where the weights are the hospital's share of patients coming from that zip code. A number of papers have used hospital-specific HHIs as a measure of hospital competition.

Melnick, et al. (1992) looked at transaction prices that a large California preferred provider organization (PPO) negotiated with hospitals in 1987. While controlling for many factors, they found that the PPO paid more in the less competitive markets. This suggests that competition does work to lower prices in hospital markets. The authors compare the results when competition is measured with a hospital-specific HHI and a county-level HHI. They conclude that the hospital-specific measure of competition performs better in explaining the price differences.

Zwanziger and Melnick (1988) use hospital-level data from California for the years 1980 to 1985 to investigate the effects of hospital competition as well as the introduction of Medicare's Prospective Payment System (PPS) on hospital costs. They find that the introduction of the PPS caused hospitals to significantly reduce their costs. They also find that hospitals in less competitive markets had higher costs prior to the introduction of the PPS, a result consistent with a medical arms race. After the PPS was introduced, hospital competition no longer had a significant effect on costs.

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[3] See Morrisey, Sloan and Valvona (1988) and Zwanziger, Melnick and Mann (1990) for reviews of defining hospital markets.

Using hospital-level data for the United States, Bamezai, et al. (1999) look at the effects of managed care, as well as market structures, on hospital operating costs. The direct effect of hospital competition is not statistically significant. However, when interacted with measures of managed care penetration, it is highly significant. This implies that “greater hospital competition is effective only in areas with high levels of managed care penetration”.

Kessler and McClellan (2000) look at the effects of hospital competition on Medicare patients’ heart attack care. They use predicted patient flows to calculate hospital-specific HHIs. They find that expenditures were 8% higher in the hospitals facing the least competition relative to those hospitals facing the most competition.

A paper close in spirit to this one is Zwanziger and Mooney (2005). They look at the effects of the deregulation of hospital prices in New York. They investigate HMO-hospital transaction prices and show that negotiated prices were lower in more competitive markets. This effect becomes larger after deregulation.

Description of data

This paper uses patient-level hospital discharge data on obstetrics patients from the state of Pennsylvania for the years 1994 to 2004.[4] The data includes information on every obstetrics patient discharged in Pennsylvania for those years, approximately 375,000 observations. The data contain detailed billing information for each patient as well as information on who paid for the medical care. While the actual amount paid is almost certainly less than the billed amount, unfortunately that amount is unknown.

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[4] For financial reasons, the data is for the 1st quarter of each year.

There is also detailed diagnosis and procedure information as well as the patient's zip code.

While it would be preferable to know the actual price paid, we can be relatively certain that the price reported is a list price rather than a negotiated price that differs for each patient or payer. Figure 3-1 plots the average price of a caesarean section by payer type. We see that the there has been a large increase in the price of a c-section, but there is not a large difference between payer types. We see the same results for premature births in Figure 3-2. Again, there has been a large increase in prices, but there is no difference between payer types. Because we expect that different organizations will pay different prices for a given procedure, the lack of differences suggests that the prices used in this paper are list prices. It is reasonable to believe that the list prices are related to actual prices paid. Because it is doubtful that anyone would pay more than the billed price, any results can be interpreted as a lower bound.

Traditionally, hospital competition is measured with a Hirschman-Herfindahl Index (HHI). This index measures competition as the sum of the squared market shares in a given geographic market. Greater levels of competition are represented by lower numbers. Figure 3-3 shows the HHI calculated at the county-level for Pennsylvania in 1994. The lighter shaded areas have the greatest amounts of competition. The two areas with the most competition are Allegheny County in the west and Philadelphia County in the east. Figure 3-4 shows the comparable HHI for 2004. It is apparent from these maps that, by this measure, there has not been a large change in competition over the intermediate years. Some of the smaller counties have lost hospitals and therefore the market has become more concentrated.

These maps also show the number of hospitals in a given county for that year. A number of counties have had decreases in the number of hospitals. Using the number of hospitals in a county as a measure of competition, it would appear that there have been changes that may not have been picked up by the HHI. As can be seen from Figure 3-5, most counties did not see a change in the number of hospitals.[5] 44 counties, out of 67 total, did not see any change at all in the number of hospitals. Only two counties gained a hospital. We also observe that most counties only have one or two hospitals. None of the counties with only one hospital in 1994 lost a hospital, and only one county with two hospitals lost one. The larger counties did lose hospitals, in some cases more than one. It is important to note, that not all of the losses are necessarily due to hospital closures. It is possible that some of these hospitals discontinued their obstetrics service while continuing to provide other forms of care.

Small hospitals (as measured by the number of patients) were more likely to close as compared to larger hospitals. Figure 3-6 is a scatter plot of the number of patients per hospital in 1994 and the number of patients per hospital in 2004.[6] The number of patients per hospital in 1994 for those hospitals that closed between 1994 and 2004 is plotted along the x-axis. It is clear that the large hospitals have a tendency to get bigger. It is also clear that the majority of hospitals have less than 300 patients in a given year. As well, it appears that most hospitals did not change their patient counts very much.

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[5] The number of counties in a cell is represented by the size of the circle. All cells greater than 1 have the number of counties inside the circle.

[6] Only one hospital had more than 1200 patients in one year, the number of patients did not vary greatly from 1994 to 2004.

We also see from Figure 3-7, that the hospitals that closed were those that were facing the higher levels of competition (as measured by the hospital-specific HHI). Again, the hospitals that closed between 1994 and 2004 are plotted along the x-axis. This figure also makes apparent that a number of hospitals faced dramatically less competition in 2004 as compared to 1994. This is almost certainly due to the hospitals that left the market.

In order to rectify these discrepancies, a different approach is required. The traditional Hirschman-Herfindahl Index is calculated using county borders as the borders of the market. As mentioned, this approach makes several strong assumptions. The assumption that no patients cross county borders for care can be shown to be false. Table 3-1 shows that in any given year, approximately 25% of patients receive treatment in a county other than their own. Allegheny and Philadelphia counties are broken out of the total, as they are the largest counties in Pennsylvania. Allegheny County is similar to the state as a whole, while in Philadelphia County approximately 16% of patients are from another county.

For ease of display, the hospital-specific HHIs are averaged at the county level for the years 1994 and 2004 (Figures 3-8 and 3-9). These maps show greater amounts of competition as compared with the traditional HHI. As expected, competition is greatest in those areas with the largest population. Figure 3-10 shows the MSAs as well as the location of the major cities in Pennsylvania. The level of hospital competition is seen to be greater on average in these areas.

Somewhat surprisingly, there is very little change over the time period in the levels of hospital competition. Figure 3-6 plots the average of the hospital-specific HHI for both counties in and out of a MSA (metro and non-metro counties). It is difficult to detect any effect from the repeal of CON. However, there is a slight upward trend over time in both areas. This implies that hospital competition has actually decreased on average over this time period, which is the opposite of what we would expect from the removal of CON. Of course, it is possible that these averages obscure the individual hospital's changing competitive environment. Related to the slight increase in the hospital-specific HHI, we see in Table 3-2 that the actual number of hospitals in Pennsylvania peaked in 1996. The number of hospitals decreases dramatically over the following years. Again, Allegheny and Philadelphia counties are broken out. We see that the number of hospitals peaks in Allegheny County in 1996 and peaks in 1997 for Philadelphia County. Although it is impossible to say with certainty, the evidence above makes it is likely that the repeal of CON led some of the weaker hospitals to discontinue their obstetrics service.

Figure 3-11 shows the average price charged for metropolitan and non-metro counties. Hospitals in metro counties charge more relative to non-metro counties. The difference increases dramatically over the time period. This difference is consistent with the Medical Arms Race hypothesis in that the areas facing the greatest competition also charge the most. It is also possible that more complex medical cases are admitted to hospitals in metro areas and thus lead to higher charges. In this case, using price as a proxy for medical complexity, we would expect to see the greatest difference between metro and non-metro areas at the top of the distribution and very little difference at the bottom of the distribution. Figures 3-8 and 3-9 plot the distribution of prices for metro counties and non-metro counties.

We would also expect to see the average length of stay to be longer in metro areas if this is true. Figure 3-14 shows the average length of stay for the two areas. We see that the average stay in non-metro counties has been relatively flat over this period, while the length of stay has increased in the metro counties. Table 3-3 shows the 90th and 99th percentiles of the length of stay for both counties over the time period. We see that the 90th percentile in non-metro counties has stayed constant at three days; the comparable percentile for metro counties is four days. At the 99th percentile, the length of stay is again greater in the metro counties as compared to the non-metro counties. It appears that some of the difference in the average price may be due to the sorting of complex medical cases.

These figures also suggest that only investigating the effects of competition on mean prices may be misleading. Because hospitals that face the most competition tend to be located where the patients are, that is in metro areas, simply regressing prices on a Herfindahl index would lead to the inference that increased levels of competition increase prices. This paper circumvents this problem by including hospital fixed effects as well as quantile regression. The fixed effects control for unobserved heterogeneity among hospitals, while quantile regression allows me to investigate the effects of CON removal as well as the effects of changing competition on prices at different points on the distribution.

Because of the concern that part of the difference in prices in metro counties versus non-metro counties may be due to the complexity of the patient care, it is important to control for premature births and caesarean sections. Figure 3-15 shows the percent of births delivered by caesarean section over the time period. There is not a large difference in caesarean rates between metro and non-metro counties. Figure 3-16 shows the percent of births that were born prematurely. At the beginning of the time period, metro counties had a higher incidence of prematurity but, this difference has disappeared by the end of the time period.

Managed care, i.e., Preferred Provider Organizations (PPOs) and Health Maintenance Organizations (HMOs) is believed to play an important part in controlling health care costs, it is important to control for this. Figure 3-17 shows the percent of patients whose primary payer was a PPO or HMO.[7] While managed care organizations have increased their penetration in both types of counties, the increase has been more dramatic in metro counties. By 2004, more than 60% of patients are in managed care in the metro counties compared with less than 40% in non-metro counties.

It is also reasonable to believe that Medicaid patients will affect the price a hospital charges. Figure 3-18 shows the percent of mothers whose primary payer was Medicaid.[8] There is a small increase in the number of Medicaid patients in non-metro counties but the increase is much larger in the metro counties, however in all years, the share of patients on Medicaid is larger in the non-metro counties.

The Repeal of Certificate of Need and Hospital Competition

The first model estimated considers the relationship between the repeal of the Certificate of Need regulation and hospital competition as measured by the hospital-specific Hirschman-Herfindahl Index (scaled to range from 0 – 100). In order for the CON repeal to have an effect in a given area, there must be multiple hospitals competing

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[7] The data does not distinguish between the two types before 2000.

[8] Some Medicaid patients are enrolled in a managed care plan.

with each other. This is more likely to occur in the metro areas as there are a greater number of potential patients. Although we do not have a truly exogenous source of variation, and therefore can not argue that this procedure will estimate a causal relation, we can use this idea to test the effect of the CON repeal on hospital competition. By comparing the change in the HHI in metro counties after the repeal to any change in non-metro counties, we can get an approximation of the effect of the repeal. The model estimated is,

$$hhi_{it} = \alpha_1 + \alpha_2 \text{ metro} + \gamma \text{ years after}_t + \delta \text{ metro x years after}_t + \varepsilon_{it} \qquad (2\text{-}1)$$

where hhi_{it} is the hospital-specific HHI for hospital *i* in year *t*, metro is an indicator equal to one if the hospital is in a metropolitan county, $year_t$ is a vector of indicators for the years after repeal, and metro x $year_t$ is a vector of indicators of metro-specific years after repeal. If there is a differential effect between the two types of counties, then the coefficients on the metro-specific year indicators will be statistically different from zero. We would expect to see that if anything, the repeal of CON has increased competition in the metro areas and therefore the estimated coefficients will be negative. Column 1 of Table 3-4 shows the estimated OLS coefficients for this model. The only coefficients statistically different from zero are the constant and the metro indicator. This implies that there was not an effect from the repeal on competition. Because it is possible that any effect would be greater in the larger or smaller areas, three quantile regressions were estimated. Columns 2–4 report the estimated coefficients for the 75^{th}, 50^{th}, and 25^{th} quantiles. In no case are any coefficients statistically significant, again except for the constant and metro indicator. While we can not say with certainty that the repeal of CON had no effect on hospital competition as measured by the hospital-specific HHI, the fact that the repeal is not correlated with changes in competition is suggestive of the idea that there was not an effect.

Hospital Competition and Prices

The basic model estimated is

$$\text{charges}_{ijt} = \beta_1 \text{ hhi}_{jt} + \beta_2 \text{ hmo}_{ijt} + \beta_3 \text{ medicaid}_{ijt} + \beta_4 \text{ csec}_{ijt} + \beta_5 \text{premature}_{ijt} + \gamma_j + \delta_t + \varepsilon_{ijt} \qquad (2\text{-}2)$$

The dependent variable is the total charges for patient *i* that the hospital *j* reported to the state in year *t*. Where hhi is the hospital-specific HHI, hmo is an indicator that the patients primary payer was a HMO, medicaid is an indicator that the patient has Medicaid, csec is an indicator that a caesarean section was performed, premature is an indicator of a premature birth, and metro is an indicator that the hospital is in a metro county, while γ_j is a hospital fixed-effect and δ_t is a year fixed-effect.

The variable of interest is hhi. Because the Herfindahl index decreases as competition increases, if hospital competition reduces prices then the coefficient on hhi will be negative. As a baseline, the model was estimated using OLS. These results are reported in the first column of Table 3-5. The coefficient on hhi is statistically insignificant, and the magnitude is small, implying that competition does not affect hospital prices. As expected, both c-sections and premature births cost more. Somewhat surprisingly, Medicaid patients are charged more as well.

The second model estimated is

$$\text{charges}_{ijt} = \beta_1 \text{ hhi}_{jt} + \beta_2 \text{ hmo}_{ijt} + \beta_3 \text{ medicaid}_{ijt} + \beta_4 \text{ csec}_{ijt} + \beta_5 \text{ premature}_{ijt} + \beta_6 \text{ year}_t + \gamma j + \varepsilon ijt \qquad (2\text{-}3)$$

This model substitutes a linear time trend instead of individual year fixed-effects. Again, this model was estimated using OLS. These results are reported in column 2 of

Table 3-5. Again, we see that the coefficient on hhi is small and statistically insignificant, implying that competition does not have an affect on hospital prices. The other coefficients are not markedly different.

The third model estimated is

$$\begin{aligned} \text{charges}_{ijt} = \beta_1\ \text{hhi}_{jt} + \beta_2\ \text{hmo}_{ijt} + \beta_3\ \text{medicaid}_{ijt} + \beta_4\ \text{csec}_{ijt} + \beta_5\ \text{premature}_{ijt} + \\ \beta_6\ \text{year}_t + \beta_7\ \text{metro x year}_t + \gamma_j + \varepsilon_{ijt} \end{aligned} \tag{2-4}$$

The third model adds a metro-county specific time trend. This controls for the different growth trajectory in metro counties seen in Figures 3-8 and 3-9 (distribution of charges). The results of this estimation are reported in column 3 of Table 3-5. The coefficient on hhi is again small and insignificant, while the other coefficients are qualitatively the same.

As can be seen from Figures 3-8 and 3-9, the distribution of prices is heavily skewed by the top of the distribution. It is reasonable to believe that only a couple of hospitals in given area are responsible for the highest charges as these would be the most medically complex. Given this, it is not surprising to find that competition does not affect average hospital prices as the average in this case is dominated by the upper half of the distribution where there is little competition. For this reason, quantile regression is employed.

It is reasonable to believe that competition would have the greatest effect at the bottom of the price distribution. These are the "simplest" medical cases. It is likely that more complicated cases can potentially be admitted to only a subset of an area's hospitals, because not every hospital would have the staff or facilities to manage a complex medical case. If this is the case, then we would expect to see competition have a greater effect on the lower quantiles. The first model is estimated at five different quantiles: .90, .75, .50, .25 and .10 in order to investigate the hypothesis that hospital competition does not affect the upper part of the distribution, but may affect the lower part.

Table 3-6 reports the results for the respective quantile regressions. All of the coefficients are statistically significant and, the coefficients are increasing as the quantiles get smaller. This supports the hypothesis that competition has a greater effect for the least complicated medical cases. For example, a one standard-deviation increase in competition would reduce the price by approximately $225 at the median price.[9] Relative to the average charge of $5950 in 1999, this implies a 3.8% change in price. If we compare the competition effect between the 75th and 25th quantiles, we see that competition matters much more for the lower quantile. A one standard deviation increase in competition would reduce the price by 1.7% at the 75th percentile; a similar change would reduce the price by 8.0% at the 25th percentile.[10] It does appear that hospital competition matters more for the lower quantiles.

The results of the quantile regressions of the second model are reported in Table 3-7. As with the OLS version, the results are qualitatively similar to the first model. The coefficients on hhi are all statistically significant but not very large. The third model is reported in Table 3-8. Again, the results are very similar to the other models. All three

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[9] The standard deviation of hhi is 15.6; this multiplied by the coefficient on hhi for the median regression (14.67) implies a price change of $229.

[10] The calculation for the 75th percentile is: 8.14*15.6 = $127 as compared to a price of $7200 in 1999. This is a difference of 1.7%. A similar calculation using an average price of $3118 in 1999 yields a difference of 8.0% for the 25th percentile.

models suggest that hospital competition has largest effect on the lower half of the price distribution.

This estimated effect can be interpreted as an upper bound. Given that the dependent variable in all three models is the billed price, not the actual price paid, it is likely that some patients paid less. It is difficult to believe that anyone would pay more than the billed price. If that is the case, the effect of competition could be even larger.

Conclusion

This paper looks at the effect of the repeal of Pennsylvania's Certificate of Need regulations in 1996 on hospital competition and hospital prices. I use a hospital-specific Hirschman-Herfindahl Index to measure hospital competition. Although the CON repeal does not appear to affect hospital competition, I show that there were changes in the number of hospitals in Pennsylvania and therefore the hospital-specific HHIs. The hospitals that were small and faced high levels of competition, as measured by the hospital-specific HHI, were more likely to discontinue their obstetrics service.

The changes in the individual HHIs was then used to determine the effects of competition on prices charged. A quantile regression approach was used because the hospital prices are heavily skewed to the right. Using this approach, increased hospital competition was found to reduce prices charged. Hospital competition is found to matter much more for the lower half of the price distribution as compared to the upper half. A one standard deviation increase in competition, as measured by the hospital-specific HHI, would reduce prices by 1.7% at the 75^{th} percentile. A comparable increase in competition would reduce prices by 8.0% at the 25^{th} percentile.

Table 3-1. Percentage of patients crossing county borders

Year	Total	Allegheny	Philadelphia
1994	0.259	0.233	0.169
1995	0.252	0.238	0.168
1996	0.259	0.253	0.171
1997	0.265	0.250	0.179
1998	0.257	0.248	0.172
1999	0.264	0.254	0.189
2000	0.261	0.244	0.182
2001	0.267	0.250	0.183
2002	0.262	0.267	0.166
2003	0.267	0.266	0.167
2004	0.272	0.270	0.160

Table 3-2. Number of hospitals in the state

Year	Metro	Non-Metro	Allegheny	Philadelphia
1994	111	40	14	17
1995	114	39	13	20
1996	116	41	14	19
1997	110	40	11	20
1998	104	40	12	16
1999	103	39	13	16
2000	103	40	12	15
2001	101	39	11	15
2002	97	38	10	13
2003	97	36	11	11
2004	89	36	10	11

Table 3-3. Percentiles of length of stay (by county type)

	90th percentile		99th percentile	
year	non-metro	metro	non-metro	metro
1994	3	4	7	9
1995	3	3	6	9
1996	3	3	6	8
1997	3	4	6	8
1998	3	4	6	8
1999	3	4	5	9
2000	3	4	5	8
2001	3	4	6	8
2002	3	4	6	8
2003	3	4	6	9
2004	3	4	6	8

Table 3-4. Effect of CON repeal on the HHI (standard errors in parentheses)

	(1) OLS	(2) Quantile (.75)	(3) Quantile (.50)	(4) Quantile (.25)
metro	-19.576	-24.277	-19.759	-18.233
	(1.484)	(2.105)	(2.291)	(2.836)
1 year after x metro	0.102	7.585	1.641	-4.536
	(2.977)	(4.211)	(4.574)	(5.675)
2 years after x metro	0.892	4.430	1.116	0.014
	(2.995)	(4.241)	(4.600)	(5.714)
3 years after x metro	-0.260	6.197	-0.721	-1.669
	(3.018)	(4.204)	(4.636)	(5.665)
4 years after x metro	1.424	9.044	-0.779	-3.525
	(2.998)	(4.236)	(4.605)	(5.708)
5 years after x metro	1.458	4.043	3.850	-0.193
	(3.025)	(4.219)	(4.645)	(5.685)
6 years after x metro	1.226	6.387	1.229	-1.429
	(3.059)	(4.287)	(4.697)	(5.776)
7 years after x metro	-0.865	9.518	-2.305	-6.416
	(3.106)	(4.394)	(4.766)	(5.920)
8 years after x metro	-0.166	8.817	-4.207	-0.640
	(3.135)	(4.434)	(4.810)	(5.975)
1 year after	0.518	-3.630	0.185	3.370
	(2.552)	(3.613)	(3.914)	(4.868)
2 years after	0.674	-0.910	1.997	0.401
	(2.552)	(3.613)	(3.914)	(4.868)
3 years after	1.420	-2.551	0.818	1.581
	(2.577)	(3.575)	(3.950)	(4.817)
4 years after	-0.303	-4.551	0.912	4.078
	(2.552)	(3.613)	(3.914)	(4.868)
5 years after	0.616	-1.210	-1.329	2.131
	(2.577)	(3.575)	(3.950)	(4.817)
6 years after	1.805	-1.718	2.306	3.448
	(2.602)	(3.633)	(3.988)	(4.895)
7 years after	2.948	-4.928	3.714	8.554
	(2.657)	(3.759)	(4.069)	(5.065)
8 years after	2.418	-3.635	4.114	4.037
	(2.657)	(3.759)	(4.069)	(5.065)
Constant	58.600	70.605	57.398	46.683
	(1.276)	(1.810)	(1.969)	(2.439)
Observations	1573	1573	1573	1573

Table 3-5. Regression results using OLS (with hospital fixed-effects)

	(1)	(2)	(3)
hhi	37.53	34.91	31.48
	(25.94)	(23.57)	(24.35)
hmo	278.69	96.50	10.82
	(156.08)	(165.38)	(170.00)
csec	5096.58	5141.49	5133.17
	(472.12)	(479.65)	(477.60)
premature	3603.95	3597.61	3608.21
	(578.50)	(576.26)	(577.70)
medicaid	415.96	463.09	431.73
	(105.66)	(107.89)	(103.62)
year		560.73	153.54
		(89.04)	(37.42)
metro_year			484.06
			(113.80)
Constant	1621.50	493.10	627.19
	(1299.44)	(1405.22)	(1402.66)
Observations	374770	374770	374770
Number of Hospitals	169	169	169
R-squared	0.05	0.05	0.05
F-Stat	29.11	45.01	39.55
Hospital Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	No	No

Table 3-6. Quantile regression results for model 1 (with Hospital Fixed-Effects)

	(.90)	(.75)	(.50)	(.25)	(.10)
hhi	7.80	8.14	14.67	16.03	12.61
	(1.34)	(0.77)	(0.59)	(0.52)	(0.55)
hmo	205.40	167.42	177.15	162.60	125.47
	(14.59)	(8.19)	(6.49)	(6.06)	(6.69)
csec	5557.68	4129.68	3210.34	2663.22	2287.21
	(14.81)	(8.31)	(6.50)	(5.93)	(6.42)
premature	6779.11	2171.95	847.43	459.40	313.57
	(23.73)	(13.28)	(10.38)	(9.49)	(10.28)
medicaid	340.14	199.82	141.81	87.25	41.94
	(14.67)	(8.09)	(6.25)	(5.66)	(6.08)
Observations	374770	374770	374770	374770	374770
Number of Hospitals	169	169	169	169	169
Pseudo R-squared	0.46	0.43	0.38	0.34	0.30
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 3-7. Quantile regression results for model 2 (with hospital fixed-effects)

	(.90)	(.75)	(.50)	(.25)	(.10)
hhi	8.18	9.29	15.58	15.59	11.74
	(1.72)	(1.00)	(0.64)	(0.50)	(0.55)
hmo	102.50	99.39	125.68	142.83	121.03
	(15.35)	(9.66)	(6.96)	(5.94)	(6.62)
csec	5760.95	4157.28	3270.89	2664.86	2285.00
	(16.13)	(10.04)	(7.03)	(5.85)	(6.39)
premature	6672.35	2185.47	883.98	462.61	315.51
	(25.84)	(16.04)	(11.23)	(9.37)	(10.27)
medicaid	388.66	255.43	172.34	90.08	44.33
	(15.93)	(9.76)	(6.75)	(5.58)	(6.07)
year	381.99	326.30	273.31	236.84	207.54
	(2.69)	(1.59)	(1.05)	(0.87)	(0.98)
Observations	374770	374770	374770	374770	374770
Number of Hospitals	169	169	169	169	169
Pseudo R-squared	0.45	0.42	0.38	0.34	0.30
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No

Table 3-8. Quantile regression results for model 3 (with hospital fixed-effects)

	(.90)	(.75)	(.50)	(.25)	(.10)
hhi	3.71	5.76	11.64	12.39	9.86
	(1.67)	(0.93)	(0.61)	(0.52)	(0.53)
hmo	57.70	51.18	87.84	109.49	102.16
	(15.12)	(9.07)	(6.63)	(6.13)	(6.34)
csec	5739.92	4157.34	3260.90	2662.78	2281.28
	(15.75)	(9.38)	(6.68)	(6.06)	(6.15)
premature	6633.41	2193.67	881.48	467.64	321.49
	(25.24)	(14.98)	(10.68)	(9.68)	(9.88)
medicaid	380.64	246.02	147.51	80.34	37.27
	(15.54)	(9.12)	(6.42)	(5.77)	(5.83)
year	198.59	149.53	114.76	89.56	77.34
	(6.17)	(3.49)	(2.36)	(2.09)	(2.15)
metro x year	236.64	230.34	208.61	189.67	165.98
	(6.70)	(3.79)	(2.54)	(2.26)	(2.33)
Observations	374770	374770	374770	374770	374770
Number of Hospitals	169	169	169	169	169
Pseudo R-squared	0.46	0.42	0.38	0.35	0.30
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No

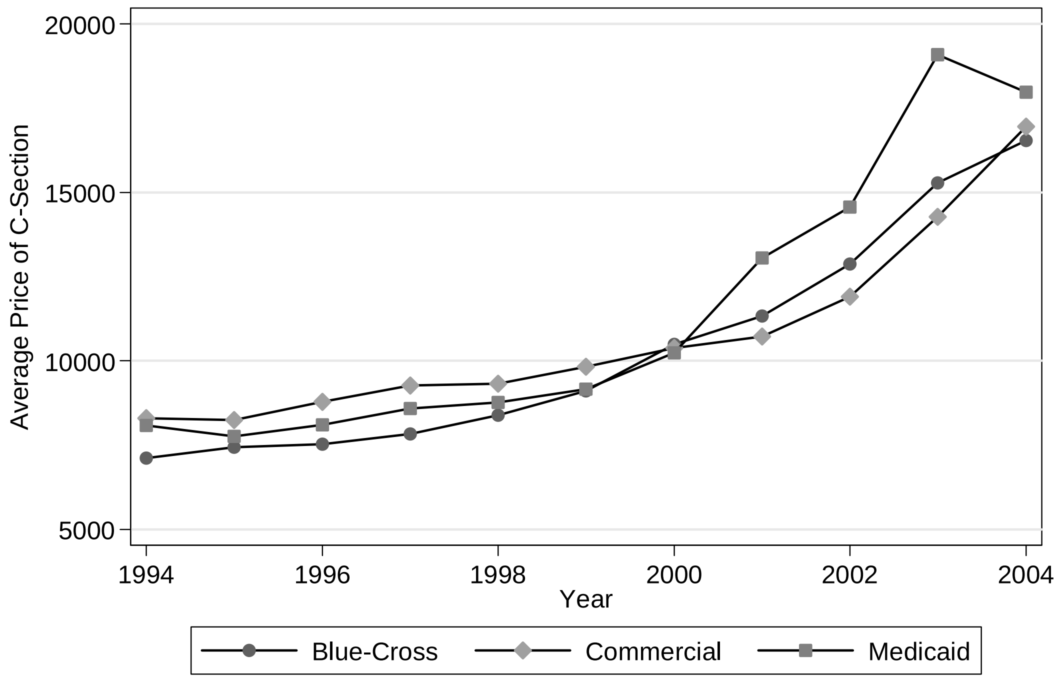

Figure 3-1. Average price of a C-Section (by Payer Type and Year)

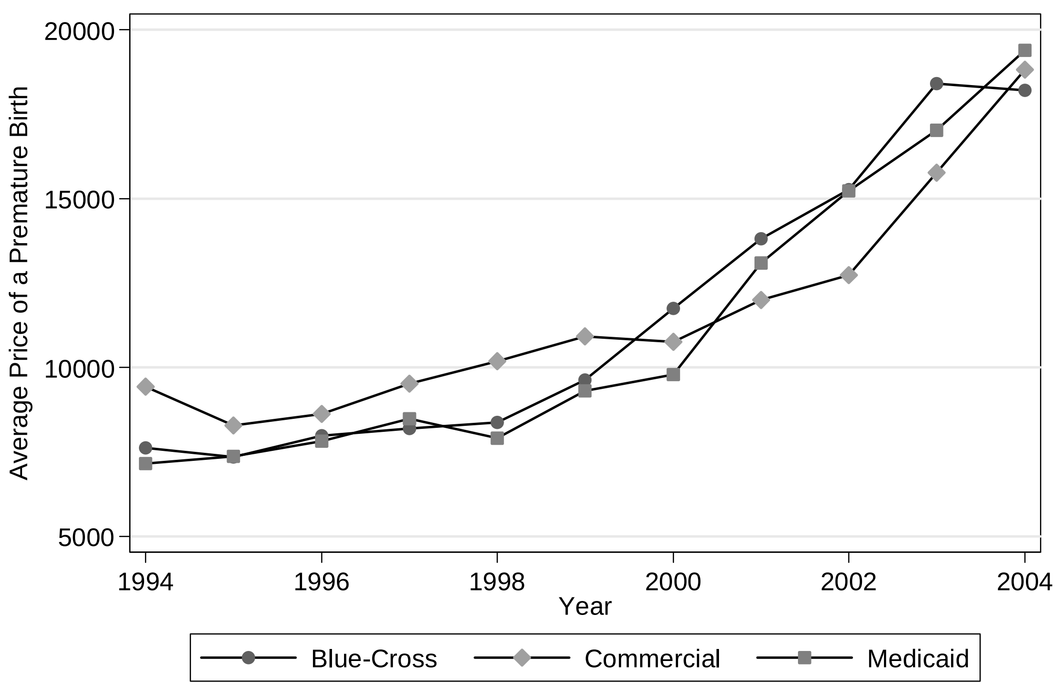

Figure 3-2. Average price of a premature birth (by payer type and year)

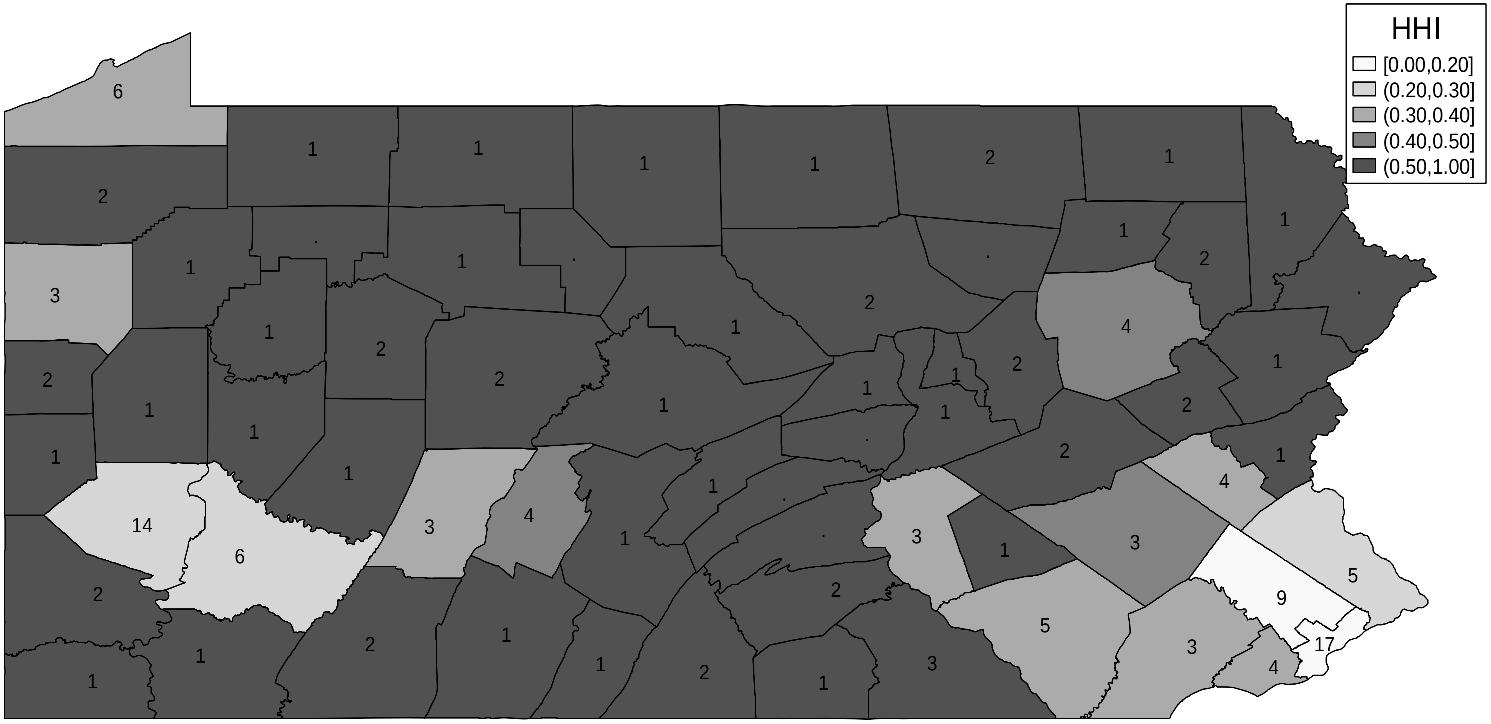

Figure 3-3. County-level HHI for 1994 (number of hospitals in county)

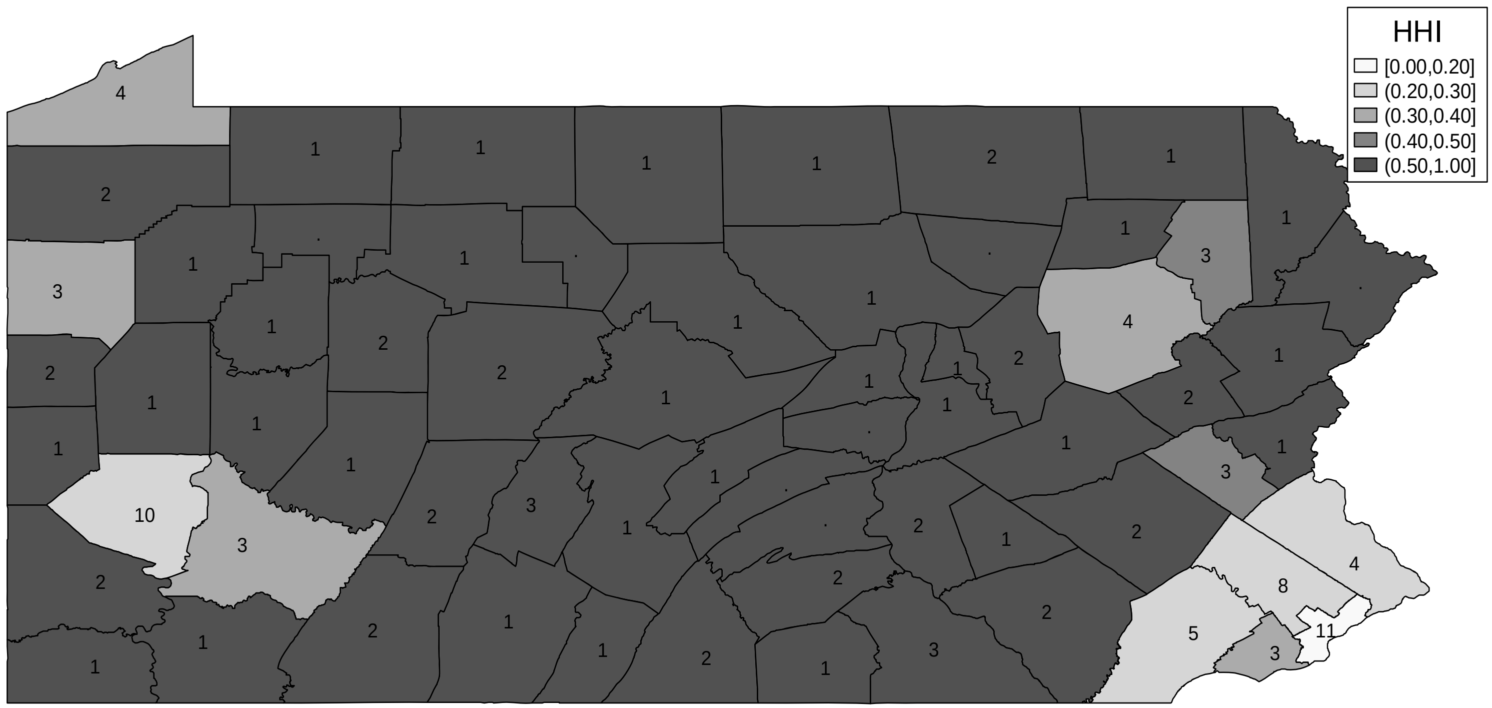

Figure 3-4. County-level HHI for 2004 (number of hospitals in county)

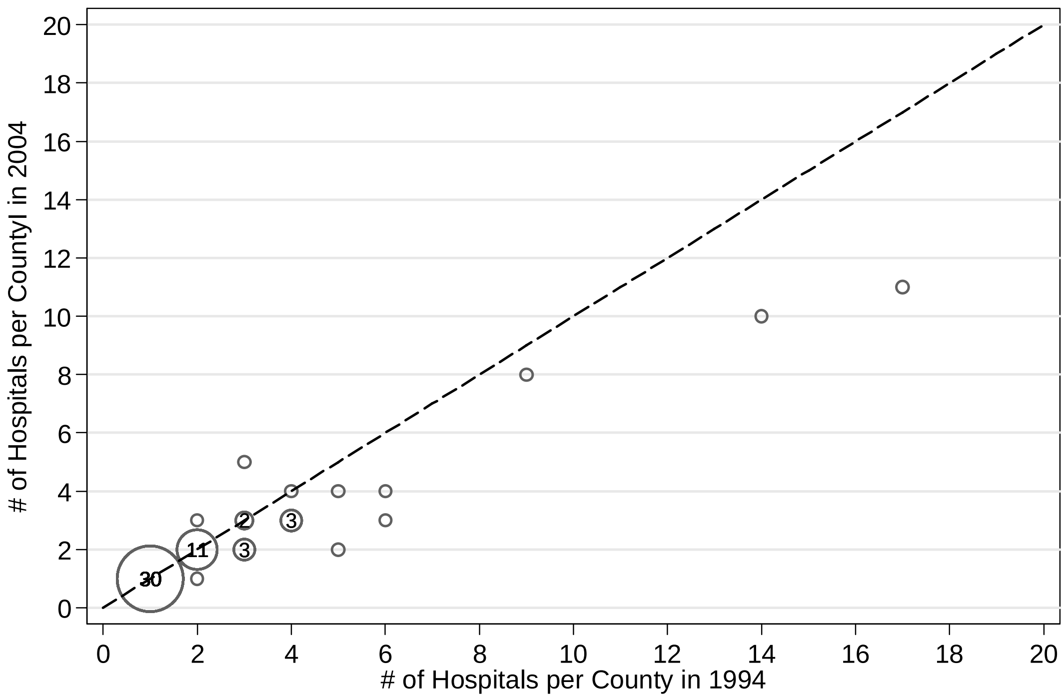

Figure 3-5. Number of hospitals per county (1994 vs. 2004)

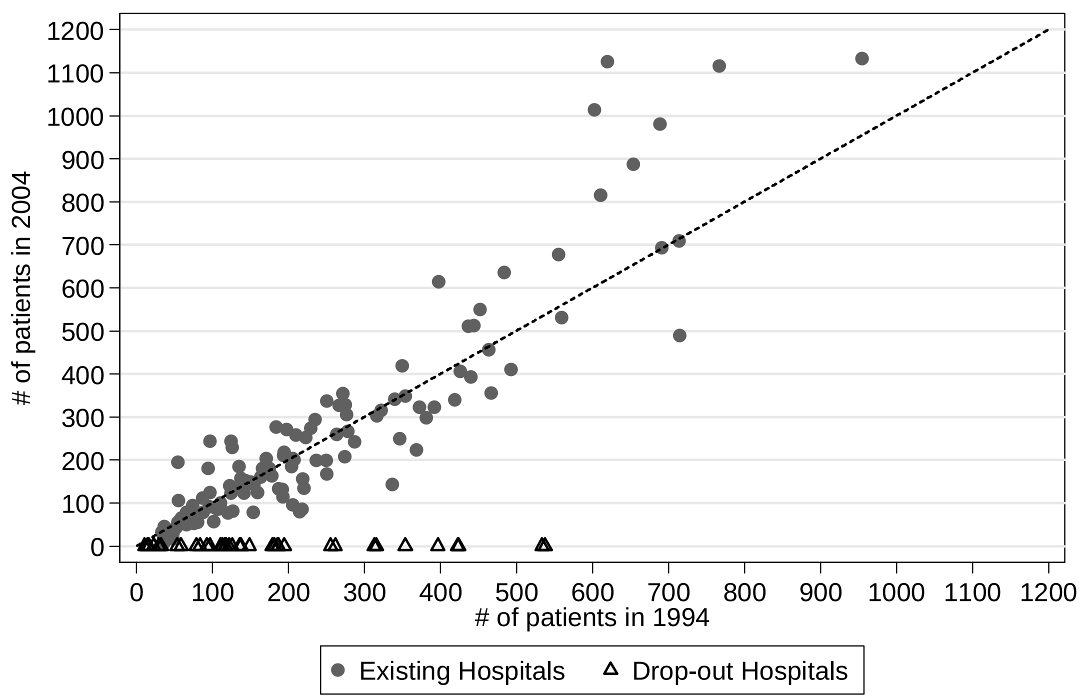

Figure 3-6. Number of patients per hospital (1994 vs. 2004)

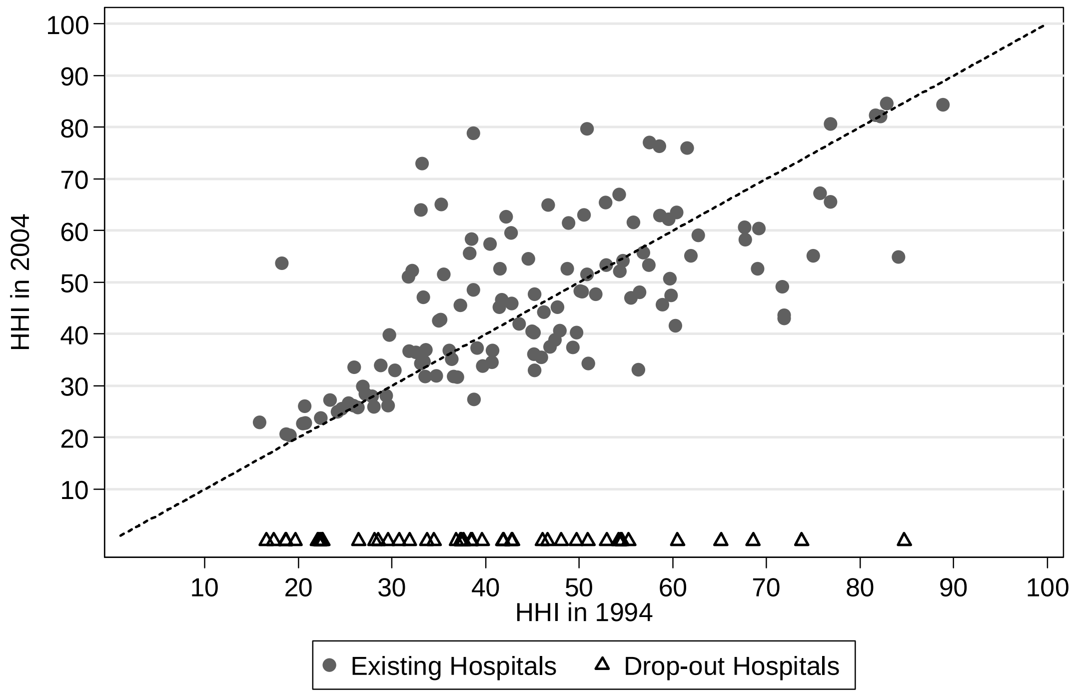

Figure 3-7. Hospital-specific HHIs (1994 vs. 2004)

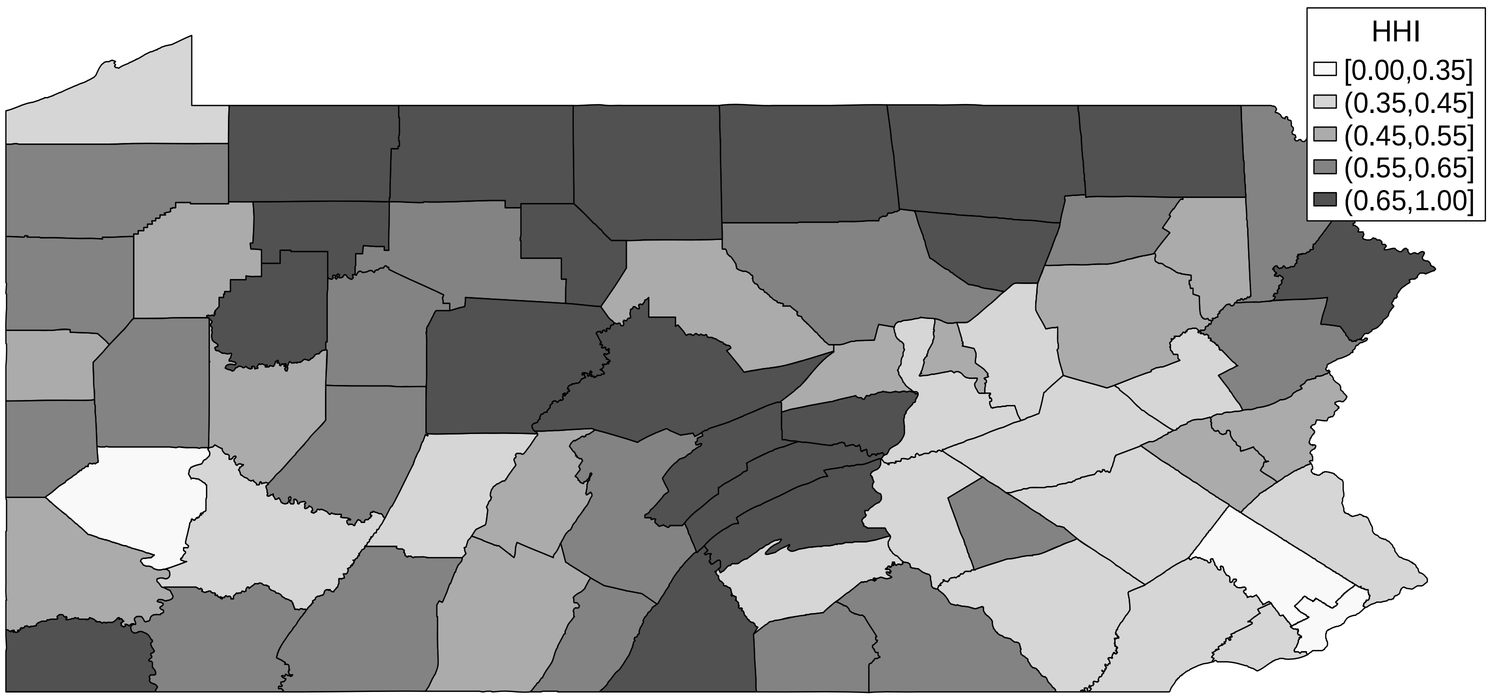

Figure 3-8. Hospital-specific HHI averaged at the county-level for 1994

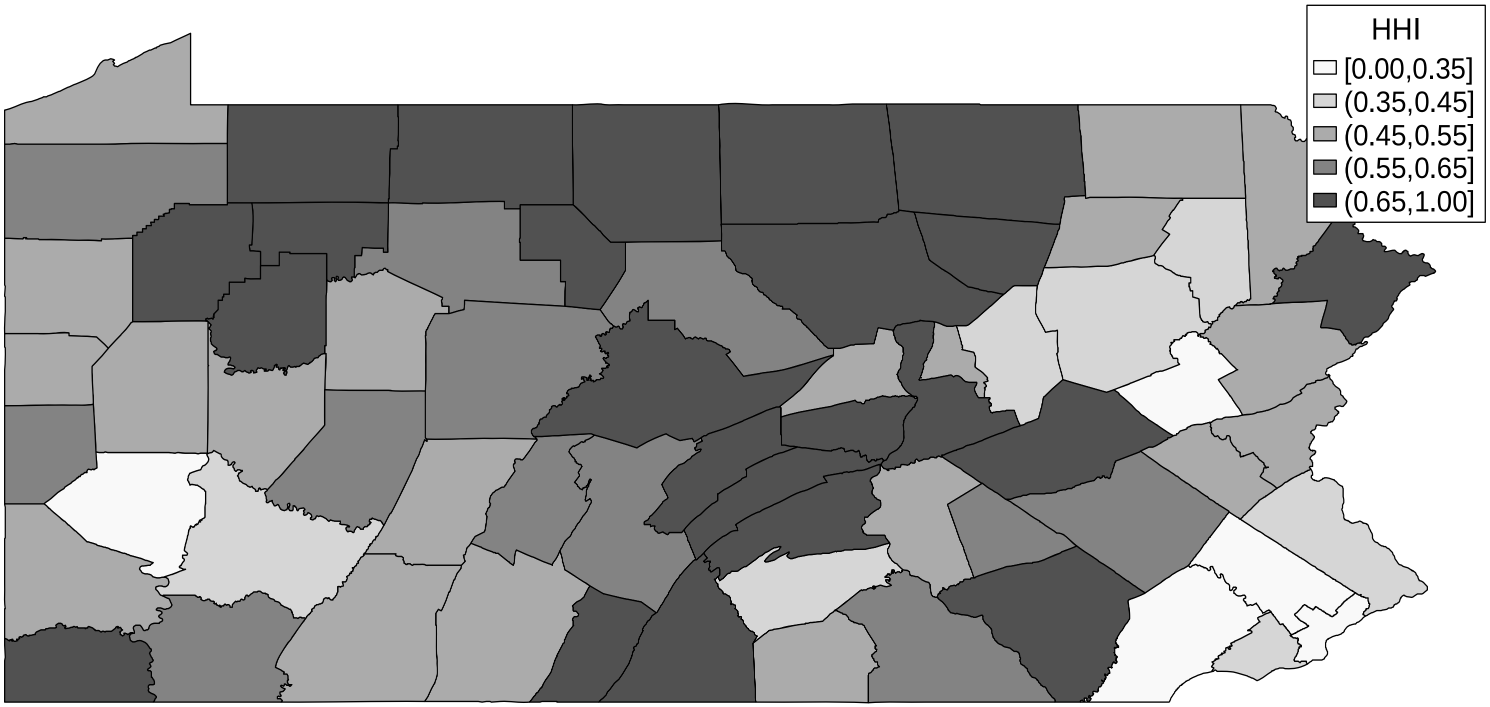

Figure 3-9. Hospital-specific HHI averaged at the county-level for 2004

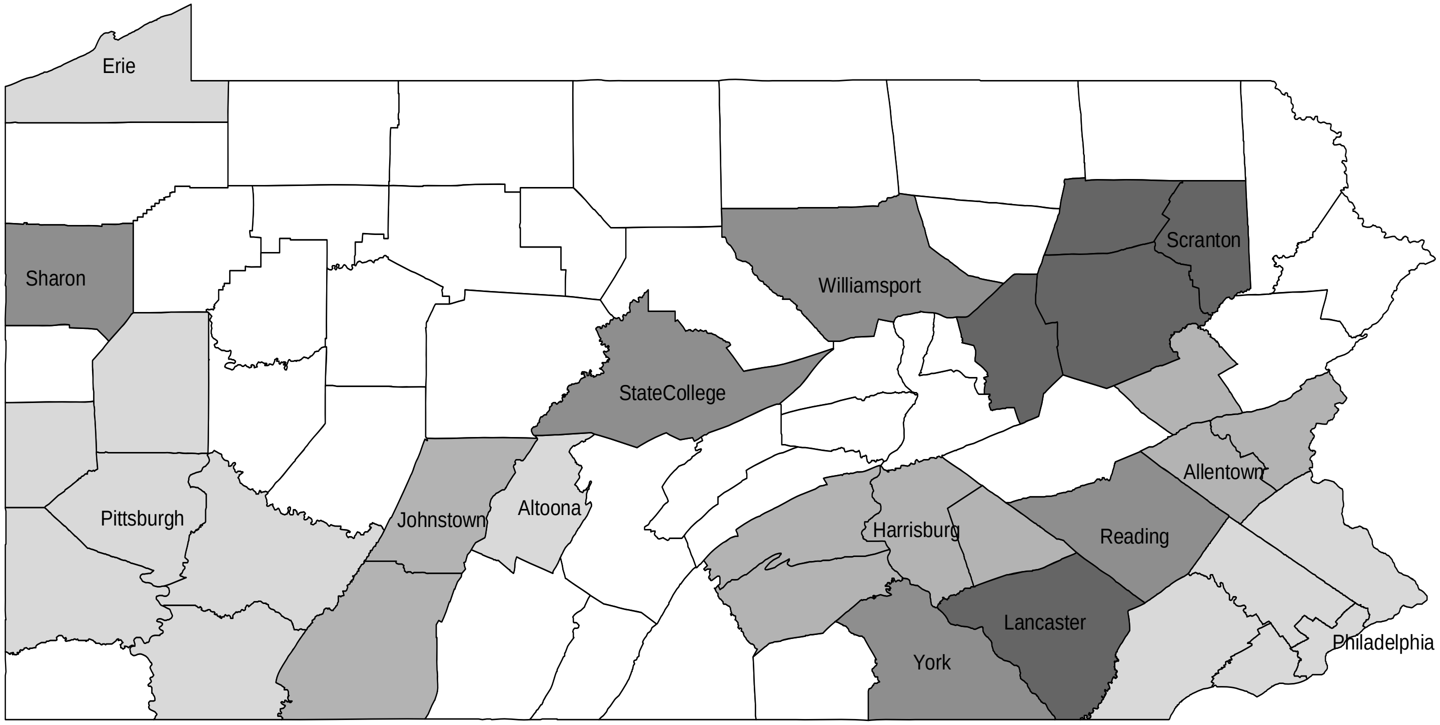

Figure 3-10. Map of MSAs and major cities in Pennsylvania

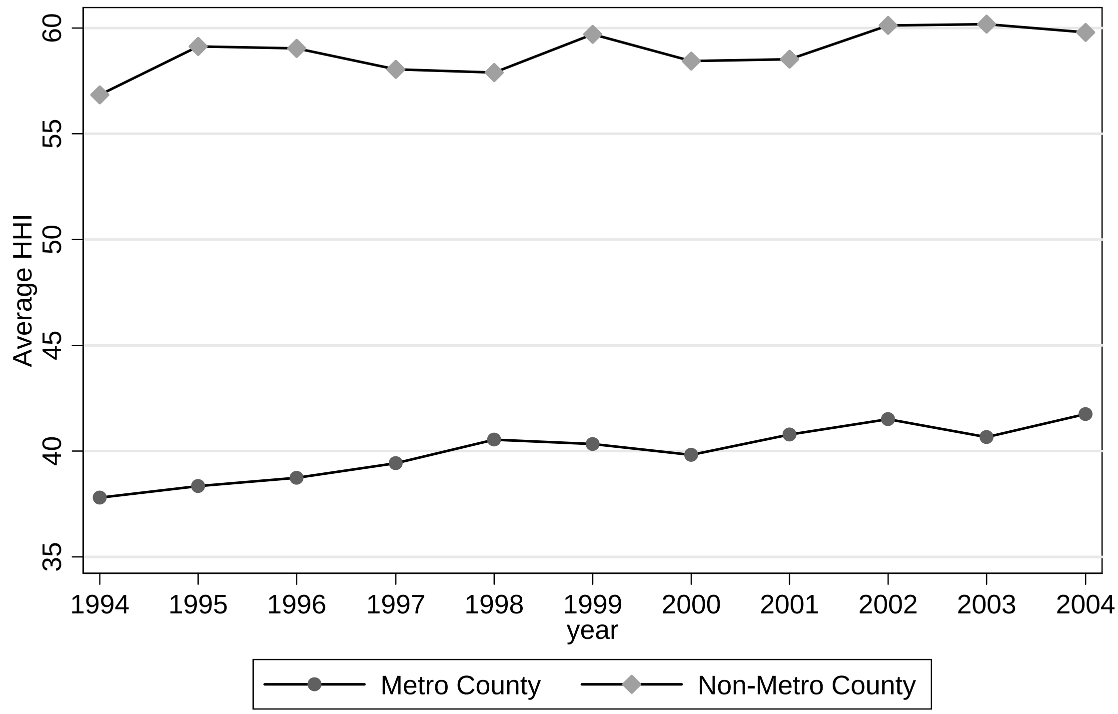

Figure 3-11. Average hospital-specific HHI (by type of county)

Figure 3-12. Average hospital charge (by type of county)

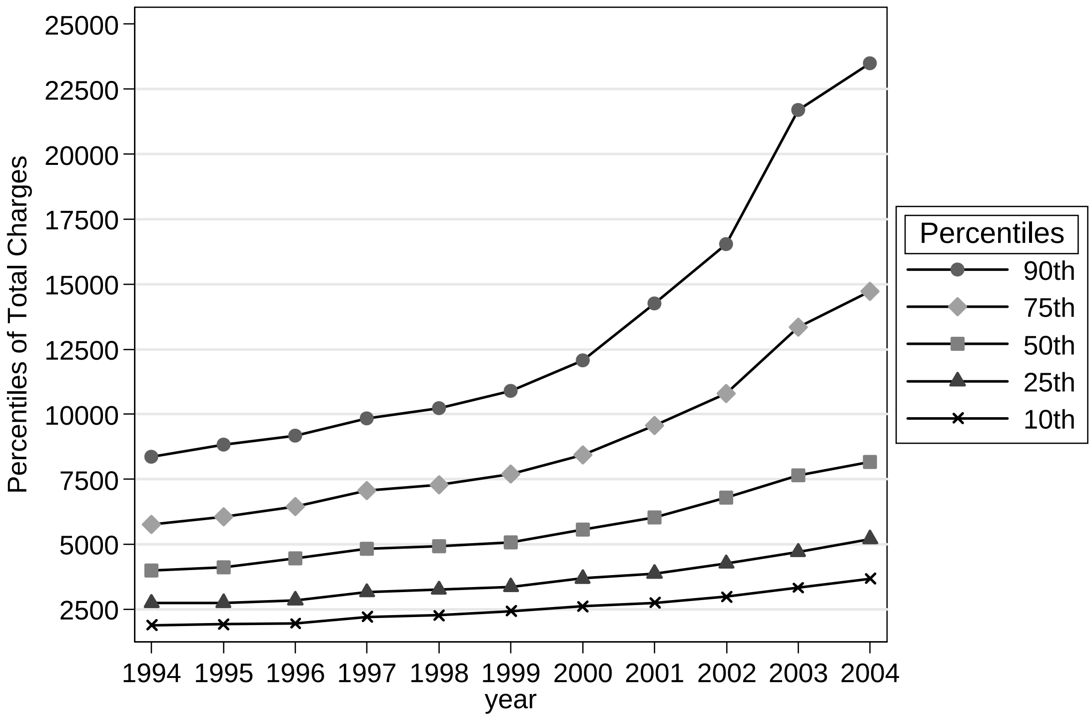

Figure 3-13. Distribution of charges for metro counties

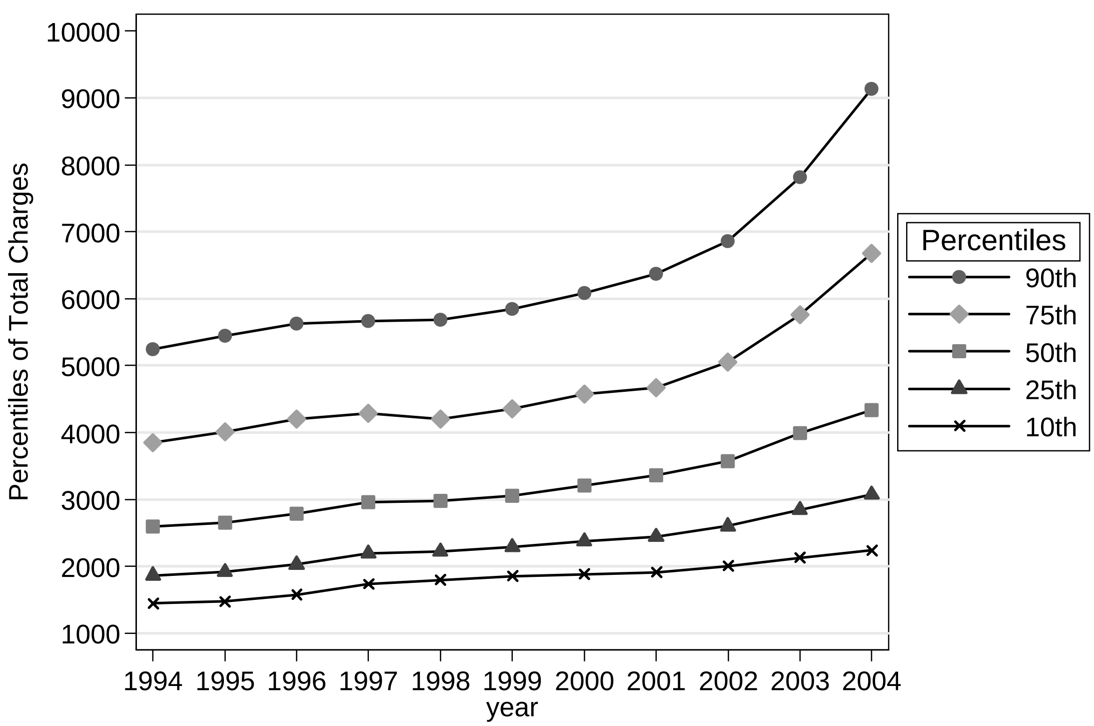

Figure 3-14. Distribution of charges for non-metro counties

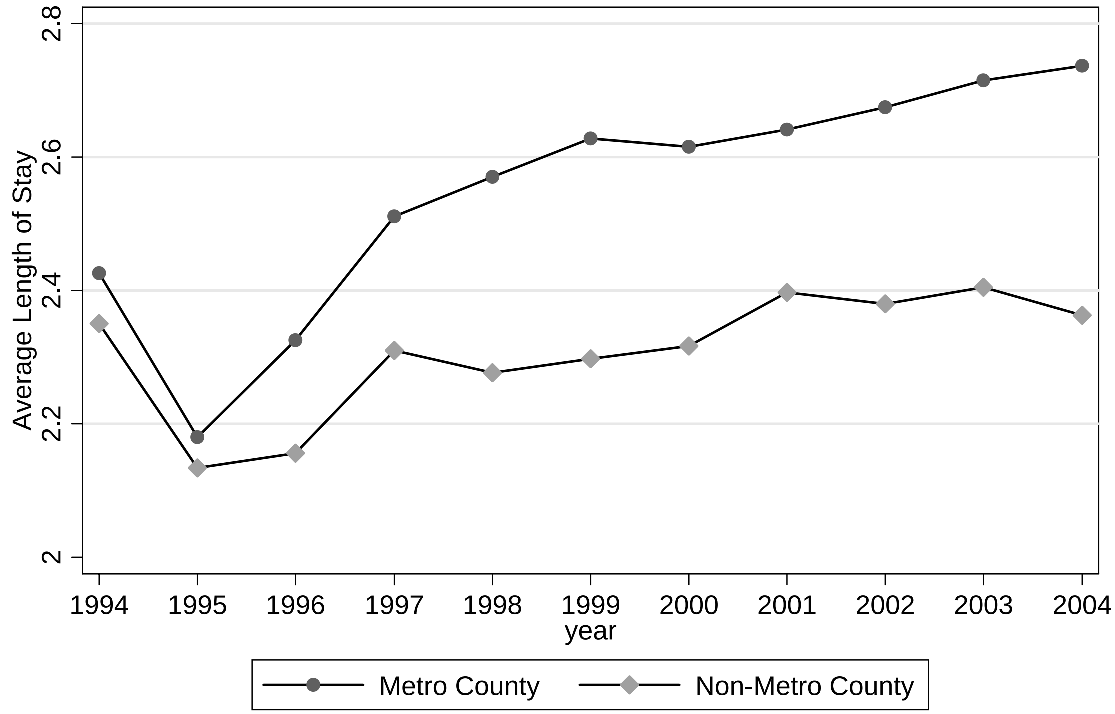

Figure 3-15. Averagelength of stay (by type of county)

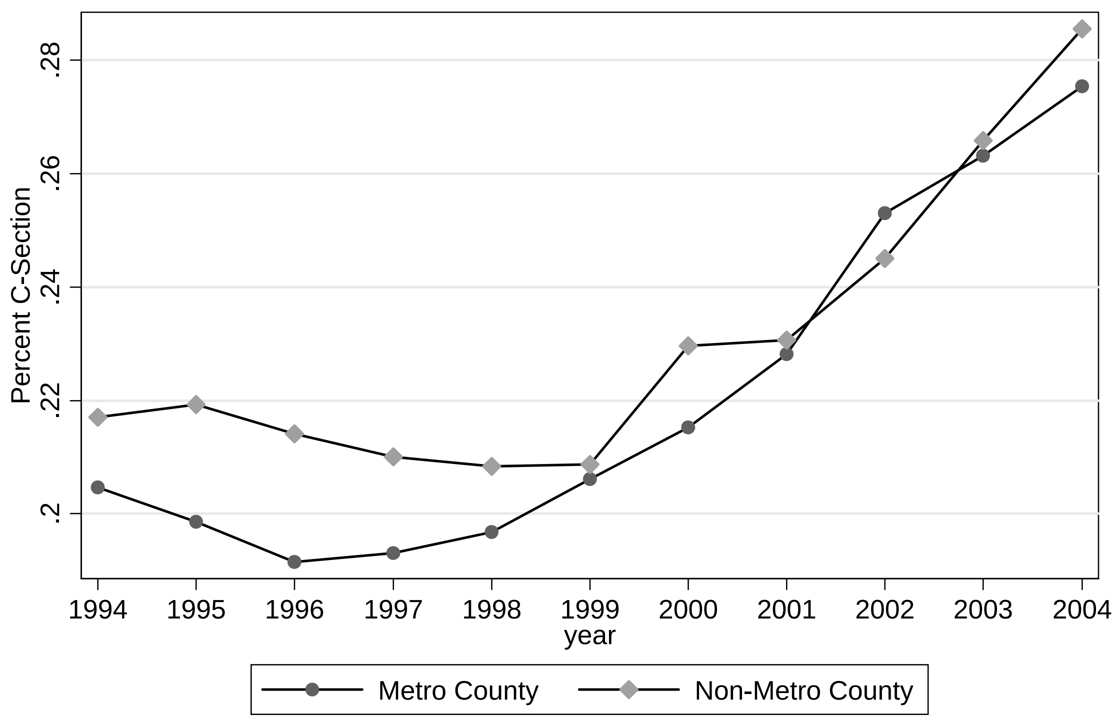

Figure 3-16. Percentage of births delivered by caesarean section (by type of county)

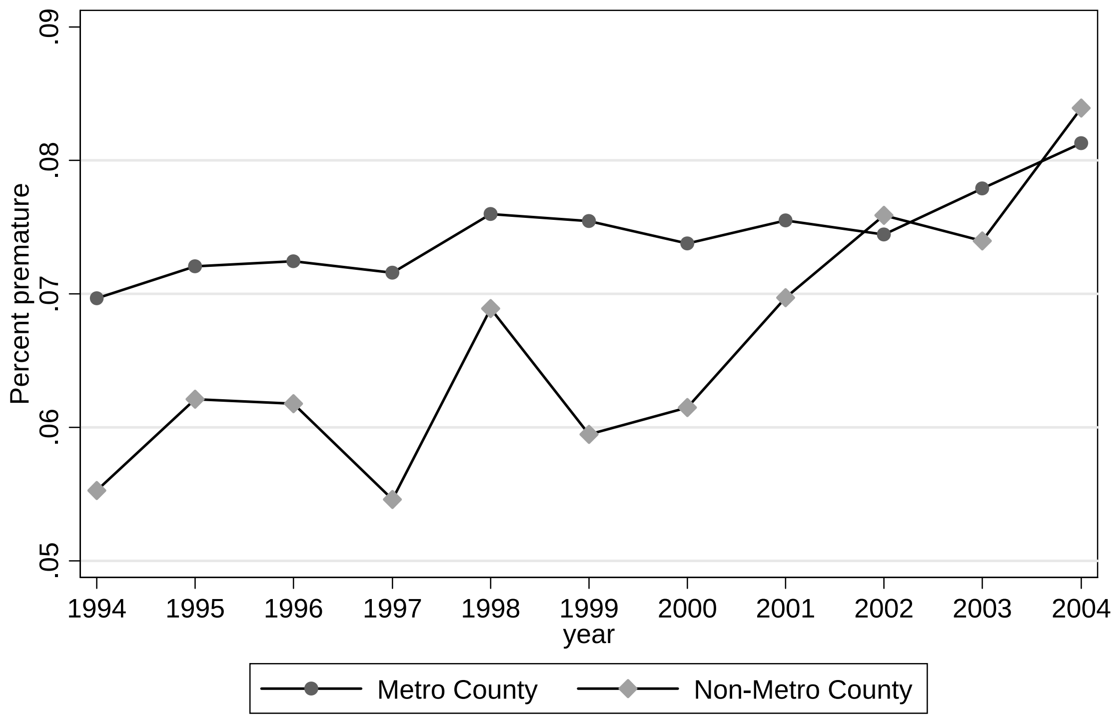

Figure 3-17. Percentage of births delivered prematurely (by type of county)

Figure 3-18. Percentage of payers who are HMOs (by type of county)

Figure 3-19. Percentage of payers who are Medicaid (by type of county)

CHAPTER 4
MALPRACTICE LAWSUITS AND MEDICAL PROCEDURE USE

> "America's health care professionals should be focused on fighting illnesses, not on fighting lawsuits. Junk lawsuits change the way docs do their job. … If you're worried about getting sued, you're going to do everything you can to make sure you don't get sued. That's why doctors practice what's called defensive medicine. That means they're writing prescriptions or ordering tests that really aren't necessary, just to reduce the potential of a future lawsuit."
>
> —George W. Bush[1]

"Defensive medicine" is a serious public policy concern and a potential contributor to the increasing cost of medical care in the United States. Anecdotal evidence indicates that the problem may be growing in severity. However, the academic literature's understanding of defensive medicine remains incomplete. The process of determining what constitutes defensive medicine has been confounded by data limitations. Current research is based on medical costs, malpractice premiums, or legal reforms - not actual medical decisions and outcomes. Thus far, the practice of defensive medicine has been inferred from proxies for the fear of malpractice lawsuits or more specifically the legal environment. This paper adds to the literature on defensive medicine by examining the effect of malpractice lawsuits on specific physician's medical procedure use. I hypothesize that defensive medicine is due to both the fear of being sued as well as to physician's responses to actually being sued. Using a panel of obstetricians, a difference in difference approach circumvents the problem of unobserved physician heterogeneity.

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[1] Speech on January 5, 2005.

While the legal environment may be the primary impetus for defensive medicine, I argue a doctor's response to litigation is interesting in its own right.

In this paper, I use hospital discharge data for maternity patients at all of the hospitals in Allegheny and Philadelphia counties for the years 1994 – 2004[2]. These data identify the physician by medical license number which was then used to identify the physician by name. The doctor's name was then matched to medical malpractice lawsuits in Allegheny County for the years 1995 – 2004 and Philadelphia County for the years 1980-2004[3]. By following the individual doctors' behavior over multiple years (both before and after a lawsuit for those sued), I am able to identify the impact of malpractice lawsuits on a physician's choice of obstetrical procedures. Using a difference in difference approach to deal with the problem of doctor heterogeneity, the results show that after being sued, a doctor increases the use of caesarean sections (c-section) by approximately 5.5% relative to doctors who were not sued in Allegheny County. The estimated effect is approximately 1.5% in Philadelphia County. It is possible that lawsuits may lead to an increase in the number of labor inductions; however, these estimates lack statistical precision.

Previous Literature

Malpractice insurance premiums are not experience rated- contrary to economic theory. That is, premiums are not based on past claims history. Rather, they are set at the community level (often at the state level) and adjusted for medical specialty and limits of

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[2] These Counties were chosen because their court systems identify lawsuits as medical malpractice cases. Due to the cost to obtain the data, the data is actually the 1st quarter of the years 1994 – 2004.

[3] The earliest court records that are online for Allegheny County begin in 1995, while the earliest court records that are online for Philadelphia County begin in 1980.

coverage (Danzon 2000)[4]. One implication of this aspect of malpractice is that doctors are somewhat isolated from the costs of their own behavior. In fact, it could be argued that the major costs, to a doctor, of a malpractice suit are time and reputation, neither of which are insurable. The lawsuit does not affect malpractice insurance premiums, except in extreme cases. Indeed, the individual doctor has very little to no control over his own malpractice insurance rates. From a purely economic point of view, a doctor provides prudent medical care to minimize these time and reputation costs, not to control his insurance rates.

This leads to the hypothesis that a doctor will seek to minimize his exposure to the court system. If a doctor perfectly forecasts the true costs of being sued, in terms of time and reputation, then a lawsuit will have no effect on his procedure use. However, without perfect foresight, it is likely that at least some doctors will underestimate these costs. It is these doctors who I expect to change their behavior after being sued. A secondary hypothesis is that the doctors with the least exposure (either themselves or their colleagues) to the courts will change their behavior the most after being sued themselves.

There has a long line of research that discusses the issue of "bounded rationality" and decision making. It has been shown that people in general do not forecast risks, or deal with probabilities, very well. Tversky and Kahneman (1974) document many biases in judgment that people make. They argue that people tend to use heuristics, or rules of thumb, to make decisions under uncertainty. This article led to a long line of research that attempted to formalize economics models of decision making that take into account

[4] Danzon (2000) presents a thorough review of medical malpractice issues.

these biases.[5] Kahneman and Tversky (1973) show that people do not behave as a statistician would when presented with probabilities. Instead “they rely on a limited number of heuristics which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors.” In this same vein, Camerer and Lowenstein (2004) argue that Bayes’ Rule is unlikely to be used correctly because “it has several features that are cognitively unrealistic”.

Lowenstein and Mather (1990) attempt to assess how accurate risk perceptions are over time as the underlying source of different risks change. They find that in many cases, the public perception of risks changes dramatically although the underlying factor has changed very little. Lowenstein, O’Donoghue and Rabin (2003) develop a model of what they term “projection bias”. They argue that people project their current preferences onto their future selves. Lowenstein (2005) discusses projection bias in the realm of medical decision making. He argues that many medical decisions involve fear, pain and discomfort and therefore affect people’s decision making. These decisions can be exacerbated by the fact that the doctor is does not adequately perceive the patient’s mental state. This research leads one to the conclusion that people do not behave in a utility-maximizing manner. It is therefore likely that physicians do not base their medical decisions on accurate estimates of future litigation costs.

Within the existing research on defensive medicine, Kessler and McClellan (1996) is one of the more prominent papers. Using data from all Medicare patients treated for serious heart disease in addition to information about changes in state malpractice laws (for example, caps on punitive damages or changes to the statute of limitations), they

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[5] See Kahneman (2003) for a review.

show that states which enact malpractice reforms have lower health care spending without a change in mortality or medical complications. They conclude that this is evidence that defensive medicine exists. Kessler and McClellan (1997) use a survey from the American Medical Association to investigate how malpractice reforms influence physician perceptions and change self-reported behavior. While the authors do not observed health outcomes or medical costs (and so cannot precisely determine the existence of defensive medicine), they find the legal environment affects both the likelihood of being sued as well as physician behavior.

One paper that deals specifically with defensive medicine in obstetrics is Dubay, et al. (1999) which uses birth certificate data for the years 1990-1992. The authors use the fact that medical malpractice insurance premiums are not experience rated. Then based on the assumption that premiums are an accurate measure of the likelihood of malpractice lawsuits in a geographic area, the premiums are used as a proxy for the likelihood of a doctor being sued. With this, the authors are able to investigate the relationship between the legal environment (and, therefore, the fear of lawsuits) and the county-level rate of caesarean sections. They show that there is an increase in the number of c-sections due to malpractice fears without a concurrent increase in the health of the babies. They argue that this is evidence of defensive medicine, but the overall effect is small. A second obstetrics related paper is Dubay, et. al (2001) which again uses the same birth certificate data and malpractice insurance premiums to show that a reasonable decrease in premiums would lead to an increase in prenatal care. While they argue that malpractice pressure reduces the supply of prenatal care, this is not shown to affect the health of newborns.

Baicker and Chandra (2004) look at the potential costs of malpractice on patient care. They find no evidence of a change in treatment patterns in response to increases in malpractice premiums. They also find no evidence that malpractice costs affect the overall number of doctors.

The influential Harvard Medical Practice Study (Brennan, et al. 1991) reviewed 7,743 medical charts for evidence of negligence. They found 1,278 adverse events of which 306 were attributed to negligence. The authors found 47 malpractice claims from these cases but, only 8 of these claims were found to have evidence of malpractice. More importantly, 40 percent of cases without negligence resulted in a payment. While the authors draw the conclusion that there are not enough malpractice lawsuits (i.e., only 15% of negligent doctors are sued), the evidence also points to the randomness of malpractice lawsuits (i.e., only 17% of malpractice claims involve actual cases of negligence). Given this apparent lack of correlation between actual malpractice by the physician and the likelihood of a lawsuit, this implies that malpractice suits can be treated as a random event.

This paper uses hospital discharge data for all births in Allegheny and Philadelphia Counties, Pennsylvania for the years 1994-2004. While earlier researchers have shown that doctors appear to respond to general malpractice pressure (i.e., the legal environment), none have been able to investigate individual doctor's responses to being sued for medical malpractice. With this dataset, I am able to isolate a doctor's response to new litigation from the preexisting legal environment.

A naïve approach to the problem of doctors' responses to lawsuits would use a cross-section of doctors and their responses to malpractice cases. However, the probability of being sued is almost certainly correlated with the difficulty of the medical cases, and hence with the procedures used. While diagnosis information is available, it is difficult to summarize and therefore difficult to control for in a regression model. Instead, to circumvent this problem of unobserved heterogeneity, a difference in difference approach is used. That is, the effect of being sued is determined by each doctor's change in behavior.

If malpractice lawsuits are a random event, controlling for patient characteristics, then it is straight forward to determine the effect of lawsuits on physician behavior. The average number of c-sections or other potentially defensive procedures performed can be compared before and after a doctor is sued. Any changes in behavior can be attributed to the lawsuit. One potential problem with this approach is the large changes in procedure use over the period. Given these time trends, it is possible that the effect of lawsuits would be overstated. The difference in difference approach, by using the "un-sued" doctors as a control group, removes this issue by assuming that both groups of doctors have the same underlying time trend.

Description of the Data

The hospital data includes detailed information for approximately 100,000 mothers in Allegheny and Philadelphia Counties, Pennsylvania for the years 1994-2004. Each mother has up to three doctors (referring, attending, and operating physicians) listed on her record. The doctors are identified by their Pennsylvania medical license number. While three doctors are possible, frequently one doctor is listed in multiple roles. While most records have both a referring and attending doctor listed, many do not have an operating doctor listed.[6] For the majority of the data, only one license number is listed for a given mother. This paper reports only the attending physician results, as the results are qualitatively similar for the other doctors. Each of these license numbers was matched to the doctor's name and the date the license was first issued using the State of Pennsylvania's license verification website[7]. The doctor names then were matched to court data on medical malpractice cases using the respective county's Prothonotary's website[8].

Annual summary statistics for doctors and patients are provided in Table 4-1 and Table 4-2. While the number of births declines in both counties over the data period, the number of doctors remains relatively constant in Allegheny and decreases in Philadelphia.

The number of c-sections increases over the years in the sample, from an average of 19% to an average of 27% (Figure 4-1). We also see a large increase in the number of labor inductions in Allegheny County and a slight rise in Philadelphia County (Figure 4-2). These changes in procedure use are a factor in the rising concern of defensive medicine. However, it is possible that this shift reflects cross-sectional changes in the composition of mothers. Mothers could be older and exhibit different c-section preferences in later periods. In addition, the use of other obstetric procedures has changed during this sample time.

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[6] The only time there is an operating doctor listed is if there was a surgical procedure performed.

[7] http://licensepa.state.pa.us/

[8] A Prothonotary is the chief legal clerk in a county in Pennsylvania. It is comparable to a clerk of the court in other states.

The percentage of vaginal births after caesarean sections (VBAC) has decreased (Figure 4-3). Given that a vaginal birth is higher risk after a previous c-section, it is reasonable to believe that some of this reduction may due to malpractice fears, i.e., defensive medicine. Grady (2004) presents anecdotal evidence that some hospitals in the U.S. no longer allow VBACs to be performed. Likewise, there is a simultaneous decrease in the percentage of pregnancies that are "prolonged" i.e., those that have gestational periods longer than 42 weeks. As prolonged pregnancies increase the risk to the mother and the baby, it is not surprising that doctors have reduced their occurrence. There are no prolonged pregnancies after 2002 compared to approximately 4% of the births in 1994 (Figure 4-4). Part of this decrease is almost certainly due to the increase in labor inductions during this period.

Over the period of the data, the occurrence of neonatal distress decreases markedly (Figure 4-5), while there is not a large change in the incidence of neonatal deaths (Figure 4-6). There is no significant change in the incidence of premature births in either county (Figure 4-7).

Two possible explanations for the increase in caesarean sections are the increase in the number of breech births (Figure 4-8) and the increase in mothers over the age of 35 (Figure 4-9), although these increases were larger in Allegheny County than in Philadelphia County. While there is some evidence for a relationship between older mothers and breech births, the possible effect is small (Rayl, Gibson, and Hickok 1996). It is also possible that mother's preferences are likely to have a large effect on caesarean sections. Anecdotally, older mothers are thought to be more likely to request a c-section, however this is difficult to determine from the data as the positive association between age and c-sections my also be due to increased pregnancy risk.

While the two counties look very similar over the time period, there is one very large difference. Both counties started the period with approximately 30% of the mothers on Medicaid. This percentage stayed the same in Allegheny County while it doubled in Philadelphia County by the end of the period (Figure 4-10).

Physicians and Medical Malpractice Lawsuits

While the total number of doctors is similar in each county in 1994, by the end of the period, the relative number in Philadelphia decreased (Table 4-3). The number of lawsuits per doctor differs dramatically between the two counties. The two counties diverge in another way as well; the total number of licenses issued in Allegheny County is almost four times the number issued in Philadelphia County.

The court data for Allegheny County begins in 1995. This unfortunately limits our sample, as this paper focuses on the effect of a physician being sued the first time. To capture this initial reaction, the first medical malpractice lawsuit must be identified for each doctor. Given the limitations of the court data, it is impossible to accurately determine the total number of malpractice lawsuits experienced by a physician who received his license before 1995. In this paper, "young doctors" refers to those licensed in 1994[9] to the present, while "old doctors" refers to those that received their license before 1994. In a later part of the paper, using the data from Philadelphia, I divide the "old doctors" into old and senior doctors. In this case, the old doctors are those who

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[9] 1994 is used as the cutoff because I have 1st quarter data. A doctor who finishes school in the spring will not appear in the hospital data until 1995.

received their license between 1980 and 1993, while the senior doctors are those who received their license before 1980.[10]

Philadelphia County court data are available beginning in 1980. Although this provides much greater detail for a given doctor, the hospital data begin in 1994. Now while we can not evaluate physician's responses to lawsuits over this whole panel, we can exploit the variation in a physician's lawsuit history. For the Philadelphia data, the physicians are segmented into age and lawsuits categories, i.e., an "old doctor" is one who received his license between 1980 and 1993. The old doctors then are grouped according to their past malpractice lawsuit history, i.e., those who have been sued and those who never have experienced a lawsuit.

Obstetricians/gynecologists are among the highest risk of malpractice lawsuits of all medical specialties. However, even with this heightened probability of legal action, the probability of a lawsuit varies greatly within the same state. Comparing Figure 4-11 and Figure 4-12, substantial differences are clear between Allegheny and Philadelphia Counties. Figure 4-11 shows the cumulative probability of a lawsuit for a given number of years of practice in Allegheny County. After practicing for five years, approximately 15% of doctors have been sued at least once[11]. In Philadelphia, the likelihood of a lawsuit is more than 20% for doctors with the same experience (Figure 4-12). By the 10th

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[10] This division is based on the court data for Philadelphia County.

[11] Because the majority of doctors received their licenses at the end of the period (when it is impossible for a doctor to have practiced for more than 5 or 6 years, the cumulative distribution is calculated with just the doctors from the 1st half of the period.

year of practice, only 20% of Allegheny doctors have been sued, while close 40% of the Philadelphia doctors have been sued at least once[12].

Responses to Lawsuits

It is reasonable to think that malpractice lawsuits are driven by doctor and patient characteristics. Known doctor characteristics are limited to experience and procedure use. I assume that malpractice lawsuits are exogenous, as earlier research has shown that lawsuits, while not entirely random, are not based on the medical record in most cases (see Harvard study). Given this exogeneity of lawsuits, the difference in difference estimate is an unbiased estimate of the effect of being sued on doctors' behavior.

Obstetrical Procedures

Of the obstetric procedures investigated as potentially defensive in nature, c-sections would seem to be the likeliest candidate. A c-section transforms a potentially litigious situation (a vaginal birth) into a controlled medical procedure. There is the added benefit that c-sections can be scheduled in advance, which is probably psychologically reassuring to both the doctor as well as the mother.

There is evidence that inducing labor on a mother who has previously had a c-section is dangerous, because of this, it is important to control for previous c-sections. However, if a doctor is fearful of a malpractice lawsuit, then he is likely to perform a c-section on a high-risk mother. The effect of malpractice lawsuits on inductions is an empirical question. While there is anecdotal evidence that fear of lawsuits has reduced

[12] These results are likely understated as it is reasonable to believe that some doctors would have stopped practicing before they appeared in the hospital data.

the use of VBACs, there are not enough women in the data that have had a previous c-section to effectively estimate an effect of a lawsuit on physician behavior.

To test the hypothesis that doctors respond to their first lawsuit, model 1 was estimated separately for each county.

$$\begin{aligned} \text{procedure}_i = {} & \alpha_1\ \text{sued1}_i + \alpha_2\ \text{sued2}_i + \alpha_3\ \text{sued3}_i + \alpha_4\ \text{sued4}_i + \\ & \beta_1\ \text{breech}_i + \beta_2\ \text{previous}_i + \beta_3\ \text{old}_i + \beta_4\ \text{medicaid}_i + \varepsilon_i \end{aligned} \tag{3-1}$$

where procedure is an indicator of either a caesarean section or an induced labor, sued1 – sued4 are indicators of the number of lawsuits a patient's doctor has experienced.[13] These indicators can change for each doctor from year to year depending on his lawsuit history. For example, a doctor who is never sued for malpractice will have all of the sued indicators equal to zero. A doctor who is sued for the first time in 1999 will have the sued1 equal one for the years after 1999. If he is sued a second time, the sued2 indicator will switch to a one, while the sued1 indicator will not change. Sued3 and sued4 are indicators of three and four lawsuits that are coded similarly. These indicators are difference in difference estimates of the effect of a given lawsuit on a doctor's behavior. The variables breech, previous, old, and Medicaid are indicators of a breech birth, a previous c-section, a mother over 35, and a mother on Medicaid. Because there are not any doctors that appear in both Philadelphia and Allegheny Counties, and the model includes doctor and year level fixed effects[14], estimating this with both

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[13] The sued indicators switch from 0 to 1 when a doctor gets sued the respective time. The indicators never switch off after being turned on.

[14] The model was also estimated with hospital fixed effects. There is no qualitative difference in the estimates.

counties jointly is not possible, unless the assumption is made that doctors in both counties react in the same manner to a lawsuit.

In order for the parameter of interest (α_1) to be identified, the time trend must be the same for the untreated group (i.e., doctors who are not sued)[15]. Because it appears that lawsuits are random, it is assumed that this condition is met. After controlling for doctor, year, and hospital effects, α_1 is the estimate of the treatment effect of being sued. If doctors react to lawsuits by increasing the number of c-sections, then α_1 should be positive. The same will be true for α_2, α_3 and α_4 if the response is not negligible for additional lawsuits. Because the variation in lawsuits occurs at the doctor level, the standard errors were clustered at the doctor level. The variables of interest in these regressions are the sued variables. If the hypothesis that at doctor only responds to a first lawsuit is true, then the coefficients on sued2 – sued4 should not be significantly different from zero.

With a binary dependent variable, a logit or probit model might be assumed. In actuality, the combination of doctor level fixed effects as well as a doctor level treatment effect implies that the dependent variable is the average of the doctor's procedure use in a given year. The same model could have been estimated by collapsing the data to doctor and year means and then applying ordinary least squares. I chose to estimate these models at the individual patient level to ensure the most precise estimates possible. The estimates are not qualitatively different when averages are used.

[15] Because of the strong time trend and the fact that there are not a large number of lawsuits in a given year, this is difficult to show.

Caesarean Sections in Philadelphia

The results for all of the doctors in Philadelphia are reported in the first column of Table 4-4. We see that as expected, breech births and previous c-sections are highly correlated with a c-section, as is the indicator for older mothers. A breech birth increases the probability of a c-section by 52%, while a previous c-section increases the probability of a c-section by 44%. We also see that Medicaid mothers are less likely to receive a c-section, although the coefficient is not very large. This may be because they are less demanding of their doctors or the doctors are less responsive to the demands of less wealthy patients. It is also possible that Medicaid reimbursement rates affect the doctor's choice of a c-section. We also see that, as predicted, doctors do respond to a malpractice lawsuit. The estimated impact of a first lawsuit on physician behavior is an increase in the c-section rate of 1.4%. Additional lawsuits have no effect. Given these results are for all of the Philadelphia doctors, young and old, it is possible that this underestimates the effect. Some of these doctors have been sued before the hospital data begins and may have adjusted their behavior already.

To address this issue, the model then was estimated with subsets of doctors. As mentioned before, the doctors were divided into "young", "old", and "senior" categories in Philadelphia County. These categories correspond to the hospital and court data. Young doctors received their license after 1994 and hence, hospital and court data is available for their whole career. Old doctors received their license between 1980 and 1993; court data is available for their whole career but not the hospital data. Lastly, senior doctors received their licenses before 1980 and thus have missing court information from the beginning of their career.

The expectation is that lawsuits will have the greatest effect on the young doctors with a possible effect on the old doctors who were not sued early in their career. The predicted effect of a lawsuit on the senior doctors is nil, it is assumed that they either have been sued previously or are experienced enough not to react in a significant manner.

The results from these additional regressions are reported in columns 2 – 4 of Table 4-4. Somewhat surprisingly, there is no statistically significant effect of a first lawsuit on young doctors while old doctors do respond to a lawsuit. As expected the senior doctors do not respond. Interestingly, when estimated separately, both the young and old doctors respond to a second lawsuit. The young doctors increase the rate of c-sections while the old doctors actually reduce their rate. It is possible that the old doctors change their patient mix in order to avoid high risk cases; however it is not possible to test this hypothesis.

It is also possible to segment the old and senior doctors into groups based on their earlier lawsuit history. Table 4-5 reports the results of regressions with the old doctors segmented into groups based on whether they were sued between 1980 and 1993. Column 1 reports the results for old doctors who were not sued before 1993. The effect of a first lawsuit on these doctors is positive but not statistically significant. Again, we find the old doctors respond to the second lawsuits by reducing the number of c-sections. They do not respond to additional lawsuits. By comparison, column 2 reports the results for the old doctors who were sued before 1993. It is these doctors who we do not expect to change their behavior in response to a lawsuit after 1994 and yet, we find that they increase their c-section rate by 3.5%. These doctors do not change their behavior in response to additional lawsuits. Columns 3 and 4 perform the same regressions for the senior doctors (i.e., those who received their licenses before 1980). As expected, in both cases, the senior doctors do not respond to a lawsuit.

Caesarean Sections in Allegheny

When the same model is estimated with the data from Allegheny County, we see that with all of the doctors, the coefficients on the control variables are similar. Although it does appear that doctors in Allegheny County have a greater propensity to perform a c-section relative to Philadelphia County, the coefficients on breech and previous are larger in Allegheny County. That is, c-sections are more likely simply due to patient attributes. Interestingly, it appears that Medicaid mothers are less likely to receive a c-section in Allegheny versus Philadelphia County. The variables of interest are the "sued" variables. With Allegheny County there is no effect of a lawsuit on behavior (column 1 of Table 4-6).[16] Again, these results are probably underestimated because some of these doctors have almost certainly been sued before.

This model again is estimated with the doctors segmented into different groups. For comparability purposes, the same divisions (young and old) are made with the Allegheny doctors even though the court data do not begin until 1995. Column 4 groups the old and senior doctors together since, they are indistinguishable in Allegheny County for all practical purposes. The results of these regressions are reported in columns 2–4 of Table 4-6. Young doctors respond in a dramatic fashion to a first lawsuit. The estimated effect is a 5.6% increase and is highly statistically significant. The young doctors do not

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[16] While it is possible that doctors are responding to a third lawsuit and no others, this is probably an artifact of the data.

respond to a second lawsuit. The old doctors do not respond to a first or second lawsuit but again, appear to respond to third lawsuit.

Labor Inductions in Philadelphia

Next, I evaluate the use of labor inductions. As mentioned previously, the predicted effect of a lawsuit on a physician's behavior is uncertain. A doctor may want to reduce the number of vaginal births he performs and so will be less willing to induce labor. However, it is also possible that the potential risk from a prolonged pregnancy will lead the doctor to induce labor instead of waiting for spontaneous labor.

We see in the first column of Table 4-7 that doctors in Philadelphia do not appear to change the number of inductions performed in response to a lawsuit. As before, it is possible that this understates the effect because a number of these doctors have probably been sued before. When, the doctors are divided into groups based on when their license was issued, it does not appear that any of the groups of doctors respond to a lawsuit by changing their behavior. Columns 2, 3 and 4 of Table 4-7 show the results of these separate regressions.

Segmenting doctors based on their lawsuit history shows differences among old doctors. Columns 1 and 3 of Table 4-8 report the results for doctors who were not sued before 1993. The senior doctors respond to a first lawsuit by reducing the number of inductions by almost 8%, while the old doctors do not change their behavior. These results may be driven by the small sample size. Columns 2 and 4 of Table 4-8 report the results for the doctors who had previously been sued. As expected, these doctors do not change the rate of inductions. Again, it is interesting to note that the doctors who had previously been sued appear to be less likely to induce labor for breech births and previous c-sections. This may imply that they have already made adjustments to their practices.

Labor Inductions in Allegheny

It appears that doctors in Allegheny County change their induction rate in response to malpractice lawsuits (Table 4-9). A first lawsuit leads to a reduction of inductions by 1.5%, while additional lawsuits do not appear to matter. Columns 2, 3 and 4 of Table 4-9 report the results for the separate age groups. While the coefficients of the first lawsuit are negative in all three cases, only the one for the old doctors is statistically significant. Again, additional lawsuits do not appear to matter.

Conclusions

While it is impossible to say that these results are proof of the existence of defensive medicine in obstetrics, evidence exists that doctors change their procedure use after being sued for malpractice. There is also evidence of differences in procedure use across geographical areas. It appears that the “age” of a doctor influences how he responds to a lawsuit.

In Allegheny County, when all doctors are included in the sample, there is no effect of lawsuits on procedure use. This lack of an effect is not surprising given that many of the doctors have been practicing medicine since the 1980s. It is likely that many of them have been sued previously and have already changed their medical practices. However, when the sample is limited to young doctors (who we can be relatively certain have not been sued before entering the data), it is estimated that a doctor will increase the number of c-sections performed by approximately 5% in response to a lawsuits. This is a large change given that the average c-section rate is 20% in 1994 and 28% in 2004. It is possible that the use of inductions is affected by lawsuits but, these estimated effects suffer from a lack of precision. Doctors in Philadelphia County, who have more Medicaid patients and much higher risk of litigation appear much less sensitive to lawsuits than doctors in Allegheny County. They also appear to be less likely to use c-sections in potentially risky situations.

In order to draw conclusions about the presence of defensive medicine in response to malpractice lawsuits, measurable outcomes are needed. Two obvious ones are maternal and fetal deaths. Thankfully (from society's point of view), these both occur infrequently; however the rarity of these outcomes makes them less than ideal for my purposes. One thing is certain; physicians do appear to respond to malpractice lawsuits by changing their practice patterns.

Table 4-1. Number of doctors by type and county

gg	Philadelphia		Pittsburg	
Year	Total Drs	Young Drs	Total Drs	Young Drs
1994	197	1	194	2
1995	188	7	188	7
1996	188	24	190	11
1997	207	31	203	22
1998	236	40	198	28
1999	158	38	205	41
2000	180	56	192	50
2001	169	57	194	63
2002	155	74	190	62
2003	126	59	192	74
2004	130	70	186	71

Table 4-2. Number of patients by doctor type and county

	Philadelphia			Pittsburg		
Year	Old Drs	Young Drs	Total	Old Drs	Young Drs	Total
1994	5,689	18	5,707	4,761	241	5,002
1995	5,213	188	5,401	4,758	212	4,970
1996	4,383	511	4,894	4,228	437	4,665
1997	3,914	720	4,634	3,983	473	4,456
1998	3,586	957	4,543	3,817	470	4,287
1999	2,548	995	3,543	3,602	747	4,349
2000	3,194	1,471	4,665	3,417	1,037	4,454
2001	2,973	1,398	4,371	3,065	1,227	4,292
2002	2,363	1,940	4,303	2,986	1,154	4,140
2003	2,044	2,203	4,247	2,959	1,313	4,272
2004	1,871	2,608	4,479	2,827	1,485	4,312

Table 4-3. Number of licenses issued and number of doctors sued by county and year the license was issued.

		Pittsburg			Philadelphia		
	Year	# issued	# Sued	Percent Sued	# issued	# Sued	Percent Sued
	1980	63	29	0.460	20	10	0.500
	1981	82	33	0.402	19	12	0.632
	1982	52	31	0.596	22	17	0.773
	1983	67	26	0.388	18	10	0.556
	1984	89	37	0.416	9	2	0.222
	1985	87	40	0.460	23	15	0.652
OLD DOCTORS	1986	89	50	0.562	15	4	0.267
	1987	92	38	0.413	27	12	0.444
	1988	64	21	0.328	18	7	0.389
	1989	75	27	0.360	12	8	0.667
	1990	86	27	0.314	18	11	0.611
	1991	77	22	0.286	29	10	0.345
	1992	87	31	0.356	33	18	0.545
	1993	120	36	0.300	25	10	0.400
	1994	78	18	0.231	29	11	0.379
	1995	103	30	0.291	34	15	0.441
	1996	81	18	0.222	29	12	0.414
	1997	92	21	0.228	21	4	0.190
YOUNG DOCTORS	1998	73	13	0.178	23	7	0.304
	1999	74	15	0.203	15	4	0.267
	2000	60	3	0.050	18	2	0.111
	2001	53	10	0.189	18	6	0.333
	2002	41	2	0.049	9	2	0.222
	2003	28	2	0.071	7	0	0.000
	Total	1813	132	0.073	491	209	0.426

Table 4-4. Philadelphia results with c-sections as the dependent variable (standard errors in parentheses)

C-section	all doctors	young doctors	old doctors	senior doctors
sued1	0.0140	0.0130	0.0232	0.0080
	(0.0070)	(0.0163)	(0.0103)	(0.0142)
sued2	-0.0072	0.0379	-0.0203	0.0066
	(0.0078)	(0.0177)	(0.0109)	(0.0174)
sued3	0.0045	-0.0293	0.0110	0.0083
	(0.0091)	(0.0220)	(0.0118)	(0.0217)
sued4	0.0047	0.0079	0.0068	-0.0216
	(0.0099)	(0.0288)	(0.0121)	(0.0238)
medicaid	-0.0253	-0.0200	-0.0298	-0.0292
	(0.0039)	(0.0075)	(0.0057)	(0.0080)
old	0.0537	0.0579	0.0587	0.0411
	(0.0048)	(0.0098)	(0.0069)	(0.0097)
previous	0.4380	0.4830	0.4252	0.4280
	(0.0050)	(0.0103)	(0.0072)	(0.0101)
breech	0.5249	0.4810	0.5293	0.5612
	(0.0064)	(0.0128)	(0.0090)	(0.0134)
Constant	0.1087	0.1405	0.0980	0.1227
	(0.0059)	(0.1261)	(0.0076)	(0.0090)
Observations	50787	13009	24804	11926
# of Doctors	577	174	257	141
R-squared	0.23	0.23	0.24	0.24
F stat	840.1	209.3	419.6	202.1

Table 4-5. Philadelphia segmented results with c-sections as the dependent variable
(standard errors in parentheses)

C-section	old doctors not sued before 1994	old doctors sued before 1994	senior doctors not sued before 1994	senior doctors sued before 1994
sued1	0.0177	0.0358	-0.0064	0.0231
	(0.0146)	(0.0165)	(0.0291)	(0.0193)
sued2	-0.0342	-0.0236	-0.4248	0.0085
	(0.0174)	(0.0152)	(0.2030)	(0.0191)
sued3	0.0057	0.0095	0.0000	0.0069
	(0.0177)	(0.0164)	0.0000	(0.0227)
sued4	-0.0017	0.0158	0.0000	-0.0043
	(0.0194)	(0.0163)	0.0000	(0.0252)
medicaid	-0.0313	-0.0255	-0.0185	-0.0389
	(0.0070)	(0.0100)	(0.0120)	(0.0109)
old	0.0660	0.0491	0.0535	0.0305
	(0.0093)	(0.0103)	(0.0142)	(0.0134)
previous	0.4079	0.4522	0.3954	0.4540
	(0.0091)	(0.0115)	(0.0152)	(0.0136)
breech	0.5131	0.5536	0.5690	0.5567
	(0.0115)	(0.0144)	(0.0205)	(0.0178)
Constant	0.0986	0.0997	0.1103	0.1329
	(0.0099)	(0.0120)	(0.0138)	(0.0120)
Observations	15349	9455	5385	6541
# of doctors	178	79	61	80
R-squared	0.22	0.26	0.22	0.25
F stat	239.4	182	96.26	118.8

Table 4-6. Allegheny results with c-sections as the dependent variable (standard errors in parentheses)

C-section	all doctors	young doctors	old doctors	all old doctors
sued1	0.0068	0.0568	-0.0034	0.0014
	(0.0062)	(0.0220)	(0.0083)	(0.0065)
sued2	-0.0133	-0.0169	-0.0046	-0.0097
	(0.0081)	(0.0353)	(0.0105)	(0.0084)
sued3	0.0322	N/A	0.0229	0.0332
	(0.0116)	N/A	(0.0142)	(0.0116)
sued4	-0.0048	N/A	-0.0150	-0.0040
	(0.0214)	N/A	(0.0249)	(0.0212)
medicaid	-0.0321	-0.0349	-0.0388	-0.0316
	(0.0044)	(0.0100)	(0.0062)	(0.0049)
old	0.0317	0.0320	0.0340	0.0319
	(0.0041)	(0.0107)	(0.0057)	(0.0045)
previous	0.4772	0.4708	0.4592	0.4778
	(0.0048)	(0.0128)	(0.0066)	(0.0052)
breech	0.6380	0.5968	0.6558	0.6476
	(0.0057)	(0.0134)	(0.0078)	(0.0063)
Constant	0.1115	0.0310	0.1157	0.1102
	(0.0056)	(0.0779)	(0.0073)	(0.0055)
Observations	48696	8293	25241	40403
# of doctors	425	141	181	284
R-squared	0.33	0.3	0.33	0.33
F stat	1302	218.9	695.3	1112

Table 4-7. Philadelphia results with inductions as the dependent variable (standard errors in parentheses)

Induce	all doctors	young doctors	old doctors	senior doctors
sued1	0.0033	-0.0126	0.0122	-0.0300
	(0.0063)	(0.0149)	(0.0090)	(0.0124)
sued2	0.0088	0.0376	0.0110	0.0113
	(0.0069)	(0.0163)	(0.0095)	(0.0153)
sued3	0.0143	-0.0357	0.0344	-0.0050
	(0.0081)	(0.0201)	(0.0102)	(0.0190)
sued4	0.0097	0.0299	0.0105	0.0036
	(0.0088)	(0.0264)	(0.0105)	(0.0208)
medicaid	-0.0049	-0.0001	-0.0078	-0.0085
	(0.0034)	(0.0068)	(0.0050)	(0.0070)
old	0.0152	0.0134	0.0151	0.0196
	(0.0043)	(0.0090)	(0.0060)	(0.0085)
previous	-0.0538	-0.0713	-0.0484	-0.0485
	(0.0045)	(0.0094)	(0.0062)	(0.0089)
breech	-0.0444	-0.0533	-0.0447	-0.0294
	(0.0057)	(0.0117)	(0.0078)	(0.0118)
Constant	0.1037	0.0806	0.1072	0.0870
	(0.0052)	(0.1154)	(0.0066)	(0.0079)
Observations	50787	13009	24804	11926
# of Doctors	577	174	257	141
R-squared	0.01	0.01	0.01	0.01
F stat	21.5	7.575	12.69	5.037

Table 4-8. Philadelphia segmented results with inductions as the dependent variable(standard errors in parentheses)

Induce	old doctors not sued before 1994	old doctors sued before 1994	senior doctors not sued before 1994	senior doctors sued before 1994
sued1	0.0110	0.0046	-0.0783	-0.0008
	(0.0125)	(0.0147)	(0.0285)	(0.0151)
sued2	-0.0171	0.0203	-0.0902	0.0134
	(0.0149)	(0.0136)	(0.1993)	(0.0149)
sued3	0.0471	0.0169	0.0000	-0.0036
	(0.0152)	(0.0146)	0.0000	(0.0177)
sued4	0.0154	-0.0012	0.0000	-0.0090
	(0.0166)	(0.0145)	0.0000	(0.0197)
medicaid	-0.0128	0.0031	0.0051	-0.0157
	(0.0060)	(0.0089)	(0.0118)	(0.0085)
old	0.0197	0.0105	0.0138	0.0244
	(0.0080)	(0.0092)	(0.0139)	(0.0104)
previous	-0.0388	-0.0630	-0.0447	-0.0514
	(0.0078)	(0.0102)	(0.0149)	(0.0107)
breech	-0.0363	-0.0584	-0.0140	-0.0397
	(0.0099)	(0.0129)	(0.0201)	(0.0139)
Constant	0.1207	0.0928	0.1023	0.0735
	(0.0085)	(0.0107)	(0.0135)	(0.0094)
Observations	15349	9455	5385	6541
# of doctors	178	79	61	80
R-squared	0.01	0.01	0.01	0.01
F stat	6.615	7.455	2.594	4.15

Table 4-9. Allegheny results with inductions as the dependent variable (standard errors in parentheses)

Induction	all doctors	young doctors	old doctors	all old doctors
sued1	-0.0154	-0.0243	-0.0186	-0.0132
	(0.0064)	(0.0228)	(0.0085)	(0.0066)
sued2	0.0096	0.0252	0.0081	0.0085
	(0.0084)	(0.0365)	(0.0108)	(0.0086)
sued3	0.0058	0.0000	0.0014	0.0059
	(0.0120)	0.0000	(0.0146)	(0.0119)
sued4	-0.0111	0.0000	-0.0075	-0.0118
	(0.0220)	0.0000	(0.0258)	(0.0218)
medicaid	-0.0199	-0.0331	-0.0155	-0.0165
	(0.0045)	(0.0103)	(0.0064)	(0.0050)
old	0.0128	0.0173	0.0126	0.0120
	(0.0042)	(0.0111)	(0.0058)	(0.0046)
previous	-0.0733	-0.1094	-0.0696	-0.0667
	(0.0049)	(0.0132)	(0.0069)	(0.0053)
breech	-0.0639	-0.0638	-0.0622	-0.0644
	(0.0059)	(0.0139)	(0.0081)	(0.0065)
Constant	0.1226	0.2561	0.1146	0.1223
	(0.0058)	(0.0805)	(0.0075)	(0.0057)
Observations	48696	8293	25241	40403
# of doctors	425	141	181	284
R-squared	0.01	0.02	0.01	0.01
F stat	35.86	7.82	18.29	30.55

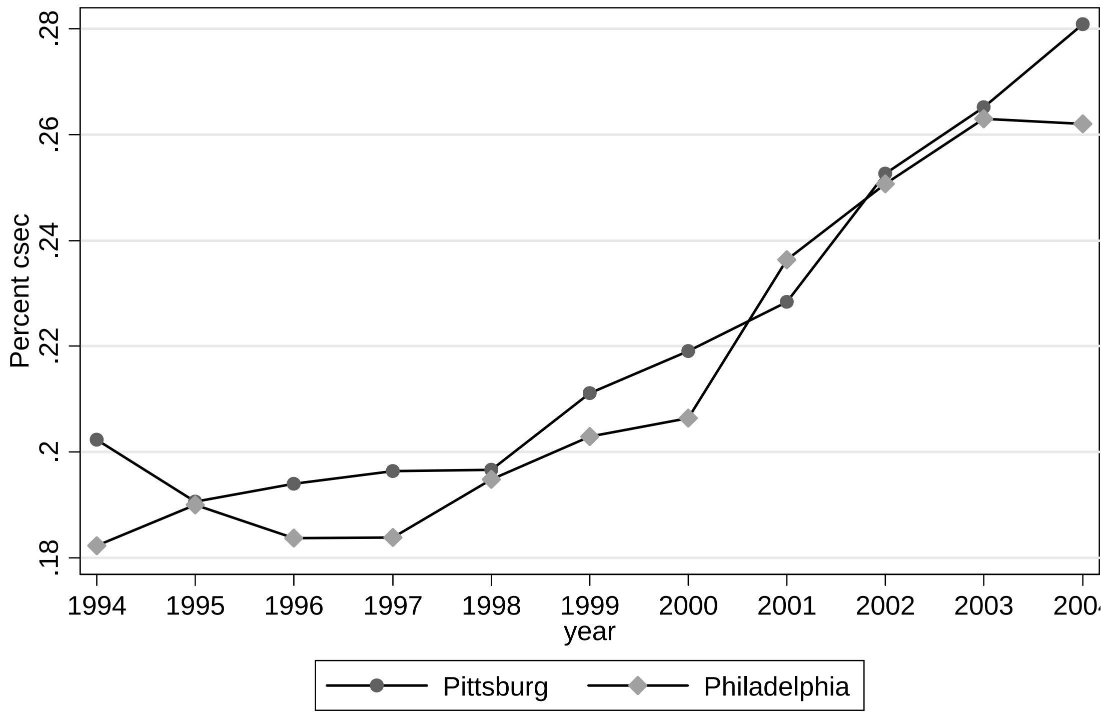

Figure 4-1. Percentage of births that are caesarean sections (by county)

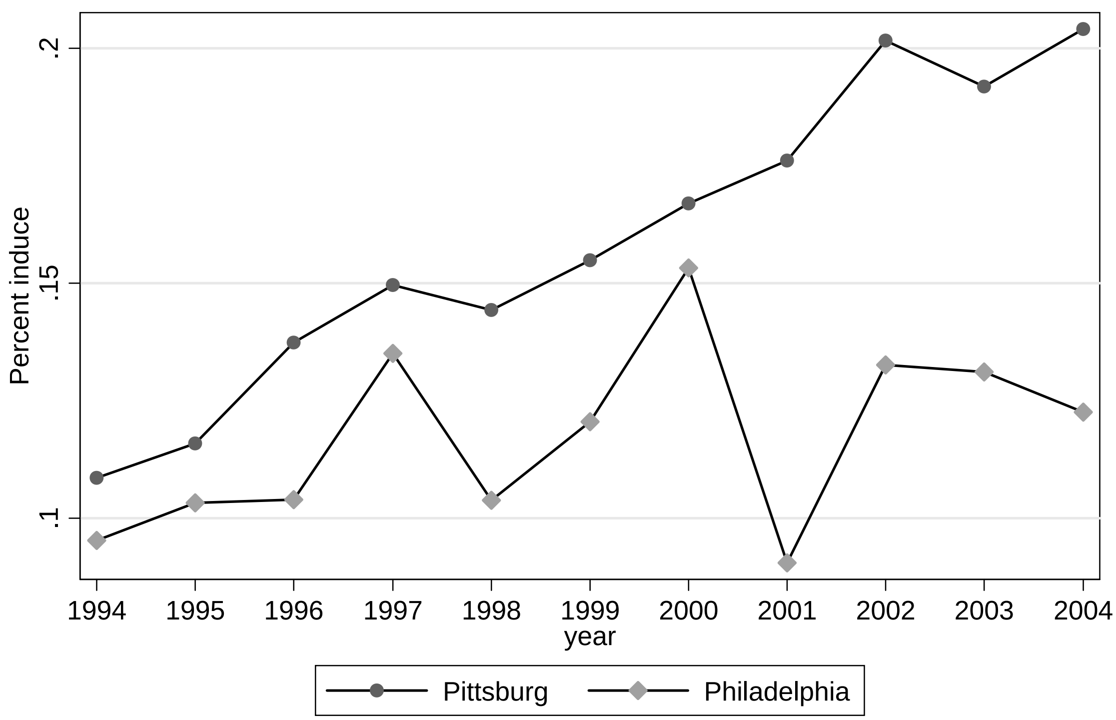

Figure 4-2. Percentage of births that are labor inductions (by county)

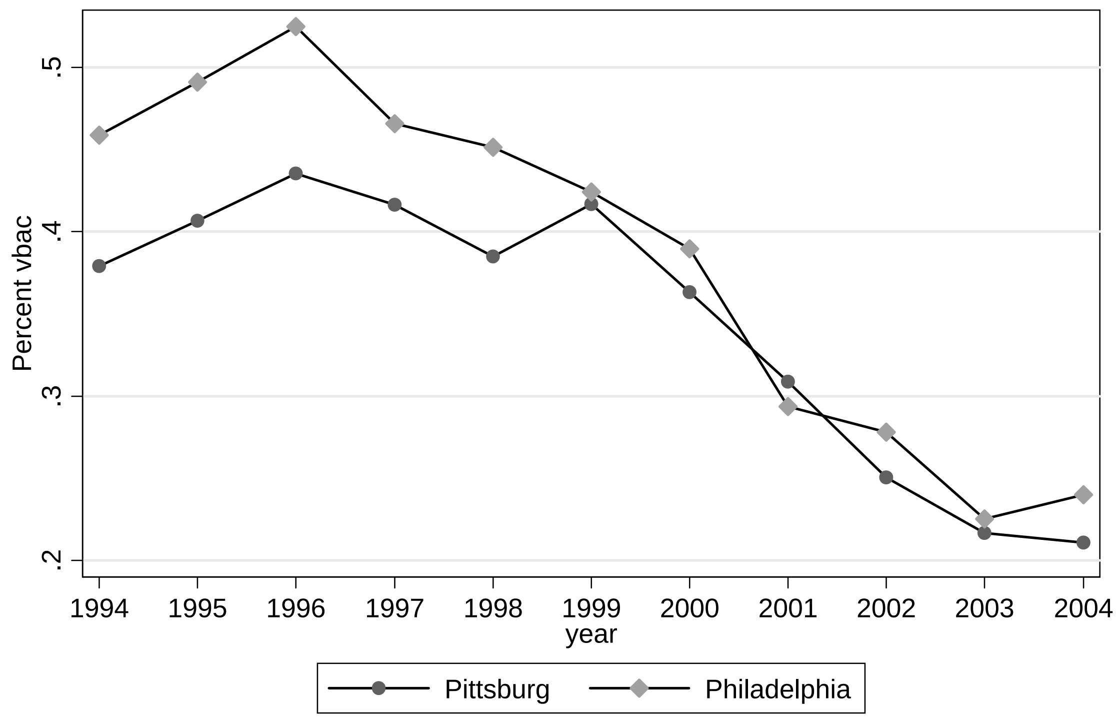

Figure 4-3. Percentage of births that are vaginal births after c-sections (by county)

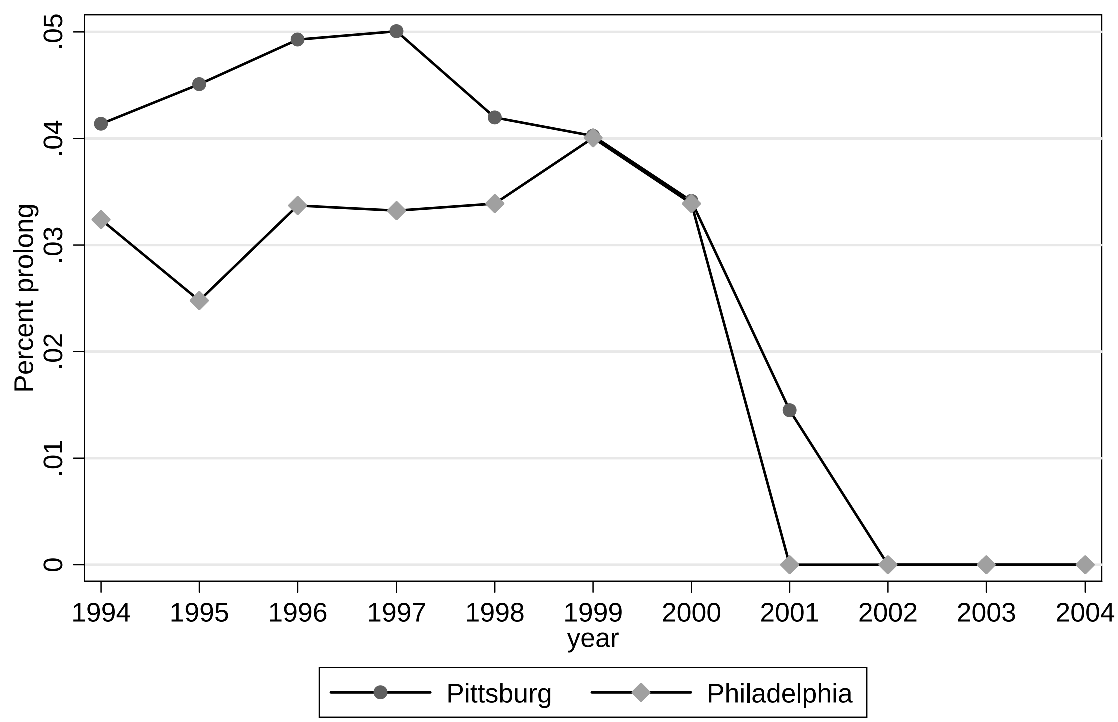

Figure 4-4. Percentage of births that are prolonged pregnancies (by county)

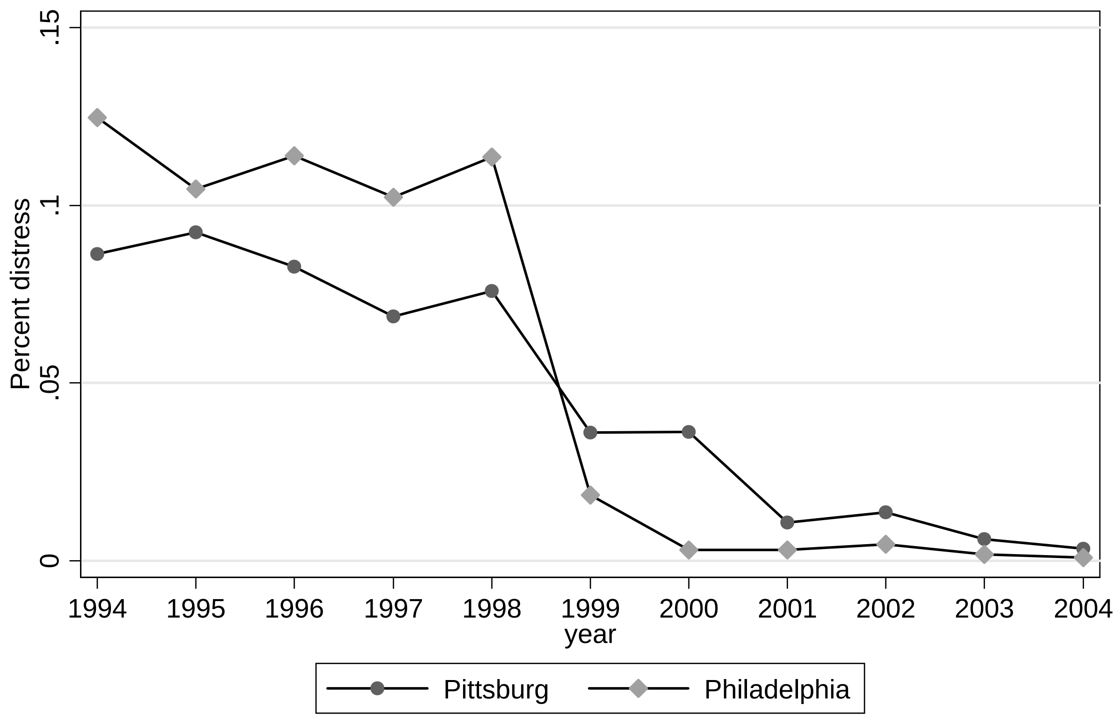

Figure 4-5. Percentage of births that experience fetal distress (by county)

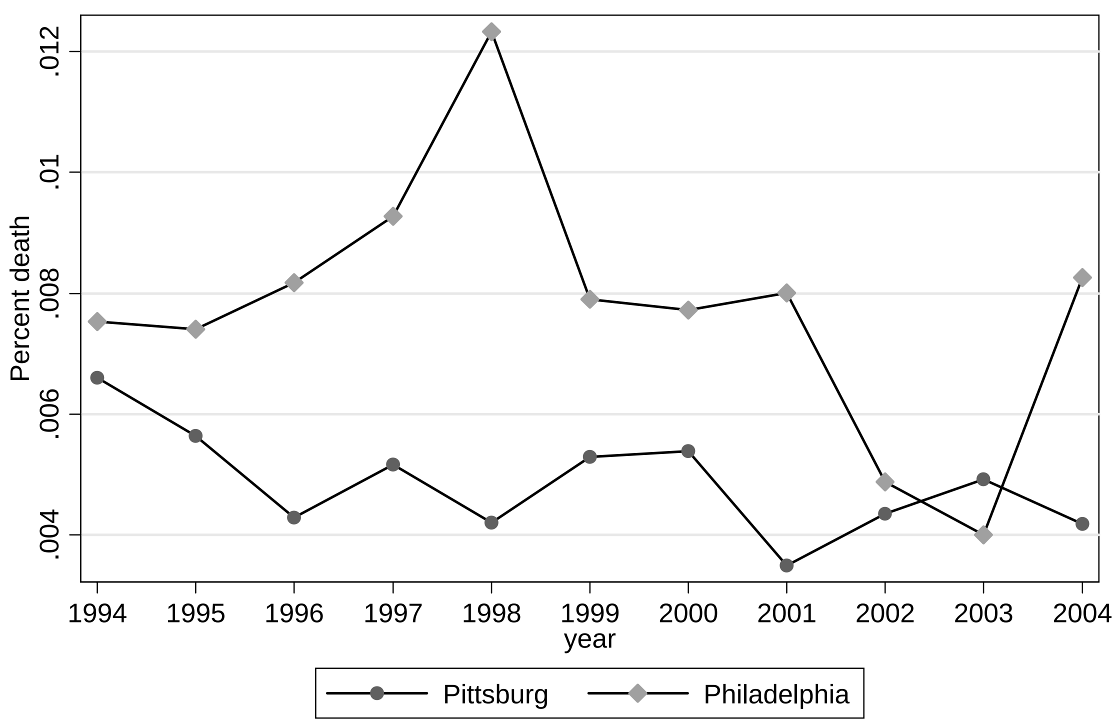

Figure 4-6. Percentage of births that lead to neonatal death (by county)

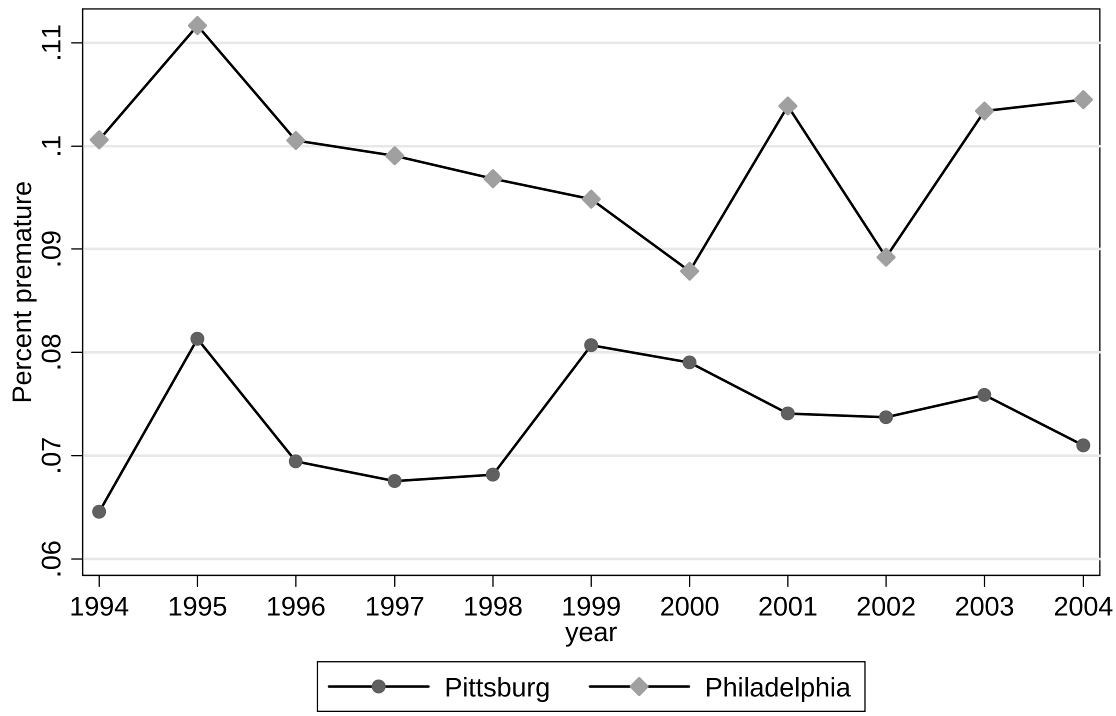

Figure 4-7. Percentage of births that are premature (by county)

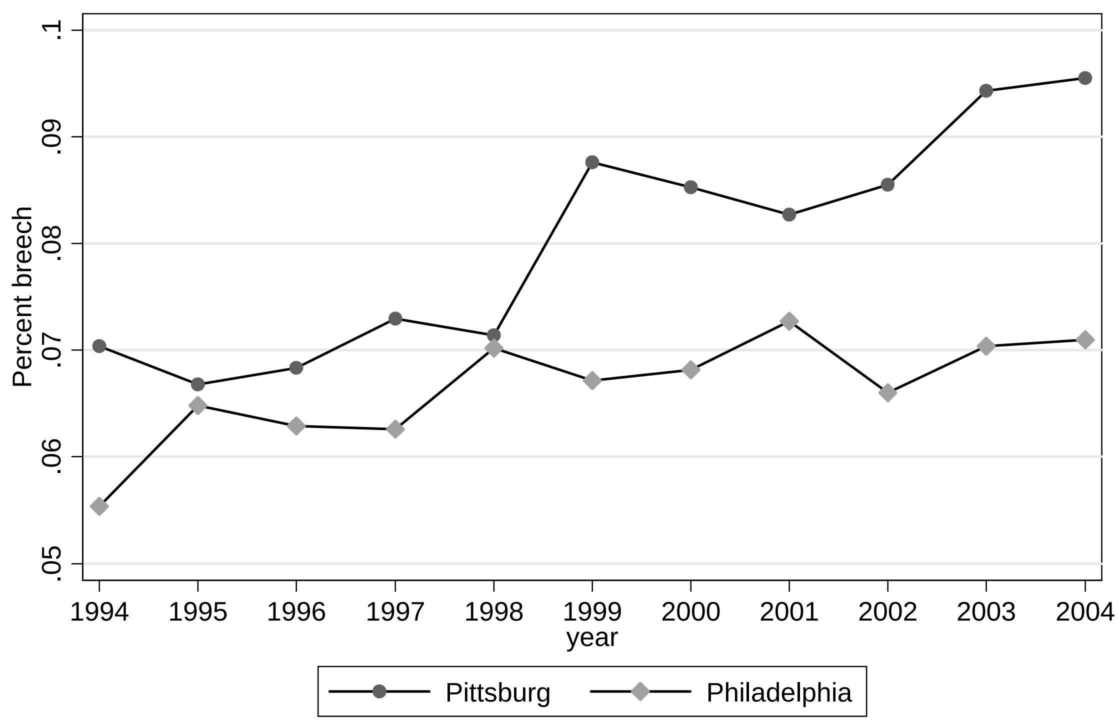

Figure 4-8. Percentage of births that are breech (by county)

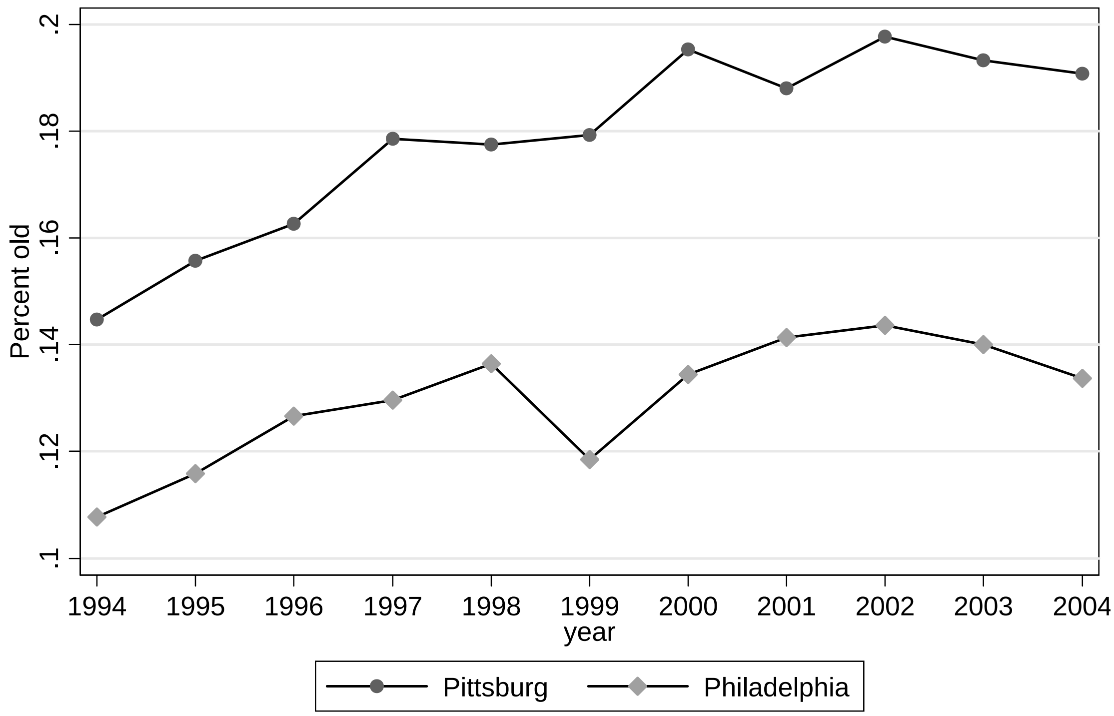

Figure 4-9. Percentage of births to mothers over 35 (by county)

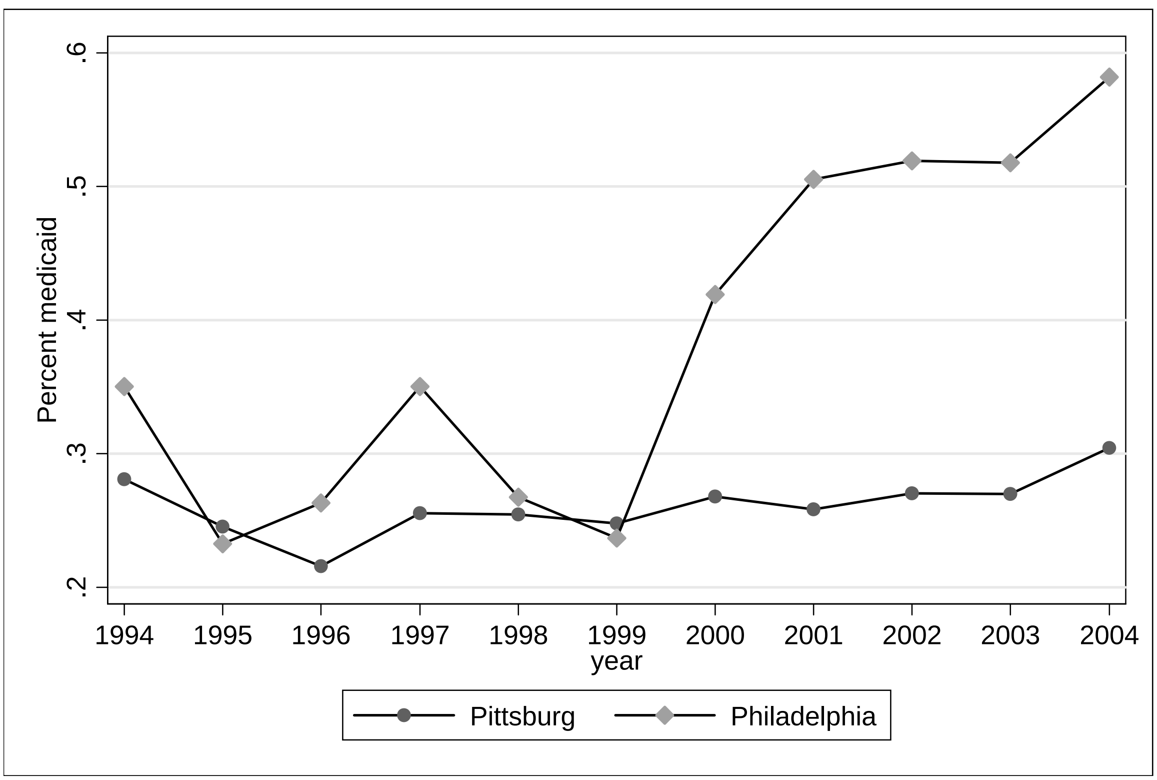

Figure 4-10. Percentage of births to medicaid mothers (by county)

Figure 4-11. Cumulative probability of a first lawsuit in allegheny county

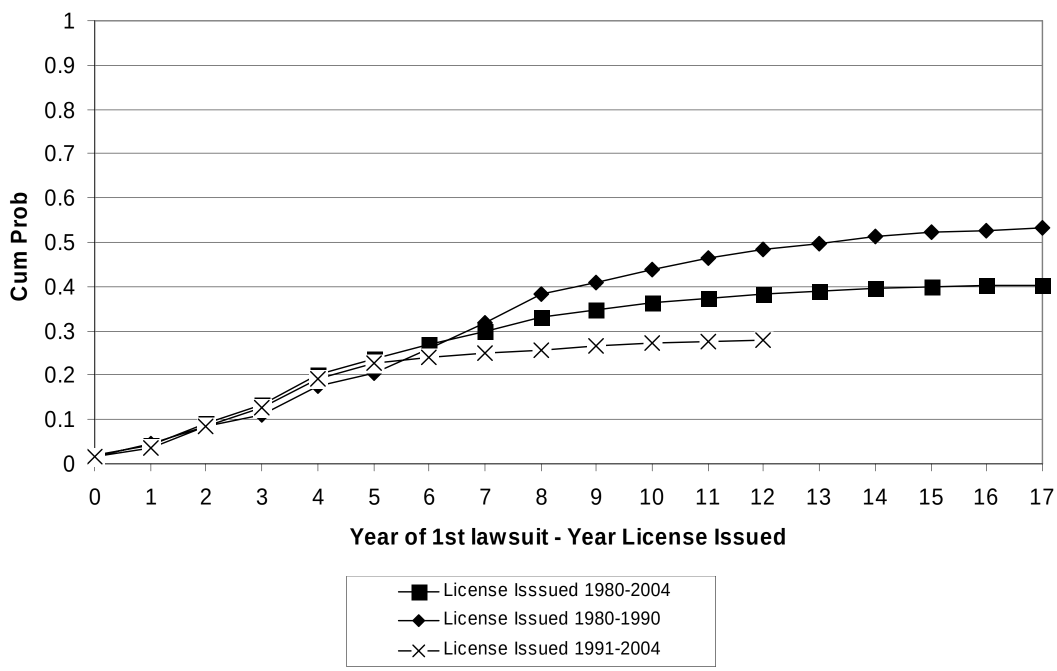

Figure 4-12. Cumulative probability of a first lawsuit in Philadelphia county

CHAPTER 5
CONCLUSION

My dissertation is investigates the some of the determinants of physician procedure use as well as the effects on prices and health outcomes. The use of data on obstetrics patients provides information on a population that has not been studied in detail by health economists. I show that removing regulatory constraints increases the probability of newborn baby being born healthy. I also show that increased levels of hospital competition lead to lower prices being charged by hospitals. Lastly, I show that medical malpractice lawsuits induce physicians to increase their use of caesarean sections, a result consistent with the defensive medicine hypothesis.

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BIOGRAPHICAL SKETCH

Before beginning the Ph.D. program at the University of Florida, Scott Hankins received a B.A. and an M.A. in economics from the University of South Florida. He became interested in health economics through his mother, a labor and delivery nurse.

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