THE RELATIONSHIP BETWEEN INSURANCE MARKET CONCENTRATION AND HEALTHCARE USE AND QUALITY: AN EXPLORATION OF THE ROLE OF MARKET DYNAMICS, PATIENT DEMAND, AND PHYSICIAN INCENTIVES.

by
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Abstract

Insurance markets in the United States are highly concentrated, which has ambiguous policy implications. Concentrated insurers negotiate lower payment rates with healthcare providers, but may not pass savings on to consumers via lower premiums. Given this ambiguity, this dissertation explores the relationship between insurance market concentration and two important outcomes, healthcare utilization and quality.

In Paper 1, I estimate longitudinal models predicting changes in inpatient utilization as a function of changes in insurer, hospital, and physician concentration. I estimate separate models for a set of highly acute, price-insensitive services and a set of more discretionary services for which demand should be more responsive to changes in price. I find that insurer concentration increases inpatient utilization, driven by more discretionary services, consistent with movement down the demand curve as concentrated insurers negotiate lower prices. The clinical benefit of this higher utilization is unclear, as I do not detect an effect on the likelihood of unplanned readmission.

In Paper 2, I use inverse-probability-weighted regression adjustment to compare the effect of insurer concentration on imaging utilization between the patients of orthopedists, neurologists, and urologists who own their own imaging equipment and patients of those specialist physicians who do not own imaging equipment and have a weaker financial incentive to order imaging. I find that the effect of insurer concentration is significantly larger among the patients of orthopedist owners compared to the patients of orthopedist non-owners, with no significant differences across the patients of neurologists or urologists. This suggests that supply-side financial incentives to provide more care contribute to the positive relationship between insurer concentration and utilization.

In Paper 3, I estimate longitudinal models predicting changes in hospital patients' experience of care as a function of changes in insurer and hospital concentration. I find that insurer concentration improves, while hospital concentration worsens, patient experience.

These results suggest that insurer concentration leads to higher levels of healthcare utilization, driven by both patient demand and the physician's financial incentive to provide more care. The effect on quality is mixed, with insurer concentration improving hospital patients' experience of care, but not significantly decreasing the likelihood of readmission.

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1. Introduction

Health insurance and healthcare provider markets in the United States are characterized by high levels of market concentration. The combined national market share of the four largest insurers, for example, was 83% in 2014 (Dafny 2015). In 2016, 90% of metropolitan areas had highly concentrated hospital markets, while 65% had highly concentrated specialist physician markets (Fulton 2017). These high levels of market concentration have implications for patients in terms of cost, quality, access to care, and utilization. On the provider side, a large literature indicates that high levels of hospital and physician market concentration are associated with higher healthcare payment rates (Gaynor, Ho and Town 2015, Baker et al. 2014, Schneider et al. 2008). A large literature also explores the effect of hospital market concentration on healthcare quality, with less clear results. The evidence suggests that hospital market competition improves quality in settings with an administered price (like Medicare), but findings in settings with negotiated prices are more mixed (Gaynor, Ho and Town 2015).

The policy implications of insurer concentration are particularly complex. Just as concentrated providers are able to negotiate higher prices, concentrated insurers aggregate the buying power of employers and individuals, giving them greater bargaining leverage to negotiate lower healthcare payment rates with hospitals and physicians

(Moriya et al. 2010, McKellar et al. 2014, Melnick et al. 2011, Halbersma et al. 2011, Trish and Herring 2015). However, concentrated insurers also have greater leverage as sellers of health plans and may charge higher premiums, or may not pass the savings from the lower negotiated prices on to patients in the form of lower premiums (Trish and Herring 2015, Dafny, Duggan and Ramanarayanan 2012 and Dafny, Gruber and Ody 2015). In light of the ambiguity around the benefits and harms to patients of insurer consolidation, an understanding of the effect of insurance market concentration on other outcomes important to patients is all the more important. This research therefore explores how insurer concentration affects the utilization of healthcare services and healthcare quality.

Prior research suggests that insurer concentration and utilization are positively related (Bates and Santerre 2008 and McKellar et al. 2014). These findings have been interpreted in the context of a theoretical model outlined by Pauly (1998), in which insurers exercise monopoly-busting market power by negotiating lower payment rates with hospitals and physicians, moving the price closer to the competitive price. Movement down the demand curve would lead, in turn, to patients demanding higher quantities of care. This explanation suggests that insurer concentration may facilitate access to care among the insured, but little work has been done to explore whether the empirical evidence is consistent with key features of this model. As it relates to quality, there is little theoretical or empirical work about how insurer concentration impacts quality. However, much as hospitals compete with each other on quality in some contexts, it is possible that insurer concentration places competitive pressure on healthcare providers to provide higher quality services.

In Paper 1, I extend the literature on insurer concentration and utilization by considering whether the empirical evidence about their relationship is consistent with the economic theory of patients demanding more healthcare services as insurers negotiate lower payment rates. I consider first whether the effect of insurer concentration on inpatient utilization is larger for healthcare services for which demand is more elastic, compared to a set of acute services for which the patient's demand should be less responsive to price. This question is motivated by the idea that movement down the demand curve as insurers negotiate lower rates should result in a larger change in utilization for more price-sensitive services. Second, I consider whether the effect is larger in more concentrated physician markets, where physicians are more able to elevate prices above marginal cost, and in less concentrated insurer markets, where insurers are less able to use managed care techniques and other plan design tools to constrain utilization. Finally, I consider whether insurer concentration is associated with improved clinical outcomes, measured through 30-day unplanned readmission after an inpatient admission. I explore these questions using longitudinal, market-level models of inpatient utilization for 2013 through 2015, which are identified by within-market variation over time in insurer, physician, and hospital market concentration. I construct measures of inpatient utilization on the extensive margin as the probability of having an admission and on the intensive margin as the price-adjusted spending on professional services during an admission using the Truven Health MarketScan Database of Commercial Claims. Measures of insurer concentration are constructed from HealthLeaders-InterStudy data, measures of physician concentration are constructed from CMS data, and measures of hospital concentration are constructed from American Hospital Association data.

In Paper 2, I consider an alternate explanation for why research suggests that insurer concentration and utilization are positively related, physicians inducing demand to maintain a higher income in the face of lower negotiated payments. I explore this question by focusing on a subset of healthcare services for which different physicians have different financial incentives to provide more care: diagnostic imaging. Non-radiologists who own imaging equipment and can bill for the scan have a strong financial incentive to order imaging services for their patients, compared to non-radiologists who refer a patient to a radiologist for imaging. I use Truven Health MarketScan data to classify orthopedists, neurologists, and urologists as owners or non-owners of imaging equipment on the basis of whether they bill for the technical component of an MRI or CT. I construct measures of the MRI and CT utilization of their patients in the 30 days following an office visit over 2015. I then test whether the effect of insurer concentration on the probability of receiving a scan varies significantly across the two groups. If it is true that demand inducement contributes to the positive relationship between insurer concentration and utilization, the effect of insurer concentration should be larger amongst the owner physicians, who have a stronger financial incentive to order imaging. I use inverse-probability-weighted regression adjustment to achieve covariate balance on observable characteristics across patients who visited physician owners of imaging equipment and patients who visited non-owners.

In Paper 3, with co-authors Bradley Herring and Erin Trish, I extend Paper 1's work on quality by exploring the effects of insurance and hospital market concentration on hospital patients' experience of care. Using patient experience data from Hospital Compare, we estimate hospital/year-level regression models predicting each hospital's patient experience measure over 2008-2015 as a function of insurance and hospital market concentration and hospital fixed effects. The model is identified by longitudinal variation in insurance and hospital concentration. We also consider how the effect of insurer concentration varies with the type of hospital (public, nonprofit independent, nonprofit part of a system, and for-profit), and how it varies with the level of insurance and hospital concentration.

I conclude by synthesizing the results of the three papers and highlighting future directions for work on this topic.

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2. Paper 1: How Does Insurance Market Concentration Affect Inpatient Utilization? Market Interactions with Physicians and the Role of Patient Demand

Caroline Hanson

Abstract

Health insurance and provider markets in the United States are highly concentrated, which affects cost, quality, and access to care. There is prior evidence that insurer concentration increases utilization, which is consistent with insurers exercising countervailing bargaining power against concentrated hospitals/physicians and negotiating lower prices that, through downward-sloping demand, result in higher utilization. There is also the potential that, if insurers are concentrated enough, they exercise monopsonistic market power and constrain utilization. I explore whether more-recent empirical evidence is consistent with two aspects of theoretical economic behavior. First, is the effect of insurer concentration on utilization larger for services for which downward-sloping demand is more elastic? Second, is the effect of insurer market concentration larger in more concentrated physician markets, where physicians are more able to elevate prices above marginal cost, and in less concentrated insurer markets, where insurers are less able to constrain utilization? Moreover, this paper explores

whether higher utilization associated with insurer concentration improves clinical outcomes to assess the key policy question of whether insurer price negotiation is increasing patient access to care or unintentionally exacerbating inefficient use of costly services.

I explore these questions using longitudinal, market-level models of inpatient utilization for 2013 through 2015, which are identified by within-market variation over time in insurer, physician, and hospital market concentration. I construct measures of the likelihood of an inpatient admission (i.e., the extensive margin) and the price-adjusted spending on professional services during an admission (i.e., the intensive margin), each adjusted for individual characteristics, using Truven Health MarketScan data. Measures of insurer concentration are constructed from HealthLeaders-InterStudy data, measures of physician concentration are constructed from CMS data, and measures of hospital concentration are constructed from American Hospital Association data. To explore whether demand elasticity modifies the effect of insurer concentration, I estimate separate models for one set of more price-sensitive planned admissions and a second set of less price-sensitive acute admissions. To explore the role of relative market power between insurers and physicians, I compare the effect of insurer concentration on utilization between high and low baseline levels of concentration in physician and insurance markets. Finally, I estimate models predicting unplanned 30-day readmission rates to explore the net effect on clinical outcomes.

Overall, a 1,000-point increase in insurer concentration increases the likelihood of an inpatient admission by 0.09 percentage points (p=0.04) and increases price-adjusted professional spending by $84.22 (p=0.03), both around 2% of the mean. Consistent with expectations linked to insurer negotiation of provider prices, insurer concentration does not affect treatment intensity of more price-inelastic acute admissions, but increases price-adjusted spending on more price-elastic planned admissions by \$200.53 (p=0.005), or 3.4% of the mean. For the results dependent on baseline levels of market concentration, the findings are mixed. The effect of insurer concentration on price-adjusted spending is, as expected, driven by markets that had relatively unconcentrated insurance markets, but is, contrary to expectation, also driven by relatively unconcentrated physician markets. Lastly, insurer concentration does not decrease the patient's likelihood of a readmission. These results are consistent with concentrated insurers negotiating lower provider prices and, in turn, higher patient utilization of non-acute planned services with unclear health benefits.

2.1 Introduction

Both health insurance and healthcare provider markets in the United States have a high degree of concentration and have become more concentrated over time. The combined national market share of the four largest insurers, for example, was 83% in 2014, and the average hospital and physician market is moderately or highly concentrated (Dafny 2015, Baker et. al 2014, Health Care Cost Institute 2015). A large literature is dedicated to what concentrated markets mean for patients, in terms of costs, quality, and access to care. Particularly for insurance markets, the theoretical predictions surrounding concentration and outcomes are often ambiguous. On one hand, insurers in concentrated markets may be able to negotiate lower prices with providers, which could be welfare increasing for consumers. At the same time, these insurers may not pass these savings on to consumers and may instead use their market power to charge higher premiums. Likewise, the effect of insurer market concentration on volume is theoretically ambiguous, as volume might either increase or decrease if the purchaser of a good or service (in this case, an insurer) has more market power. Given this broad theoretical uncertainty about the effects of insurer concentration, additional analysis is needed to understand the ways in which insurer concentration affects volume, and how that varies by market.

Pauly (1998) presents a conceptual framework for the effect of a managed care organization's (MCO) buying power on healthcare prices and volume. In a provider-market (hospital or physician) monopoly, a concentrated MCO can exercise monopoly-busting power, moving the market closer to a competitive outcome with lower healthcare prices, and because of downward-sloping demand, higher volumes. By contrast, if the provider-market is competitive, a concentrated MCO may hypothetically exercise monopsony power, limiting quantity and pushing price down the supply curve, resulting in both prices and quantity that are below the competitive equilibrium. Their ability to limit quantity may depend on the exercise of monopoly power as sellers of health plans, using tools like covered benefits, claims review, and high cost-sharing. In both cases, concentrated MCO markets put downward pressure on healthcare prices, but because the effect on quantity is divergent, Pauly argued that the observed relationship between insurance concentration and volume could serve as a test of whether MCOs in a given market provide countervailing bargaining power (i.e., higher volume through lower healthcare prices) or exercise monopsonistic market power (i.e., lower volume through managed care). Bates and Santerre (2008) and McKellar et al. (2014) provide empirical evidence of a positive relationship between insurer concentration and volume, suggesting that insurer concentration plays a role by pushing healthcare markets towards a competitive outcome.

Because insurance shields patients from the full cost of healthcare, the competitive outcome may nevertheless contribute to inefficiently high spending. The U.S. healthcare system is known for having high levels of spending that are incommensurate with its relatively poor outcomes. For example, the United States has the highest per-capita utilization of costly diagnostic imaging services (Squires and Anderson 2015, Emanuel and Fuchs 2008). One study on waste in the U.S. healthcare system estimates that overtreatment accounted for between $158 and $226 billion in unnecessary spending in 2011 (Berwick and Hackbarth 2012). In light of this, understanding the role that insurer concentration plays in driving utilization and whether that utilization translates to improvements in clinical outcomes is an important concern for policy-makers, particularly antitrust regulators.

Using data from HealthLeaders-InterStudy, Truven Health MarketScan, the Centers for Medicare and Medicaid Services (CMS), and the American Hospital Association, this paper estimates longitudinal, market-level models of inpatient healthcare utilization as a function of insurer concentration, measured using the Herfindahl-Hirschman Index (HHI), and other confounders. The models are identified by within-market changes in concentration from 2013 to 2015, with market fixed effects controlling for time-invariant confounding factors that might correlate with both market concentration and healthcare utilization. Market-level healthcare utilization is measured on both the extensive margin, as the probability of having an admission, and on the intensive margin, as the intensity of physician and other professional services provided during an inpatient admission, each adjusted for individual characteristics. I find that a 1,000-point increase in insurer HHI increases both utilization measures by approximately 2%. Further, this paper distinguishes between admissions that are likely planned in advance versus those that are acute. For the former, demand is (on average) more downward-sloping, and hence the Pauly (1998) model predicts relatively larger effects; the latter acute admissions are (on average) highly insensitive to healthcare price. Consistent with expectations, I find no effect of insurance concentration on acute utilization, but that a 1,000-point increase in insurer concentration increases intensive utilization for planned admissions by approximately 3.4%.

This paper also explores whether the effect of insurer concentration depends on the relative levels of bargaining power between insurers and physicians, as the extent to which an insurer is able to exercise monopoly-busting (or monopsonistic) market power presumably depends on the level of insurer and physician concentration. In particular, I estimate stratified models to test whether the effect is higher in concentrated physician markets, where physicians are presumably able to exercise market power to hold healthcare prices farther above marginal cost, and hence where the exercise of countervailing bargaining power by insurers to lower these prices would increase utilization. And I also test whether the effect is larger in less concentrated insurer markets, where sufficient competition from other insurers for patients might prevent insurers from exercising marginal increases in (monopsonistic) market power to constrain demand for healthcare services. While I indeed detect a larger effect of insurer concentration among less concentrated insurer markets, I instead find, contrary to expectations, a larger effect of insurer concentration within less concentrated physician markets; this suggests that physicians may exercise market power even in relatively unconcentrated markets, and perhaps that marginal increases in insurer concentration are more impactful when providers are less concentrated. Finally, this paper explores the effect of insurance concentration on hospital readmissions, in order to help discern whether higher utilization associated with insurer consolidation translates to improved clinical outcomes due to improved access to care, but finds no beneficial effect.

2.2 Literature Review

This paper builds on a large literature exploring the effect of market concentration on patients. Both health insurance and provider markets in the United States have a high level of market concentration. A commonly used measure of market concentration is the

Herfindahl-Hirschman Index (HHI), the sum of the squared market shares of all competitors in a market, which equals 10,000 in a perfectly monopolistic and approaches 0 in a perfectly competitive market (Department of Justice 2018). The Department of Justice and Federal Trade Commission generally consider markets with an HHI of between 1,500 and 2,500 to be moderately concentrated and markets with an HHI greater than 2,500 to be highly concentrated. Data from 2014 indicates that the average HHI for health insurance markets across states was 4,497 in the large group market, 3,860 in the small group market, and 4,226 in the individual market (The Henry J. Kaiser Family Foundation 2018). Moreover, the combined market share of the four largest insurers is estimated to have grown from an already high level of 74% in 2006 to 83% in 2014 (Dafny 2015). On the provider side, a Health Care Cost Institute (2015) study reports a mean CBSA-level hospital HHI of 1,885 in 2013 (where CBSA stands for Core-Based Statistical Area). Baker et al. (2014) report mean specialty-specific physician HHIs ranging from 1,744 in the least concentrated specialty (internal medicine) to 4,648 in the most concentrated specialty (urology) in 2010. Hence, even in the physician specialties with relatively low barriers to entry, the average market is moderately concentrated.

The degree of concentration in healthcare markets has been shown to influence a number of outcomes, with a large literature focusing on the relationship between market concentration and healthcare price and quality, predominantly focusing on hospital markets. Gaynor, Ho and Town (2015) provide a recent review of this literature, and Gaynor and Town (2011) provide an older but more thorough review. Across a range of methodological approaches, including studies that attempt to instrument for hospital HHI and studies that use a difference-in-difference design comparing hospitals involved in mergers to control hospitals, the evidence suggests that hospital market concentration pushes prices upward. The relationship between hospital concentration and quality (also reviewed by Gaynor and Town 2011 and Gaynor, Ho and Town 2015) is less conclusive, with most studies in an administered price setting (like Medicare in the U.S. and the National Health Service in England) finding that hospital consolidation is harmful to quality, but studies in commercial settings finding evidence in both directions.

Due mainly to data limitations, the literature on both physician markets and insurance markets is smaller and more recent. The few studies of physician markets have similarly found a positive relationship between provider market concentration and price. For example, Schneider et al. (2008) examine the effect of health plan and physician organization HHI on prices in California and find no effect for health plan HHI but, for most categories studied, a positive relationship between price and physician HHI. Baker et al. (2014) examine the relationship between physician HHI and a county-level price index for office visits separately for 10 specialties and find that prices were between 8.3% and 16.1% higher in the counties in the 90th percentile of the HHI distribution compared to the 10th percentile. Focusing on cardiologists and orthopedists, Dunn and Shapiro (2014) also find that physician market concentration leads to higher physician prices.

Additionally, several studies have documented that insurance market concentration puts downward pressure on provider prices. Moriya et al. (2010) use a longitudinal design with market fixed effects to find that insurer HHI decreases hospital price, while hospital HHI does not have a significant effect. McKellar et al. (2014) use a cross-sectional design with the same result for aggregated hospital and physician price.

Melnick et al. (2011) also find that health plan concentration decreases hospital prices, but find, consistent with much of the rest of the literature, that hospital market concentration increases prices as well. Likewise, in a study based on the Netherlands, in a specification based on a Structure-Conduct-Performance model, Halbersma et al. (2011) find that the hospital concentration increases prices, while insurer concentration decreases prices. While Trish and Herring (2015) focus their analysis on insurance premiums rather than service prices, they find that an insurer HHI measure more relevant to the negotiation between insurers and hospitals is associated with a decrease in premiums, presumably a result of lower negotiated prices, while a hospital HHI measure is associated with an increase in premiums, presumably a result of higher negotiated prices. (For an alternative insurer HHI measure more relevant to the negotiation between insurers and employers, insurer concentration is associated with increases in premiums, likely a function of concentrated insurers claiming more profits).[1]

Conversely, however, Ho and Lee (2017) find that healthcare prices may increase or decrease when an insurer exits the market, depending on whether hospitals are able to extract price increases from the higher premium charged to patients, or whether the remaining insurers are able to negotiate lower prices. In their studies of physician markets, both Schneider et al. (2008) and Dunn and Shapiro (2014) find a largely null relationship between insurer or health plan HHI and provider price. While the results across these studies are not entirely consistent, with some studies reporting null findings on either provider or insurer HHI, the balance of evidence suggests a positive relationship

[1] Other studies have also documented a positive relationship between insurer HHI and premiums or premium growth, including Dafny, Duggan and Ramanarayanan (2012) and Dafny, Gruber and Ody (2015).

between price and provider HHI and a negative relationship between price and insurer HHI.

A few studies have explored the relationship between insurance or provider market characteristics and volume. Regarding insurance market concentration and volume, Bates and Santerre (2008) use firm-size and the number of firms to instrument for insurer concentration and find that hospital volume rises with insurer concentration. McKellar et al. (2014) find a negative relationship between insurer market concentration and commercial healthcare price and a positive relationship with utilization, with a negative net relationship on spending. They observe no effect for hospital market concentration. In terms of health plan generosity, Pelech (2018) provides evidence from Medicare Advantage that market exit by insurers results in reduced generosity of the health plans remaining on the market.

Regarding provider market concentration and volume, Dunn and Shapiro (2017) analyze physician market competition's effect on volume and find that more intensive treatment for myocardial infarction patients was provided by cardiologists in more concentrated cardiology markets, and that there were fewer readmissions. Because they focus on emergent treatment for which the patient's demand is inelastic and treatment decisions are likely made solely by providers, their results suggest that physicians respond to financial incentives by providing more services when payments are higher.

This research makes several key contributions to this literature. First, it adds evidence related to the impact of insurer concentration on utilization using longitudinal models with recent data. It incorporates measures of physician concentration, and explores interactions between both levels of physician and insurance concentration and the effect of insurance concentration on utilization. It distinguishes between the effect of insurance concentration on utilization for categories of admissions for which demand is more and less price-sensitive. Finally, it adds to an emerging literature on the relationship between insurance concentration and quality (Hanson, Herring and Trish 2018).

2.3 Conceptual Framework

As previously noted, Pauly (1998) provides a useful framework for thinking about health insurance market power and how utilization can (theoretically) be used to distinguish between a concentrated MCO busting the exercise of market pricing power by healthcare providers versus a concentrated MCO exercising its own (monopsonistic) market power. In the remainder of this section, I summarize the model and highlight some of its key implications. ln the following section, I provide an overview of the key empirical analyses I conduct and relate them to this conceptual framework.

The intuition of Pauly's model is easiest understood in the case of a single monopoly seller of health services (i.e., a hospital system or physician practice) and a single monopsony buyer (an MCO). Note that this refers to the market interaction between insurers and healthcare providers; a monopsonist insurer may be a monopoly seller of MCO products to employers and individuals, if the geographic markets for health plans and health services are comparable. If both markets are competitive, or if they exert comparable levels of countervailing bargaining power against each other, the outcome is determined by the intersection of supply and demand. If instead the hospital system is a monopolist and insurers have no market power, the hospital provides the quantity determined by the intersection of the supply curve and the marginal revenue curve and sets the price at the willingness-to-pay implied by the demand curve. And if the insurer is a monopsonist and hospitals have no market power, the insurer purchases the quantity determined by the intersection of market demand and the marginal factor curve, which lies above the competitive market supply curve, and sets the price at the lowest price at which providers will supply that quantity.[2]

Hence, Pauly notes that relative to the scenario with a single provider exerting monopoly power, the competitive outcome has a lower healthcare price. Likewise, relative to the competitive outcome, the scenario with a single insurer exerting monopsony power has an even lower price. In both cases, the concentrated insurance market puts downward pressure on prices. However, the effect on quantity in these two situations is opposite. Moving towards the competitive outcome from a provider monopoly outcome increases the quantity (due to insurer pressure on prices indirectly affecting quantity), while moving away from the competitive outcome towards an insurer monopsony outcome decreases the quantity (due to insurer pressure directly on quantity).

In practice, there are very few, if any, markets characterized by a single buyer or seller. However, the framework can still be used to conceptualize the exercise of market power that, on the one hand, leads closer to a competitive outcome, or on the other, closer to a monopsony outcome. While this framework was proposed in the context of managed care HMOs in the 1990s, when MCOs are assumed to have tighter control over quantity than is likely true of most health plans in the United States today, insurers still have tools

[2] The marginal factor curve lies above the supply curve because, if the monopsonistic insurer purchases an additional unit, as the sole purchaser, the insurer pays a higher rate for that additional unit and for all the units up to that unit. This is parallel logic to the more familiar monopolist case, where marginal revenue lies below demand because if the monopolist chooses to sell an additional (lower-price) unit, the price of all units sold must be lowered.

like covered benefits, cost-sharing, claims review, and in some plan types, gatekeeping, to constrain quantity. Their ability to utilize these tools, which are unpopular with patients, presumably depends on the extent to which insurers have market power as sellers of health plans.

One implication of Pauly's model, which assumes that demand slopes downward, is that the elasticity of the demand curve determines how large the effect of insurer concentration on utilization will be.[3] If the quantity demanded is not related to healthcare price, changes in the negotiated price would not affect utilization. Past research indicates that the demand for healthcare is on average downward sloping, with the Rand Health Insurance Experiment suggesting a price elasticity of -0.2 (Manning et al. 1987). However, evidence suggests the demand for some services (like appendectomy) is almost perfectly inelastic, while the demand for more elective services is somewhat sensitive to price (see, e.g., Duarte (2012) and Kowalski (2016)).

While it is generally true that a competitive outcome is more efficient than a monopoly outcome, in healthcare the competitive outcome is not necessarily efficient. Because of moral hazard, lower healthcare prices may translate to inefficiently high levels of utilization. As insured patients are shielded from the full cost of care, as long as the marginal benefit to them is greater than their out-of-pocket cost, they are incentivized to consume beyond the point at which their marginal benefit equals the total cost of care. Pauly (1968) described this as a prisoner's dilemma, because even if an individual recognizes that high levels of utilization push up health insurance premiums and that everyone would be better off by reducing utilization, the individual's incentive is still to

[3] The model also assumes that long-run supply slopes upward.

overutilize. High provider prices resulting from high provider concentration may paradoxically lead to reductions in inefficient overutilization.

The Pauly (1998) model for MCO market concentration is also complicated by the unique nature of healthcare, in which the physician’s expertise enables him or her to affect the patient’s demand for services. Physicians may act as a perfect agent for the patient, but more likely, they are motivated by both altruism and by their own financial self-interest. For example, McGuire and Pauly (1991) present a mathematical model of physician behavior under different fees, in which physicians may respond to a fee change by inducing demand for their services and/or by substituting the volume of services provided across their mix of patients, balancing the marginal utility of treating patients with the higher profit margin with the disutility of inducement. Dunn and Shapiro (2017) provide empirical evidence related to this, with cardiologists in more concentrated markets, presumably with higher prices, providing more intensive treatment.

2.4 Overview of Empirical Analyses

In order to estimate how insurer concentration affects utilization and whether the empirical evidence offers support for Pauly’s model for MCO concentration, this paper’s analyses makes two important distinctions between the types of utilization. One distinguishes between the extensive and intensive margin by creating separate measures of the likelihood of having an admission and of the intensity of services provided during an admission. The second distinction explores whether the effect of insurer concentration on utilization varies across admissions for which demand is more and less inelastic, as implied by Pauly’s model. The analyses also consider how the effect of insurance concentration on utilization compares across markets where healthcare providers and insurers have varying levels of market power. Finally, it explores how higher utilization affects clinical outcomes, measured as readmission. The motivation and framework for these analyses is described immediately below, while a detailed description of the data sources and construction of the variables follows in Section 2.5 and a description of the statistical models examining insurance concentration's effect on utilization follows in Section 2.6.

2.4.1 Overall Utilization on the Extensive and Intensive Margin

Broadly speaking, there are two means by which insurer concentration may affect inpatient utilization. First, an enrollee may become more or less likely to have an inpatient admission. Second, conditional on having an admission, a patient may be provided with more or fewer services. In order to capture both of these mechanisms, two measures of volume are constructed, one capturing the extensive margin, as the probability of having any inpatient admission, and one capturing the intensive margin, as the intensity-weighted volume of services provided in an admission. The conceptual model predicts that the exercise of monopoly-busting power should cause utilization to increase with increases in insurer concentration, but does not suggest whether one or both of these mechanisms underlie the relationship. Moreover, measuring utilization on both margins is important to account for the possibility that more concentrated insurers may be better able to target less complex cases to the (cheaper) outpatient setting (decreasing extensive utilization), leaving more complex, higher-need patients in the inpatient setting (increasing intensive utilization).

Before proceeding, it is important to note that this research focuses on interactions between insurers and physicians (not hospitals), but focuses on utilization provided in an inpatient setting. This is because, for both of these measures of utilization, the physician is arguably more important in determining the level of utilization than the hospital facility. For the extensive margin of an admission, the physician is generally either deciding to admit, or for more discretionary services, helping the patient decide; and for the intensive margin of service-intensity for an admission, the physicians is likewise deciding what services to provide, or advising the patient on the appropriate services. For example, Pauly and Redisch (1973) treat the non-profit hospital as a physician cooperative organized to maximize physicians' net income. Ellis and McGuire (1986) posit a theory of physician behavior in which physicians make treatment decisions, maximizing their own utility as a function of benefits to the patient and profit to the hospital. Empirically, there is a large literature exploring how physicians respond to financial incentives in an inpatient context (see, e.g., Dunn and Shapiro (2017), Grant (2009), Yip (1998)). Because clinicians play a large role in patient decision-making (and may fully supplant patient decision-making for some types of acute treatments), perhaps to the extent of inducing demand, professional service utilization is arguably the most appropriate measure on the intensive side. Moreover, a physician's decision-making about appropriate medical care presumably serves as the trigger for many types of facility fees.

For the intensive measure of service intensity, therefore, this analysis focuses on the services provided by healthcare professionals, referred to as professional services, rather than include the hospital's facility services such as room and board, the use of laboratory and imaging equipment, and medical/surgical supplies. While it is true that facility services make up the majority of total spending in an inpatient admission, there is another reason to prefer a measure based on professional services (beyond the importance of physician decision-making). The revenue codes used for facility billing vary greatly in specificity in claims data, making it difficult to credibly measure intensity across hospitals.[4] Moreover, the degree of specificity in the codes used may depend on how the insurer compensates the hospital, whether it is on a fee-for-service basis, with a per-diem, or with an episode-based payment (as in Medicare's Diagnostic Related Group payment system). By contrast, professional services are based on the more standardized Current Procedural Terminology (CPT) codes, which is the basis for how most individual providers are paid, under both Medicare and private insurance, meaning there should be coding consistency across hospitals.

2.4.2 Planned versus Acute Treatments

The analyses also explore how differences in the elasticity of demand affect the relationship between insurance concentration and utilization, by identifying a set of admissions for acute diagnoses generally requiring immediate treatment and a set of admissions for diagnoses likely to have been scheduled in advance. Planned treatments may permit price-shopping between providers, a comparison between alternate treatments, research on the likely risks/benefits, and other types of strategic decision-

[4] For example, in some cases, the claim simply lists a facility revenue code of "total charge." Similarly, room and board can be coded as either a general, all-inclusive rate, or be broken into subcategories of room type (i.e., private, 2-beds, 3-beds) by department (i.e., pediatric, oncology). There are also concerns about the completeness of the revenue codes reported in the data. The MarketScan User Guide notes the following of the revenue codes assigned to facility fees: "UB04 revenue codes are retained in the MarketScan data when available; however, not all data contributors provide the codes on adjudicated claims."

making. By contrast, treatment for acute diagnoses requiring immediate treatment offers few of these opportunities and patients are likely to defer to their physician. The monopoly-busting model of a concentrated insurer predicts an effect on volume only if the demand curve is downward-sloping, implying that there should be a larger effect of insurance concentration on volume for planned treatments (for which demand is more elastic) than for acute treatments.[5]

The method to identify acute and planned conditions is loosely based on Card, Dobkin, and Maestas (2009), which identified acute conditions as a set of diagnosis codes for which admission through the Emergency Department was as likely on a Saturday or Sunday as on a weekday (or, in other words, diagnoses for which the share of weekend admissions through the Emergency Department was statistically equal to 2/7 or 0.286). Following the intuition that conditions requiring immediate treatment should not be less likely to occur on the weekend, the set of DRGs with a share of weekend admissions of 0.25 or higher are classified as acute. Conversely, the set of DRGs with a share of weekend admissions of 0.15 or below are classified as planned. Appendix Table 2.1 lists the DRGs assigned to each category. The list of planned conditions includes Cesarean section, joint replacement, spinal fusion, and obesity procedures, among others. The list of acute conditions includes septicemia, hemorrhage, pneumonia, poisoning, and myocardial infarction. While planned utilization should not in general be thought of as unnecessary utilization or overutilization, there is evidence that some of these planned

[5] To the extent that there is a meaningful volume effect for acute conditions, it may be driven by reverse causality. Insurers may make consolidation decisions in response to high levels of utilization, and would presumably due so in response to both planned and acute utilization. It may also be driven by physician-driven responses to payment incentives, with physicians inducing demand when prices are lower, which Dunn and Shapiro (2017) suggests is possible even in acute settings (though they find evidence of higher use when prices are higher).

conditions are related to overuse, including unnecessary joint replacement surgery in the United States for patients with mild loss of mobility (Lam, Teutsch, and Fielding 2018), and high rates of C-Section, which are compensated above vaginal delivery (Teleki 2017).

I use this classification for acute versus planned admissions based on DRG to construct additional market-level measures of both extensive and intensive utilization; i.e., acute extensive utilization, planned extensive utilization, acute intensive utilization, and planned intensive utilization. As the 0.25 and 0.15 thresholds for identifying acute and planned admissions are somewhat arbitrary, I test the sensitivity to using alternate cut points.

2.4.3 Market Stratifications

Additionally, the Pauly model for MCO concentration implies that the effect of changes in insurance concentration may depend on the level of provider and insurer concentration. First, the idea of insurers counteracting market power pre-supposes that providers were exercising market power to begin with. Though market concentration is not a perfect measure of market power, Pauly's model suggests that increases in insurer concentration should have a larger effect in provider markets that were initially concentrated, and hence where providers were likely able to hold healthcare prices farther above marginal cost at baseline.

Pauly's model also implies that the effect of a change in insurance concentration depends on the baseline level of insurer concentration. From the insurer's perspective, if a negative consequence of negotiating lower healthcare prices is higher utilization, insurers have an incentive to dampen utilization via, for example, claims review, changes in covered benefits, or cost-sharing. At the (hypothetical) extreme, a monopsonist insurer could constrain demand to impose the decreases in utilization hypothesized in the Pauly model. By contrast, an insurer may be less able to dampen utilization in an unconcentrated insurance market, where competition from other health plans increases the pressure to provide more generous insurance. Though the commercially-insured beneficiaries in this analysis primarily receive coverage through a self-insured employer, and hence the insurer negotiating lower prices does not typically bear the risk, several of these mechanisms are still applicable. For example, the insurer providing third-party administrator services likely does not distinguish between fully- and self-insured claims when it conducts claims review.

In order to explore how the level of provider and insurer market concentration affects the relationship between insurer concentration and utilization, I estimate stratified models of intensive and extensive utilization (and acute vs. planned utilization) based on the degree of market concentration in the baseline year. As the analysis focuses on professional fees, I treat physician concentration as the primary measure of provider concentration for the purposes of market stratifications.

2.4.4 Readmissions

To the extent that insurance market concentration increases utilization, a natural question is whether those increases translate into quality improvements. On one hand, the insurer's bargaining power might reduce healthcare prices and improve access to high-value care otherwise deemed unaffordable. On the other hand, the competitive outcome for provider prices, as previously noted, may be inefficient because the patient does not typically face the full cost of care. To explore this issue surrounding consumer welfare, I conduct additional analyses exploring the effect of insurer concentration on a relatively narrow measure of quality, namely unplanned 30-day readmissions after a discharge. Readmissions are, of course, related to utilization, and so another way of framing this issue is whether higher intensive utilization decreases the probability of (additional) extensive utilization.

2.5 Data Measures for Market Concentration and Utilization

In order to explore the questions outlined above, this paper's analyses use a longitudinal study design, with the effect of insurer concentration on utilization identified by variation within a market over time. I construct measures of insurer, physician, and hospital concentration from HealthLeaders-InterStudy, Centers for Medicare and Medicaid Services (CMS) publicly available files, and American Hospital Association (AHA) Annual Survey data, respectively. I use individual-level data on healthcare utilization for the commercially-insured population from the Truven Health MarketScan Database of Commercial Claims to construct several market-level measures of utilization (i.e., extensive vs. intensive, planned vs. acute) that control for variation in individual characteristics, including age, gender, plan type, and comorbidities. Additional data on market-level confounders comes from a variety of publicly available sources. A detailed description of data sources, variable measurement, and construction of the analytic sample follows. (The description of the statistical models and sensitivity analyses is provided in Section 6.)

2.5.1 Measurement of Market Concentration

As noted previously, a standard measure of market concentration is the Herfindahl-Hirschman Index (HHI). Measuring the HHI requires defining the relevant geographic and product market. The measures of insurance market concentration relevant to negotiated provider prices were developed by Trish and Herring (2015) using HealthLeaders-InterStudy data. The product market was defined as enrollment across all self-insured and fully-insured private plans and the geographic market is defined as Core-Based Statistical Areas. For the 11 largest CBSAs, which are further divided into smaller metropolitan divisions, these smaller areas were used. As these markets are based on commuting patterns, and hence economic activity, they represent a reasonable geographic area for insurers to compete within. (As previously noted, CBSAs have also been used in previous literature). Core-Based Statistical Areas generally line up with the Metropolitan Statistical Areas used in the Truven Health MarketScan data, but as necessary, geographic areas are aggregated by taking an average weighted by population.

Measures of physician market concentration derive from archived CMS Physician Compare data from March 2014, April 2015, and April 2016 and the Medicare Physician and Other Supplier Data for 2013-2015, both publicly available data sources.[6] The Physician Compare data includes physician-level data on specialty, credential, practice locations, and critically, a group practice identifier that can be used to link physicians operating under the same practice. (It is not possible to measure physician concentration using the Truven Health MarketScan data, as the data does not contain any information about affiliations between physicians.) The CMS Supplier Public Use Files (PUFs)

[6] Physician Compare data available here: https://data.medicare.gov/data/archives/physician-compare. Supplier Data available here: https://data.cms.gov/utilization-and-payment/related-data.

include physician-level data on the total Medicare allowed amounts paid to each physician each year, which is the product market in my measures of market share. Because the appropriate geographic market likely varies with the type of service being provided, with the geographic market for primary care physicians smaller than for specialist physicians, the geographic market for family practice physicians is defined as the county. For all other specialties, the geographic market is defined as the CBSA and the metropolitan divisions therein. For all specialties, however, concentration measures are aggregated to the Truven MSA level, weighted by population.

Because these physician concentration measures are specialty-specific, I combine them into a single summary physician concentration measure that aggregates across the 10 largest physician specialties that are measurable in the CMS data. (Pediatrics and obstetrics/gynecology cannot be measured, but the sample is limited to adults, and the findings are robust to constructing utilization measures that exclude obstetric or gynecologic admissions.) Each specialty receives a weight based on the proportion of procedures attributed to that specialty for the set of DRGs used in the intensive volume analysis (described below). As a sensitivity analysis, I calculate these weights separately by market, so that each market receives its own combination of weights (but these weights were held constant over time). These measures are weighted towards physicians in internal medicine, cardiology, and family practice. A detailed explanation of how I use these files to create measures of physician concentration is available in Appendix 2A.

For hospital market concentration, the product market is inpatient days. The market shares of hospitals in hospital systems are summed for these calculations. Geographic hospital markets are also defined by CBSAs with the metropolitan subdivisions described above.

2.5.2 Individual-Level Sample Definition

As noted previously, I use commercial claims from Truven Health MarketScan to construct measures of market-level utilization. This population primarily consists of beneficiaries receiving insurance from a self-insured employer or from smaller health plans, and covers a broad but not nationally representative geographic area. The sample of beneficiaries used to create the yearly utilization measures for 2013-2015 excludes those enrolled for a partial year. In other words, someone enrolled from July 2013-January 2015 contributes data to the 2014, but not 2013 or 2015 utilization measure. The analysis is limited to adults aged 18 or above and aged 64 or below. Enrollees in Puerto Rico, with a geographic location of Nation (region unknown), and in non-metro areas are dropped from the analysis. For the extensive measures of having any inpatient utilization, I restrict the sample to enrollees who were never enrolled in an HMO or capitated plan during the course of a year. For the intensive measures of the intensity of inpatient utilization, I restrict the sample to enrollees who never had a capitated claim during that year. Claims with no health plan type listed are dropped. The primary sample restricts to full-year enrollees, but sensitivity analyses include a sample enrolled for a year prior to the observation year (without restrictions on the observation year enrollment) and a sample continuously enrolled from 2013 through 2015.

2.5.3 Measurement of Individual-Level Utilization

For the individual-level data, I measure utilization on the extensive margin as simply a binary indicator for having any inpatient admission over the course of a year. Measurement for the intensive margin is more complex. Adapting the general method that has been used in several papers (see, e.g., Dunn, Shapiro, and Liebman (2013) and McKellar et al. (2014), I create a utilization index that re-prices professional services using the mean for that billing code across the entire sample and then sums an individual's spending on these re-priced services over the period of an inpatient admission. Specifically, if $\bar{p}_s$ is defined as the mean price for service *s* administered during an admission *a* to a patient living in market i in year t, the price-adjusted professional spending for that individual's admission, Q_{ait} is given by:

$$Q_{ait} = \sum_{s} \bar{p}_s \qquad [1]$$

This value can be interpreted as the dollar value of the intensity of services provided in an admission. Mean prices are calculated for each CPT code based on the sum of all covered payments (inclusive of the insurer's payment and the patient's out-of-pocket expenses) for inpatient services. This method therefore removes price variation from the measure but captures the variation in the types and intensity of services across markets, assigning more weight to services that are (on average) reimbursed at higher rates.

2.5.4 Measurement of Individual-Level Readmissions

In order to measure clinical quality, I construct a measure of 30-day all-cause unexplained readmissions using the Truven Health MarketScan data in order to test for the effect of insurance market concentration on quality of care. The measure follows the CMS method for identifying all-cause unplanned hospital readmissions (YNHHS/CORE 2012), supplemented by a revision to account for updates to diagnostic and procedural coding systems (Centers for Medicare and Medicaid Services 2017). Following the CMS method, certain inpatient admissions are dropped from the sample of index admissions (i.e., admissions that ended in discharge against medical advice), and admissions for CMS-designated planned procedures (i.e., pregnancy) are not counted as readmissions.[7] CMS identifies 5 patient cohorts with broadly similar readmission patterns, and this analysis uses the same approach to constructing cohorts.

2.5.5 Individual-Level Control Variables

The Truven Health MarketScan data includes limited demographic information, including sex and age. I use the pre-coded categorical age variables of 18-34, 35-44, 45-54, and 55-64 in this analysis. After removing enrollees with capitated claims, Truven Health MarketScan includes indicators for the following health plan types: comprehensive, exclusive provider organization (EPO), point of service (POS), preferred provider organization (PPO), consumer-directed health plan (CDHP), and high-deductible health plan (HDHP). Most models include binary indicators for the enrollee's health plan at the time of the encounter. However, for the models used to construct the

[7] Note this CMS definition of "planned" does not correspond to the definition of "planned" used in the remainder of this analysis.

measures of extensive utilization, where the outcome is measured over a year rather than a single admission, plan type enters the analysis as a continuous variable measuring the share of the year that the enrollee spent in each plan.

Adjustments to individual-level utilization based on health status use Version 22 of Medicare's Hierarchical Condition Categories (HCC), a set of 79 health condition indicators mapped from ICD diagnosis codes.[8] I assign yearly HCC codes to enrollees based on all the diagnoses appearing on any of their claims over a year. This method accounts for both pre-existing conditions and for diagnoses following from their health care encounter. While age, gender, and health status are the only individual-level data available in the MarketScan data, additional market-level demographic and socioeconomic variables, described below, are included in the market-level outcome models.

2.5.6 Construction of Market-Level Utilization Measures

For each of the three sets of individual-level outcomes described above – extensive volume, intensive volume, and readmissions – I use the same basic strategy to create measures of market-level extensive and intensive utilization and readmissions, adapted from McKellar et al. (2014). The goal of this strategy is to use as much data about the individual and the type of admission as possible to explain the observed utilization and readmission, so that the component of utilization that is unexplainable at

[8] As the switchover from the ICD-9 to ICD-10 coding system occurred over the study period, both coding systems are present in the data and the HCC mappings were based on the appropriate coding system. Crosswalks between the appropriate ICD and CC version were accessed here: http://www.nber.org/data/icd-hcc-crosswalk-icd-rxhcc-crosswalk.html. Code on imposing hierarchies was adapted from here: http://www.nber.org/risk-adjustment/2014/hcc/22/.

the individual level can then be used in a market-level model and explained by market-level factors. In brief, the individual-level measures are regressed on all of the available individual demographic, health, and plan controls, discussed in detail above, and the residuals from these models by year and market are used to construct the market-level measures used in this analysis. This approach allows the creation of a market-level unit of observation, while also making use of all available micro-level data.

More specifically, in the following specification, Q_{ait} is the individual-level outcome measure – either an indicator for an enrollee *a* having an admission, the measure of price-adjusted professional spending over admission *a* constructed in equation [1], or an indicator for an enrollee's admission *a* resulting in a readmission – in market *i* and year *t*. φ_2, φ_3, and φ_4 represent a vector of coefficients corresponding to age group, plan type, and Hierarchical Condition Category, respectively. φ_5, φ_6, and φ_7 represent a vector of coefficients corresponding to interactions between sex and age group, plan type and age group, and sex and plan type.

$$\begin{aligned} Q_{ait} = \varphi_0 + \varphi_1 Sex_{ait} + \varphi_2 AgeGrp_{ait} + \varphi_3 PlanTyp_{ait} + \varphi_4 HCC_{ait} + \varphi_5 Sex_{ait} AgeGrp_{ait} \\ + \varphi_6 PlanTyp_a AgeGrp_{ait} + \varphi_7 Sex_a PlanTyp_{ait} + \epsilon_{ait} \end{aligned} \qquad [2]$$

For each outcome, the mean of the residuals ϵ_{ait} from equation [2] is taken by market and year to create a measure of annual market-level utilization left unexplained by (observable) individual characteristics.

$$Y_{it} = \frac{1}{n}\sum_{a=1}^{n} \epsilon_{ait} \qquad [3]$$

This mean residual for the market then serves as the dependent variable in the market-level models predicting utilization or readmissions as a function of insurance concentration.

While the construction of a market-level measure follows the same basic strategy for all outcomes, there are a few details specific to each type of measure. For the extensive margin (which measures the likelihood of having an admission) I estimate equation [2] with a linear probability model (and logistic regression in a sensitivity analysis). The mean residual is then the probability of beneficiaries in a market and year having an inpatient admission that could not be explained by their individual characteristics. (For ease of interpretation, I multiply these average residuals by 100). As noted above, rather than a binary plan type indicator, plan type enters these extensive models as the percentage of a year the enrollee belonged to each plan.

For the intensive utilization measure, I estimate equation [2] separately for the set of admissions assigned to each diagnosis related group (DRG) using ordinary linear regression. Rather than estimating a single model of inpatient intensive utilization, estimating a series of DRG-specific models allows the model to better account for the fact that different types of admissions have different mean levels of spending (captured via the intercept term), and to account for the fact that the control variables, particularly the HCC codes, will predict a different impact on the price-adjusted spending depending on the type of admission. I estimate models on the set of DRGs with at least 5,000 admissions in the sample, which captures over 70% of admissions. This threshold was selected based on a statistical power analysis for multiple regression using the G*Power software, calculated assuming an effect size of 0.01, an alpha of 0.05, a power of 0.9, and

100 predictors. The residuals are then aggregated across all models, and the mean by market and year reflects unexplained utilization for patients being treated for a broadly similar set of diagnoses. Because the residuals are taken from DRG-specific models, a market having an above average mean is a function of patients receiving more services for the same type of admission, rather than by the market having an above average number of admissions with high average spending.

For the readmissions measure, like that for extensive utilization, I estimate a linear probability model. Risk adjustment is based on HCC codes, though unlike the risk adjustment in the utilization models, it is based on diagnoses codes from inpatient admissions up to a year prior to the index admission, and does not risk adjust for diagnoses codes from the index admission that may be a complication of care. In order to guarantee a year of risk adjustment data, I restrict the sample to enrollees with two continuous years of enrollment, rather than the one year used in the main utilization models. I estimate models following the form of equation [2] separately for each of the patient cohorts identified in the CMS methodology. Then the mean residual across all cohort models is taken by market and year (multiplied by 100 for ease of interpretation), and so the market-level measure reflects the percentage of patients with an eligible admission who then had a readmission within 30-days that could not be explained by individual characteristics.

2.5.7 Market-Level Control Variables

The analysis of market-level utilization incorporates several market-level control variables, which focus primarily on capturing the type of demographic and socioeconomic information that might correlate with both utilization and insurer concentration and which are not available at the individual level. These variables include the median real income and percent in poverty from the Census Small Area Income and Poverty Estimates (SAIPE), the percent uninsured from the Census Small Area Health Insurance Estimates (SAHIE), the unemployment rate from Bureau of Labor Statistic Local Area Unemployment Statistics (BLS LAUS), and the percent nonwhite and percent with a bachelor's degree from the Area Health Resource File (AHRF). The market-level control variables also include healthcare supply variables that might confound the relationship between insurer and provider concentration and utilization, including the total number of beds, the number of doctors per 1,000 residents and Medicare Advantage penetration, each from the AHRF. Most variables were aggregated from the county to the market level using an average weighted by the county population from the AHRF. The total number of beds was simply summed.

2.6 Statistical Models for Insurance Concentration's Effect on Market-Level Utilization

The measures of annual market-level utilization (Y_{it}) for market *i* in year *t* from equation [3], for both extensive and intensive utilization, are then used as the dependent variable in a model as a function of market concentration and other market confounders described above, with market fixed effects to control for time-invariant unobservable market characteristics. These main models take the following form:

$$Y_{it} = \beta_0 + \beta_1 InsHHI_{it} + \beta_2 PhysHHI_{it} + \beta_3 HospHHI_{it} + \beta_4 Market_{it} + \beta_5 Year_t + \alpha_i + \varepsilon_{it} \quad [4]$$

$InsHHI_{it}$, $PhysHHI_{it}$, and $HospHHI_{it}$ are measures of insurer, physician, and hospital concentration, respectively. $Market_{it}$ is the vector of time-variant market-level control variables described above, and α_i is a market fixed effect. $Year_t$ is a set of year indicators. The identifying assumption is that the factors confounding the relationship between insurance market concentration and healthcare utilization are time invariant from 2013 through 2015. The parameter of primary interest is β_1, which measures the effect of an increase in insurer HHI on either: for the extensive margin, the percentage of beneficiaries with an unexplained inpatient admission; or for the intensive margin, the unexplained price-adjusted professional spending on inpatient services. These regressions are weighted by the number of observations that generated the mean residual, in order to assign more weight to markets for which the outcome could be measured with more precision. In all models, I cluster standard errors at the market level. I also estimate models in the form of equation [4] for extensive and intensive planned and acute utilization. Likewise, models in the form of equation [4] estimate whether insurer HHI affects unplanned 30-day readmissions.

In order to explore whether the effect of insurer HHI on utilization is modified by the initial level of market concentration, I estimate stratified models. In particular, I estimate Equation [4] separately for markets with low/moderate versus high physician market concentration at baseline (2013), and for markets with low/moderate versus high insurance market concentration at baseline, with the HHI cutoffs for moderate versus high defined at the DOJ level of 2,500. I then estimate these models for each pairwise combination of low/moderate versus high physician and insurer concentration at baseline. Tests for significant differences in the primary coefficients of interest across these stratified models are conducted using the seemingly unrelated estimation (*suest)* post-estimation command in Stata.[9] These stratified models by provider and insurer concentration are estimated for overall utilization, planned utilization, acute utilization, and readmissions.

2.6.1 Identification

As noted above, the effect of insurer concentration on utilization is identified by within-market changes in insurer concentration, which over the study period was driven by insurers entering and exiting markets, changes in the distribution of market shares of existing insurers, and a few small mergers.[10] Figure 2.1 shows the distribution of the changes in insurer HHI over the study period, separately by the baseline level of insurer and physician HHI. There are comparable levels of variation across the market stratifications, suggesting that null findings across market stratifications are driven by a null effect rather than a lack of identifying variation.

Drawing a causal conclusion from this study depends on the assumption that unobservable factors confounding the relationship are constant over the study period. Of course, insurer decisions about where to operate and which products to offer are not

[9] An alternative approach to test for effect modification is to include interaction terms between the HHI measures and binary indicators for the baseline concentration measures. However, this would introduce a high degree of correlation between terms.

[10] For example, Medical Mutual exited South Carolina markets and greatly decreased its presence in Indiana and Georgia between 2013 and 2014 ("Medical Mutual"). MVP Health Care exited New Hampshire markets and increased its presence in several Vermont and New York counties. ("MVP to pull"). Aetna and United exited the individual markets in California, though their presence was already small ("United HealthCare to Stop"), and Health Care Service Corporation expanded its presence in several Montana counties in 2014, perhaps following from its merger with Blue Cross/Blue Shield of Montana in 2013 ("Blue Cross of Montana"). Between 2013 and 2014, 46 states experienced a decrease in the number of insurers in the individual market, with fewer states experiencing a decrease in the small and large group market, and 123 insurers, mostly very small, entered a market ("ACA Round-up"). There were no large national mergers over the study period.

random. They depend, for example, on the level of physician and hospital market concentration, which affects their ability to negotiate lower rates. To the extent possible, these time-variant factors (such as provider market concentration) are controlled for in the model.

However, there are a few specific threats to this identification strategy that this research attempts to rule out. Of particular importance to this research is how the level of utilization in a market relates to an insurer's expectations about their profit margin, and hence, their decision about whether to enter/exit a market or pursue a merger. Insurers may pursue a merger in or exit markets with exogenously high utilization, in which case the causal pathway moves from volume to insurer concentration, rather than from insurer concentration to volume. This threat is arguably tested by the analysis of the effect on acute utilization. If it is true that insurers consolidate in response to increasing utilization, that should be true for any type of utilization, including for acute treatments unlikely to be affected by patient demand (but affected by changes in underlying health status or potentially by provider behavior).

Along these same lines, it is possible that changes in the (unobserved) health or insurance status of the underlying population are related to both insurer consolidation and utilization. For example, insurers may exit a market where a sicker population narrows their profit margin, or enter markets where they expect a healthier patient pool. I explore this threat by conducting sensitivity analysis on a sample of beneficiaries that were continuously enrolled over the study period. This sample restriction roughly holds constant the health of the sample in order to rule out the possibility that the results are driven by changes in the Truven Health MarketScan sample (perhaps reflective of ACA-related changes in the commercially insured population more broadly) that are correlated with changes in insurer concentration. It also precludes the possibility of the changes being driven by previously uninsured beneficiaries entering the sample with different utilization patterns.

2.6.2 Sensitivity Analyses

In addition to conducting analyses that add credibility to the identification strategy, I make several efforts to test the robustness of the results, many of them already mentioned. First, I (further) explore the sensitivity to the sample definition, as inclusion in the primary sample requires a full year of enrollment, which may bias the sample towards beneficiaries that experienced fewer (and less fatal) health shocks and little employment churn. I therefore estimate the main model for intensive utilization, and the acute and planned intensity models, on a sample that was enrolled for a full year prior to the study period, but with no restriction on the observation year's enrollment. In order to use a full year of data for risk adjustment, the hierarchical condition categories are also based on the prior year, and so this analysis serves the secondary purpose of testing the sensitivity to risk adjusting based on conditions recorded in the year prior to the observation period. (Models for extensive utilization are not estimated on this alternative sample, as that outcome is measured over a year rather than an admission, making full-year enrollment a necessary restriction.)

I also estimate the main models with the alternate summary physician concentration measure, mentioned above, which assigns specialty weights specific to each market (rather than a constant set of specialty weights across markets), in order to account for the fact that physician specialists may have more bargaining power in some markets than others based on how frequently their services are utilized. Additionally, I use two different sets of alternate thresholds to distinguish between acute and planned conditions, one defining the groups more broadly and one more restrictively. Acute conditions are defined alternately as DRGs with a weekend share of admissions of at least 0.20 and as DRGs with a weekend share of admissions between 0.26 and 0.31. Likewise, planned conditions are defined as those with a weekend share of below 0.20, and as those with a weekend share below 0.08.

Given the skewness in healthcare spending with a long right tail in the distribution of individual-level utilization (and, correspondingly, a left tail in the distribution of market-level residuals), I use two approaches to remove the influence of outliers. First, I obtain the residuals from the DRG-specific models of equation [2] and then divide by the standard error of the residuals (i.e., studentize). I then drop observations resulting in an absolute value studentized residual of above three as outlying observations, and re-estimate the DRG-specific models on the subset of non-outlying observations to create an alternate measure of unexplained utilization. Second, I estimate models using the full individual-level sample to construct an average market-level residual, but then truncate the left tail of the distribution these average residuals, dropping markets with outlying mean residuals from the sample.

Finally, I test sensitivity to different methods of constructing the outcome. For the extensive margin measures of utilization, I estimate the individual-level models using logistic regression instead of linear probability models, and for the intensive margin measures of utilization, I estimate models using gamma regression with a log link (instead of ordinary least squares). Additionally, I estimate market-level models that use the median (rather than mean) residual as the outcome.

2.7 Results

2.7.1 Summary Statistics

Table 2.1 describes the characteristics of the individual-level Truven-MarketScan population used to construct the market-level measures of utilization. The first column presents summary statistics for models estimating extensive volume (where the unit of observation is a beneficiary enrolled for a year). The second column presents summary statistics for the sample of all inpatient admissions in DRGs with at least 5,000 admissions (where the unit of observation is a beneficiary's inpatient admission), while the third and fourth column describe the sample of the subset of planned and acute admissions, respectively. The final column presents the sample corresponding to the set of index admissions used in constructing readmissions. (The extensive acute and planned samples are the same as the overall extensive sample).

Over the 2013-2015 period, there were 44,445,328 beneficiary-years of enrollment in the extensive sample, with about 4.59% of those observations resulting in an inpatient admission that year. From that pool, there were 1,816,817 admissions in the intensive sample for the set of DRGs with at least 5,000 admissions. The average price-adjusted professional spending (intensive utilization) for those admissions is $3,604.72. Price-adjusted professional spending is, on average, higher for planned than acute admissions. About 8.12% of eligible admissions result in an unplanned readmission within 30-days. Comparing the demographic and plan characteristics between the extensive and intensive sample, the beneficiaries with an inpatient admission are more likely to be female and younger (likely due to obstetric admissions) or older than the sample of all enrollees.

Figure 2.2 illustrates the distribution of mean residuals by market (metropolitan area) and year for the main outcome measures. To demonstrate how these residuals are produced, Appendix Table 2.2 reports the parameter estimates from the underlying models for the extensive sample predicting any admission. As I estimate the intensive models separately by DRG, it is not practical to show all of those results, but I report results for the largest non-obstetric DRG (Major joint replacement without major complication or comorbidity).

Table 2.2 presents summary statistics describing the markets used in the analysis for the main extensive and intensive outcomes. As these summary statistics are weighted by the number of observations that generated the volume measure, there are small differences between the intensive and extensive samples (and because the differences are small, summary statistics are not provided for each iteration of the outcome measures). On average, insurance markets are just over the threshold for high concentration (i.e., an HHI of 2,500), while hospital markets are well above that threshold. Physician markets, on average, fall just under the threshold for moderate concentration (i.e., an HHI of 1,500).

2.7.2 Main Results

Figure 2.3 illustrates the distribution in the difference of the mean residuals for overall extensive and intensive utilization from 2015 compared to 2013, plotted separately for markets that experienced a decrease in insurer HHI of at least 250 points, for markets that experienced an increase in insurer HHI of at least 250 points, and for markets that experienced changes of less than 250 points. While the probability of having any admission (adjusted for beneficiary characteristics) generally decreased over time for all three groups, in markets where the insurer HHI decreased the decrease was larger in magnitude, and in markets with no changes or an increase in insurer HHI the decrease in admissions was smaller in magnitude. The change in intensive utilization is centered around zero for markets where insurer HHI decreased and more positive for markets where insurer HHI increased or did not change. Both of these patterns in this figure are consistent with increasing insurer concentration increasing utilization.

To formalize these descriptive findings, Table 2.3 reports the results of estimating equation [4], with models predicting the unexplained percentage having any inpatient admission and the unexplained price-adjusted professional spending of inpatient admissions (in DRGs with adequate sample size) presented in columns 1 and 2, respectively. Insurer concentration increases utilization on the extensive margin, with a 1,000-point increase in HHI translating to a 0.09 percentage point increase (95% CI: 0.003, 0.19) in the probability of having an admission. This magnitude can be understood in the context of the percentage with an admission (4.59%, reported in Table 2.1). A 1,000-point change in insurer HHI therefore explains about 2.1% of the mean admission rate. Likewise, insurer concentration increases utilization on the intensive margin, with a 1,000-point increase in HHI causing price-adjusted professional spending to increase by $84.22 (95% CI: 7.9, 160.6), or about 2.3% of the mean level of utilization ($3,605).

Somewhat unexpectedly, hospital and physician concentration do not significantly affect utilization. Moreover, most of the other market-level covariates are not significant in either model. (The individual-level covariates were highly significant in the individual-level models.) In the intensive model, the percent uninsured is the only significant variable besides insurer HHI, perhaps due to the fairly large changes in the rate over the study period due to ACA-related insurance expansions, and it has a large effect. When the uninsured rate decreases, price-adjusted utilization increases, which could be due to previously uninsured people entering the sample and "catching up" on healthcare services. In the extensive models, increases in the total number of beds decrease the probability of having an admission. (As many of these sets of covariates are highly correlated and statistical insignificance may be driven by variance inflation, sensitivity to using a subset is tested, in results not shown; most covariates remain insignificant.)

Columns 3-6 of Table 2.3 present the results of estimating the effect on the set of admissions identified as planned and acute. Insurer concentration does not significantly affect the probability of having an admission designated as planned, which is somewhat surprising. It does, however, significantly affect intensive utilization for these admissions, with a 1,000-point increase in insurance HHI increasing price-adjusted spending by around $201 (95% CI: 60.5, 340.6), about 3.4% of the average for planned admissions ($5,830). By contrast, insurance HHI does not significantly affect either the likelihood of experiencing or the intensity of professional services provided during an acute admission; these insignificant findings for acute utilization were expected. The general pattern of these findings is consistent with a theory of insurer concentration affecting utilization through downward-sloping demand. Percent uninsured remains the most significant other predictor in these models.

2.7.3 Market Stratifications

The results of estimating the models separately by the level of insurer and physician market concentration at baseline are presented in Table 2.4, which shows the coefficients and standard errors of the effect of insurance market concentration on overall extensive (Panel A) and intensive (Panel B) utilization (see Appendices Tables 2.3-2.4 for the full set of regression coefficients). The stratified p-value reports the result of a two-sided test of equality of the coefficients. The effect in physician markets with an HHI above 2,500 is tested against physician markets with an HHI below 2,500. Likewise, the effect in insurance markets with an HHI above 2,500 is tested against insurance markets with an HHI below 2,500. And the effect in markets with low physician and high insurer concentration, with high physician and low insurer concentration, and with high physician and high insurer concentration are each tested against markets with low physician and insurer concentration.

On the extensive margin, there are no significant differences in the effect of insurer concentration by market stratification, though the significant finding in the main model appears to be driven by the effect in competitive physician markets. On the intensive margin, however, there are (borderline) significant differences by physician stratification (p=0.08), with no effect of insurer concentration in highly concentrated physician markets, and a 1,000-point increase in insurer HHI in a low/moderate concentration physician market increasing intensive utilization by $142 (95% CI: 22.8, 261.5). A similar, though statistically weaker, dynamic is observed in low/moderate concentration insurance markets compared to highly concentrated insurance markets (p=0.13), with a 1,000-point increase in insurer HHI in less concentrated insurer markets increasing intensive utilization by $196 (p=0.07, 95% CI: -17.4, 410.1), but no significant effect in highly concentrated insurance markets. Finally, the point estimate is largest when both insurer and physician markets are less concentrated and smallest (negative) when both are highly concentrated, though neither the estimates nor the difference in the estimates are statistically significant.

Appendix Table 2.5 reports the stratified results for acute and planned extensive utilization, which, like the overall extensive results (with the exception of a borderline significant impact on acute admissions in competitive provider markets), are not affected by insurer concentration. Table 2.5 shows the coefficients and standard errors of the effect of insurance market concentration on acute (Panel A) and planned (Panel B) intensive utilization, with the full set of regression coefficients in Appendices 2.6-2.7. On the intensive margin for planned utilization, the variation in effects by market stratification follows a similar pattern as that observed for overall intensive utilization, with a 1,000-point increase in insurance HHI increasing price-adjusted professional spending by roughly $300 (95% CI: 82.2, 517.5) in less concentrated physician markets and $407 (95% CI: 41.9, 772.4) in less concentrated insurance markets. (The differences in coefficients between low and high concentration physician and high and low concentration insurance markets fall just short of significance at the 10% level.) A large effect is also detected when physician markets are highly concentrated but insurance markets are less concentrated, though it is not significantly different from the effect when both are competitive (p=0.63).

2.7.4 Readmissions

Appendix Table 2.8 presents the results predicting unexplained readmissions. In the overall model, neither physician nor insurer concentration significantly affects readmissions, though both are negatively signed. Notably, hospital market concentration increases readmissions, consistent with much of the prior literature related to hospital concentration and quality. Because hospital and physician market concentration are correlated, I re-estimate these models without hospital market concentration (Column 2) in order to determine whether the coefficient on physician concentration is positively signed when it is the only provider concentration measure. It remains insignificant.

In stratified models (Columns 3-6), the effect of insurance market concentration remains insignificant. Moreover, the correlation between the readmission residual and the utilization residual is virtually zero. To the extent that downward-sloping demand explains the increases in utilization observed in these analyses, on this measure they do not improve the patient's outcome. It is also worth noting that physician market concentration decreases readmissions in concentrated insurance markets. While this research does not replicate the finding of Dunn and Shapiro (2017) that physician concentration increases treatment intensity, it does support their finding that physician concentration decreases readmissions, though only in some markets.

2.7.5 Results for Continuously Enrolled Sample

In order to test the possibility that the results are driven by unobserved changes in the health status of the underlying population, potentially correlated with both utilization and insurer concentration, I replicate the full set of analyses on a sample of beneficiaries continuously enrolled for all three years. Table 2.6 indicates that the major findings are largely robust to using this sample. (See Appendix Tables 2.9 and 2.10 for summary statistics and full model results, respectively.) As in the primary sample (of people continuously enrolled for at least one year), there is a comparatively large effect on treatment intensity in low/moderate physician and insurance markets and for planned admissions. Contrary to the results for main sample, I detect no effect on overall extensive utilization, though the result is qualitatively similar. Also unlike in the primary sample, there is a significant negative effect on readmissions in this continuously-enrolled sample. As shown in Appendix Table 2.11, this effect for readmissions is fairly constant across markets, and not limited to (or larger in) the markets where the effect of insurer concentration is positive. It is also worth noting that the uninsured rate is not significant in these models, which would be consistent with an explanation of previously uninsured people catching up on services in the main sample.

2.7.6 Sensitivity Analyses

Table 2.7 presents the results of the sensitivity analyses. The findings are robust to including the observations of beneficiaries who were enrolled for only a partial year (though fully enrolled in the prior year), for whom risk adjustment was based on conditions recorded in the prior year. The results are likewise robust to using an alternate measure of physician concentration (and in results not shown, to stratifying using this physician concentration measure). The finding that there is a large effect of insurer concentration on intensive utilization for planned but not acute admissions is robust to using different thresholds of the weekend share of admissions to categorize admissions. On the extensive margin, there is one borderline significant effect on acute utilization for one of the alternate thresholds, but as it is negatively signed, it works against the hypothesis of reverse causality.

The main source of sensitivity is related to model specification and construction of the market-level measure, particularly to approaches to address the skew in the distribution of intensive utilization. The findings are largely robust to using two different approaches to removing outlying measures of intensive utilization, one that identified individual-level outliers and one that identified market-level outliers. However, while the findings related to extensive utilization are robust to estimating equation [2] with logistic regression rather than a linear probability, the intensive utilization findings are not robust to using a gamma-log model, nor to defining the outcome as the median rather than mean residual. In results not shown, the effect is positive and significant at each quartile of the residual distribution in models that rely on cross-sectional variation, which may suggest that because there is less variation in the median, it is harder to detect an effect in models that include market fixed effects. It is also possible that there is no effect on the median, and that the effects are stronger among a subset of patients.

2.8 Discussion

This research finds that a 1,000-point increase in insurer HHI increases overall utilization by roughly 2% on both the intensive and extensive margin, with a larger effect (3.4%) on the intensity of planned admissions. The overall positive (rather than negative) relationship between insurer concentration and utilization provides suggestive evidence of insurers playing, on average, a monopoly-busting role as opposed to exercising monopsony power against physicians. The larger effect for planned admissions, and the null effect for acute admissions, further suggests that the relationship is driven by higher demand when prices fall for the subset of relatively more price-elastic services, consistent with the exercise of countervailing bargaining power against more concentrated providers.

The findings related to the market stratifications are more difficult to reconcile with the conceptual model, but offer suggestive evidence related to the market interactions between insurers and providers, and between insurers and patients. The effect of insurance concentration is larger in insurance markets that were relatively unconcentrated at baseline, which may suggest that if insurer consolidation enables insurers to negotiate larger price discounts across all markets, insurers in more concentrated markets have a stronger ability to constrain the higher demand for healthcare services corresponding to those lower prices. On the provider side, an effect driven by downward-sloping demand would presumably be larger in the markets where providers were able to exercise market power and elevate price farther above marginal cost at baseline. However, the effect is larger in physician markets that were relatively unconcentrated at baseline.

One possible explanation for this finding is that, even in low/moderate physician concentration markets, the prices at baseline were high enough above marginal cost that there was still room for more concentrated insurers to negotiate price discounts. If that is true, then it is perhaps unsurprising that an increase in insurer concentration would have a larger effect in less concentrated physician markets. In more concentrated physician markets, providers may be more able to resist the countervailing bargaining power that insurers acquire when insurer concentration increases, compared to in less concentrated physician markets.

To put the magnitude of the findings of this analysis in context, the average increase in insurance concentration over the study period was only 49 points. In 2015, there were over 177 million people with employer or non-group commercial coverage. If the baseline utilization and the effect on the broader commercially insured population was comparable to the effect in the Truven Health MarketScan sample, that 49-point change translates to an estimated 8,197 additional beneficiaries with an inpatient admission that year. If the effect on the admissions in DRGs with fewer than 5,000 admissions is comparable to the effect on the admissions used in this analysis, price-adjusted professional spending increased by an estimated $29.6 million in new admissions and $33.7 million in more intensive admissions. Presumably there is some spillover effect onto facility utilization, which would increase this amount by several multiples.

Relative to the scale of healthcare spending in the United States, these numbers are fairly small. It is notable, however, that this analysis is based on a period with limited merger activity. The recently blocked mergers between Aetna and Humana and Anthem and Cigna indicate that insurers would pursue greater levels of consolidation if the regulatory environment permitted it ("Aetna and Humana" 2017, "Judge Blocks" 2017). If the average insurance HHI had instead increased by 500-points, the estimated effect on utilization would be between $2 and $5 billion. It is clear, therefore, that insurer consolidation has the potential to lead to large increases in utilization, and that, in terms of total spending, these increases partially offset the effect of negotiating lower prices. It is possible that increases in utilization contribute to the premium growth associated with insurer consolidation.

It is important to emphasize that this research did not measure overutilization, and that increases in utilization associated with insurer consolidation may be good or bad for consumers. The average level of utilization is not necessarily the clinically appropriate level of utilization, and increases in utilization are driven both by average/high utilizers becoming higher utilizers, and by low utilizers becoming average utilizers. While it is likely that some of the observed effect is due to overuse, it is also likely partly because of greater access to needed health services. Having said that, on the one measure of consumer welfare explored in this study (readmissions), there was no evidence that higher utilization translated to improved outcomes. Moreover, this research finds a fairly large effect on intensive utilization for the types of treatments that are (typically) planned in advance. Some of those treatments are discretionary and generally associated with overuse. By contrast, there was no significant impact on the types of acute events for which demand is presumably highly inelastic, indicating that treatment decisions for urgently needed medical interventions in the commercially insured population are not dependent on insurer concentration.

Heterogeneity in the effect of insurer consolidation by the level of provider and insurer concentration provides important information for regulators trying to estimate the likely impact of a merger or acquisition in a given market. This research suggests that the utilization effect will be much larger if either the insurance market or the physician market is relatively unconcentrated. In some markets, if there is relatively poor access to healthcare, regulators and/or policymakers may view a large utilization effect as pro-competitive; and conversely, in markets with indicators of overuse, policymakers may view large expected utilization increases as an argument against insurer consolidation, alongside other concerns such as the effect on premium growth.

Finally, this research attempts to exclude the possibility that the positive relationship between insurer concentration and utilization is primarily about insurer consolidation in markets where utilization is already high, or about changes in the risk pool causing both utilization and insurance concentration to change. If high overall utilization drives insurer consolidation, then high acute utilization should also drive insurer consolidation; but the analysis finds no significant relationship between insurance concentration and acute utilization. Moreover, the consistency in the findings between the underlying sample in the main models (which required only full-year enrollment) and the sample that was continuously-enrolled for the full study period, a sample restriction that approximately holds constant the health characteristics of the pool of beneficiaries, further supports this conclusion.

2.9 Limitations

This research makes several contributions. It extends the literature on the relationship between insurer concentration and utilization using a different methodology with updated data, incorporates measures of physician concentration, explores the interaction between insurer consolidation and baseline levels of physician and insurer concentration, explores the effect on services for which demand is more and less price elastic, and includes a measure of hospital quality. Nevertheless, there are several important limitations to note.

The most important limitation of the analysis is that causal inferences depend on the assumption that, conditional on the observable control variables, confounding factors are time invariant over the study period. While this research has found suggestive evidence against reverse causality, and has sought to control for several time-variant confounding variables like provider concentration and the uninsured rate, it is possible that there is an unobserved confounder correlated with both changes in insurer concentration and utilization that explains the observed relationship between changes in utilization and changes in insurance market concentration. On that note, there is limited individual-level information available to use as control variables, and the market-level controls are not based on the same population as the sample in the Truven Health MarketScan data, which limits their ability to control for changes in the underlying population.

Moreover, the Pauly (1998) model provides a useful framework for thinking about how insurer and provider market concentration and healthcare utilization interact, and the findings of this research are interpreted in that context. But the relationship between the empirical findings and the theoretical predictions are only suggestive. For example, the monopsony framework, where insurers exercise market power to constrain utilization, provides an explanation for why lower prices negotiated by insurers might not translate to higher utilization. The fact that the evidence suggests that there is a positive and significant effect on utilization in low/moderate, but not high concentration, insurance markets is interpreted in light of that framework; more concentrated insurers, facing less competition from other insurers, may be more able to utilize the tools that allow them to limit utilization. However, this research did not attempt to tease out the underlying mechanism, and so this is only a hypothesis and further developing the evidence is an area for future research. For example, another potential pathway is that when insurers have market power selling administrative services to employers, employers may decrease the generosity of benefits for their employees to offset higher administrative markups.

Another limitation of the research is the inability to account for vertical integration between insurers and healthcare providers. This work is based on a model of insurers and physicians as distinct entities with opposing interests in price negotiations, and is not translatable to a context where they are part of a larger system with aligned incentives. Relatedly, the research also does not fully account for vertical integration between physicians and hospitals. To the extent that hospital and physician integration results in horizontal integration between physicians (by introducing affiliations between the physician practices that become acquired by a hospital system) the physician concentration measures account for this. They do not, however, account for the fact that a hospital affiliation may confer bargaining power to a physician practice, even holding constant the physician HHI.

Related to physician concentration more broadly, the measure is based on a Medicare population, prohibiting the measure of certain specialties not frequently used by an aged population, and the best way to aggregate across physician specialties is not clear. This may explain why the research finds physician concentration as a significant effect modifier (based on a dichotomous, cross-sectional measure, which presumably carries a fairly strong signal), and not as significant on its own in models that rely on longitudinal variation (and where issues of measurement error are exacerbated).

Additionally, the analysis is limited to a commercially-insured population receiving coverage from either self-insured firms or small health plans. It does not assess spillovers onto publicly-insured patients, such as Traditional Medicare or Medicaid beneficiaries, and nor does it explore the effect on commercially-insured patients receiving coverage through Medicare Advantage, Medicaid HMO plans, or on the Health Insurance Exchanges. It is also somewhat limited in geographic scope. It focuses on non-rural areas and includes only the metropolitan areas available in the Truven Health MarketScan database, which has broad but not nationally representative geographic coverage.

Finally, readmissions are an important, but narrow measure of consumer welfare. It is possible that on other measures insurer consolidation's impact on utilization may result in quality improvements. Hanson, Herring and Trish (2018) provide early evidence that insurer concentration increases hospital patients' self-reported experience of care.

Further research is needed to better understand the welfare-increasing and welfare-decreasing impacts of insurer consolidation.

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2.11 Tables

Table 2.1: Characteristics of the Sample Used to Construct Market-Level Utilization Measures, Mean and Standard Deviation

	Sample for Extensive Utilization Measures		Samples for Intensive Utilizations Measures		Sample for Readmission Measure
	Beneficiary-Years of Enrollment N=44,445,328	All Inpatient Admissions N=1,816,617	Planned Inpatient Admissions N=613,756	Acute Inpatient Admissions N=188,499	Eligible Inpatient Admissions N=1,501,036
Percent with Any Admission	4.59 (20.93)				
Percent with a Planned Admission	1.32 (11.41)				
Percent with an Acute Admission	0.40 (6.35)				
Percent with a Readmission (30-days)					8.12 (27.32)
Price-Adjusted Professional Spending		3,604.72 (3,660.02)	5,829.86 (4,791.11)	2,446.71 (2,193.69)	
Fraction Male	0.48 (0.50)	0.29 (0.45)	0.25 (0.43)	0.49 (0.50)	0.35 (0.48)
Fraction Female	0.52 (0.50)	0.71 (0.45)	0.75 (0.43)	0.51 (0.50)	0.65 (0.48)
Fraction Aged 18-34	0.32 (0.47)	0.39 (0.49)	0.30 (0.46)	0.15 (0.36)	0.30 (0.46)
Fraction Aged 35-44	0.21 (0.41)	0.18 (0.39)	0.20 (0.40)	0.15 (0.36)	0.18 (0.38)
Fraction Aged 45-54	0.25 (0.43)	0.18 (0.38)	0.19 (0.40)	0.28 (0.45)	0.21 (0.41)
Fraction Aged 55-64	0.22 (0.41)	0.25 (0.43)	0.30 (0.46)	0.41 (0.49)	0.32 (0.47)
Fraction in Comprehensive Plan	0.02 (0.15)	0.03 (0.17)	0.03 (0.16)	0.04 (0.20)	0.04 (0.19)
Fraction in EPO Plan	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)	0.02 (0.13)
Fraction in POS Plan	0.08 (0.27)	0.08 (0.27)	0.08 (0.27)	0.08 (0.28)	0.08 (0.28)
Fraction in PPO Plan	0.70 (0.46)	0.71 (0.45)	0.71 (0.45)	0.70 (0.46)	0.70 (0.46)
Fraction in CDHP Plan	0.10 (0.30)	0.09 (0.29)	0.10 (0.29)	0.09 (0.29)	0.10 (0.30)
Fraction in HDHP Plan	0.08 (0.27)	0.07 (0.25)	0.06 (0.24)	0.06 (0.23)	0.06 (0.24)

Notes: Data comes from the Truven Health MarketScan Database of Commercial Claim, 2013-2015. The measure of price-adjusted spending reprices services using the mean payment rate observed in the data and sums over all professional services provided in an admission. The intensive sample includes the set of diagnosis-related-groups (DRGs) with at least 5,000 admissions. For the extensive sample, the fraction in a plan is the average fraction of a year that enrollees spent in each plan. For the intensive sample, it is the fraction of the sample enrolled in that plan at the point of admission. Acute admissions are the set of DRGs with at least 5,000 admissions with a weekend share of admissions above 25%, while planned admissions have weekend admission shares of below 15%.

Table 2.2: Market-Level Summary Statistics, 2013-2015

	Extensive Utilization Sample: Any Admission Number of Observations: 1,166		Intensive Utilization Sample: Price-Adjusted Professional Spending Number of Observations: 1,166	
	Mean	Std. Dev.	Mean	Std. Dev.
Insurance Market HHI (1000s)	2.58	0.81	2.61	0.82
Hospital Market HHI (1000s)	3.20	2.18	3.22	2.16
Physician Market HHI (1000s)	1.44	1.25	1.44	1.25
Percent Uninsured	13.58	4.88	13.61	4.89
Median Real Income	59.96	12.33	59.56	12.16
Percent Unemployed	6.36	1.66	6.36	1.62
Percent in Poverty	14.95	3.67	14.98	3.65
Percent Nonwhite	38.09	16.84	37.50	16.57
Percent with Bachelor's Degree	32.03	7.36	31.71	7.23
Total Beds	688.26	1,040.04	675.78	1,032.87
MDs per 1,000	2.76	1.00	2.75	0.99
Medicare Advantage Penetration	31.16	12.20	31.02	12.08

Notes: All market concentration measures are HHIs. Measures of insurance market concentration are based on shares of fully- and self-insured commercial enrollment from the HealthLeaders-InterStudy data. Hospital market concentration is based on shares of inpatient days from the American Hospital Association Annual Survey. Physician market concentration is based on shares of allowed amounts from CMS Physician Compare Data and the Physician and Other Supplier Data (PUF). Other variables come from the Census SAIPE, Census SAHIE, BLS LAUS, and the AHRF. Small differences in the summary statistics between the two samples are driven by slightly different weights.

Table 2.3: Full Regression Results, Extensive and Intensive Utilization

	All Admissions		Planned Admissions		Acute Admissions	
	Extensive: Any Admission	Intensive: Price-Adjusted Professional Spending	Extensive: Any Admission	Intensive: Price-Adjusted Professional Spending	Extensive: Any Admission	Intensive: Price-Adjusted Professional Spending
	(1)	(2)	(3)	(4)	(5)	(6)
Insurance Market HHI (1,000s)	0.0941**	84.22**	0.00983	200.5***	0.0134	17.89
	(0.0465)	(38.83)	(0.0281)	(71.23)	(0.0103)	(54.34)
Hospital Market HHI (1,000s)	-0.0133	-27.29	-0.00526	-32.02	0.00196	-6.961
	(0.0343)	(26.02)	(0.0169)	(41.72)	(0.00803)	(32.77)
Physician Market HHI (1,000s)	-0.0136	-9.275	-0.0303*	-20.48	0.00369	12.07
	(0.0363)	(27.68)	(0.0163)	(52.26)	(0.00863)	(46.57)
Percent Uninsured	-0.0183	-23.35***	-0.00733*	-37.03***	-0.00180	-19.67
	(0.0112)	(7.234)	(0.00427)	(13.46)	(0.00230)	(12.25)
Median Real Income	0.0176*	3.792	0.00553	6.875	0.00318**	-3.977
	(0.00927)	(6.455)	(0.00407)	(12.81)	(0.00161)	(9.288)
Percent Unemployed	-9.7e-05	20.68	0.00109	34.85	0.00206	8.730
	(0.0222)	(21.65)	(0.0115)	(43.48)	(0.00398)	(21.63)
Percent in Poverty	0.0122	-9.821	0.00368	-24.73	-0.000213	-18.17
	(0.0125)	(11.54)	(0.00595)	(21.08)	(0.00254)	(13.86)
Percent Non-White	0.0239	8.303	0.0207	9.478	-0.00834	39.54
	(0.0555)	(47.13)	(0.0216)	(88.22)	(0.0110)	(50.83)
Percent Bachelor's	-0.00755	-19.75	0.00190	-69.60	0.00290	-18.80
	(0.0347)	(38.65)	(0.0159)	(70.79)	(0.00809)	(42.52)
Total Beds	-1.2e-04***	-0.0323	-6.0e-05***	-0.0188	-1.1e-05**	-0.0488*
	(2.01e-05)	(0.0331)	(9.58e-06)	(0.0602)	(4.47e-06)	(0.0286)
MDs per 1,000	-0.484**	-192.8	-0.158	-395.8	-0.0282	104.6
	(0.244)	(224.2)	(0.146)	(454.9)	(0.0506)	(299.9)
Medicare Adv. Penetration	-0.00657	-0.978	-0.000960	-4.713	-0.000790	-3.695
	(0.00634)	(7.569)	(0.00317)	(12.69)	(0.00138)	(8.705)
Year = 2014	-0.401***	78.83	-0.107***	111.4	-0.0420***	65.79
	(0.0486)	(49.69)	(0.0202)	(89.72)	(0.0110)	(49.75)
Year = 2015	-0.703***	68.29	-0.276***	87.23	-0.0728***	126.6
	(0.0924)	(88.18)	(0.0377)	(159.6)	(0.0193)	(93.28)
Constant	0.121	839.1	-0.487	2,878	0.147	-393.7
	(2.564)	(2,015)	(1.056)	(3,757)	(0.485)	(2,151)
Observations	1,166	1,166	1,166	1,166	1,166	1,165
R-squared	0.924	0.918	0.867	0.911	0.789	0.797

Notes: The unit of observation is a market-year. The outcome in each model is the mean residual by market and year from models predicting having any admission (extensive). price-adjusted professional spending (intensive), or readmission as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the samples in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Acute admissions are the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was above 25%, while planned admissions have weekend admission shares of below 15%. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Effect of Insurance Market Concentration on Utilization, Stratified by Physician and Insurer Concentration

Panel A: Extensive Utilization (Any Admission)
Unadjusted Mean: 4.59

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 0.09** (0.05) N= 1,166	Beta (SE)= 0.13* (0.06) N= 538	Beta (SE)= 0.04 (0.07) N= 584 Stratified P-value=0.34
Insurance HHI <2,500	Beta (SE)= 0.06 (0.07) N= 475	Beta (SE)= 0.09 (0.09) N= 288	Beta (SE)= -0.00 (0.10) N= 187 Stratified P-value= 0.35
Insurance HHI >2,500	Beta (SE)= 0.08 (0.06) N= 647 Stratified P-value= 0.77	Beta (SE)= 0.09 (0.09) N= 250 Stratified P-value= 0.99	Beta (SE)= 0.04 (0.08) N= 397 Stratified P-value= 0.72

Panel B: Intensive Utilization (Price-Adjusted Professional Spending)
Unadjusted Mean: 3,604.72

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 84.22** (38.83) N= 1,166	Beta (SE)= 142.1** (60.49) N= 538	Beta (SE)= -6.716 (45.46) N= 584 Stratified P-value=0.08
Insurance HHI <2,500	Beta (SE)= 196.4* (108.2) N= 475	Beta (SE)= 211.7 (133.9) N= 288	Beta (SE)= 163.3 (126.7) N= 187 Stratified P-value= 0.76
Insurance HHI >2,500	Beta (SE)= 22.92 (35.39) N= 647 Stratified P-value= 0.13	Beta (SE)= 52.40 (56.94) N= 250 Stratified P-value= 0.2	Beta (SE)= -35.67 (46.29) N= 397 Stratified P-value= 0.23

Notes: The unit of observation is a market-year. Full model results in Appendix Tables 2.3 and 2.4. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Stratified p-values report the results of a test of the equality of coefficients between market stratifications, with the effect in concentrated physician (insurance) markets tested against competitive physician (insurance) markets, and high/low, low/high, and high/high concentration physician/insurance markets tested against low/low concentration physician/insurance markets. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Effect of Insurance Market Concentration on Acute and Planned Intensive Utilization, Stratified by Physician and Insurer Concentration

Panel A: Acute Intensive Utilization (Price-Adjusted Professional Spending)
Unadjusted Mean: 2,446.71

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 17.89 (54.34) N= 1,165	Beta (SE)= 40.12 (75.08) N= 538	Beta (SE)= -38.98 (86.56) N= 584 Stratified P-value=0.46
Insurance HHI <2,500	Beta (SE)= -37.36 (134.8) N= 475	Beta (SE)= 6.290 (170.4) N= 288	Beta (SE)= -201.0 (193.0) N= 187 Stratified P-value= 0.31
Insurance HHI >2,500	Beta (SE)= 6.817 (54.33) N= 647 Stratified P-value= 0.76	Beta (SE)= -1.631 (65.83) N= 250 Stratified P-value= 0.96	Beta (SE)= -8.214 (97.03) N= 397 Stratified P-value= 0.96

Panel B: Planned Intensive Utilization (Price-Adjusted Professional Spending)
Unadjusted Mean: 5,829.86

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 200.5*** (71.23) N= 1,166	Beta (SE)= 299.8*** (110.3) N= 538	Beta (SE)= 54.44 (82.76) N= 584 Stratified P-value=0.12
Insurance HHI <2,500	Beta (SE)= 407.2** (184.9) N= 475	Beta (SE)= 396.4* (223.3) N= 288	Beta (SE)= 525.4** (225.4) N= 187 Stratified P-value= 0.63
Insurance HHI >2,500	Beta (SE)= 91.44 (65.90) N= 647 Stratified P-value= 0.11	Beta (SE)= 157.1 (113.4) N= 250 Stratified P-value= 0.26	Beta (SE)= -23.81 (81.71) N= 397 Stratified P-value= 0.22

Notes: The unit of observation is a market-year. Full model results in Appendix Tables 2.6 and 2.7. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Acute admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was above 25%, while planned admissions have weekend admission shares of below 15%. Stratified p-values report the results of a test of the equality of coefficients between market stratifications, with the effect in concentrated physician (insurance) markets tested against competitive physician (insurance) markets, and high/low, low/high, and high/high concentration physician/insurance markets tested against low/low concentration physician/insurance markets. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Effect of Insurance Market Concentration, Continuously Enrolled Sample

	Beta	SE
Overall Utilization		
Extensive: Any Admission	0.0628	(0.0583)
Intensive: All Utilization	127.2**	(52.73)
Market Stratifications		
Intensive: Physician HHI<2500	195.2*	(81.51)
Intensive: Physician HHI>2500	43.08	(58.15)
Intensive: Insurance HHI<2500	344.2*	(128.5)
Intensive Insurance HHI>2500	23.23	(51.31)
Acute versus Planned		
Extensive: Acute Utilization	0.00297	(0.00906)
Extensive: Planned Utilization	-0.0188	(0.0294)
Intensive: Acute Utilization	-5.634	(61.72)
Intensive: Planned Utilization	194.9**	(87.17)
Readmissions		
Unplanned 30-day Readmissions	-1.857**	(0.735)

Notes: This analysis was restricted to a sample continuously enrolled from 2013 through 2015. The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive), price-adjusted professional spending (intensive), and readmissions as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Appendix Table 2.9, with full model results in Appendix Table 2.10. For intensive utilization, separate models are estimated for each DRG. Planned admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was below 15%. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

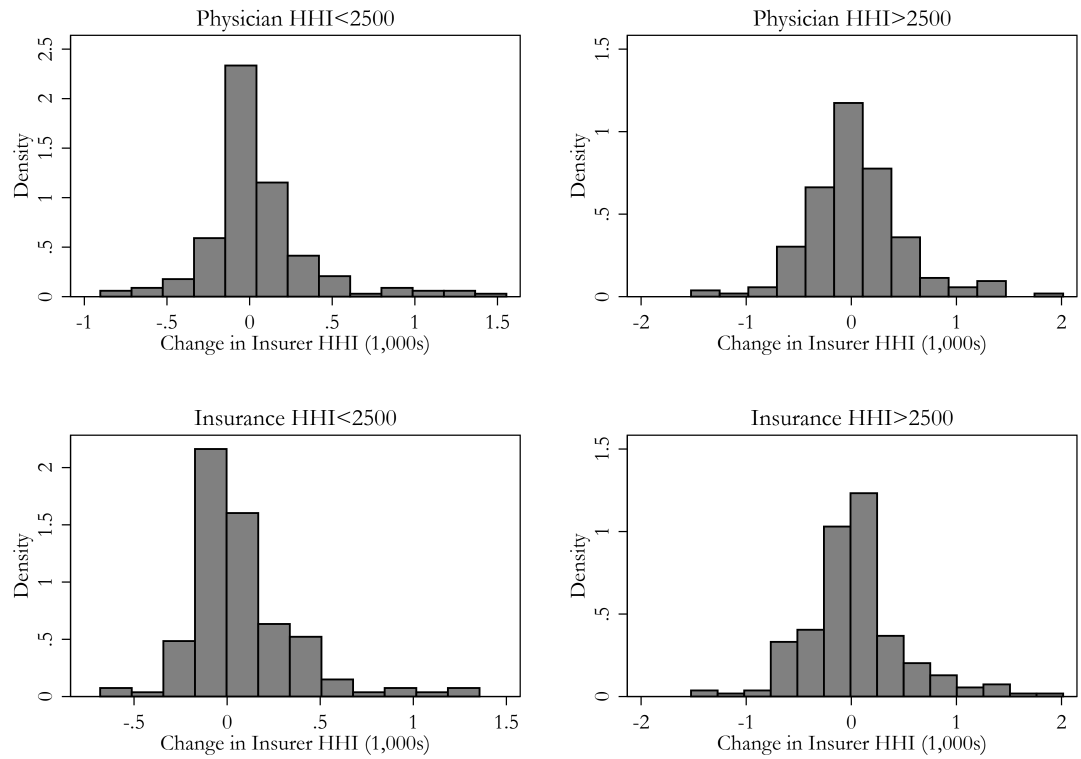
Table 2.7: Coefficients on Insurance Market Concentration, Sensitivity Analyses

	Beta	SE
Alternate Sample: Partial Year Enrollment		
Intensive: All Utilization	121.6***	(42.96)
Intensive: Acute Utilization	17.21	(47.93)
Intensive: Planned Utilization	229.7***	(81.23)
Alternate Physician Concentration		
Extensive: Any Admission	0.0943**	(0.0465)
Intensive: All Utilization	84.32**	(38.76)
Alternate Definitions of Acute/Planned		
Acute Extensive: Weekend Share>=.20	0.0260	(0.0320)
Acute Extensive: Weekend Share Between .26 and .31	-0.00919*	(0.00539)
Planned Extensive: Weekend Share<.20	0.0164	(0.0309)
Planned Extensive: Weekend Share<=.08	0.00338	(0.0208)
Acute Intensive: Weekend Share>=.20	5.892	(38.40)
Acute Intensive: Weekend Share Between .26 and .31	57.71	(60.51)
Planned Intensive: Weekend Share<.20	161.9***	(57.59)
Planned Intensive: Weekend Share<=.08	240.6***	(92.07)
Alternate Approaches to Outliers		
Intensive: Drop Individual-Level Outliers (via Studentized Residual)	55.97*	(33.69)
Intensive: Drop Market-Level Outliers (Mean Residuals <-1,000)	60.89*	(34.83)
Alternate Construction of Market-Level Utilization		
Extensive: Logistic Regression	0.0943**	(0.0446)
Intensive: Median Residual	6.511	(24.54)
Intensive: Gamma-Log GLM	22.72	(29.42)

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive), price-adjusted professional spending (intensive), and readmissions as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1, unless otherwise specified. For intensive utilization, separate models are estimated for each DRG. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

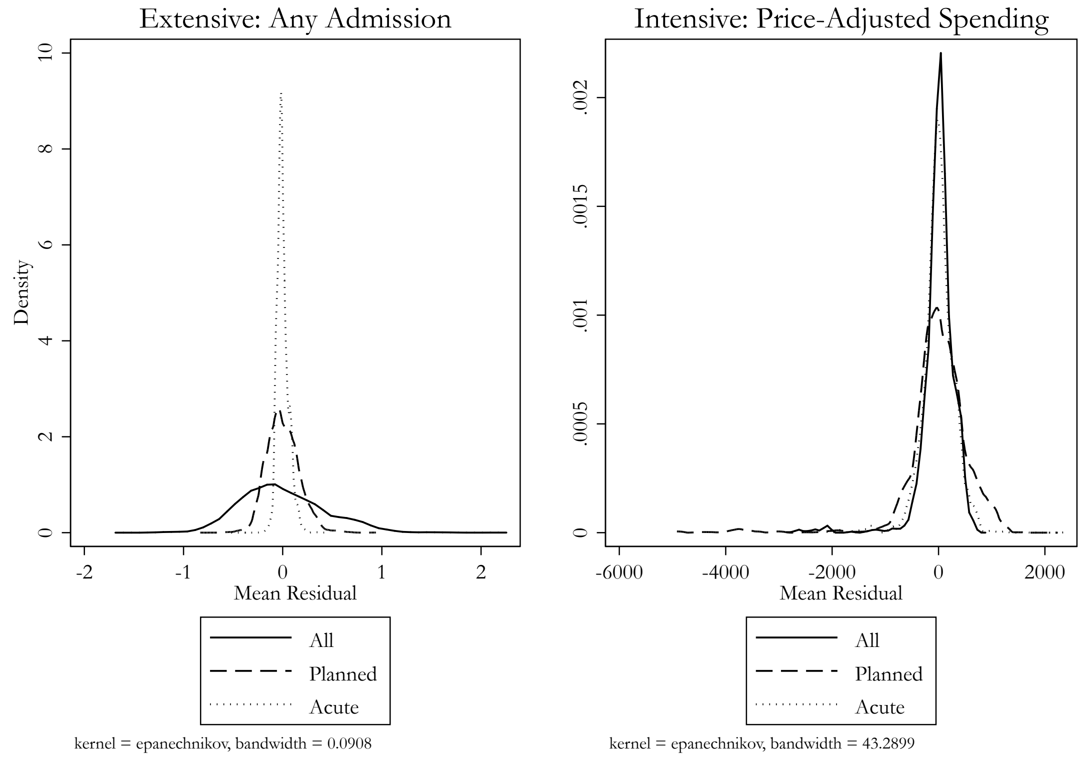
2.12. Figures

Figure 2.1: Distribution of the Change in Insurer Concentration from 2013 to 2015, by Baseline Level of Insurer and Physician Market Concentration



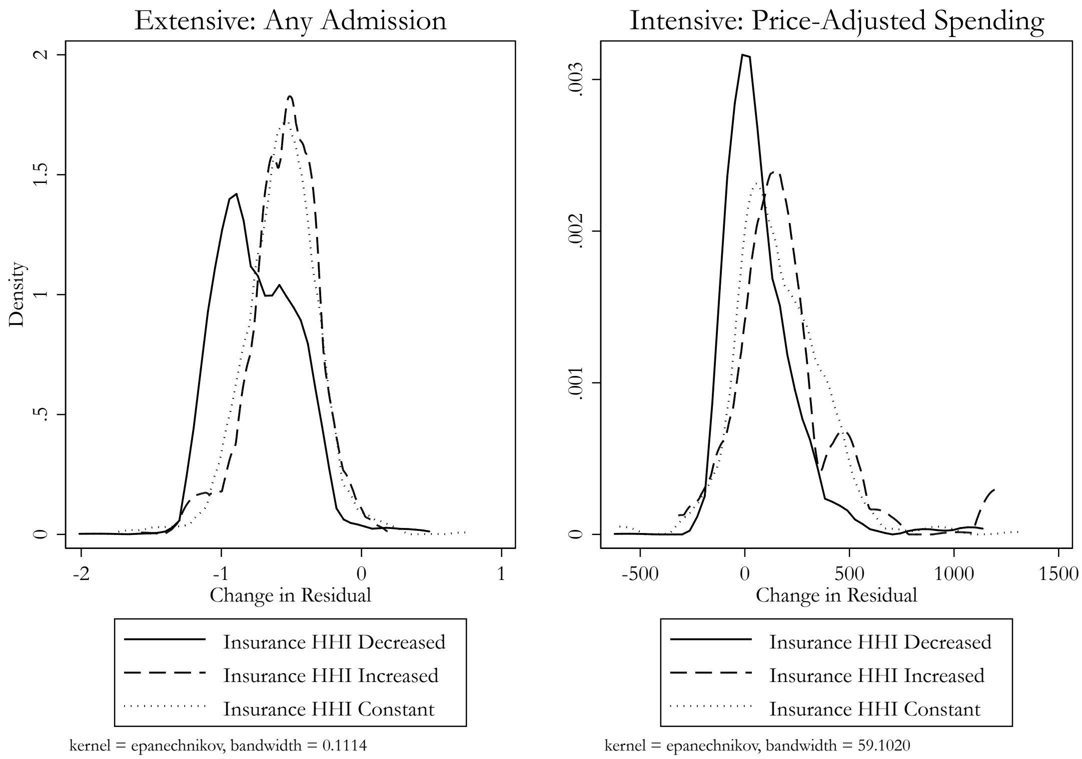
Notes: Measures of HHI are based on shares of fully- and self-insured enrollment from the HealthLeaders-InterStudy data, with the geographic market defined as a core-based statistical area and divisions therein.

Figure 2.2: Kernel Density of Market-Level Measures of Utilization



Notes: Mean residuals by market and year are plotted from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Acute admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was above 25%, while planned admissions have weekend admission shares of below 15%.

Figure 2.3: Kernel Density of Change in Market-Level Measures of Utilization Over Time



Notes: The change in mean residuals from 2013 to 2015 by market are plotted from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Markets are identified as either having an insurer HHI that decreased by at least 250-points, increased by at least 250-points, or changed (in either direction) by fewer than 250-points.

2.13. Appendices

Appendix 2A: Constructing Physician Concentration

Yearly specialty-specific physician concentration measures were created using archived Physician Compare data from March 2014, April 2015, and April 2016 and the Medicare Physician and Other Supplier Data for 2013-2015. These files were linked by National Provider Identifier and year, with the quality of the match between the Physician Compare and Part B files suggesting that the March 2014 Physician Compare data is most reflective of the 2013 Calendar Year (compared to the 2014 Calendar Year), and so on.

Because both Physician Compare and the Supplier Data include information on non-physician healthcare providers, the first step was to narrow the data to physicians. Providers were identified as non-physicians, either by having a non-doctoral degree listed in Physician Compare or by being listed under a non-physician provider type (i.e., CRNA or Licensed Clinical Social Worker) in either Physician Compare or the Supplier Data.

The physician's total allowed amounts were evenly divided between the practice locations listed in Physician Compare. (Allowed charges are the unit of service that the FTC and DOJ uses in monitoring ACOs and which have been implemented in several past studies.)[11] Practice Locations were assigned to a County and a CBSA first on the basis of zip code from Physician Compare, then on zip code from the Supplier PUF, and lastly from the city listed in either file.[12] As some zip codes and cities map to multiple counties, weights were assigned to each match based on the portion of the addresses in each zip code or city that belong to each county (i.e., a practice in a zip code that crosses a county line, where 95% of the address in the zip code belong to County 1 and 5% belong to county 2, is assigned to both counties with weights of .95 and .05, respectively). If a physician had multiple practice locations, and each practice location mapped to multiple counties, then that physician's allowed amounts were evenly divided between practices, and then each county was assigned a share of that practice's allowed amounts based on the weight.

Some physicians were in one but not both databases. All physicians appearing in either database were included in the concentration calculations. Physicians that were not identified in Physician Compare were assumed to operate in a solo practice at the location listed in the Supplier PUF. Physicians that were not identified in the Supplier data were assigned the average allowed amount by for that specialty in that geographic area (County or CBSA).

Physician concentration measures were constructed first defining the geographic market as a County and then as a CBSA. For physicians in group practices, the allowed

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[11] "FTC-DOJ Enforcement Policy Statement Regarding Accountable Care Organizations Participating In the Medicare Shared Savings Program | Federal Trade Commission," accessed April 5, 2017, https://www.ftc.gov/policy/federal-register-notices/ftc-doj-enforcement-policy-statement-regarding-accountable-care; Baker et al., "Physician Practice Competition and Prices Paid by Private Insurers for Office Visits."

[12] The crosswalk between zip code and county was accessed here: https://www.huduser.gov/portal/datasets/usps_crosswalk.html#codebook. The crosswalk between city and county was accessed here: http://mcdc.missouri.edu/websas/geocorr14.html.

amounts were aggregated onto the Organizational PAC ID. If no Organizational PAC ID was listed, the physician was assumed to work as a solo practitioner. Allowed amounts were summed by specialty, year, and geographic market, and market shares were calculated for each organizational ID or NPI. These market shares were used to construct specialty-specific physician HHIs.

The specialty-specific physician HHIs were then aggregated into a single summary physician concentration measure. The first step in this aggregation was to assign a weight to each specialty. These weights were constructed from the set of inpatient admissions in the Truven Health MarketScan data over 2013-2015 that contributed to the intensive volume measure (and hence, that had at least 5,000 admissions). The weights were the share of procedures performed by physicians in the 10 largest physician specialties over those admissions. As a sensitivity analysis, these specialty weights were assigned separately for each market.

This method of constructing physician concentration, which relies solely on publicly available data, has not, to my knowledge, been used before. In order to validate the measure, it was compared against others methods of constructing physician concentration using a 20% sample of Medicare claims data for 2015. First, the method was replicated as closely as possible using claims data, defining the geographic market as a County and as a CBSA, assigning physicians to practices using a tax identification number, and using allowed amounts to define market shares. The correlation between the specialty-specific measures using these two approaches was .93. This confirms that using publicly available data captures a comparable number of physicians and assigns them to group practices in a similar way.

A more rigorous method uses patient flows and allows the geographic market served by each practice to vary based on the zip codes of its patients, assigns each practice an HHI based on the other practices serving those zip codes, and aggregates up to some larger geographic level (see, principally, Baker et al. (2014)). [13] The correlation between a specialty-specific patient-flow based measure and the specialty-specific measure feasible with publicly available data is .73.

There are weaknesses to this approach to measuring physician concentration, primarily that it does not use patient flow data in order to construct a geographic market. Only the location of the physician is known, not the location of the beneficiaries treated by that physician. However, because this measure can be constructed with publicly available data, because it is available for three years instead of one, and because it has a high degree of correlation with more rigorous measures, it is the appropriate approach for this study.

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[13] Laurence C. Baker et al., "Physician Practice Competition and Prices Paid by Private Insurers for Office Visits," *JAMA* 312, no. 16 (October 22, 2014): 1653–62, https://doi.org/10.1001/jama.2014.10921. A summary of the patient flow method is as follows: Practices are identified as a group of physicians with the same specialty billing under the same tax identification number. The product market is defined as all services provided by the physicians within a relevant specialty, measured using allowed charges. Each practice's service area is defined as the set of zip codes from which the practice draws 75% of its total allowed charges. For each zip code, an HHI is calculated based on the market shares of the practices for whom that zip code is in their 75% service area. The HHI faced by each practice is then the mean of the zip code level HHIs from their service area. These HHIs are then averaged over a county, to create a county-level, specialty-specific measure of HHI.

Appendix Table 2.1: DRG Codes Categorized as Planned vs. Acute

	DRG Codes Categorized as Planned
766	CESAREAN SECTION W/O CC/MCC
470	MAJOR JOINT REPLACEMENT OR REATTACHMENT OF LOWER
765	CESAREAN SECTION W CC/MCC
743	UTERINE & ADNEXA PROC FOR NON-MALIGNANCY W/O CC/MCC
621	O.R. PROCEDURES FOR OBESITY W/O CC/MCC
460	SPINAL FUSION EXCEPT CERVICAL W/O MCC
330	MAJOR SMALL & LARGE BOWEL PROCEDURES W CC
945	REHABILITATION W CC/MCC
473	CERVICAL SPINAL FUSION W/O CC/MCC
742	UTERINE & ADNEXA PROC FOR NON-MALIGNANCY W CC/MCC
331	MAJOR SMALL & LARGE BOWEL PROCEDURES W/O CC/MCC
708	MAJOR MALE PELVIC PROCEDURES W/O CC/MCC
847	CHEMOTHERAPY W/O ACUTE LEUKEMIA AS SECONDARY DIAGNOSIS W
472	CERVICAL SPINAL FUSION W CC
620	O.R. PROCEDURES FOR OBESITY W CC
25	CRANIOTOMY & ENDOVASCULAR INTRACRANIAL PROCEDURES W MCC
234	CORONARY BYPASS W CARDIAC CATH W/O MCC
164	MAJOR CHEST PROCEDURES W CC
462	BILATERAL OR MULTIPLE MAJOR JOINT PROCS OF LOWER EXTREMITY
581	OTHER SKIN, SUBCUT TISS & BREAST PROC W/O CC/MCC
520	BACK & NECK PROC EXC SPINAL FUSION W/O CC/MCC
251	PERC CARDIOVASC PROC W/O CORONARY ARTERY STENT W/O MCC
327	STOMACH, ESOPHAGEAL & DUODENAL PROC W CC
580	OTHER SKIN, SUBCUT TISS & BREAST PROC W CC
982	EXTENSIVE O.R. PROCEDURE UNRELATED TO PRINCIPAL DIAGNOSIS W
	DRG Codes Categorized as Acute
871	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC
872	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W/O MCC
418	LAPAROSCOPIC CHOLECYSTECTOMY W/O C.D.E. W CC
439	DISORDERS OF PANCREAS EXCEPT MALIGNANCY W CC
65	INTRACRANIAL HEMORRHAGE OR CEREBRAL INFARCTION W CC OR TPA IN 24 HRS
249	PERC CARDIOVASC PROC W NON-DRUG-ELUTING STENT W/O MCC
193	SIMPLE PNEUMONIA & PLEURISY W MCC
440	DISORDERS OF PANCREAS EXCEPT MALIGNANCY W/O CC/MCC
694	URINARY STONES W/O ESW LITHOTRIPSY W/O MCC
389	G.I. OBSTRUCTION W CC
312	SYNCOPE & COLLAPSE
552	MEDICAL BACK PROBLEMS W/O MCC
64	INTRACRANIAL HEMORRHAGE OR CEREBRAL INFARCTION W MCC
494	LOWER EXTREM & HUMER PROC EXCEPT HIP,FOOT,FEMUR W/O CC/MCC
918	POISONING & TOXIC EFFECTS OF DRUGS W/O MCC
917	POISONING & TOXIC EFFECTS OF DRUGS W MCC
417	LAPAROSCOPIC CHOLECYSTECTOMY W/O C.D.E. W MCC
493	LOWER EXTREM & HUMER PROC EXCEPT HIP,FOOT,FEMUR W CC
669	TRANSURETHRAL PROCEDURES W CC
281	ACUTE MYOCARDIAL INFARCTION, DISCHARGED ALIVE W CC
282	ACUTE MYOCARDIAL INFARCTION, DISCHARGED ALIVE W/O CC/MCC

Appendix Table 2.2: Representative Results From Individual-Level Models

	Extensive: Any Admission			Intensive: Price-Adjusted Spending, Major Joint Replacement w/o MCC		
	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
Male	-0.0025	0.0004	0.0000	11.71	32.82	0.72
Age 18-34 (Ref: 55-64)	0.0649	0.0015	0.0000	-69.36	185.12	0.71
Age 35-44 (Ref: 55-64)	0.0276	0.0016	0.0000	-77.80	79.81	0.33
Age 45-54 (Ref: 55-64)	0.0003	0.0015	0.6486	-33.96	36.48	0.35
Comprehensive (Ref: EPO)	0.0012	0.0006	0.0032	-327.09	35.08	0.00
POS (Ref: EPO)	0.0004	0.0005	0.3214	-215.73	31.53	0.00
PPO (Ref: EPO)	0.0016	0.0004	0.0000	-88.67	26.02	0.00
CDHP (Ref: EPO)	0.0001	0.0005	0.7087	31.10	31.17	0.32
HDHP (Ref: EPO)	0.0002	0.0006	0.7209	142.26	50.36	0.00
Male, Age 18-34	-0.0673	0.0002	0.0000	158.15	98.11	0.11
Male, Age 35-44	-0.0288	0.0003	0.0000	120.52	41.00	0.00
Male, Age 45-54	-0.0024	0.0002	0.0000	17.94	17.94	0.32
Male, Comprehensive	0.0059	0.0012	0.0000	-86.80	49.25	0.08
Male, POS	0.0030	0.0011	0.0000	83.40	42.12	0.05
Male, PPO	0.0019	0.0011	0.0000	-33.13	33.51	0.32
Male, CDHP	0.0028	0.0011	0.0000	-29.17	40.84	0.48
Male, HDHP	0.0036	0.0011	0.0000	-103.99	65.11	0.11
Age 18-34, Comprehensive	-0.0086	0.0017	0.0000	-1,447.78	409.78	0.00
Age 35-44, Comprehensive	-0.0080	0.0018	0.0000	-453.45	167.93	0.01
Age 45-54, Comprehensive	0.0000	0.0016	0.9735	-333.30	65.25	0.00
Age 18-34, POS	-0.0033	0.0016	0.0000	95.36	238.53	0.69
Age 35-44, POS	-0.0030	0.0017	0.0000	-191.54	106.13	0.07
Age 45-54, POS	-0.0005	0.0015	0.4301	-104.33	47.84	0.03
Age 18-34, PPO	-0.0023	0.0015	0.0000	4.99	186.56	0.98
Age 35-44, PPO	-0.0048	0.0017	0.0000	-81.53	81.01	0.31
Age 45-54, PPO	-0.0012	0.0015	0.0365	-20.59	37.04	0.58
Age 18-34, CDHP	-0.0023	0.0016	0.0002	219.82	240.09	0.36
Age 35-44, CDHP	-0.0061	0.0017	0.0000	-8.18	101.34	0.94
Age 45-54, CDHP	-0.0017	0.0015	0.0077	37.96	45.37	0.40
Age 18-34, HDHP	-0.0037	0.0016	0.0000	749.08	398.56	0.06
Age 35-44, HDHP	-0.0062	0.0017	0.0000	-207.65	167.83	0.22
Age 45-54, HDHP	-0.0023	0.0015	0.0007	-95.42	72.46	0.19
HCC 1	0.0122	0.0006	0.0000	99.98	101.32	0.32
HCC 2	0.3958	0.0006	0.0000	-76.35	41.62	0.07
HCC 6	0.0588	0.0011	0.0000	-63.26	106.76	0.55
HCC 8	0.1526	0.0006	0.0000	592.91	57.33	0.00
HCC 9	0.0837	0.0007	0.0000	54.68	62.27	0.38
HCC 10	0.0590	0.0004	0.0000	149.25	39.54	0.00
HCC 11	0.0811	0.0004	0.0000	74.73	40.59	0.07
HCC 12	0.0405	0.0002	0.0000	31.02	19.10	0.10
HCC 17	0.2295	0.0009	0.0000	222.46	86.90	0.01

HCC 18	0.0163	0.0002	0.0000	73.99	17.94	0.00
HCC 19	0.0116	0.0001	0.0000	19.90	11.03	0.07
HCC 21	0.1207	0.0008	0.0000	74.25	52.32	0.16
HCC 22	0.1290	0.0002	0.0000	25.55	10.26	0.01
HCC 23	0.0234	0.0003	0.0000	55.15	23.88	0.02
HCC 27	0.0896	0.0010	0.0000	-75.35	87.39	0.39
HCC 28	0.0442	0.0009	0.0000	27.52	65.90	0.68
HCC 29	0.0194	0.0006	0.0000	-3.95	52.29	0.94
HCC 33	0.4129	0.0005	0.0000	126.51	38.78	0.00
HCC 34	0.2191	0.0012	0.0000	49.69	112.70	0.66
HCC 35	0.0482	0.0004	0.0000	53.63	36.67	0.14
HCC 39	0.1711	0.0006	0.0000	50.65	16.17	0.00
HCC 40	0.0143	0.0002	0.0000	25.40	13.64	0.06
HCC 46	0.1072	0.0010	0.0000	169.58	76.58	0.03
HCC 47	0.0503	0.0004	0.0000	96.07	36.70	0.01
HCC 48	0.1024	0.0003	0.0000	101.53	17.42	0.00
HCC 54	0.4409	0.0007	0.0000	-7.50	50.66	0.88
HCC 55	0.1427	0.0003	0.0000	52.06	27.22	0.06
HCC 57	0.2155	0.0009	0.0000	18.87	104.43	0.86
HCC 58	0.0458	0.0002	0.0000	54.31	15.72	0.00
HCC 70	0.0009	0.0019	0.6416	-133.32	228.93	0.56
HCC 71	0.0960	0.0018	0.0000	284.19	183.80	0.12
HCC 72	0.1300	0.0006	0.0000	-35.84	55.48	0.52
HCC 73	0.0003	0.0028	0.9094	-0.23	261.26	1.00
HCC 74	-0.0131	0.0013	0.0000	44.71	156.34	0.77
HCC 75	0.0381	0.0007	0.0000	31.69	50.62	0.53
HCC 76	-0.0002	0.0022	0.9188	-15.03	227.92	0.95
HCC 77	0.0171	0.0005	0.0000	49.74	55.62	0.37
HCC 78	0.0353	0.0011	0.0000	15.01	73.66	0.84
HCC 79	0.0569	0.0003	0.0000	-51.02	34.27	0.14
HCC 80	0.1462	0.0011	0.0000	261.92	131.35	0.05
HCC 82	-0.0781	0.0019	0.0000	-133.76	221.83	0.55
HCC 83	0.1988	0.0034	0.0000	713.20	543.01	0.19
HCC 84	0.2659	0.0006	0.0000	0.33	42.66	0.99
HCC 85	0.0752	0.0003	0.0000	32.25	21.13	0.13
HCC 86	0.5791	0.0008	0.0000	-46.93	72.77	0.52
HCC 87	0.2019	0.0006	0.0000	69.04	41.44	0.10
HCC 88	0.0495	0.0005	0.0000	24.60	38.75	0.53
HCC 96	0.0782	0.0003	0.0000	120.96	16.91	0.00
HCC 99	0.2640	0.0011	0.0000	-134.51	113.93	0.24
HCC 100	0.1753	0.0005	0.0000	55.00	42.88	0.20
HCC 103	0.1397	0.0010	0.0000	67.89	86.71	0.43
HCC 104	0.0862	0.0017	0.0000	318.89	128.16	0.01
HCC 106	0.1038	0.0015	0.0000	367.35	125.47	0.00
HCC 107	0.1505	0.0005	0.0000	129.83	30.01	0.00
HCC 108	0.0468	0.0003	0.0000	78.27	15.57	0.00

HCC 110	0.1186	0.0021	0.0000	283.16	322.42	0.38
HCC 111	0.0640	0.0003	0.0000	24.76	16.61	0.14
HCC 112	0.0432	0.0005	0.0000	38.48	36.95	0.30
HCC 114	0.0917	0.0011	0.0000	4.46	83.92	0.96
HCC 115	0.1433	0.0012	0.0000	-16.75	107.86	0.88
HCC 122	-0.0037	0.0007	0.0000	119.06	79.76	0.14
HCC 124	-0.0010	0.0015	0.5058	-168.54	119.36	0.16
HCC 134	0.0807	0.0014	0.0000	12.66	206.90	0.95
HCC 135	0.3122	0.0005	0.0000	205.24	27.99	0.00
HCC 136	0.0072	0.0011	0.0000	-33.31	103.17	0.75
HCC 137	-0.0125	0.0013	0.0000	-60.89	92.09	0.51
HCC 157	-0.1800	0.0037	0.0000	-275.14	293.90	0.35
HCC 158	-0.0917	0.0029	0.0000	-47.04	189.01	0.80
HCC 161	0.0227	0.0005	0.0000	8.46	39.08	0.83
HCC 162	0.2243	0.0038	0.0000	101.21	283.39	0.72
HCC 166	0.0507	0.0041	0.0000	42.09	387.43	0.91
HCC 167	0.1158	0.0008	0.0000	-72.06	83.74	0.39
HCC 169	0.1151	0.0008	0.0000	136.47	60.70	0.02
HCC 170	0.2482	0.0009	0.0000	350.31	25.34	0.00
HCC 173	0.1114	0.0009	0.0000	181.70	56.24	0.00
HCC 176	0.1930	0.0005	0.0000	95.87	15.55	0.00
HCC 186	0.0274	0.0011	0.0000	-103.80	94.05	0.27
HCC 188	0.0933	0.0008	0.0000	-23.26	76.79	0.76
HCC 189	0.0229	0.0016	0.0000	15.68	88.00	0.86
Number of Observations	46,518,630			121,612		
R-Square	0.21			0.01		

Notes: Data comes from the Truven Health MarketScan Database of Commercial Claim for 2013-2015, based on the sample in Table 2.1. The measure of price-adjusted spending reprices all services using the mean payment rate observed in the data and sums over all services provided in an admission. Major Joint Replacement w/o MCC corresponds to DRG 470.. For the extensive sample, the fraction in each plan is the average fraction of a year that enrollees spent in each plan. For the intensive sample, it is the fraction of the sample enrolled in that plan at the point of admission.

Appendix Table 2.3: Models of Extensive Utilization, Full Stratified Results

VARIABLES	(1) Physician HHI < 2500	(2) Physician HHI > 2500	(3) Insurance HHI < 2500	(4) Insurance HHI > 2500	(5) Physician HHI < 2500 Insurance HHI < 2500	(6) Physician HHI > 2500 Insurance HHI < 2500	(7) Physician HHI < 2500 Insurance HHI > 2500	(8) Physician HHI > 2500 Insurance HHI > 2500
Insurance Market	0.125*	0.0377	0.0605	0.0844	0.0937	-0.00222	0.0944	0.0449
Concentration (1,000s)	(0.0639)	(0.0655)	(0.0695)	(0.0592)	(0.0865)	(0.0963)	(0.0877)	(0.0767)
Hospital Market	-0.0309	0.0977	-0.0602	0.0184	-0.104	0.0715	0.0265	0.120
Concentration (1,000s)	(0.0396)	(0.0812)	(0.0483)	(0.0424)	(0.0656)	(0.0738)	(0.0450)	(0.178)
Physician Market	-0.0849	0.0150	-0.0275	-0.0232	-0.0469	0.0115	-0.142	0.00862
Concentration (1,000s)	(0.0844)	(0.0402)	(0.0552)	(0.0516)	(0.138)	(0.0543)	(0.136)	(0.0587)
Percent Uninsured	-0.0151	-0.0333**	-0.0107	-0.0401**	-0.00687	-0.0137	-0.0435*	-0.0401**
	(0.0130)	(0.0141)	(0.0133)	(0.0168)	(0.0137)	(0.0223)	(0.0237)	(0.0188)
Median Real Income	0.0221*	0.0146	0.0145	0.0310***	0.0167	0.00557	0.0471***	0.0175
	(0.0119)	(0.0105)	(0.0127)	(0.0109)	(0.0148)	(0.0175)	(0.0164)	(0.0122)
Percent Unemployed	-0.000762	-0.00312	-0.0552	0.0449*	-0.0491	-0.0443	0.0651**	0.0186
	(0.0277)	(0.0288)	(0.0348)	(0.0247)	(0.0381)	(0.0655)	(0.0306)	(0.0298)
Percent in Poverty	0.0151	0.0172	0.0333*	-0.000511	0.0362	0.0142	-0.00837	0.0108
	(0.0174)	(0.0171)	(0.0186)	(0.0173)	(0.0237)	(0.0256)	(0.0283)	(0.0215)
Percent Non-White	0.0308	-0.0136	0.0240	0.0826	0.0155	0.205	0.136	-0.0785
	(0.0609)	(0.0833)	(0.0705)	(0.0857)	(0.0802)	(0.138)	(0.0922)	(0.0945)
Percent Bachelor's Degree	-0.0202	0.00504	-0.00934	0.00390	-0.0399	0.0515	0.0159	-0.0266
	(0.0494)	(0.0460)	(0.0560)	(0.0470)	(0.0681)	(0.0937)	(0.0748)	(0.0527)
Total Beds	-0.00012***	2.96e-05	-0.000101***	-3.54e-05	-9.77e-05***	0.00101**	-3.88e-05	-6.44e-05
	(2.08e-05)	(0.000166)	(2.33e-05)	(7.64e-05)	(2.61e-05)	(0.000449)	(8.36e-05)	(0.000150)
MDs per 1,000	-0.816***	0.0568	-0.457	-0.570*	-0.730*	1.197	-1.163**	-0.161
	(0.300)	(0.487)	(0.341)	(0.336)	(0.393)	(0.727)	(0.486)	(0.490)

Medicare Advantage	-0.00770	-0.00282	-0.00842	-0.00176	-0.00429	-0.0305*	-0.000699	0.00348
Penetration	(0.00804)	(0.00837)	(0.0120)	(0.00755)	(0.0137)	(0.0155)	(0.0117)	(0.00834)
Year = 2014	-0.379***	-0.450***	-0.437***	-0.438***	-0.395***	-0.497***	-0.453***	-0.401***
	(0.0617)	(0.0671)	(0.0737)	(0.0717)	(0.0900)	(0.138)	(0.103)	(0.0673)
Year = 2015	-0.675***	-0.744***	-0.722***	-0.838***	-0.648***	-0.813***	-0.924***	-0.681***
	(0.117)	(0.123)	(0.130)	(0.138)	(0.161)	(0.230)	(0.193)	(0.132)
Constant	0.868	-0.779	0.438	-2.676	2.128	-7.228*	-4.256	1.853
	(3.280)	(2.998)	(3.467)	(3.490)	(4.501)	(4.258)	(4.382)	(3.790)
Observations	538	584	475	647	288	187	250	397
R-squared	9.36e-01	8.93e-01	9.44e-01	9.06e-01	9.50e-01	9.30e-01	9.27e-01	8.78e-01

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.4: Models of Intensive Utilization, Full Stratified Results

VARIABLES	(1) Physician HHI < 2500	(2) Physician HHI > 2500	(3) Insurance HHI < 2500	(4) Insurance HHI > 2500	(5) Physician HHI < 2500 Insurance HHI < 2500	(6) Physician HHI > 2500 Insurance HHI < 2500	(7) Physician HHI < 2500 Insurance HHI > 2500	(8) Physician HHI > 2500 Insurance HHI > 2500
Insurance Market	142.1**	-6.716	196.4*	22.92	211.7	163.3	52.40	-35.67
HHI (1,000s)	(60.49)	(45.46)	(108.2)	(35.39)	(133.9)	(126.7)	(56.94)	(46.29)
Hospital Market	-25.08	-50.93	-31.44	-22.96	-36.94	-47.67	-16.95	-67.46
HHI (1,000s)	(29.04)	(45.65)	(48.38)	(32.05)	(63.42)	(61.63)	(36.08)	(72.92)
Physician Market	-14.86	-12.73	7.928	-13.04	102.8	-25.92	-65.21	-2.322
HHI (1,000s)	(74.55)	(24.49)	(50.72)	(31.00)	(124.6)	(41.42)	(81.21)	(29.93)
Percent Uninsured	-22.24**	-28.82**	-18.84*	-21.03*	-14.42	-25.10	-16.15	-31.39*
	(8.851)	(12.12)	(10.31)	(11.34)	(12.77)	(15.57)	(15.02)	(16.85)
Median Real Income	3.115	4.566	2.153	0.258	3.143	-2.632	2.099	9.762
	(8.833)	(9.004)	(8.559)	(9.774)	(10.10)	(11.08)	(14.59)	(12.97)
Percent Unemployed	16.56	18.39	17.75	25.51	32.17	-13.44	21.12	28.86
	(27.36)	(24.95)	(31.30)	(24.77)	(40.11)	(43.69)	(31.93)	(29.72)
Percent in Poverty	-15.39	-0.297	-12.34	-5.569	-14.48	-9.611	-2.837	0.459
	(17.54)	(14.09)	(21.18)	(12.90)	(27.27)	(26.18)	(20.21)	(14.92)
Percent Non-White	18.52	-16.05	14.85	-32.80	-5.714	7.645	-32.33	-40.18
	(54.68)	(69.62)	(85.15)	(67.00)	(101.9)	(81.04)	(83.42)	(87.24)
Percent Bachelor's	-18.44	-20.10	-4.735	-45.62	-23.86	-38.66	-56.44	-21.78
Degree	(60.18)	(30.90)	(53.40)	(41.12)	(66.59)	(68.52)	(81.65)	(36.88)
Total Beds	-0.0320	-0.0679	-0.0395*	0.00853	-0.0397	0.294	0.00296	-0.0881
	(0.0354)	(0.156)	(0.0232)	(0.102)	(0.0259)	(0.212)	(0.113)	(0.166)
MDs per 1,000	-282.5	-78.07	-305.2	-261.8	-519.9	625.4	-287.3	-180.0
	(311.3)	(277.8)	(328.6)	(260.8)	(388.8)	(479.9)	(539.3)	(288.8)
Medicare Advantage	-0.881	-2.873	9.405	-7.138	13.38	-5.954	-7.951	-2.738
Penetration	(9.977)	(7.258)	(14.52)	(6.060)	(17.15)	(16.16)	(9.648)	(8.584)

Year = 2014	70.48	82.73	72.10	124.0***	123.1	20.13	131.7*	119.5
	(64.60)	(61.82)	(92.66)	(45.91)	(125.7)	(57.74)	(66.50)	(81.41)
Year = 2015	52.19	85.08	61.54	146.6*	146.8	10.40	161.4	124.2
	(116.2)	(105.9)	(160.9)	(79.29)	(217.5)	(101.6)	(118.1)	(139.1)
Constant	668.7	1,402	-74.22	3,517	1,574	231.1	3,896	2,215
	(2,804)	(2,029)	(3,517)	(2,498)	(4,757)	(3,398)	(4,236)	(2,658)
Observations	538	584	475	647	288	187	250	397
R-squared	0.917	0.895	0.897	0.940	0.891	0.923	0.953	0.883

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1 separately for each DRG. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.5: Effect of Insurance Market Concentration on Acute and Planned Extensive Utilization, Stratified by Physician and Insurer Concentration

Panel A: Acute Extensive Utilization (Any Admission)
Unadjusted Mean: 0.40

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 0.0134 (0.0103) N= 1,166	Beta (SE)= 0.0237* (0.0138) N= 538	Beta (SE)= -0.00136 (0.0152) N= 584 Stratified P-value=0.2
Insurance HHI <2,500	Beta (SE)= 0.00991 (0.0161) N= 475	Beta (SE)= 0.0147 (0.0187) N= 288	Beta (SE)= 0.00912 (0.0351) N= 187 Stratified P-value= 0.81
Insurance HHI >2,500	Beta (SE)= 0.0111 (0.0122) N= 647 Stratified P-value= 0.95	Beta (SE)= 0.0178 (0.0156) N= 250 Stratified P-value= 0.88	Beta (SE)= -0.00624 (0.0167) N= 397 Stratified P-value= 0.47

Panel B: Planned Extensive Utilization (Any Admission)
Unadjusted Mean: 1.32

	All Physician Markets	Physician HHI <2,500	Physician HHI > 2,500
All Insurance Markets	Beta (SE)= 0.00983 (0.0281) N= 1,166	Beta (SE)= 0.0161 (0.0414) N= 538	Beta (SE)= -0.00232 (0.0295) N= 584 Stratified P-value=0.75
Insurance HHI <2,500	Beta (SE)= -0.0176 (0.0602) N= 475	Beta (SE)= -0.00114 (0.0763) N= 288	Beta (SE)= -0.0624 (0.0856) N= 187 Stratified P-value= 0.5
Insurance HHI >2,500	Beta (SE)= 0.0160 (0.0270) N= 647 Stratified P-value= 0.61	Beta (SE)= 0.0144 (0.0411) N= 250 Stratified P-value= 0.83	Beta (SE)= 0.0121 (0.0325) N= 397 Stratified P-value= 0.91

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Planned admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was below 15%. Stratified p-values report the results of a test of the equality of coefficients between market stratifications, with the effect in concentrated physician (insurance) markets tested against competitive physician (insurance) markets, and high/low, low/high, and high/high concentration physician/insurance markets tested against low/low concentration physician/insurance markets. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.6: Models of Acute Intensive Utilization, Full Stratified Results

VARIABLES	(1) All Markets	(2) Physician HHI < 2500	(3) Physician HHI > 2500	(4) Insurance HHI < 2500	(5) Insurance HHI > 2500	(6) Physician HHI < 2500 Insurance HHI < 2500	(7) Physician HHI > 2500 Insurance HHI < 2500	(8) Physician HHI < 2500 Insurance HHI > 2500	(9) Physician HHI > 2500 Insurance HHI > 2500
Insurance Market	17.89	40.12	-38.98	-37.36	6.817	6.290	-201.0	-1.631	-8.214
Concentration (1,000s)	(54.34)	(75.08)	(86.56)	(134.8)	(54.33)	(170.4)	(193.0)	(65.83)	(97.03)
Hospital Market	-6.961	-9.212	47.55	39.47	-29.56	36.68	6.420	-26.79	-6.074
Concentration (1,000s)	(32.77)	(35.62)	(81.94)	(75.45)	(31.47)	(89.17)	(85.17)	(35.23)	(162.6)
Physician Market	12.07	-35.78	-14.38	-44.65	32.68	-21.34	-67.63	17.50	32.01
Concentration (1,000s)	(46.57)	(92.37)	(47.44)	(70.89)	(56.50)	(143.9)	(65.04)	(127.4)	(57.77)
Percent Uninsured	-19.67	-20.00	-21.31	-19.21	-17.70	-17.03	-18.95	-16.73	-18.52
	(12.25)	(13.99)	(18.79)	(13.80)	(14.74)	(15.67)	(30.87)	(18.14)	(23.56)
Median Real Income	-3.977	-0.944	-14.35	-2.813	-10.60	2.005	-21.37	-4.383	-8.770
	(9.288)	(12.03)	(14.31)	(11.50)	(14.33)	(13.86)	(18.87)	(20.18)	(19.81)
Percent Unemployed	8.730	-1.309	29.73	-35.01	29.91	-34.86	4.064	21.08	37.53
	(21.63)	(26.25)	(33.55)	(44.23)	(22.17)	(51.38)	(73.16)	(27.17)	(37.63)
Percent in Poverty	-18.17	-12.82	-26.38	-21.11	-11.89	-10.75	-50.73	-2.312	-14.95
	(13.86)	(19.91)	(19.86)	(19.89)	(19.01)	(25.49)	(33.78)	(29.60)	(25.96)
Percent Non-White	39.54	38.35	138.2	-10.82	59.65	-31.59	326.7	45.63	80.78
	(50.83)	(56.09)	(158.0)	(87.34)	(70.28)	(102.7)	(221.2)	(76.75)	(196.4)
Percent Bachelor's	-18.80	-34.69	34.12	-30.71	-24.23	-35.42	-62.62	-78.60	47.84
Degree	(42.52)	(63.96)	(53.87)	(60.77)	(54.35)	(72.00)	(122.0)	(100.6)	(63.47)
Total Beds	-0.0488*	-0.0477	-0.180	-0.0493	-0.0286	-0.0456	0.689	-0.0188	-0.214
	(0.0286)	(0.0313)	(0.200)	(0.0300)	(0.0963)	(0.0334)	(0.545)	(0.110)	(0.213)
MDs per 1,000	104.6	180.7	-54.16	419.9	-28.59	213.3	1,544	337.1	-344.1
	(299.9)	(386.8)	(466.0)	(470.6)	(334.1)	(561.9)	(944.5)	(516.2)	(420.6)
Medicare Advantage	-3.695	-5.747	3.543	14.27	-12.12	17.59	0.801	-21.43**	4.342

	(8.705)	(11.67)	(10.43)	(16.18)	(7.568)	(18.94)	(20.01)	(9.289)	(12.19)
Year = 2014	65.79	61.51	48.07	1.340	123.3**	17.03	6.166	160.6*	76.17
	(49.75)	(62.50)	(89.64)	(93.85)	(61.29)	(119.1)	(150.3)	(81.15)	(114.9)
Year = 2015	126.6	122.9	61.02	38.46	208.9*	73.09	-33.74	268.5*	134.8
	(93.28)	(119.8)	(161.6)	(167.6)	(113.4)	(211.7)	(279.4)	(156.9)	(197.5)
Constant	-393.7	-225.6	-3,245	859.2	-46.34	1,789	-5,743	828.4	-2,151
	(2,151)	(2,822)	(4,110)	(3,625)	(2,758)	(4,686)	(5,868)	(4,148)	(5,506)
Observations	1,165	538	584	475	647	288	187	250	397
R-squared	0.797	0.836	0.639	0.818	0.795	0.831	0.707	0.859	0.626

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive) and price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Acute admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was above 25%. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.7: Models of Planned Intensive Utilization, Full Stratified Results

VARIABLES	(1) All Markets	(2) Physician HHI < 2500	(3) Physician HHI > 2500	(4) Insurance HHI < 2500	(5) Insurance HHI > 2500	(6) Physician HHI < 2500 Insurance HHI < 2500	(7) Physician HHI > 2500 Insurance HHI < 2500	(8) Physician HHI < 2500 Insurance HHI > 2500	(9) Physician HHI > 2500 Insurance HHI > 2500
Insurance Market	200.5***	299.8***	54.44	407.2**	91.44	396.4*	525.4**	157.1	-23.81
Concentration (1,000s)	(71.23)	(110.3)	(82.76)	(184.9)	(65.90)	(223.3)	(225.4)	(113.4)	(81.71)
Hospital Market	-32.02	-22.16	-122.9	-62.60	-9.684	-65.46	-92.10	5.153	-174.4
Concentration (1,000s)	(41.72)	(45.50)	(100.9)	(79.07)	(49.97)	(96.02)	(147.1)	(56.01)	(143.8)
Physician Market	-20.48	-12.80	-25.45	17.58	-27.63	174.0	-27.27	-71.36	-18.58
Concentration (1,000s)	(52.26)	(133.6)	(49.51)	(94.30)	(59.77)	(216.1)	(83.44)	(149.0)	(57.10)
Percent Uninsured	-37.03***	-35.67**	-42.68*	-25.45	-42.37*	-17.72	-28.70	-38.98	-54.13
	(13.46)	(16.41)	(24.44)	(18.53)	(24.48)	(22.51)	(31.72)	(33.34)	(33.75)
Median Real Income	6.875	2.821	13.11	4.003	-1.869	4.574	1.517	-3.020	23.56
	(12.81)	(17.02)	(17.96)	(15.99)	(18.42)	(18.38)	(22.07)	(27.05)	(25.41)
Percent Unemployed	34.85	29.94	21.74	58.69	31.15	96.46	-62.33	21.22	44.24
	(43.48)	(55.05)	(48.96)	(55.26)	(50.46)	(70.15)	(88.63)	(64.96)	(57.38)
Percent in Poverty	-24.73	-39.76	-4.241	-37.86	-15.08	-45.51	-17.00	-10.47	-2.970
	(21.08)	(31.34)	(27.21)	(37.58)	(24.48)	(47.00)	(50.54)	(38.12)	(28.32)
Percent Non-White	9.478	29.47	-38.53	30.54	-81.72	-22.18	-71.06	-83.78	-73.99
	(88.22)	(101.4)	(124.8)	(148.6)	(133.1)	(174.3)	(158.9)	(169.1)	(146.6)
Percent Bachelor's	-69.60	-66.31	-79.62	-78.14	-94.49	-119.9	-172.7	-97.65	-66.82
Degree	(70.79)	(108.6)	(62.12)	(99.15)	(79.17)	(122.1)	(146.6)	(153.4)	(69.56)
Total Beds	-0.0188	-0.0158	-0.272	-0.0386	0.0154	-0.0396	0.147	0.0140	-0.294
	(0.0602)	(0.0669)	(0.283)	(0.0405)	(0.192)	(0.0430)	(0.381)	(0.206)	(0.304)
MDs per 1,000	-395.8	-586.6	-124.1	-505.3	-697.7	-920.7	1,179	-889.9	-309.8
	(454.9)	(633.9)	(516.3)	(634.6)	(568.7)	(712.5)	(936.9)	(1,140)	(549.0)
Medicare Advantage	-4.713	-5.807	-7.624	8.466	-12.82	14.93	-25.04	-14.65	-6.101

Penetration	(12.69)	(16.47)	(14.49)	(24.11)	(11.80)	(28.65)	(31.98)	(18.12)	(17.34)
Year = 2014	111.4	97.81	117.4	165.9	143.3	287.3	59.10	134.7	163.3
	(89.72)	(114.0)	(113.6)	(161.4)	(92.45)	(215.4)	(107.0)	(133.4)	(147.2)
Year = 2015	87.23	64.33	113.1	195.0	134.3	402.3	66.63	124.4	139.4
	(159.6)	(205.1)	(199.2)	(278.6)	(160.8)	(371.1)	(183.4)	(232.9)	(259.6)
Constant	2,878	2,875	3,744	1,938	8,228	6,069	4,422	9,337	4,842
	(3,757)	(5,047)	(3,860)	(6,397)	(5,073)	(8,289)	(6,339)	(8,460)	(4,786)
Observations	1,166	538	584	475	647	288	187	250	397
R-squared	0.911	0.916	0.850	0.895	0.928	0.895	0.891	0.947	0.836

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having price-adjusted professional spending (intensive) as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1. For intensive utilization, separate models are estimated for each DRG. Planned admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was below 15%. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.8: Models of Readmissions

VARIABLES	(1) Readmissions	(2) Readmissions Drop Hospital HHI	(3) Readmissions Physician HHI<2500	(4) Readmissions Physician HHI>2500	(5) Readmissions Insurance HHI<2500	(6) Readmissions Insurance HHI>2500
Insurance Market	-0.551	-0.571	-0.213	-0.658	-0.620	-0.715
Concentration (1,000s)	(0.583)	(0.589)	(0.742)	(1.002)	(1.112)	(0.673)
Hospital Market	0.947***		0.931**	1.075	0.317	1.271***
Concentration (1,000s)	(0.353)		(0.382)	(1.520)	(0.853)	(0.374)
Physician Market	-0.851	-0.790	-1.736	-0.678	0.235	-1.437*
Concentration (1,000s)	(0.629)	(0.630)	(1.130)	(0.786)	(0.998)	(0.780)
Percent Uninsured	-0.0295	-0.0176	-0.0139	-0.0498	0.0788	-0.251
	(0.116)	(0.116)	(0.132)	(0.278)	(0.152)	(0.217)
Median Real Income	-0.0696	-0.0771	-0.0932	0.0129	-0.0905	-0.0628
	(0.109)	(0.109)	(0.125)	(0.243)	(0.145)	(0.169)
Percent Unemployed	-0.0212	-0.0456	-0.280	0.764	0.322	-0.0931
	(0.242)	(0.241)	(0.275)	(0.473)	(0.493)	(0.284)
Percent in Poverty	-0.140	-0.128	-0.115	-0.0462	-0.136	-0.0878
	(0.185)	(0.186)	(0.222)	(0.318)	(0.294)	(0.260)
Percent Non-White	0.0640	0.113	-0.0615	1.305	-0.512	0.0529
	(0.434)	(0.440)	(0.447)	(1.629)	(0.697)	(0.656)
Percent Bachelor's Degree	0.379	0.379	0.436	0.233	0.410	0.252
	(0.426)	(0.432)	(0.533)	(0.792)	(0.752)	(0.496)
Total Beds	-0.000415**	-0.000342*	-0.000244	-0.00434*	-0.000353	-0.00163
	(0.000204)	(0.000198)	(0.000196)	(0.00246)	(0.000268)	(0.00100)
MDs per 1,000	3.309	3.117	3.161	4.042	4.607	1.780
	(2.925)	(2.935)	(3.673)	(4.611)	(4.396)	(3.741)
Medicare Advantage Penetration	0.00823	0.00823	0.0142	-0.0309	0.198	-0.0655
	(0.0788)	(0.0797)	(0.0890)	(0.144)	(0.150)	(0.0859)

Year = 2014	-0.396	-0.363	-0.596	0.284	0.326	-0.875
	(0.484)	(0.494)	(0.571)	(1.164)	(0.836)	(0.734)
Year = 2015	-0.299	-0.189	-0.484	0.0121	1.154	-1.418
	(0.882)	(0.893)	(1.049)	(2.104)	(1.480)	(1.404)
Constant	-16.62	-14.69	-11.31	-52.40	-7.293	-2.405
	(21.60)	(22.25)	(25.77)	(52.08)	(31.90)	(31.44)
Observations	1,163	1,165	537	583	475	645
R-squared	0.498	0.493	0.566	0.407	0.489	0.523

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting experiencing a readmission as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Table 2.1, with separate models for 5 cohorts of patients (defined by CMS methodology). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.9: Summary Statistics, Continuously Enrolled Sample

	Extensive N= 18,871,962		Intensive N= 519,057		Acute Intensive N= 34,640		Planned Intensive N= 211,909		Readmissions N= 601,370	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Percent with Any Admission	4.40	20.50								
Price-Adjusted Professional Spending			3,822.89	3,370.13	2,567.02	2,088.12	5,629.98	4,150.82		
Percent with a Readmission									7.66	26.60
Fraction Male	0.48	0.50	0.24	0.43	0.49	0.50	0.21	0.41	0.35	0.48
Fraction Female	0.52	0.50	0.76	0.43	0.51	0.50	0.79	0.41	0.65	0.48
Fraction Aged 18-34	0.26	0.44	0.42	0.49	0.11	0.31	0.30	0.46	0.26	0.44
Fraction Aged 35-44	0.22	0.42	0.20	0.40	0.15	0.35	0.22	0.42	0.18	0.38
Fraction Aged 45-54	0.28	0.45	0.16	0.37	0.31	0.46	0.19	0.40	0.23	0.42
Fraction Aged 55-64	0.24	0.42	0.21	0.41	0.44	0.50	0.29	0.45	0.34	0.47
Fraction in Comprehensive Plan	0.03	0.18	0.04	0.19	0.06	0.24	0.04	0.19	0.06	0.23
Fraction in EPO Plan	0.01	0.08	0.01	0.08	0.01	0.08	0.01	0.08	0.01	0.08
Fraction in POS Plan	0.08	0.27	0.08	0.27	0.09	0.28	0.08	0.27	0.09	0.29
Fraction in PPO Plan	0.67	0.47	0.69	0.46	0.67	0.47	0.69	0.46	0.64	0.48
Fraction in CDHP Plan	0.14	0.34	0.13	0.33	0.13	0.33	0.13	0.34	0.15	0.35
Fraction in HDHP Plan	0.07	0.26	0.06	0.24	0.05	0.22	0.06	0.23	0.06	0.23

Notes: Data comes from the Truven Health MarketScan Database of Commercial Claim for 2013-2015. The sample was restricted to beneficiaries continuously enrolled from 2013 through 2015. The measure of price-adjusted spending reprices all services using the mean payment rate observed in the data and sums over all professional services provided in an admission. The intensive sample is restricted to the set of admissions for the set of diagnosis-related-groups (DRGs) with at least 5,000 admissions. For the extensive sample, the fraction in each plan is the average fraction of a year that enrollees spent in each plan. For the intensive sample, it is the fraction of the sample enrolled in that plan at the point of admission. Planned admissions are the subset of those admissions for which the share of weekend admissions was below 15%, and acute admissions are the subset for which the share of weekend admissions was above 25%.

Appendix Table 2.10: Sensitivity Analysis, Continuously Enrolled Sample

	Extensive (Any Admission)			Intensive (Price-Adjusted Professional Spending)							Readmissions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All	Acute	Planned	All	Phys HHI <2500	Phys HHI >2500	Ins HHI <2500	Ins HHI >2500	Acute	Planned	
Insurance Market	0.0628	0.00297	-0.0188	127.2**	195.2**	43.08	344.2***	23.23	-5.634	194.9**	-1.857**
Conc. (1,000s)	(0.0583)	(0.00906)	(0.0294)	(52.73)	(81.51)	(58.15)	(128.5)	(51.31)	(61.72)	(87.17)	(0.735)
Hospital Market	-0.00367	-0.00483	0.00881	-58.82	-61.84	-50.13	-73.40	-39.22	-43.84	-73.02	0.481
Conc. (1,000s)	(0.0481)	(0.00941)	(0.0216)	(38.78)	(44.42)	(48.41)	(62.12)	(51.66)	(70.94)	(59.38)	(0.500)
Physician Market	0.00329	0.00484	-0.0197	-1.835	-26.65	1.478	40.90	-21.92	48.80	-40.55	-1.234*
Conc. (1,000s)	(0.0474)	(0.00707)	(0.0216)	(34.00)	(95.17)	(33.46)	(65.81)	(31.20)	(68.40)	(59.10)	(0.738)
Percent Uninsured	0.00919	-0.000275	0.00600	-11.29	-10.02	-9.855	-8.282	-13.74	-5.800	-15.82	-0.0384
	(0.0101)	(0.00167)	(0.00424)	(10.99)	(13.50)	(11.58)	(15.35)	(11.75)	(20.11)	(18.85)	(0.149)
Median Real Income	0.00899	0.00120	0.00265	0.889	-0.876	7.783	-3.938	5.013	-0.508	7.813	-0.145
	(0.00871)	(0.00134)	(0.00422)	(6.864)	(9.891)	(9.907)	(10.27)	(8.748)	(15.42)	(12.59)	(0.153)
Percent Unemployed	0.0104	0.00875**	-0.00282	19.45	9.580	44.90*	42.72	18.33	30.66	17.07	0.307
	(0.0271)	(0.00397)	(0.0134)	(22.78)	(29.64)	(24.12)	(40.58)	(22.88)	(30.43)	(37.72)	(0.375)
Percent in Poverty	0.00498	0.00267	0.00483	-10.94	-13.18	-6.727	4.959	-20.14	-30.00	-22.64	0.0162
	(0.0156)	(0.00247)	(0.00786)	(14.01)	(22.62)	(15.90)	(27.58)	(14.59)	(24.17)	(23.16)	(0.272)
Percent Non-White	-0.00698	-0.00482	-0.0249	-2.204	-1.953	-40.61	29.45	-50.84	28.51	-7.965	0.0692
	(0.0567)	(0.00912)	(0.0227)	(58.18)	(69.05)	(73.44)	(122.3)	(45.03)	(85.10)	(97.39)	(0.654)
Percent Bachelor's	0.0320	0.00671	0.0131	-16.02	-10.17	-22.31	41.34	-60.15*	-3.616	-39.52	0.895
Degree	(0.0442)	(0.00637)	(0.0200)	(37.99)	(58.03)	(33.65)	(62.23)	(32.70)	(58.73)	(59.17)	(0.630)
Total Beds	-5.62e-05**	-2.49e-06	-1.92e-05	0.0132	0.0192	0.0136	-0.00604	0.0772	0.0363	0.0374	-0.000395
	(2.26e-05)	(5.17e-06)	(1.25e-05)	(0.0268)	(0.0290)	(0.187)	(0.0240)	(0.0950)	(0.0417)	(0.0438)	(0.000327)
MDs per 1,000	-0.640**	-0.0263	-0.174	-111.2	-210.4	-49.42	-215.2	-204.6	252.5	-273.0	7.396
	(0.278)	(0.0390)	(0.122)	(259.0)	(380.1)	(212.3)	(498.9)	(208.5)	(458.4)	(447.7)	(4.584)

Medicare Advantage	-0.00344	0.00145	-0.000189	-8.952	-9.068	-8.869	4.988	-17.02**	-8.256	-18.02	0.135
Penetration	(0.00825)	(0.00128)	(0.00381)	(7.815)	(10.28)	(6.864)	(13.96)	(7.448)	(11.88)	(11.41)	(0.0947)
Year = 2014	-0.317***	-0.0141*	-0.0541**	106.9*	105.1	123.5**	90.82	150.9***	43.52	137.5	-0.265
	(0.0609)	(0.00839)	(0.0254)	(61.41)	(78.29)	(60.84)	(112.9)	(53.53)	(81.02)	(100.1)	(0.724)
Year = 2015	-0.578***	-0.0304**	-0.152***	123.9	118.9	177.9*	105.0	174.3**	79.87	122.6	0.314
	(0.112)	(0.0152)	(0.0463)	(108.0)	(137.5)	(95.01)	(195.4)	(88.31)	(146.3)	(174.4)	(1.333)
Constant	0.492	-0.153	0.831	1,094	1,265	1,410	-2,724	4,586**	-975.3	2,513	-42.36
	(2.600)	(0.369)	(1.012)	(2,407)	(3,353)	(2,177)	(4,492)	(2,010)	(3,587)	(3,899)	(28.32)
Observations	1,166	1,166	1,166	1,166	520	602	475	647	1,123	1,166	1,152
R-squared	0.895	0.619	0.785	0.913	0.911	0.895	0.872	0.951	0.709	0.904	0.487

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting having any admission (extensive), price-adjusted professional spending (intensive), and readmissions as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Appendix Table 2.9. For intensive utilization, separate models are estimated for each DRG. This sample was restricted to beneficiaries continuously enrolled from 2013 through 2015. Acute admissions are defined as the set of DRGs with at least 5,000 admissions for which the share of weekend admissions was above 25%, while planned admissions have weekend admission shares of below 15%. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.11: Readmissions for Continuously Enrolled Sample, Stratified Results

VARIABLES	(1) Readmissions Physician HHI < 2500	(2) Readmissions Physician HHI > 2500	(3) Readmissions Insurance HHI < 2500	(4) Readmissions Insurance HHI > 2500
Insurance Market HHI (1,000s)	-1.367*	-2.481*	-2.164**	-1.893*
	(0.807)	(1.428)	(1.032)	(0.985)
Hospital Market HHI (1,000s)	0.399	2.399	-0.569	1.181**
	(0.547)	(1.860)	(1.004)	(0.566)
Physician Market HHI (1,000s)	-3.459***	-0.494	-1.140	-1.228
	(1.205)	(0.890)	(1.068)	(1.013)
Percent Uninsured	-0.0153	-0.0982	0.197	-0.551
	(0.166)	(0.423)	(0.164)	(0.334)
Median Real Income	-0.154	-0.179	-0.187	-0.216
	(0.152)	(0.356)	(0.168)	(0.281)
Percent Unemployed	-0.0567	1.073	0.578	0.430
	(0.460)	(0.661)	(0.571)	(0.486)
Percent in Poverty	-0.0501	0.110	0.0588	-0.0806
	(0.321)	(0.418)	(0.322)	(0.416)
Percent Non-White	-0.0335	1.971	-0.716	0.478
	(0.712)	(2.436)	(0.830)	(1.174)
Percent Bachelor's Degree	1.092	0.990	1.310	0.506
	(0.788)	(1.002)	(0.946)	(0.783)
Total Beds	-0.000250	-0.00468	-0.000270	-0.00175
	(0.000328)	(0.00404)	(0.000348)	(0.00161)
MDs per 1,000	10.43*	2.199	12.59***	1.366
	(5.344)	(7.163)	(4.614)	(5.495)
Medicare Advantage Penetration	0.0955	0.220	0.285	0.0986
	(0.120)	(0.159)	(0.182)	(0.109)
Year = 2014	-0.628	-0.00671	1.106	-1.781*
	(0.883)	(1.630)	(1.089)	(1.077)
Year = 2015	-0.263	0.00609	2.496	-2.165
	(1.669)	(2.820)	(1.971)	(2.056)
Constant	-48.95	-89.75	-46.46	-13.33
	(35.12)	(74.46)	(35.38)	(49.32)
Observations	517	592	472	637
R-squared	0.546	0.420	0.515	0.490

Notes: The unit of observation is a market-year. The outcome variable in each model is the mean residual by market and year from models predicting experiencing a readmission as a function of age, sex, plan type, the pairwise interactions between those variables, and hierarchical conditional categories estimated using the sample in Appendix 11, with separate models for 5 cohorts of patients (defined by CMS methodology). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3. Paper 2: Do Physician Financial Incentives Matter in the Relationship Between Insurance Market Concentration and Imaging Utilization?

Caroline Hanson

Abstract

A small literature documents that insurance market concentration is positively related to healthcare utilization. While this may be related to patients demanding more healthcare services as insurers negotiate lower rates, it is also possible that healthcare providers recommend more services in order to maintain higher revenues as the per-unit payment rate falls. Diagnostic imaging presents an opportunity to explore how financial incentives modify the relationship between insurer concentration and utilization, as non-radiologists who own imaging equipment and can bill for the scan have a strong financial incentive to order imaging services for their patients, compared to non-radiologists who refer a patient to a radiologist for imaging.

For a set of physician specialties disproportionately associated with ownership of MRI (orthopedics and neurology) or CT (urology), I construct specialty-specific measures of a patient having any MRI or CT utilization in the 30-days following a new patient office visit using Truven Health MarketScan data for 2015. I then test whether the

effect of insurer concentration on the probability of receiving a scan varies significantly across the patients of owners and non-owners, using inverse-probability-weighted regression adjustment to mitigate confounding. Measures of insurance and physician market concentration are constructed from HealthLeaders-InterStudy data and publicly available Medicare files, respectively. I also estimate models predicting low-value imaging - the use of back MRI following an office visit with a diagnosis of back pain, the use of head MRI following an office visit with a diagnosis of headache, and the use of abdomen CT with and without contrast material.

I find that for neurology and urology, imaging ownership does not significantly affect the relationship between insurer concentration and utilization. However, the effect of insurer concentration on overall imaging and low-value imaging is significantly more positive for orthopedists who own imaging equipment. A 1,000-point increase in insurer HHI leads to a 4% increase in the probability of imaging following a new patient visit with an orthopedist non-owner, compared to an 11.9% increase following a visit with an owner, a difference that is significant at below the 1% level. The difference in the effect on the probability of low back imaging is borderline significant, with a 1,000-point increase in insurer HHI having no effect on the imaging utilization of patients of non-owners, compared to a 9.5% increase among the patients of owners. These findings suggest that healthcare providers' financial interests may contribute to the higher utilization associated with insurer consolidation, though not in all contexts.

3.1 Introduction

A small and growing literature finds a positive relationship between insurer concentration and healthcare utilization. This literature has largely been framed around a model of insurers exercising countervailing bargaining power against hospitals and physicians to negotiate lower prices that lead, through movement down the demand curve, to higher utilization. However, this model does not incorporate the role that supply-side financial incentives might play in a provider's treatment decisions as insurers negotiate lower payment rates. A range of empirical literature in health economics has found that provider behaviors respond to financial incentives, including work around diagnostic and procedural upcoding, physician self-referral, and inducement of demand following a cut in administered prices.

In light of this evidence, it is possible that physicians increase the number of services provided to their patients as payment rates fall, contributing to the positive relationship between insurer concentration and utilization. To explore that possibility, this paper tests for demand inducement using a subset of private utilization for which different physicians likely face different incentives to provide more care. In particular, I test whether the effect of insurer concentration on imaging utilization varies for physicians who own their own imaging equipment and have a strong financial incentive to order more imaging, compared to physicians who instead refer their patients to other providers for imaging services.

Though Stark laws prevent physician self-referral, there are exceptions for in-office axillary services, including imaging. Non-radiologists ordering imaging services for their patients have a financial incentive to increase utilization when they themselves bill for the service, while those non-radiologists lack that incentive when they do not bill for the service because they instead refer a patient to a radiologist for imaging. Imaging therefore presents an important opportunity to identify differences in a physician's financial incentive to provide more services, which are not typically observable in commercial claims or other utilization data. This difference in financial incentives can help disentangle the volume changes that could arise from patient-driven increases in demand from those that arise from a physician inducing demand. If there is a significant difference in the effect of health insurance market concentration on the imaging utilization of patients based on a physicians' ability to bill for the imaging, that would suggest that supply-side financial incentives contribute to the volume response.

Though diagnostic imaging is a narrow subset of healthcare utilization, it is also a costly service associated with overuse, with the United States having the highest per-capita utilization of costly diagnostic imaging services (Emanuel and Fuchs, 2008; Squires and Anderson, 2015). It therefore serves as a meaningful case study for exploring the connection between insurer concentration and utilization related to supply-side incentives.

I identify three physician specialties with disproportionate rates of ownership of imaging equipment – orthopedics and neurology associated with ownership of MRI, and urology associated with ownership of CT. I construct measures of imaging utilization in the 30 days following an office visit with one of these specialists using the Truven MarketScan Database of Commercial Claims for 2015. I use measures of insurer concentration in 2015 derived from HealthLeaders-Interstudy data, and construct specialty-specific measures of physician concentration in 2015 from publicly available

Medicare files. I then test whether the effect of insurance market concentration on utilization differs significantly between the patients who visited owners and the patients who visited non-owners. I use inverse-probability-weighted regression adjustment to balance the patients who visited owners of imaging equipment and patients who visited non-owners of imaging equipment on observable characteristics. For each physician specialty, I estimate two models. The first model predicts utilization in the 30-days following a new patient visit, and the second model predicts low-value imaging in the 30-days following a visit associated with overuse. The low-value models cover the use of back MRI following an office visit with a diagnosis of back pain for orthopedics, the use of head MRI following an office visit with a diagnosis of headache for neurology, and the use of abdomen CT with and without contrast material for urology.

I find that the effect of insurer concentration on utilization varies significantly between patients seen by imaging owners (with a strong financial incentive) and patients seen by non-owners (with a weak financial incentive), but only for the patients of orthopedists. For these patients, a 1,000-point increase in insurer HHI increases the probability of imaging after a new patient visit by an estimated 4% among the patients of non-owners, compared to an 11.9% increase among the patients of owners, a difference that is significant at below the 1% level. Likewise, a 1,000-point increase in insurer HHI does not significantly affect the probability of low back imaging within 30-days of an orthopedist office visit associated with back pain among the patients of non-owners, but increases the probability among the patients of owners by 9.5%; this difference falls just short of significance at the 10% level.

3.2 Conceptual Framework

Pauly (1998) describes a model for the relationship between insurer concentration and healthcare utilization that is based on the exercise of countervailing bargaining leverage against healthcare providers to negotiate lower prices that lead, in turn, to higher quantities of care demanded by consumers. However, the presence of asymmetric information between patients and healthcare providers regarding appropriate treatment complicates this picture. The patient's demand is, in part, shaped by the recommendation made by their physician.

In light of this asymmetric information, the theory of demand inducement could apply to the relationship between insurer concentration and utilization. McGuire and Pauly (1991) presented a mathematical model of physician behavior under a fee change. In this model, physician utility is increasing in revenue and leisure time and decreasing in demand inducement. The total number of services they provide is a function of the level of inducement, and their remaining leisure time is a function of the number of services. Their choice variable is therefore inducement. Their response to a fee change depends on whether the physician has strong preferences around a certain income. Under a single payer, if income effects are large enough, the supply curve slopes downward and the physician will respond to a fee decrease by increasing inducement, and hence, quantity. Under multiple payers, as is the case of most physicians providing care in the U.S., each payer accounts for a smaller percentage of a physician's income than in the single-payer case. The volume offsets in order to maintain income are therefore smaller, but the analysis is also complicated by substitution effects. In addition to adjusting the total volume of services, physicians may also adjust the distribution of the services they provide across their mix of patients (i.e., Medicare vs. commercially insured patients). The profit margin for the service will vary with the patient group, and the physician will shift towards the group with the higher profit margin, weighing the relative profit against a growing disutility of inducement. If commercial rates are higher than Medicare rates, as is true on average in the United States, more demand will tend to be induced in the commercial population.

This model suggests that if in more concentrated insurance markets, negotiated rates are lower, physicians with preferences around achieving or maintaining a certain income may provide more healthcare services. If payments are nevertheless higher for commercial patients, this inducement will be targeted towards the commercially insured, implying a positive relationship between insurer concentration and overall utilization. The effect on imaging utilization in particular depends on whether the physician can bill for their own imaging services or refers their patients to a radiologist for imaging. In the latter case, the financial incentive associated with demand inducement is weak or non-existent. This suggests that, if demand inducement is present, the effect of insurer concentration on imaging utilization should be higher among the patients who were treated by imaging owners.

3.3 Literature

This paper builds on three key subsets of the health economics literature – research on healthcare market concentration, on demand inducement, and on financial incentives around radiology utilization.

First, a large literature explores the effect of concentration in healthcare markets on outcomes important to patients. Studies implementing a range of methodological approaches find that hospital prices increase as hospital concentration increases (Gaynor, Ho and Town 2015). A smaller literature indicates that the prices of physician services increase with physician concentration (Baker et al. 2014, Dunn and Shapiro 2014). By contrast, the balance of evidence suggests that insurer concentration decreases the negotiated prices between insurers and healthcare providers (Moriya et al. 2010, McKellar et al. 2014, Melnick et al. 2011, Halbersma et al. 2011, Trish and Herring 2015), though there are some inconsistencies (Ho and Lee 2017, Schneider et al. 2008, Dunn and Shapiro 2014). Regarding volume, Bates and Santerre (2008), McKellar et al. (2014), and Hanson (2019) find that insurer concentration is positively related to utilization. On the provider side, Dunn and Shapiro (2017) find that more intensive treatment for myocardial infarction patients was provided by cardiologists in more concentrated cardiology markets, though Hanson (2019) finds no relationship between overall inpatient utilization and hospital or physician market concentration.

Second, this paper builds on empirical work around demand inducement. Several studies have explored the demand inducement hypothesis proposed by McGuire and Pauly, using Medicare fee changes to identify an effect on Medicare and commercial utilization. For example, Yip (1998) uses a policy shift towards the Medicare Fee System, which reduced compensation for surgical procedures generally and incorporated an additional reduction for CABG surgery. Moreover, the reduction in payment varied geographically, depending on the local prevailing average compared to the national average. Her study estimates the effect using a first difference model and finds that physicians did compensate for income loss by increasing volume for both Medicare and commercial patients. Nguyen and Derrick (1997) use a similar mandated fee reduction to estimate a fixed effects model of the effect of variation in a price index on a (Medicare) volume index. They find that physicians replace $0.40 of a $1.00 reduction in fees with increased volume. Jacobson et al. (2010) examines the effect of a reduction in Medicare payment rates for chemotherapy drugs on treatment for lung cancer patients following the Medicare Prescription Drug, Improvement, and Modernization Act. The study finds that the probability of receiving chemotherapy treatment increases and that the percentage treated by the lowest-margin drugs decreases while the percentage treated by the highest-margin drugs increases. Each of these three studies finds evidence of compensating behavior by physicians facing a fee decrease, and one study finds that it affects both patient populations. All of these studies have focused on changes in Medicare fees, rather than changes in private prices.

Finally, this paper builds on several studies that have examined the effect of having an ownership interest in imaging equipment on utilization and spending. Baker (2010) examined utilization and spending by orthopedists and neurologists who began billing for MRI scans between 1999 and 2005. He identifies a set of physicians who began billing for the technical component of an MRI procedure, which covers the use of a machine as opposed to the interpretation of results, and compares the number of MRIs received by their patients on their first visit, and within 30 and 90 days, before and after acquisition. He also compares these trends to a comparison group that never billed for the technical component. For both orthopedists and neurologists, he observes an increase in MRI usage, driven by usage in the first 30 days, after first billing for the technical component. Hughes, Bhargavan and Sunshine (2010) examine self-referral in Medicare claims and find that a physician who both referred for and performed an imaging procedure had patient episodes with higher costs but, for the most part, no corresponding decrease in the length of illness. This suggests that the effect on utilization of financial incentives does not generally benefit the patient. Flug et al. (2016) compare the rate of "double scans", or performing a CT scan with and without contrast material, between radiologists and non-radiologists before and after a CMS monitoring and reporting initiative. Rates of double scans were higher for non-radiologists than for radiologists and declined more slowly after the policy change. Bhargavan et al. (2011) addresses the criticisms of this literature that the results are not generalizable, that patient adjustment is not adequate, and that a financial interest has not been correctly identified. Their finding that utilization is higher amongst physicians with a financial interest in imaging is robust to many different medical conditions, different methods of identifying a financial interest, and different degrees of adjustment.

This paper extends these sets of literature in several ways. First, it adds to the literature on insurer concentration and utilization by focusing on a subset of utilization associated with overuse (imaging). Second, it uses insights from the literature on self-referral in diagnostic imaging to isolate supply-side financial incentives that contribute to the relationship between insurer concentration and utilization. Finally, it adds to the literature on demand inducement, focusing on how commercial utilization responds to changes in insurer concentration that should affect commercial prices, distinct from the bulk of this literature, which has focused on changes in commercial and Medicare utilization resulting from changes in Medicare prices.

3.4 Data and Methods

I use commercial claims data to identify the patients treated by orthopedists, neurologists, and urologists, to construct measures of their imaging utilization in the 30-days following an office visit with those physicians ("index visits"), and to determine whether the physician owned imaging equipment. I use measures of insurance market concentration from HealthLeaders-Interstudy and measures of physician concentration constructed from publicly available Medicare files. I use inverse-probability-weighted regression adjustment to balance the characteristics of patients treated by owners compared to non-owners on observable factors, and then compare the effect of insurance market concentration on imaging utilization between the two groups. I estimate these models separately for each type of physician specialist, and for each specialty, I estimate a model of utilization following a new patient visit, and the use of low-value imaging following a new or established patient visit. This empirical approach is described in detail below.

3.4.1 Data

The primary sample consists of beneficiaries aged 18-64 who were continuously enrolled in a non-capitated plan over 2014 and 2015. I further limit the sample to adults aged 18 or above and aged 64 or below, and excluded enrollees in Puerto Rico, with a geographic location of Nation (region unknown), and in non-metro areas. From this pool of eligible beneficiaries, I identify the subset of patients with a new patient and/or established patient office visit with a physician of the relevant specialty. To facilitate matching on observable market characteristics, I narrow the sample to beneficiaries living in markets for which I observe patients of both owner and non-owner physicians.

I focus on three physician specialties, each of which is associated with disproportionate ownership of either MRI (orthopedics and neurology) or CT (urology). (I also identified the patients of otolaryngologists, associated with ownership of CT. However, the IPWRA approach did not achieve balance on observable covariates). I look at two broad types of imaging utilization. First, I look at the probability of having an MRI or CT in the 30 days following a new patient office visit (index visit) with a specialist of one of the four specialties. Second, for each of the three types of specialties, I identify a type of low-value imaging, and look at utilization of that imaging in the 30 days following a new or established patient office visit. Due to the narrow parameters that define these low-value services, and correspondingly low sample size, I include both new and established office visits in the index visit. For simplicity, I refer to these two sets of models as “new patient” or “low-value” models, respectively.

For orthopedics, the type of low-value imaging I focus on is utilization of MRI for imaging of the back following an office visit associated with low back pain. For neurology, I look at utilization of MRI of the head following an office visit associated with uncomplicated headache. For each of these types of low-value imaging, I construct measures following Schwartz et al. (2014), which provides detailed information on the procedural and diagnosis codes that meet the inclusion criteria, in addition to details on excluding patients with histories of certain clinical conditions, for which these types of imaging may be more appropriate. For urology, for the subset of patients who had an abdomen CT in the 30-days following an office visit, I look at the use of abdomen CT both with and without contrast material ("double-scans"). The measurement of abdominal double-scans is based on the methodology used for the public reporting of this measure (for outpatient hospital procedures) on Hospital Compare (YNHHSC/CORE 2016).

I identify ownership of either MRI or CT primarily as the physician billing for the technical component of an imaging claim. The technical component of the claim covers the utilization of the machine, while the professional component covers the interpretation of the scan, for which a non-owner can bill.

I measure market concentration using the Herfindahl-Hirschman Index, which is widely used in the literature and by the regulatory agencies. It is measured as the sum of squared market shares on a scale from 0 to 10,000, with 10,000 representing a monopoly and HHIs approaching 0 representing perfect competition. Measures of health insurance market concentration are constructed from HealthLeaders-Interstudy, based on Trish and Herring (2015), where markets are defined by enrollment in all self-insured and fully-insured private plans within a Core-Based Statistical Area (CBSA). The 11 largest CBSAs are further divided into smaller metropolitan divisions, and these smaller areas were used in this analysis. Measures of specialty-specific physician market concentration derive from archived CMS Physician Compare data from March 2014, April 2015, and April 2016 and the Medicare Physician and Other Supplier Data for 2013-2015, both publicly available data sources. A detailed description of how these files were used to construct physician concentration is provided in Appendix 3A.

The analysis also incorporates several market-level control variables, describing economic and demographic characteristics that might be correlated with both utilization and market concentration. These variables include the percent in poverty from the Census

Small Area Income and Poverty Estimates (SAIPE), the percent uninsured from the Census Small Area Health Insurance Estimates (SAHIE), the unemployment rate from Bureau of Labor Statistic Local Area Unemployment Statistics (BLS LAUS), and the percent nonwhite from the Area Health Resource File (AHRF). The market-level control variables also include healthcare supply variables that might confound the relationship between insurer and provider concentration and utilization, including the total number of beds, the number of doctors per 1,000 residents and Medicare Advantage penetration, each from the AHRF. Most variables were aggregated from the county to the market level using an average weighted by the county population from the AHRF.

3.4.2. Econometric Methods

I use inverse-probability-weighted regression adjustment (IPWRA) to mitigate confounding resulting from differences in the patient populations that select a non-owner specialist versus those that select an owner specialist. The first step of this approach is to specify a treatment model, using observable patient and market characteristics to predict the probability of visiting an owner versus a non-owner. The second step of this approach is to specify an outcome model, adjusting imaging utilization for observable patient and market characteristics, which is estimated separately for the treatment (owner) and comparison (non-owner) group. The inverse probability of treatment from the treatment model is used to weight the outcome models, and the "treatment effect" is the difference in the predicted outcome between the two groups. However, the treatment effect is not the focus of this research, but rather how treatment – or the physician's differential financial incentives – modifies the effect of insurance market concentration on imaging utilization. I therefore test for significant differences in the coefficient on insurer concentration in the outcome model between patients who visited owners and patients who visited non-owners. Because physician concentration, associated with lower negotiated rates, may also affect utilization in the opposite way as insurer concentration, I also test for significant differences in the coefficient on physician concentration.

The treatment model, for the construction of inverse-probability-weights, uses logistic regression to predict the probability P of visiting an owner ($T_i = 1$) during a patient visit i.

$$Ln\left(\frac{P(T_i=1)}{1-P(T_i=1)}\right) = \gamma_0 + \gamma_1 InsHHI_i + \gamma_2 PhysHHI_i + \gamma_3 Patient_i + \gamma_4 Market_i + \varepsilon_i \qquad [1]$$

This probability is predicted as a function of insurance and physician concentration in the patient's market, the other market confounders outlined above, and patient characteristics including age, sex, plan type, and clinical conditions in the year prior to the observation year (2014). The probabilities predicted from [1] are used to construct inverse-probability-weights, w_i.

$$w_i = \frac{T_i}{\hat{P}_i} + \frac{1-T_i}{1-\hat{P}_i} \qquad [2]$$

The outcome models, weighted by the weights from [2] and estimated separately for the treatment and comparison group, include the same set of covariates, but replace pre-year clinical conditions with clinical conditions observed in 2015.

$$P(I_{i|T_i=0} = 1) = \beta_{0a} + \beta_{1a}InsHHI_i + \beta_{2a}PhysHHI_i + \beta_{3a}Patient_i + \beta_{4a}Market_i + \varepsilon_i \quad [3]$$

$$P(I_{i|T_i=1} = 1) = \beta_{0b} + \beta_{1b}InsHHI_j + \beta_{2b}PhysHHI_j + \beta_{3b}Patient_i + \beta_{4b}Market_j + \varepsilon_i \quad [4]$$

The primary question of interest is whether β_{1a} and β_{1b} significantly differ. In the primary specification, the outcome model is specified as a linear probability model. To account for the correlation of errors with a geographic market, I use the clustered bootstrap to estimate standard errors.

3.4.3 Sensitivity Analyses

To explore the robustness of the findings, I include four different sensitivity analyses for each model. First, I relax the enrollment restriction, requiring only that the beneficiary is not enrolled in a capitated plan as of the date of the office visit. In these models, I risk adjust on the basis of observation year (2015) claims in both the treatment and outcome models. Second, I loosen the assignment criterion to the treatment group, by defining imaging owners as physicians who either bill for the technical component, or who do not specify the component they are billing for (i.e., who do not include a procedural code modifier). These physicians may be billing for the global claim, inclusive of both the technical and professional component. (Because these claims may simply not include modifier codes, this approach likely overstates the number of physician owners and is not the preferred approach.) Third, rather than using clinical conditions recorded in the prior year for the treatment assignment model, but clinical conditions recorded in the observation year for the outcome model, I test sensitivity to risk adjusting on the basis of the prior year (2014) conditions in both models. Finally, I re-estimate the main specification using logistic regression to estimate the outcome model, rather than a linear probability model.

3.5 Results

3.5.1 Treatment Model and Weighted Summary Statistics

The samples for the first set of utilization models consist of 275,801 patients with a new patient office visit to an orthopedist, 38,377 with a new patient office visit to a neurologist, and 62,323 with a new patient office visit to a urologist in 2015. The low-value samples consist of 48,089 patients with a new/established patient visit to an orthopedist with a diagnosis of back pain, 13,830 patients with a new/established patient visit to a neurologist with a diagnosis of headache, and 13,020 patients with a new/established patient to a urologist who received an abdomen CT within 30 days. The percentage of these visits with an imaging owner ranged from a low of 11.2% for the new patient neurology model to a high of 27% for the low-value urology model. The unweighted summary statistics describing these underlying samples are presented in Appendix Tables 3.1 and 3.2.

Table 3.1 illustrates the coefficients on the key covariates of interest, insurer and physician concentration, from fitting equation [1], the treatment assignment model that predicts whether the patient visited an imaging owner. Across the three specialties and the two corresponding imaging modalities, physician concentration is positively and significantly associated with a patient visiting an imaging owner. Conversely, the point estimate of the effect of insurer concentration is negative across all six models, though it is statistically significant in only three of them. Figure 3.1 illustrates the improvement in covariate balance between the patients of owners and non-owners resulting from applying the inverse probability weights derived from these treatment models. It plots the standardized mean differences (SMD) between the groups for each covariate before and after weighting, separately for each category of office visit to a specialist. For each model, the SMDs are much more clustered around zero in the weighted specification. Across all models, the maximum SMD decreases from 0.46 to 0.10, and the minimum SMD increases from -0.39 to -0.05. The magnitude of the average SMD decreases substantially, moving from -0.012 to 8.36E-05.

Table 3.2 reports the weighted summary statistics describing the patients treated by owners compared to non-owners for each of the new patient models. Across the three specialties, the percentage of patients who received a scan within 30 days of their visit is between 2 and 4 percentage points higher among patients who saw an owner compared to a non-owner, consistent with the empirical evidence around higher imaging utilization amongst imaging owners. After weighting, the remaining characteristics of patients of owners and non-owners are similar, consistent with Figure 3.1. Table 3.3 provides the corresponding weighted summary statistics for the subset of imaging associated with overuse. The findings follow a similar pattern, with the exception of receiving a double abdominal CT among patients who visited a urologist, where the percentage of patients receiving a scan both with and without contrast material was lower among the patients of owners.

3.5.1 Outcome Model Predicting Imaging Utilization

Table 3.4 presents parameters of primary interest from the inverse-probability-weighted regression equations in [3] and [4], with Panel A presenting results for models predicting imaging within 30-days of a new patient visit, and Panel B presenting results for the low-value utilization models. The first column presents the estimated average treatment effect, or the difference in the probability of receiving imaging for the patients of owners compared to non-owners, weighted by the inverse probability of treatment and adjusted for observable characteristics. The estimated treatment effects are largely consistent with the existing empirical literature, finding that patients of the financially incentivized owners are more likely to receive imaging. However, the estimated treatment effect associated with visiting a neurologist for headache or a urologist and receiving an abdominal scan are both statistically insignificant.

The next two columns of Table 3.4 present the coefficient on insurer concentration in the model predicting imaging utilization, first among the patients of non-owners and then among the patient of owners. Across both owners and non-owners, among those models where insurer concentration significantly affects imaging utilization, the effect is positive, consistent with the other studies of insurer concentration and utilization. The following column presents the p-value testing the equality of these coefficients across the two outcome models. The relative magnitudes of the point estimates comparing the effect among the patients of owners and non-owners do not follow a clear pattern, with the insurer coefficient among the treated group larger in magnitude in three of six models, and smaller in magnitude in the remaining three models.

However, in the only two models where these differences were statistically significant (or nearly significant), the effect of insurer concentration was greater amongst patients of owners. A 1,000-point increase in insurer HHI increases the probability of imaging within 30-days of a new patient visit with an orthopedist by 0.025 points (95% CI: 0.013, 0.036) among the patients of owners, compared to 0.007 points (95% CI: 0.002, 0.12) among the patients of non-owners, a difference that is significant at below the 1% level. These magnitudes translate to 4% of the unadjusted fraction with a scan among the patients of non-owners, compared to 11.9% of the unadjusted fraction with a scan among the patients of owners. Likewise, a 1,000-point increase in insurer HHI increases the probability of low back imaging within 30-days of an orthopedist office visit associated with back pain by 0.019 points (95% CI: -0.0001, 0.038) among the patients of owners, compared to no significant effect among the patients of non-owners, a difference that falls just short of significance at the 10% level. The magnitudes of these point estimates translate to a (statistically insignificant) 0.18% decrease in the unadjusted fraction with a scan among the patients of non-owners, compared to a 9.5% increase among the patients of owners. It is worth noting that the effect of insurer concentration is positive and significant among new patients of non-owner urologists (95% CI: 0.001, 0.015), compared to an insignificant effect among the patients of owners, a finding that is inconsistent with the orthopedics results and with demand inducement. However, the difference is not significant (p=0.18), and the opposite pattern emerges in the low-value urology model.

The final three columns of Table 3.4 present the same information for the coefficients on physician concentration. The findings related to physician concentration are more mixed, with the relationship between physician concentration and utilization being significant and negative in two models, but significant and positive in one. As with insurer concentration, the relationship between the point estimates does not hold systematically across the six models. However, also as with insurer concentration, in the two models where both the effect of physician concentration is significant, and the differences across the owner and non-owner models are significant – the new patient and low-value orthopedist models – the point estimates on physician concentration are more negative among the patients of owners. In the low-value neurology model, the difference is borderline significant (p=0.10) and the coefficient on physician concentration is more negative among the patients of owners, though in that case neither of the point estimates are statistically different from zero.

Tables 3.5-3.6 report the results of the sensitivity analysis, illustrating coefficients on the primary exposures of interest and the p-value testing their equality across the owner and non-owner groups. The results are largely robust to changes to the sample definition, changes to the approach to identifying owner physicians, and to using logistic regression rather than a linear probability model. The estimated effect of insurance concentration is larger among the patients of orthopedist owners in both the new patient and low-value models, and the difference is at least borderline significant in most models. Likewise, the estimated effect of physician concentration is more negative amongst the patients of orthopedist owners, with those differences significant in most models. There are not significant differences in either the new patient or low-value models associated with neurology or urology.

3.6 Discussion and Limitations

This paper adds to the evidence around insurer concentration and utilization being positively related, while the relationship between physician concentration and utilization does not follow a consistent pattern. In terms of how this relationship is modified by the physician's financial incentive, I find that the effect of insurer concentration on imaging utilization is significantly larger for patients treated by orthopedists who own their own imaging equipment, compared to patients of orthopedists who do not own their own imaging equipment. Likewise, the effect of physician concentration is more negative for patients treated by orthopedist owners, compared to non-owners. These findings are consistent with financially incentivized physicians ordering higher levels of imaging in markets where more concentrated insurer markets and less concentrated physician markets result in lower negotiated payment rates. I do not detect significant differences in the relationship between insurance market concentration and the utilization patterns of patients treated by neurologists or urologists.

An important caveat to this latter finding is that in the new patient urology model, the effect of insurer concentration was larger in magnitude for the patients of non-owners, and while the difference was not statistically significant, the sample size was also smaller. Further research, perhaps pooling the sample over multiple years, can explore whether this difference is significant in a better powered study. (Pooling across years is not possible with available data sources, as an encrypted physician NPI, used for identifying a physician's billing patterns across data contributors, was not added to the Truven Health MarketScan data until 2015).

While not the focus of this research, it is also interesting that while insurer concentration is positively predictive of utilization, it is negatively predictive of visiting an owner. Meanwhile, physician concentration is positively predictive of visiting an owner. This may be because physicians organized in larger practices (and therefore capturing larger market share) are able to spread the high cost of acquiring the technology over more physicians.

This study has several limitations worth noting. The IPWRA approach is doubly robust, meaning that if either the outcome model (the regression adjustment) or the treatment model (for constructing weights) is correctly specified, the estimate of treatment effect is unbiased. However, it only achieves balance on observable characteristics, and there may be unobservable characteristics contribution to a patient's selection of physician. For example, patients may have a priori knowledge about their own high likelihood of getting a scan, and select a physician with in-office imaging for convenience. This is a particularly important consideration when interpreting the estimated average treatment effect of visiting an owner versus a non-owner. This is, however, somewhat less of a concern for the principal question explored in this research – how the effect of insurance market concentration differs between patients of the two types of physicians – as those unobservable characteristics would need to also be correlated with insurer concentration to confound the relationship of interest.

While the Truven Health MarketScan data is a rich data source, it has several limitations. There may be some inconsistencies in the use of procedural modifier codes by data contributors. Only using the technical component of a claim to identify owners likely understates the number of owners, while using both the technical component and a global claim (i.e., no modifier code) like overstates the number of owners. Relatedly, there are financial incentives that are not observable in the data. For example, imaging ownership is determined at the level of the individual provider (by NPI), rather than at the practice level. Physicians in a multi-specialty practice might have a financial interest in the income of the practice as a whole, which would not be evident in the data if their patients are treated by a radiologist in their practice

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3.8 Tables

Table 3.1: Effect of Insurer and Physician Market Concentration on Likelihood of Visiting an Imaging Owner

	Effect of Insurer HHI (1,000s), Log Odds (SE)	**Effect of Physician HHI (1,000s), Log Odds (SE)**
Panel A: Assignment to an Owner for a New Patient Visit		
Orthopedics (MRI), N=275,801	-0.395** (0.159)	0.237*** (0.0666)
Neurology (MRI), N=38,377	-0.808*** (0.302)	0.231*** (0.0856)
Urology (CT), N=62,323	-0.332 (0.220)	0.126** (0.0553)
Panel B: Assignment to an Owner for a Low-Value Visit		
Orthopedics for Back Pain (MRI), N=48,089	-0.203 (0.218)	0.332*** (0.0605)
Neurology for Headache (MRI), N=13,830	-0.806*** (0.237)	0.346*** (0.0668)
Urology for Abdomen Double Scan (CT), N=13,020	-0.0639 (0.267)	0.157*** (0.0602)

Notes: In addition to insurer and physician HHI, models include the county's percent uninsured, percent unemployed, percent non-white, the total number of beds, the number of doctors per-capita, Medicare advantage penetration, and age, sex, plan type, and hierarchical condition categories based on the patient's 2014 diagnosis codes. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015. Models are estimated using *teffects* in Stata, and clustered standard errors are estimated using the clustered bootstrap. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.2: Weighted Summary Statistics Describing New Patient Sample by Specialty

	Orthopedics (MRI)		Neurology (MRI)		Urology (CT)	
	Patients of Non-Owners N=139,106.1	**Patients of Owners N=136,694.9**	**Patients of Non-Owners N=19,170.3**	**Patients of Owners N=19,206.7**	**Patients of Non-Owners N=31,481.8**	**Patients of Owners N=30,841.2**
Fraction with Scan in 30 days	0.17 (0.38)	0.21 (0.41)	0.26 (0.44)	0.3 (0.46)	0.12 (0.32)	0.14 (0.34)
Insurance Market HHI (1000s)	2.56 (0.79)	2.57 (0.83)	2.44 (0.78)	2.49 (0.92)	2.56 (0.82)	2.54 (0.8)
Physician Market HHI (1000s)	1.84 (2.01)	1.89 (1.63)	1.4 (1.54)	1.55 (1.44)	2.94 (2.42)	3.05 (2.11)
Percent Uninsured	10.78 (4.13)	10.84 (4.07)	10.36 (4.04)	10.62 (4.24)	10.78 (4.15)	10.87 (4.03)
Percent Unemployed	5.13 (0.93)	5.12 (0.86)	5.12 (0.9)	5.1 (0.99)	5.14 (0.93)	5.11 (0.92)
Percent Nonwhite	38.44 (15.9)	38.65 (14.79)	39.09 (15.74)	38.81 (15.29)	38.19 (16.03)	38.15 (15.08)
Total Beds	628.47 (871.72)	620.27 (855.08)	639.03 (872.59)	668.98 (850.47)	633.7 (861.21)	623.64 (922.99)
MDs per 1,000	2.84 (1.02)	2.84 (0.82)	2.96 (1)	2.97 (0.91)	2.86 (1.05)	2.81 (0.9)
Medicare Advantage Penetration	33.37 (12.21)	32.91 (10.85)	34.83 (11.69)	34.89 (12.51)	34.14 (12.22)	34.04 (10.42)
Fraction Female	0.56 (0.5)	0.56 (0.5)	0.63 (0.48)	0.63 (0.48)	0.3 (0.46)	0.3 (0.46)
Age Group (Ref: 55-64)						
Fraction 18-34	0.18 (0.39)	0.18 (0.39)	0.2 (0.4)	0.2 (0.4)	0.22 (0.41)	0.22 (0.41)
Fraction 35-44	0.29 (0.46)	0.29 (0.45)	0.27 (0.44)	0.27 (0.44)	0.26 (0.44)	0.26 (0.44)
Fraction 45-54	0.34 (0.47)	0.34 (0.47)	0.31 (0.46)	0.32 (0.46)	0.34 (0.47)	0.33 (0.47)
Plan Type (Ref: Comprehensive)						
Fraction in EPO	0.01 (0.09)	0.01 (0.09)	0.01 (0.12)	0.01 (0.11)	0.01 (0.09)	0.01 (0.09)
Fraction in POS	0.09 (0.28)	0.09 (0.28)	0.1 (0.3)	0.11 (0.31)	0.09 (0.29)	0.09 (0.29)
Fraction in PPO	0.72 (0.45)	0.73 (0.44)	0.72 (0.45)	0.72 (0.45)	0.71 (0.45)	0.72 (0.45)
Fraction in CDHP	0.08 (0.27)	0.07 (0.26)	0.07 (0.25)	0.05 (0.23)	0.08 (0.27)	0.08 (0.26)
Fraction in HDHP	0.06 (0.24)	0.06 (0.25)	0.06 (0.23)	0.07 (0.25)	0.06 (0.24)	0.06 (0.24)

Notes: Summary statistics are weighted by the inverse-probability-weights derived from the treatment assignment model, whose results are partially presented in Table 3.1. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015.

Table 3.3: Weighted Summary Statistics Describing Low-Value Sample by Specialty

	Orthopedics for Low Back Pain (Back MRI)		Neurology for Headache (Head MRI)		Urology (Double Abdominal CT)	
	Patients of Non-Owners N=24,504.9	**Patients of Owners N=23,584,1**	**Patients of Non-Owners N=7,002.7**	**Patients of Owners N=6,827.3**	**Patients of Non-Owners N=6,622,9**	**Patients of Owners N=6,397.1**
Fraction with Scan in 30 days	0.17 (0.38)	0.2 (0.4)	0.13 (0.33)	0.14 (0.35)	0.26 (0.44)	0.23 (0.42)
Insurance Market HHI (1000s)	2.63 (0.8)	2.62 (0.79)	2.48 (0.74)	2.49 (0.78)	2.54 (0.76)	2.52 (0.8)
Physician Market HHI (1000s)	1.89 (2.2)	1.86 (1.65)	1.3 (1.5)	1.36 (1.32)	2.99 (2.4)	3.07 (2.13)
Percent Uninsured	11.15 (3.95)	11.17 (3.98)	10.91 (4.17)	10.94 (4.47)	10.94 (4.25)	11.04 (3.96)
Percent Unemployed	5.22 (0.88)	5.21 (0.86)	5.11 (0.85)	5.1 (0.99)	5.14 (0.86)	5.11 (0.85)
Percent Nonwhite	40.57 (14.95)	40.66 (14.14)	40.9 (14.88)	41.05 (14.46)	38.65 (15.62)	38.18 (15.12)
Total Beds	654.91 (829.19)	660.27 (822.77)	768.16 (885.95)	806.1 (849.82)	693.33 (894.71)	682.27 (991.97)
MDs per 1,000	2.87 (1.01)	2.86 (0.88)	2.98 (0.95)	3.02 (0.86)	2.85 (0.88)	2.81 (0.83)
Medicare Advantage Penetration	33.26 (12.05)	32.91 (10.46)	34.76 (11.18)	34.35 (12.22)	34.65 (12)	34.19 (10.03)
Fraction Female	0.55 (0.5)	0.55 (0.5)	0.75 (0.43)	0.74 (0.44)	0.4 (0.49)	0.4 (0.49)
Age Group (Ref: 55-64)						
Fraction 18-34	0.17 (0.38)	0.17 (0.38)	0.25 (0.43)	0.25 (0.43)	0.15 (0.36)	0.15 (0.36)
Fraction 35-44	0.3 (0.46)	0.3 (0.46)	0.29 (0.45)	0.27 (0.44)	0.29 (0.45)	0.29 (0.45)
Fraction 45-54	0.4 (0.49)	0.4 (0.49)	0.22 (0.42)	0.24 (0.42)	0.45 (0.5)	0.45 (0.5)
Plan Type (Ref: Comprehensive)						
Fraction in EPO	0.01 (0.09)	0.01 (0.09)	0.01 (0.11)	0.01 (0.11)	0.01 (0.1)	0.01 (0.09)
Fraction in POS	0.1 (0.3)	0.1 (0.3)	0.11 (0.32)	0.13 (0.34)	0.1 (0.3)	0.09 (0.29)
Fraction in PPO	0.74 (0.44)	0.74 (0.44)	0.73 (0.44)	0.71 (0.45)	0.73 (0.45)	0.74 (0.44)
Fraction in CDHP	0.06 (0.24)	0.06 (0.24)	0.06 (0.24)	0.05 (0.22)	0.07 (0.25)	0.07 (0.25)
Fraction in HDHP	0.05 (0.22)	0.06 (0.23)	0.05 (0.21)	0.05 (0.23)	0.05 (0.22)	0.05 (0.22)

Notes: Summary statistics are weighted by the inverse-probability-weights derived from the treatment assignment model, whose results are partially presented in Table 3.1. Data comes from the 2015 Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources.

Table 3.4: Inverse Probability Weighted Regression Adjustment Predicting Imaging Within 30 Days of an Office Visit, Selected Regression Coefficients and Standard Errors

	Estimated Effect of Visiting Owner	Insurer HHI (1,000s), Patients of Non-Owners	Insurer HHI (1,000s), Patients of Owners	P-Value of Difference	Physician HHI (1,000s), Patients of Non-Owners	Physician HHI, Patients of Owners	P-Value of Difference
Panel A: Imaging After a New Patient Visit							
Orthopedics (MRI), N=275,801	0.0386***	0.00746***	0.0249***	0.0007	-0.00180	-0.0141**	0.023
	(0.0116)	(0.00263)	(0.00585)		(0.00197)	(0.00604)	
Neurology (MRI), N=38,377	0.0382**	0.0177**	0.0140	0.8306	-0.00537	0.00601	0.1992
	(0.0183)	(0.00873)	(0.0128)		(0.00469)	(0.00777)	
Urology (CT), N=62,323	0.0217***	0.00825**	-0.00263	0.1764	0.00275*	0.00182	0.7073
	(0.00513)	(0.00359)	(0.00968)		(0.00146)	(0.00234)	
Panel B: Low-Value Imaging After a New or Established Patient Visit							
Orthopedics for Back Pain (MRI), N=48,089	0.0257***	-0.000306	0.0191*	0.1009	0.00184	-0.00660*	0.01
	(0.00752)	(0.00659)	(0.00980)		(0.00242)	(0.00377)	
Neurology for Headache (MRI), N=13,830	0.0151	-0.00880	-0.0172	0.7676	-0.00355	0.0104	0.1007
	(0.0157)	(0.0117)	(0.0240)		(0.00478)	(0.00836)	
Urology for Abdomen Double Scan (CT), N=13,020	-0.0275	0.00935	0.0359	0.1898	0.00609	-0.00305	0.2082
	(0.0195)	(0.0185)	(0.0267)		(0.00484)	(0.00648)	

Notes: In addition to insurer and physician HHI, the outcome models include the county's percent uninsured, percent unemployed, percent non-white, the total number of beds, the number of doctors per-capita, Medicare advantage penetration, and age, sex, plan type, and hierarchical condition categories based on the patient's 2015 diagnosis codes. Models are weighted by the inverse-probability-weights derived from the treatment assignment model, whose results are partially presented in Table 3.1. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015. Models are estimated using *teffects* in Stata, and clustered standard errors are estimated using the clustered bootstrap. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: Results of Sensitivity Analysis for New Patient Sample, Selected Regression Coefficients Predicting Imaging Within 30 Days of an Office Visit

	Insurer HHI (1,000s), Patients of Non-Owners	Insurer HHI (1,000s), Patients of Owners	P-Value of Difference	Physician HHI (1,000s), Patients of Non-Owners	Physician HHI (1,000s), Patients of Owners	P-Value of Difference
Orthopedics (MRI)						
Inclusive Sample, 2015 Adjustment, N=414,611	0.00665**	0.0237**	0.1009	-0.00132	-0.0131**	0.0063
Less Restrictive Treatment Assignment, N=277,990	0.00986**	0.0152***	0.2842	-0.00305*	-0.00836***	0.1061
2014 Adjustment, N=275,801	0.00737***	0.0248***	0.0007	-0.00184	-0.0142**	0.0237
Logistic Regression (Log Odds), N=275,801	0.0533***	0.151***	0.0019	-0.0130	-0.0887**	0.0273
Neurology (MRI)						
Inclusive Sample, 2015 Adjustment, N=61,194	0.0108	0.0109	0.9964	-0.00373	0.00485	0.181
Less Restrictive Treatment Assignment, N=41,837	0.0121	0.0251*	0.4403	-0.00395	-0.0113	0.3111
2014 Adjustment, N=38,377	0.0181**	0.0138	0.7836	-0.00589	0.00613	0.1842
Logistic Regression (Log Odds), N=38,377	0.0957**	0.0668	0.7332	-0.0306	0.0278	0.1958
Urology (CT)						
Inclusive Sample, 2015 Adjustment, N=95,435	0.00653**	-0.000889	0.527	0.00279***	0.00171	0.7692
Less Restrictive Treatment Assignment, N=64,518	0.00881***	0.00229	0.2257	0.00132	0.00309	0.4983
2014 Adjustment, N=62,323	0.00824**	-0.00284	0.1656	0.00277*	0.00173	0.6716
Logistic Regression (Log Odds), N=62,323	0.0816**	-0.0180	0.2091	0.0268*	0.0140	0.559

Notes: In addition to insurer and physician HHI, the outcome models include the county's percent uninsured, percent unemployed, percent non-white, the total number of beds, the number of doctors per-capita, Medicare advantage penetration, and age, sex, plan type, and hierarchical condition categories based on the patient's 2015 diagnosis codes. Models are weighted by the inverse-probability-weights derived from the treatment assignment model corresponding to each sensitivity analysis. The inclusive sample does not impose an enrollment restriction beyond being currently enrolled in a non-capitated plan and risk adjusts on the basis of 2015 diagnoses in both the treatment and outcome models. The less restrictive treatment assignment includes physicians who did not use a procedure modifier code, and who may have been billing for both the technical and professional component of the scan. The 2014 adjustment model risk adjusts on the basis of 2014 diagnoses in both the treatment and outcome model. The logistic regression model is the same as the main model, but estimates the outcome model using logistic regression. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015. Models are estimated using *teffects* in Stata, and clustered standard errors are estimated using the clustered bootstrap. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

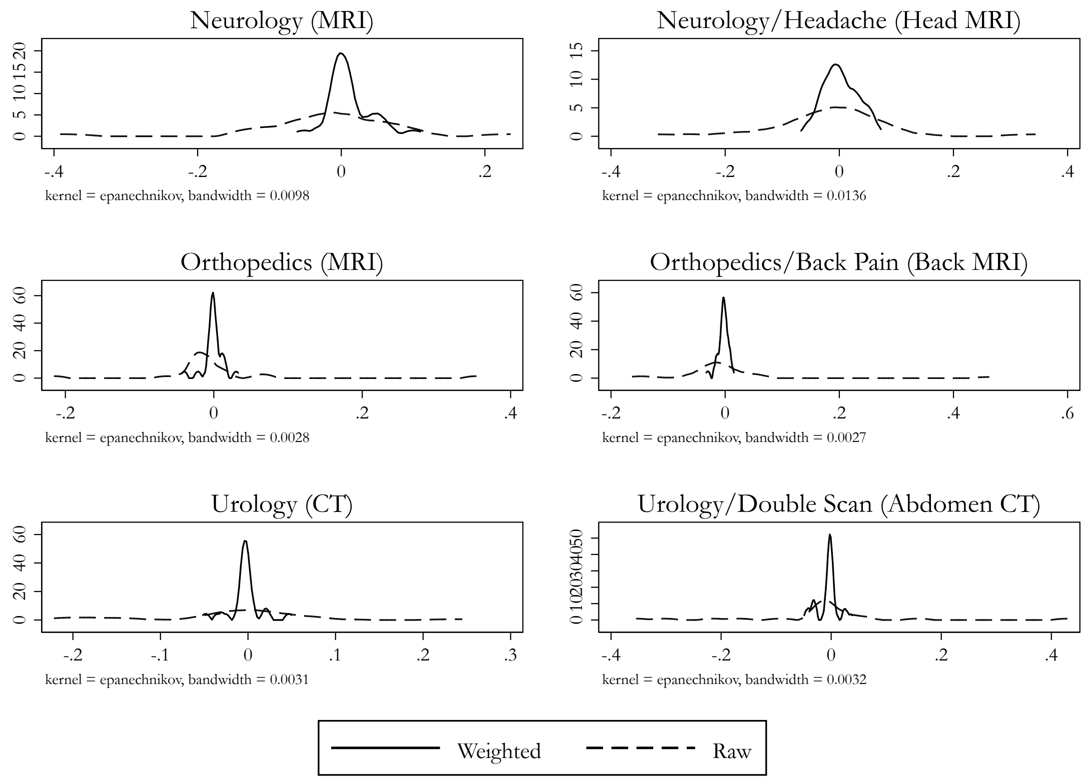
Table 3.6: Results of Sensitivity Analysis for Low-Value Sample, Selected Regression Coefficients Predicting Imaging Within 30 Days of an Office Visit

	Insurer HHI (1,000s), Patients of Non-Owners	Insurer HHI (1,000s), Patients of Owners	P-Value of Difference	Physician HHI (1,000s), Patients of Non-Owners	Physician HHI (1,000s), Patients of Owners	P-Value of Difference
Orthopedics (Back Pain MRI)						
Inclusive Sample, 2015 Adjustment, N=73,857	-0.000238	0.0152**	0.0502	0.00171	-0.00595**	0.0261
Stricter Treatment Assignment, N=50,881	-0.00460	0.0128**	0.0822	0.000706	-0.00244	0.3232
2014 Adjustment, N=48,089	-0.000177	0.0181*	0.1147	0.00171	-0.00648*	0.0063
Logistic Regression (Log Odds), N=48,089	-0.00203	0.120**	0.1139	0.0121	-0.0417*	0.0123
Neurology (Headache MRI)						
Inclusive Sample, 2015 Adjustment, N=23,416	-0.00727	-0.0105	0.8346	-0.00281	0.00783	0.1969
Stricter Treatment Assignment, N=16,427	-0.00634	0.0101	0.4939	-0.00175	-0.00105	0.9288
2014 Adjustment, N=13,830	-0.00923	-0.0192	0.7012	-0.00385	0.0113	0.111
Logistic Regression (Log Odds), N=13,830	-0.0799	-0.138	0.8327	-0.0407	0.0710	0.1979
Urology (Double CT Scan of Abdomen)						
Inclusive Sample, 2015 Adjustment, N=19,027	0.00598	0.0320	0.1782	0.00641	1.70e-05	0.3061
Stricter Treatment Assignment, N=13,466	0.00518	0.0276	0.3636	0.00717	-0.000649	0.2135
2014 Adjustment, N=13,020	0.0108	0.0379	0.1613	0.00512	-0.00358	0.2412
Logistic Regression (Log Odds), N=13,020	0.0532	0.203	0.1924	0.0331	-0.0221	0.2197

Notes: In addition to insurer and physician HHI, the outcome models include the county's percent uninsured, percent unemployed, percent non-white, the total number of beds, the number of doctors per-capita, Medicare advantage penetration, and age, sex, plan type, and hierarchical condition categories based on the patient's 2015 diagnosis codes. Models are weighted by the inverse-probability-weights derived from the treatment assignment model corresponding to each sensitivity analysis. The inclusive sample does not impose an enrollment restriction beyond being currently enrolled in a non-capitated plan and risk adjusts on the basis of 2015 diagnoses in both the treatment and outcome models. The less restrictive treatment assignment includes physicians who did not use a procedure modifier code, and who may have been billing for both the technical and professional component of the scan. The 2014 adjustment model risk adjusts on the basis of 2014 diagnoses in both the treatment and outcome model. The logistic regression model is the same as the main model, but estimates the outcome model using logistic regression. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015. Models are estimated using *teffects* in Stata, and clustered standard errors are estimated using the clustered bootstrap. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.9 Figures

Figure 3.1: Kernel Density of Standardized Mean Difference in Covariates Between Patients of Owners and Non-Owners, Weighted and Raw



Notes: Inverse-probability-weights are derived from the treatment assignment model, whose results are partially presented in Table 3.1. Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015.

3.10 Appendices

Appendix 3A: Constructing Physician Concentration

Yearly specialty-specific physician concentration measures were created using archived Physician Compare data from March 2014, April 2015, and April 2016 and the Medicare Physician and Other Supplier Data for 2013-2015. These files were linked by National Provider Identifier and year, with the quality of the match between the Physician Compare and Part B files suggesting that the March 2014 Physician Compare data is most reflective of the 2013 Calendar Year (compared to the 2014 Calendar Year), and so on.

Because both Physician Compare and the Supplier Data include information on non-physician healthcare providers, the first step was to narrow the data to physicians. Providers were identified as non-physicians, either by having a non-doctoral degree listed in Physician Compare or by being listed under a non-physician provider type (i.e., CRNA or Licensed Clinical Social Worker) in either Physician Compare or the Supplier Data.

The physician's total allowed amounts were evenly divided between the practice locations listed in Physician Compare. (Allowed charges are the unit of service that the FTC and DOJ uses in monitoring ACOs and which have been implemented in several past studies.)[14] Practice Locations were assigned to a County and a CBSA first on the basis of zip code from Physician Compare, then on zip code from the Supplier PUF, and lastly from the city listed in either file.[15] As some zip codes and cities map to multiple counties, weights were assigned to each match based on the portion of the addresses in each zip code or city that belong to each county (i.e., a practice in a zip code that crosses a county line, where 95% of the address in the zip code belong to County 1 and 5% belong to county 2, is assigned to both counties with weights of .95 and .05, respectively). If a physician had multiple practice locations, and each practice location mapped to multiple counties, then that physician's allowed amounts were evenly divided between practices, and then each county was assigned a share of that practice's allowed amounts based on the weight.

Some physicians were in one but not both databases. All physicians appearing in either database were included in the concentration calculations. Physicians that were not identified in Physician Compare were assumed to operate in a solo practice at the location listed in the Supplier PUF. Physicians that were not identified in the Supplier data were assigned the average allowed amount by for that specialty in that geographic area (County or CBSA).

Physician concentration measures were constructed first defining the geographic market as a County and then as a CBSA. For physicians in group practices, the allowed

[14] "FTC-DOJ Enforcement Policy Statement Regarding Accountable Care Organizations Participating In the Medicare Shared Savings Program | Federal Trade Commission," accessed April 5, 2017, https://www.ftc.gov/policy/federal-register-notices/ftc-doj-enforcement-policy-statement-regarding-accountable-care; Baker et al., "Physician Practice Competition and Prices Paid by Private Insurers for Office Visits."

[15] The crosswalk between zip code and county was accessed here: https://www.huduser.gov/portal/datasets/usps_crosswalk.html#codebook. The crosswalk between city and county was accessed here: http://mcdc.missouri.edu/websas/geocorr14.html.

amounts were aggregated onto the Organizational PAC ID. If no Organizational PAC ID was listed, the physician was assumed to work as a solo practitioner. Allowed amounts were summed by specialty, year, and geographic market, and market shares were calculated for each organizational ID or NPI. These market shares were used to construct specialty-specific physician HHIs.

The specialty-specific physician HHIs were then aggregated into a single summary physician concentration measure. The first step in this aggregation was to assign a weight to each specialty. These weights were constructed from the set of inpatient admissions in the Truven Health MarketScan data over 2013-2015 that contributed to the intensive volume measure (and hence, that had at least 5,000 admissions). The weights were the share of procedures performed by physicians in the 10 largest physician specialties over those admissions. As a sensitivity analysis, these specialty weights were assigned separately for each market.

This method of constructing physician concentration, which relies solely on publicly available data, has not, to my knowledge, been used before. In order to validate the measure, it was compared against others methods of constructing physician concentration using a 20% sample of Medicare claims data for 2015. First, the method was replicated as closely as possible using claims data, defining the geographic market as a County and as a CBSA, assigning physicians to practices using a tax identification number, and using allowed amounts to define market shares. The correlation between the specialty-specific measures using these two approaches was .93. This confirms that using publicly available data captures a comparable number of physicians and assigns them to group practices in a similar way.

A more rigorous method uses patient flows and allows the geographic market served by each practice to vary based on the zip codes of its patients, assigns each practice an HHI based on the other practices serving those zip codes, and aggregates up to some larger geographic level (see, principally, Baker et al. (2014)). [16] The correlation between a specialty-specific patient-flow based measure and the specialty-specific measure feasible with publicly available data is .73.

There are weaknesses to this approach to measuring physician concentration, primarily that it does not use patient flow data in order to construct a geographic market. Only the location of the physician is known, not the location of the beneficiaries treated by that physician. However, because this measure can be constructed with publicly available data, because it is available for three years instead of one, and because it has a high degree of correlation with more rigorous measures, it is the appropriate approach for this study.

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[16] Laurence C. Baker et al., "Physician Practice Competition and Prices Paid by Private Insurers for Office Visits," *JAMA* 312, no. 16 (October 22, 2014): 1653–62, https://doi.org/10.1001/jama.2014.10921. A summary of the patient flow method is as follows: Practices are identified as a group of physicians with the same specialty billing under the same tax identification number. The product market is defined as all services provided by the physicians within a relevant specialty, measured using allowed charges. Each practice's service area is defined as the set of zip codes from which the practice draws 75% of its total allowed charges. For each zip code, an HHI is calculated based on the market shares of the practices for whom that zip code is in their 75% service area. The HHI faced by each practice is then the mean of the zip code level HHIs from their service area. These HHIs are then averaged over a county, to create a county-level, specialty-specific measure of HHI.

Appendix Table 3.1: Unweighted Summary Statistics Describing Sample with a New Patient Visit by Specialty

	Orthopedics (MRI)		Neurology (MRI)		Urology (CT)	
	Patients of Non-Owners N=215,862	Patients of Owners N=59,939	Patients of Non-Owners N=34,077	Patients of Owners N=4,300	Patients of Non-Owners N=48,481	Patients of Owners N=13,482
Insurance Market HHI (1000s)	2.6 (0.81)	2.43 (0.76)	2.47 (0.79)	2.18 (0.7)	2.6 (0.84)	2.43 (0.71)
Physician Market HHI (1000s)	1.65 (1.73)	2.29 (1.9)	1.35 (1.43)	1.74 (1.86)	2.8 (2.3)	3.36 (2.29)
Percent Uninsured	10.8 (4.15)	10.73 (4.11)	10.33 (4.02)	10.59 (4.35)	10.72 (4.13)	10.94 (4.07)
Percent Unemployed	5.12 (0.93)	5.14 (0.85)	5.13 (0.89)	5.04 (1)	5.19 (0.93)	4.99 (0.87)
Percent Nonwhite	38.59 (15.76)	38.13 (15.12)	39.07 (15.66)	39.65 (15.48)	38.83 (15.91)	36.16 (15.06)
Total Beds	638.58 (872.19)	609.4 (865.09)	649.67 (879.04)	553.83 (785.99)	661.3 (871.47)	544.57 (865.61)
MDs per 1,000	2.86 (1.01)	2.8 (0.83)	2.96 (0.98)	2.93 (0.94)	2.9 (1.06)	2.74 (0.85)
Medicare Advantage Penetration	33.48 (12.16)	33.22 (10.54)	34.98 (11.62)	33.74 (11.48)	34.02 (12.21)	34.64 (10.38)
Fraction Female	0.56 (0.5)	0.55 (0.5)	0.63 (0.48)	0.62 (0.49)	0.29 (0.46)	0.32 (0.47)
Age Group (Ref: 55-64)						
Fraction 18-34	0.18 (0.39)	0.18 (0.39)	0.2 (0.4)	0.19 (0.39)	0.21 (0.41)	0.23 (0.42)
Fraction 35-44	0.29 (0.45)	0.3 (0.46)	0.27 (0.44)	0.28 (0.45)	0.26 (0.44)	0.26 (0.44)
Fraction 45-54	0.35 (0.48)	0.34 (0.47)	0.32 (0.46)	0.3 (0.46)	0.34 (0.47)	0.32 (0.47)
Plan Type (Ref: Comprehensive)						
Fraction in EPO	0.01 (0.08)	0.01 (0.12)	0.01 (0.11)	0.02 (0.15)	0.01 (0.09)	0.01 (0.1)
Fraction in POS	0.09 (0.28)	0.08 (0.28)	0.1 (0.3)	0.07 (0.26)	0.1 (0.29)	0.09 (0.28)
Fraction in PPO	0.72 (0.45)	0.74 (0.44)	0.72 (0.45)	0.74 (0.44)	0.71 (0.46)	0.75 (0.44)
Fraction in CDHP	0.08 (0.27)	0.08 (0.27)	0.06 (0.24)	0.09 (0.28)	0.08 (0.27)	0.07 (0.26)
Fraction in HDHP	0.06 (0.24)	0.06 (0.25)	0.05 (0.23)	0.07 (0.26)	0.06 (0.24)	0.07 (0.25)

Notes: Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015.

Appendix Table 3.2: Unweighted Summary Statistics Describing Low-Value Sample by Specialty

	Orthopedics for Low Back Pain (Back MRI)		Neurology for Headache (Head MRI)		Urology (Double Abdominal CT)	
	Patients of Non-Owners N=35,299	Patients of Owners N=12,790	Patients of Non-Owners N=11,927	Patients of Owners N=1,903	Patients of Non-Owners N=9,455	Patients of Owners N=3,565
Insurance Market HHI (1000s)	2.63 (0.8)	2.62 (0.8)	2.51 (0.75)	2.28 (0.67)	2.54 (0.76)	2.55 (0.79)
Physician Market HHI (1000s)	1.52 (1.66)	2.36 (1.97)	1.19 (1.21)	1.75 (1.98)	2.66 (2.14)	3.61 (2.28)
Percent Uninsured	11.31 (3.99)	10.79 (3.87)	10.89 (4.16)	10.93 (4.6)	10.75 (4.18)	11.39 (4.02)
Percent Unemployed	5.23 (0.87)	5.21 (0.83)	5.12 (0.81)	5.04 (1.14)	5.2 (0.83)	5.02 (0.86)
Percent Nonwhite	41.5 (14.72)	39.15 (14.05)	41.13 (14.72)	39.96 (15.08)	39.53 (15.53)	37.02 (14.58)
Total Beds	676.39 (829.8)	642.49 (813.71)	785.14 (887.99)	683.39 (812.69)	774.54 (929.35)	508.02 (825.65)
MDs per 1,000	2.88 (0.9)	2.88 (0.92)	2.99 (0.92)	2.95 (0.95)	2.95 (0.87)	2.66 (0.76)
Medicare Advantage Penetration	33.65 (12.01)	32.88 (10.49)	35.17 (11.09)	32.78 (11.49)	35.1 (11.89)	34.07 (10.31)
Fraction Female	0.55 (0.5)	0.55 (0.5)	0.75 (0.43)	0.75 (0.43)	0.39 (0.49)	0.42 (0.49)
Age Group (Ref: 55-64)						
Fraction 18-34	0.17 (0.38)	0.17 (0.37)	0.24 (0.43)	0.25 (0.43)	0.15 (0.36)	0.16 (0.37)
Fraction 35-44	0.3 (0.46)	0.3 (0.46)	0.29 (0.46)	0.28 (0.45)	0.28 (0.45)	0.29 (0.46)
Fraction 45-54	0.4 (0.49)	0.41 (0.49)	0.22 (0.42)	0.21 (0.41)	0.46 (0.5)	0.44 (0.5)
Plan Type (Ref: Comprehensive)						
Fraction in EPO	0.01 (0.09)	0.01 (0.11)	0.01 (0.12)	0.01 (0.11)	0.01 (0.1)	0.01 (0.09)
Fraction in POS	0.1 (0.3)	0.12 (0.32)	0.12 (0.33)	0.08 (0.26)	0.11 (0.31)	0.1 (0.3)
Fraction in PPO	0.73 (0.44)	0.75 (0.43)	0.72 (0.45)	0.78 (0.42)	0.72 (0.45)	0.75 (0.44)
Fraction in CDHP	0.06 (0.25)	0.06 (0.23)	0.06 (0.24)	0.08 (0.28)	0.07 (0.25)	0.07 (0.25)
Fraction in HDHP	0.05 (0.23)	0.05 (0.21)	0.05 (0.21)	0.05 (0.21)	0.05 (0.23)	0.05 (0.22)

Notes: Data comes from the Truven Health MarketScan database of commercial claims, HealthLeaders-Interstudy, and other publicly available sources for 2015.

4. Paper 3: Do Health Insurance and Hospital Market Concentration Influence Hospital Patients' Experience of Care?

Caroline Hanson, Bradley Herring, Erin Trish

Abstract

Objective: To examine the effects of insurance and hospital market concentration on hospital patients' experience of care, as hospitals may compete on quality for favorable insurance contracts.

Data Sources/Study Setting: Secondary data for 2008-2015 on patient experience from Hospital Compare's patient survey data, hospital characteristics from the American Hospital Association (AHA) Annual Survey, and insurance market characteristics from HealthLeaders-InterStudy.

Study Design: Hospital/year-level regressions predict each hospital's patient experience measure as a function of insurance and hospital market concentration and hospital fixed effects. The model is identified by longitudinal variation in insurance and hospital concentration.

Data Collection/Extraction Methods: Hospital/year-level data from Hospital Compare and the AHA merged by market/year to insurance and hospital concentration measures.

Principal Findings: Changes in patient satisfaction are positively associated with increases in insurance concentration and negatively associated with increases in hospital concentration. Moving from a market with 20th percentile insurance concentration and 80th percentile hospital concentration to a market with 80th percentile insurance concentration and 20th percentile hospital concentration increases the share of patients that rated the hospital highly from 66.9% (95% CI: 66.5-67.2%) to 67.9% (95% CI: 67.5-68.3%) and the share of patients that definitely recommend the hospital from 69.7% (95% CI: 69.4-70.0%) to 70.8% (95% CI: 70.5-71.2%). The relationship for insurance concentration is stronger in more concentrated hospital markets while the relationship for hospital concentration is stronger in less concentrated hospital markets.

Conclusions: These findings add to the evidence on the harms of hospital consolidation but suggest that insurer consolidation may improve patient experience.

Key Words: Anti-Trust/Health Care Markets/Competition, Patient Assessment/Satisfaction, Observational Data/Quasi-Experiments

4.1 Introduction

The relationship between hospital market concentration and hospital quality has achieved substantial attention in the literature. In an administered-price setting where hospitals cannot compete on price, theory suggests that hospitals compete on quality to attract patients, so that increases in hospital market concentration worsen hospital performance.[1] The empirical literature largely supports this, with studies of the US Medicare program and England's National Health Service finding that hospital competition decreases mortality and readmission rates.[2,3] In settings with market-determined prices, where hospitals compete on quality and price (and perhaps make tradeoffs between the two), the theoretical predictions are ambiguous, and the empirical findings more mixed. Some studies have found that hospital market concentration decreases quality,[4,5] though other studies have found no effect,[6,7] and some have found a positive effect.[8,9] In addition to the literature examining hospital quality, a robust literature documents that increases in hospital market concentration increase hospital prices.[10]

However, little is known about the effect of insurance market concentration on hospital quality. Similar to hospitals competing with each other on quality dimensions to attract patients, hospitals may compete on quality to attain favorable contracts with insurers. As insurers consolidate, hospitals may increasingly view quality as a means to maintain bargaining leverage in their negotiations. For example, as insurance market concentration increases, hospitals may increase quality in order to increase patient pressure on the insurer to keep the hospital in-network, or to strengthen their ability to negotiate higher prices. The literature on insurance concentration and price is smaller and more recent than the literature on hospital concentration and price, but several studies have shown that concentrated insurers do negotiate lower hospital prices,[11,12,13,14,15,16] but do not pass savings on to consumers in the form of lower premiums.[17,18,19]

We address this important gap in the literature by empirically analyzing the relationship between insurance market concentration, hospital market concentration, and hospital quality, measured here as patient experience of care.

We estimate hospital/year-level regression models predicting changes in patient experience over time as a function of changes in insurance and hospital market concentration, with hospital fixed effects to control for time-invariant unobservable hospital and market characteristics. Hospital-level data for 2008-2015 come from merging patient experience data from the Centers for Medicare and Medicaid Services' (CMS) Hospital Compare with other hospital characteristics from the general medical and surgical community hospitals in the American Hospital Association (AHA) Annual Survey. The CMS Hospital Compare data we use are Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) measures. Market-level Herfindahl-Hirschman Indices (HHI) for insurance market concentration are constructed from HealthLeaders-InterStudy data for commercial enrollment market shares, while HHIs for hospital concentration are constructed from AHA data for all inpatient days aggregated to the system level.

We hypothesize that insurance market concentration is positively related to hospital quality, measured as patients' experience of care. We also expect that, consistent with much of the prior research, hospital concentration is negatively related to patient experience. Moreover, we hypothesize that the impact of insurer concentration will be stronger in more concentrated hospital markets, where hospital market competition plays less of a role in improving patient experience.

4.2 Data

This section first describes our hospital-level dataset and both our dependent variable and hospital controls included in the data. It then describes our market-level measures for insurance and hospital market concentration, as well as our county-level controls. Our empirical methodology is described in the subsequent section.

4.2.1 Hospital-Level Dataset

We use measures of patient experience based on the HCAHPS survey, which is randomly sampled from adult patients across payer categories with at least one inpatient stay for a non-psychiatric diagnosis.[20,21] CMS publicly reports summary HCAHPS results by hospital, adjusted for patient-mix (self-reported health status, education, service line, age, admission source, and primary language), survey mode, and non-response bias, on the Hospital Compare website.[22] We use data collected over January-to-December for each year during 2008-2015. (There are no quality-oriented measures other than the HCAHPS measures that are available through Hospital Compare spanning such a long period of time with annual measures. For example, Hospital Compare's mortality and readmission rates are measured over a 36-month period and there is a shorter panel of data.)

Our analysis is based on the two HCAHPS global items. The first asks patients for their overall rating of the hospital, and the second asks whether the patient would recommend the hospital. Scores are aggregated by hospital and publicly reported as the percentage of a hospital's patients in a given time period responding above a certain threshold. Our first outcome measure is the hospital's percentage of patients rating it a 9 or 10 (out of 10); this measure has been used in previous studies,[23] and is the global measure used for the hospital's Experience of Care score in the CMS Hospital Value-Based Purchasing Program.[24] Our second outcome measure, which is highly correlated, is the hospital's percentage of patients reporting that they would definitely recommend the hospital. We test the sensitivity of our results for these two primary measures by using the remaining data on global patient experience to construct a measure of the percent of patients rating the hospital a 7 or higher and the percent of patients reporting that they would definitely or probably recommend the hospital.

These two global scores presumably reflect several dimensions of the patient's experience, including communication with doctors and nurses, satisfaction with the hospital facilities, and perception of clinical quality. A systematic review of the relationship between patient experience and other quality measures finds that patient experience is positively associated with self-reported health status and objective measures of clinical quality, though some studies have reported a weak or no relationship.[25] For example, studies have found that patients treated at hospitals in the top quartile of patient satisfaction scores had lower mortality, but findings on other measures including readmissions and complications are inconsistent.[26,27,28] In light of this evidence, patient experience scores should be thought of as one dimension of hospital quality, not a proxy for clinical quality.

We obtain information on hospital characteristics from the AHA Annual Survey of Hospitals to include as time-varying covariates in the analyses in addition to hospital fixed effects. Relevant hospital characteristics include ownership type (public, nonprofit independent, nonprofit part of a system, and for-profit), number of beds, payer mix, whether it has an accredited Graduate Medical Education program, and average length of stay. We merged the HCAHPS data to the AHA data on the basis of the CMS Certification Number, which is not a perfect one-to-one match. There is only a small number of hospitals with HCAHPS data for which there is no match in the AHA data (e.g., 92 out of 4,240 for 2015), and a larger number of hospitals in the AHA data with no HCAHPS data (e.g., 568 out of 4,612 for 2015). We restrict to hospitals with patient experience data for 2008-2015, which excludes hospitals that opened or closed over the study period, but includes hospitals whose ownership changed, as long as there is a valid CMS Certification Number for merging. The excluded hospitals are disproportionately small and rural, and so the data we use covers over 89% of all inpatient days over our study period. Compared to the hospitals covering the remaining 11% of inpatient days, our sample of hospitals significantly differs on most covariates, which is expected as having missing Hospital Compare data is unlikely to be random. These descriptive statistics for the included versus excluded hospitals are in Appendix Table 4.1.

4.2.2. Market-Level Concentration Measures

We construct measures of insurance and hospital market concentration and merge these market concentration measures to the hospital/year-level data. We measure market concentration using the HHI, which is widely used in the literature and by the regulatory agencies. It is measured as the sum of squared market shares on a scale from 0 to 10,000, with 10,000 representing a monopoly and HHIs approaching 0 representing perfect competition. Our empirical model (described below) uses hospital fixed effects to focus on changes in insurance and hospital market concentration over time.

For our measure of insurance market HHI, we calculate shares of commercial enrollment using the HealthLeaders-InterStudy census of private insurers. We include both fully-insured and self-insured business, as insurers would use the combined market share of both types of enrollees when negotiating provider contracts.[28] Moreover, we measure market share based on combined enrollment in both the individual (nongroup) and employer markets. (We exclude exchange enrollment, though our results are robust to insurance HHI measures that do include exchange enrollment for 2014 and 2015.) We use the State Rating Areas defined by CMS' Center for Consumer Information and Insurance Oversight (CCIIO) to define the geographic markets for insurers.[29] Most states use metropolitan core-based statistical areas (CBSAs) as the basis for grouping their urban and suburban counties into Rating Areas; micropolitan and rural counties are then typically combined either with these existing Rating Areas and/or with each other. The median number of Rating Areas in a state is 7.

For our primary measure of hospital market HHI, we calculate shares of all inpatient days, aggregated to the system level, using the AHA Annual Survey. We use the

Dartmouth Atlas' Hospital Referral Regions (HRR) to define the geographic markets for hospitals.[30] We test the sensitivity of the results to different hospital HHI measures based on alternative ways of measuring market shares (using Medicare days, privately insured days, and all inpatient stays) and geographic markets (using counties).

We also collect a number of time-varying county-level control variables from various sources and merge them to the hospital-level data. These covariates control for changes in local-level characteristics which could be correlated with changes in either market concentration measure and changes in hospital patient experience over time. For example, a county's socioeconomic characteristics may affect the attractiveness of a market for a potential insurer entrant and may also be associated with patient experience. Hence, one set of county-level controls characterize the demographics of the county, including the percentage of the county's population aged 65 and over and the percentage nonwhite from the Area Health Resource File. Additionally, we include the county's real median income from the Census' Small Area Income and Poverty Estimates database, and the unemployment rate from Bureau of Labor Statistics' Local Area Unemployment Statistics. Another set of county-level controls characterize the healthcare market. We include the uninsured rate from the Census' Small Area Health Insurance Estimates; the HMO/POS commercial penetration rate from the HealthLeaders-InterStudy data; and Medicare Advantage penetration, number of doctors per 1,000 residents, number of hospital inpatient days per capita, and number of Federally Qualified Health Centers from the Area Health Resource File.

4.3 Model/Methods

We estimate hospital/year-level models of hospital patient experience as a function of the observable market, hospital, and county characteristics discussed above, in addition to hospital fixed effects to account for unobserved, time-invariant factors that might affect both market concentration and patient satisfaction. Our models are identified by variation in the level of hospital and insurance market concentration within a market over time. To illustrate the variation, Appendix Figure 4.1 plots the change in hospital market concentration over the study period against the change in insurance market concentration over time for each hospital. (Note that we keep consistent geographic market definitions over time, so this variation results from changes in insurer and hospital market shares.) The model takes the following form, which we estimate using OLS regression, as the dependent variables (i.e., the hospital's percentage of patients rating it a 9 or 10 out of 10, or the hospital's percentage of patients reporting they would definitely recommend the hospital) both have an approximate normal distribution:

$$Y_{it} = \beta_0 + \beta_1 InsHHI_{kt} + \beta_2 HspHHI_{lt} + \beta_3 Hospital_{it} + \beta_4 County_{jt} + \beta_5 Year_t + \alpha_i + \varepsilon_{it} \quad [1]$$

In the above specification, we estimate the patient experience score Y_{it} of hospital i, in county j, in insurance market k (defined as CCIIO Rating Areas), and in hospital market l (defined as Dartmouth Atlas HRRs), and in year t. $InsHHI_{kt}$ and $HspHHI_{lt}$ are the insurance and hospital market concentration measures, respectively; and so our coefficients of interest are β_1 and β_2. We are interested in estimating β_1 and β_2 coefficients both for the entire sample of hospitals and (based on expectations described further below) for various stratified subsamples of hospitals based on the type of hospital and initial levels of market concentration (rather than additional interaction terms in the full sample's model). $Hospital_{it}$ is a vector of time-varying hospital characteristics, and $County_{jt}$ is a vector of time-varying county characteristics, both described in the Data section above. $Year_t$ is a vector of binary year indicators, which account for time trends in patient satisfaction that were common across markets. The hospital fixed effects are denoted by α_i. Each hospital/year observation is weighted by the number of hospital beds. To account for correlation in the error terms within markets, we cluster the standard errors at the insurance market level.

4.3.1 Sensitivity Analyses

We conduct three sets of sensitivity analyses to determine whether the β_1 and β_2 parameters from our main model are robust to alternative specifications. The first set of sensitivity analyses use alternative satisfaction measures for the dependent variable: defining the rating outcome measure as the percentage of respondents rating the hospital a 7 or higher (rather than 9 or higher) and defining the satisfaction outcome measure as the percentage of respondents definitely or probably recommending the hospital (rather than definitely recommending).

The second set of sensitivity analyses uses an alternative sample. We estimate the model excluding the observations of vertically integrated hospital systems, including Kaiser Permanente, Geisinger Health System, and Intermountain Healthcare. These systems still exert competitive pressure on the other actors in the market, and are therefore included in the measures of insurance and hospital concentration; but because they do not undergo the typical bargaining process between an insurer and hospital, their patient experience scores may be unresponsive to insurance market concentration.

The third set of sensitivity analyses use alternative hospital HHI measures. The first subset uses alternative hospital utilization measures to determine market shares. We re-estimate the model with hospital HHI measures using, alternately, only Medicare inpatient days, only commercially-insured inpatient days, and all hospital admissions (rather than all-payer inpatient days). The rationale for the latter is that less-efficient hospitals with longer average lengths of stay may have larger market shares based on days. The second subset uses counties to define geographic hospital markets instead of the Dartmouth Atlas HRRs.

4.3.2 Stratified Analyses

The extent to which hospitals respond to the competitive pressures exerted by other hospitals and by insurers may depend on certain hospital characteristics. For example, nonprofit hospitals, particularly those in systems which are often affiliated with academic medical centers, might be intrinsically motivated to provide high-quality care, so they may be relatively less sensitive to market concentration. We therefore estimate separate models for subsamples by hospital ownership type: public hospitals, nonprofit independent hospitals, nonprofit hospitals in systems, and for-profit hospitals.

Additionally, the extent to which insurers can exert pressure on hospital quality may depend on the level of hospital concentration that those insurers face, as hospitals in more competitive hospital markets may have already increased quality considerably and thus be less sensitive to insurer pressures. Similarly, the extent to which hospital competition with each other influences quality may depend on the level of insurance market concentration. We therefore consider how hospital and insurance market concentration interact with each other to affect patient experience by estimating models stratified by market concentration at the 2008 baseline. The Federal Trade Commission (FTC) and Department of Justice (DOJ) use an HHI cutoff of 2,500 to distinguish between "moderately concentrated" and "highly concentrated" markets, and we follow this benchmark.[31,32] We estimate separate models for low/moderate vs. high concentration levels for hospital markets, for low/moderate vs. high concentration levels for insurance markets, and for each pair of low/moderate vs. high concentration levels for both.

We test the significance of differences between coefficients on insurance and hospital market concentration across stratified analyses (both by hospital type and by market concentration) using seemingly unrelated estimation in Stata.

4.4 Results

The sample of hospitals, after imposing the restrictions described above, result in a total of 25,180 observations at 3,154 hospitals over eight years and 465 insurance markets and 306 hospital markets. (Because of sporadically missing confounder data, the number of observations is not an exact multiple of the number of hospitals.)

The first panel of Table 4.1 presents summary statistics for the analytical sample over the 2008-2015 period, weighted by number of beds. Across hospitals, the mean percentage of patients rating their hospital a 9 or 10 over the study period was 67.4% and the mean percentage of patients reporting they would definitely recommend the hospital was 70.3%, with standard deviations across hospitals of 7.94% and 8.74%, respectively. Appendix Figure 4.2 illustrates the change in these average scores over the study period. The average insurance market HHI faced by hospitals during this time was 2,726, while the average hospital market HHI was 2,459; both are right around the FTC/DOJ "highly concentrated" benchmark of 2,500. (Note that the unit of observation here is the hospital, so these measures of mean market concentration differ from means reported elsewhere that reflect averages across markets or the population.) Appendix Table 4.2 provides more detail on the distribution of the patient experience scores and insurance and hospital concentration measures over hospital/years. The typical hospital bed in our sample is in a hospital that is a member of a nonprofit hospital system with between 200 and 299 beds and located in a metropolitan market.

The second and third panels of Table 4.1 present the results for the main model. A 1,000-point increase in insurance concentration increases the percentage who rate the hospital a 9 or 10 by 0.273 percentage points (p=0.032) and the percentage who would definitely recommend the hospital by 0.268 percentage points (p=0.030), while a 1,000-point increase in hospital concentration decreases these scores by 0.291 percentage points (p=0.069) and 0.350 percentage points (p=0.017). With the inclusion of hospital fixed effects, the control variables should be interpreted as changes in these characteristics over time. There is also a notable time trend (consistent with Appendix Figure 4.2), with patient experience scores moving steadily upward over the study period.

To illustrate the magnitude of these results for changes in insurance and hospital market concentration, we consider the change in patient experience associated with moving to the 20th percentile of hospital concentration observed in the data (HHI=1,293) and the 80th percentile of insurance concentration (HHI=3,332) from the 80th percentile of hospital concentration (HHI=3,439) and the 20th percentile of insurance concentration (HHI=2,004). About 4.4% of the hospital/year observations jointly have these lowest levels of hospital concentration and highest levels of insurance concentration, while about 4.0% of the hospital/year observations jointly have these highest levels of hospital concentration and lowest levels of insurance concentration. (Appendix Figure 4.3 illustrates the joint distribution of insurance and hospital market concentration across the hospitals in our sample for 2015.) This change in the joint distribution of market concentration would increase the percentage who rate the hospital a 9 or 10 from about 66.9% (95% CI: 66.5-67.2%) to about 67.9% (95% CI: 67.5-68.3%) and would increase the percentage who would definitely recommend the hospital from about 69.7% (95% CI: 69.4-70.0%) to about 70.8% (95% CI: 70.5-71.2%); both of which are differences of about 0.13 standard deviations in the measures across hospitals. These changes correspond to a hospital's patient rating increasing from roughly the 41st to 45th percentile of its distribution and a hospital's patient satisfaction moving from the 48th to 52nd percentile. Figures 4.1A-4.1B show these two predicted patient experience measures for all possible combinations of insurance and hospital market concentration.

Table 4.2 presents the results of the sensitivity analyses, with only the coefficients on insurance and hospital market concentration reported and the first and second columns corresponding to the rating and recommended measures, respectively. In the first set of sensitivity results, the effect of hospital market concentration is robust to redefining the outcome measure as a rating of 7 or higher and to redefining the outcome measure as definitely/probably recommend the hospital, while the effect of insurance concentration is comparable but not statistically significant. In the second set of sensitivity results, the findings are robust to excluding vertically integrated systems. In the third set of sensitivity analyses, the effect of insurance market concentration is robust to calculating hospital HHIs with Medicare days, with private days, and with hospital admissions instead of inpatient days. However, hospital HHIs calculated using private hospital days do not significantly affect patient satisfaction, suggesting that the findings in the main model may be primarily driven by competition for Medicare patients. While this is somewhat surprising because hospital HHI measures are highly correlated whether defined by all patients, Medicare patients, or private patients, this pattern is plausible given that hospital competition should have stronger quality implications in Medicare where prices are administered. The results on insurance market concentration are robust to using counties to define the geographic hospital market; the effect of hospital market concentration is not robust to using counties to define hospital markets.

Table 4.3 presents the results for the analysis stratified by hospital type. While we do not generally observe statistically significant differences between the coefficients for the hospital type stratifications, the magnitude of the coefficient for insurance market concentration is slightly larger among independent nonprofit systems and for-profit hospitals, relative to hospitals in a nonprofit system; for the definitely recommend outcome measure, the effect of insurance concentration among for-profit hospitals is significantly different from nonprofit systems (p=0.046). The magnitudes of the effect of hospital market concentration are slightly larger among hospitals that are not members of a nonprofit system, though in general, neither the point estimates nor the tests of differences are statistically significant. We also considered whether the effect varied by a hospital's teaching status, but we do not report those results as those magnitudes were similar to each other.

Table 4.4 presents the results for the analyses stratified by low/moderate versus high insurance and hospital market concentration, again reporting only the coefficients on hospital and insurance market concentration for the two outcome measures. The insurance market concentration's coefficient is larger in magnitude in more concentrated (HHI > 2,500) hospital markets, with a 1,000-point increase in insurance HHI increasing patient experience by 0.590 percentage points (p=0.002) for the rating measure and 0.469 percentage points (p=0.009) for the recommendation measure. For the rating outcome measure, this difference is statistically significant (p=0.03). Conversely, the hospital market concentration's coefficient is larger in magnitude, though not significantly different, in less concentrated hospital markets, with a 1,000-point increase in hospital HHI in a hospital market with low/moderate concentration at baseline decreasing the patient rating score by 0.591 points (p=0.047) and the recommend score by 0.560 points (p=.033), compared to no effect in a hospital market that was highly concentrated at baseline. The hospital market concentration's coefficient is larger in magnitude, though not statistically different, in more concentrated insurance markets, with a 1,000-point increase in hospital HHI decreasing patient satisfaction by 0.352 percentage points (p=0.077) or 0.393 percentage points (p=0.026). Moreover, the insurance market concentration's coefficient is largest when insurance markets are not concentrated and hospital markets are concentrated, improving patient experience by 1.181 percentage points (p=0.032) or 0.799 percentage points (p=0.104).

4.5 Discussion and Limitations

We find that insurance market concentration positively impacts the patient's experience of care, an important dimension of hospital quality, and that, consistent with much of the prior research, hospital concentration negatively impacts this measure of hospital quality. Moving from a market at the 20th percentile of insurance concentration and the 80th percentile of hospital concentration (consistent with 4.0% of the joint distribution) to a market at the 80th percentile of insurance and the 20th percentile of hospital concentration (consistent with 4.4% of the joint distribution) increases the patient rating score from 66.9% to 67.9% and the patient recommendation score from 69.7% to 70.8%. These changes in patient satisfaction would be consistent with moving from the 41st percentile to the 45th percentile in the distribution of patient rating scores across hospitals and with moving from the 48th percentile to the 52nd percentile in the distribution of patient recommendation scores. We interpret these as relatively modest yet nontrivial direct impacts on patient experience.

Moreover, insurance market consolidation is relatively more beneficial to patient experience when the hospital market is more concentrated, and hospital market consolidation is relatively more detrimental to patient experience when the hospital market is less concentrated. This suggests that when a hospital market is not concentrated, other hospitals exert enough competitive pressure that insurance concentration has no additional impact on quality, but when a hospital market is concentrated (and hence has fewer competitors), pressure by insurers becomes more important.

We also find that the positive association of insurance market concentration with patient experience is particularly pronounced among for-profit hospitals and independent nonprofit hospitals. This may suggest that these types of hospitals are more responsive to competitive market pressures compared to nonprofit hospital systems and public hospitals. The former, which are commonly affiliated with academic medical centers and generally tend to have higher patient satisfaction scores, may be more intrinsically likely to prioritize quality absent competitive pressure. Public hospitals tend to serve a different patient population and, as a result, not be as affected by commercial insurance market conditions.

Our analyses have several limitations. First, HCAHPS patient experience measures may not correlate very strongly with more clinically-oriented quality measures, and we have a limited ability to explore the effect on patients who rate the hospital very poorly. Second, consistently defining insurance and hospital markets across the country is a challenge. There is variation across states in how those regulators elected to define insurance rating areas for CCIIO. The Dartmouth HRRs reflect geographic markets for tertiary care hospitals, which are likely larger than the relevant geographic market for community hospitals. Furthermore, the proper utilization measure to define hospital market shares is unclear, though we used several approaches. Finally, hospital and insurer decisions to merge or enter/exit a market are not random, and drawing a causal conclusion from our study relies on the assumption that the (unmeasured) confounding factors were constant over time.

Regarding the policy implications of these findings, most analyses of market dynamics on provider quality focus on provider market concentration, but we find that insurance market concentration also impacts this dimension of quality. As noted above, we view the magnitude of the effects we observe as modest but not trivial. An overall assessment of the effects of consolidation in insurance and provider markets weighs the benefits against the harms (with those harms largely being tied to higher insurer administrative overhead and higher provider prices). Our research furthers the prior evidence on the harms of hospital market consolidation (observed, as noted above, in a portion of that literature) but suggests that, at least on this dimension, insurance market concentration may have some benefits, particularly in markets that lack robust hospital competition.

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4.7 Tables

Table 4.1: Summary Statistics and Main Model's Full Regression Results

			Regression: Rating 9/10		Regression: Recommend	
	Mean	**SD**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Percent Giving 9/10 Quality	67.4	7.94				
Percent Giving a 7+ Quality	90.8	3.96				
Percent Definitely	70.3	8.74				
Pct. Def./Probably	94.5	3.06				
Market Concentration:						
Insurance HHI (1,000s)	2.73	0.98	0.273**	[0.127]	0.268**	[0.124]
Hospital HHI (1,000s)	2.46	1.50	-0.291*	[0.160]	-0.350**	[0.146]
Hospital Characteristics						
Type: Nonprofit Ind.	0.20	0.40				
Type: Nonprofit System	0.51	0.50	-0.572**	[0.272]	-0.725**	[0.293]
Type: For-Profit	0.14	0.35	-1.795***	[0.472]	-2.016***	[0.460]
Type: Public Nonfederal	0.14	0.35	-0.213	[0.553]	-0.473	[0.543]
Size: 6-24 Beds	0.003	0.06				
Size: 25-49 Beds	0.02	0.15	-0.073	[0.630]	-0.088	[0.654]
Size: 50-99 Beds	0.06	0.23	-0.037	[0.702]	-0.413	[0.754]
Size: 100-199 Beds	0.18	0.38	0.079	[0.768]	-0.267	[0.811]
Size: 200-299 Beds	0.18	0.39	0.438	[0.809]	0.046	[0.847]
Size: 300-399 Beds	0.16	0.36	0.408	[0.843]	-0.026	[0.886]
Size: 400-499 Beds	0.11	0.32	0.971	[0.907]	0.339	[0.951]
Size: 500+ Beds	0.28	0.45	1.423	[0.945]	0.829	[0.967]
Medicare Share (Days)	0.49	0.13	-1.499***	[0.567]	-1.398***	[0.538]
Medicaid Share (Days)	0.21	0.12	0.263	[0.624]	-0.060	[0.689]
Graduate Medical	0.51	0.50	0.010	[0.194]	-0.042	[0.193]
Average Length of Stay	4.99	2.06	-0.072**	[0.033]	-0.079***	[0.029]
County Characteristics						
Non-CBSA (vs. CBSA)	0.04	0.19				
Fraction Age 65+	0.14	0.03	-14.05	[9.194]	-14.98	[9.288]
Fraction Nonwhite	0.37	0.21	2.341	[6.461]	1.860	[6.615]
Median Income ($1,000s)	55.9	14.2	-0.012	[0.025]	-0.022	[0.024]
Unemployment Rate	0.08	0.03	5.050	[5.593]	1.562	[5.277]
Fraction Uninsured	0.16	0.06	-7.288*	[4.079]	-5.662	[3.564]
HMO/POS Penetration	0.35	0.16	1.853**	[0.805]	1.726**	[0.760]
Medicare Adv.	0.27	0.14	-1.885	[2.120]	-0.300	[2.009]
MDs per 1,000	2.94	2.04	0.019	[0.172]	0.106	[0.179]
Inpatient Days Per Capita	0.71	0.51	0.058	[0.138]	0.0126	[0.141]
FQHC in County	0.86	0.35	0.056	[0.322]	-0.097	[0.303]
Year Indicators (2008)						
2009			2.335***	[0.224]	1.593***	[0.211]
2010			3.915***	[0.261]	2.505***	[0.253]
2011			4.946***	[0.281]	3.073***	[0.280]
2012			6.175***	[0.293]	3.773***	[0.304]
2013			7.039***	[0.326]	4.032***	[0.343]
2014			7.166***	[0.416]	3.979***	[0.408]
2015			7.648***	[0.518]	3.972***	[0.499]
Constant			65.60***	[3.594]	71.77***	[3.724]
R-Squared			0.842		0.874	

Notes: Sample consists of 25,180 observations over 3,154 unique hospitals. Summary statistics and regressions are weighted by the number of hospital beds. The regressions include hospital fixed effects. HHI=Herfindahl-Hirschman Index; FQHC=Federally Qualified Health Center. Statistical Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 4.2: Results from Sensitivity Analyses: Coefficients for Insurance and Hospital Market Concentration

	DV = Percent Giving a Rating of 9 or 10		DV = Percent Definitely Recommending	
Model Specification:	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**
Main Model	0.273**	-0.291*	0.268**	-0.350**
	[0.127]	[0.160]	[0.124]	[0.146]
Alternative Dependent Variables:				
Percent Giving a Quality Rating of 7+	0.151	-0.227***		
	[0.097]	[0.084]		
Percent Definitely/Probably Recommending			0.101	-0.174***
			[0.064]	[0.053]
Alternative Sampling:				
Drop Vertically Integrated Systems	0.253**	-0.253	0.249**	-0.321**
	[0.129]	[0.161]	[0.125]	[0.147]
Alternative Hospital HHI Measures:				
Uses Medicare Days for Market Share	0.264**	-0.450***	0.261**	-0.444***
	[0.126]	[0.151]	[0.122]	[0.142]
Uses Private Days for Market Shares	0.276**	0.0537	0.273**	-0.0155
	[0.128]	[0.126]	[0.125]	[0.122]
Uses All Hospital Admissions for Market Shares	0.270**	-0.559***	0.265**	-0.592***
	[0.126]	[0.202]	[0.123]	[0.190]
Uses Counties for Geographic Areas	0.270***	-0.071	0.208	-0.103
	[0.103]	[0.083]	[0.147]	[0.090]

Notes: The main model on the first row repeats the results shown in Table 4.1. DV=Dependent Variable. HHI=Herfindahl-Hirschman Index. Regressions are weighted by the number of hospital beds and include hospital fixed effects. Standard errors are shown in brackets.
Statistical Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Standard errors are shown in brackets.

Table 4.3: Results from Stratified Analyses by Hospital Type

	DV = Percent Giving a Rating of 9 or 10		DV = Percent Definitely Recommending	
Subsample:	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**
Main Model (Not Stratified)	0.273**	-0.291*	0.268**	-0.350**
(N=25,180)	[0.127]	[0.160]	[0.124]	[0.146]
Nonprofit System Hospital Subsample	0.113	0.060	0.113	-0.053
(N=11,235)	[0.241]	[0.226]	[0.223]	[0.213]
Nonprofit Independent Hospital Subsample	0.418**	-0.487	0.397*	-0.248
(N=5,440)	[0.195]	[0.299]	[0.216]	[0.292]
For-Profit Hospital Subsample	0.652**	-0.541	0.727***+	-0.733*
(N=4,191)	[0.266]	[0.419]	[0.271]	[0.386]
Public Hospital Subsample	0.060	-0.504	-0.083	-0.701**
(N=4,314)	[0.263]	[0.322]	[0.279]	[0.348]

Notes: The main model on the first row repeats the results shown in Table 4.1. DV=Dependent Variable. HHI=Herfindahl-Hirschman Index. Regressions are weighted by the number of hospital beds and include hospital fixed effects. Standard errors are shown in brackets.
Statistical Significance: *** p<0.01, ** p<0.05, * p<0.10. + Indicates that coefficient is significantly different from comparison coefficient at the 0.05 level. The coefficients for nonprofit independent hospitals, for-profits, and public hospitals are each tested against the coefficient for nonprofit hospitals in a system.

Table 4.4: Results from Stratified Analyses by Low/Moderate Vs. High Market Concentration

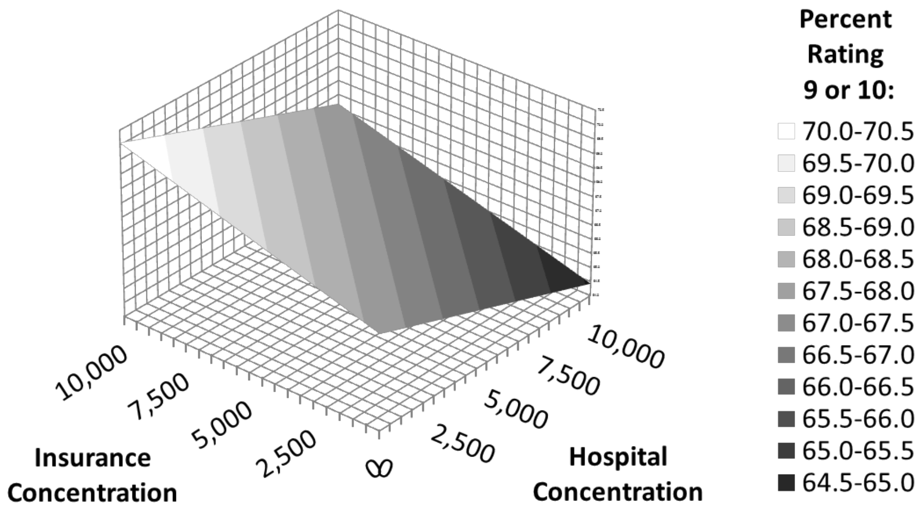
	DV = Percent Giving a Rating of 9 or 10		DV = Percent Definitely Recommending	
Subsample:	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**	**Insurance Market HHI Coefficient**	**Hospital Market HHI Coefficient**
All Insurance Markets, All Hospital Markets	0.273**	-0.291*	0.268**	-0.350**
(N=25,180)	[0.127]	[0.160]	[0.124]	[0.146]
All Insurance Markets, Hospital HHI < 2,500	0.106	-0.591**	0.164	-0.560**
(N=16,780)	[0.153]	[0.297]	[0.153]	[0.262]
All Insurance Markets, Hospital HHI > 2,500	0.590***+	-0.125	0.469***	-0.220
(N=8,398)	[0.187]	[0.180]	[0.178]	[0.164]
Insurance HHI < 2,500, All Hospital Markets	0.186	-0.082	0.269	-0.179
(N=10,050)	[0.320]	[0.221]	[0.290]	[0.213]
Insurance HHI > 2,500, All Hospital Markets	0.151	-0.352*	0.120	-0.393**
(N=15,130)	[0.128]	[0.198]	[0.132]	[0.175]
Insurance HHI < 2,500, Hospital HHI < 2,500	-0.276	-0.584	-0.001	-0.598
(N=7,061)	[0.352]	[0.499]	[0.346]	[0.463]
Insurance HHI > 2,500, Hospital HHI < 2,500	0.0465	-0.442	0.0176	-0.330
(N=9,719)	[0.155]	[0.352]	[0.160]	[0.307]
Insurance HHI < 2,500, Hospital HHI > 2,500	1.181**+	0.102	0.799	-0.0513
(N=2,989)	[0.540]	[0.215]	[0.486]	[0.221]
Insurance HHI > 2,500, Hospital HHI > 2,500	0.345*	-0.206	0.282	-0.318*
(N=5,409)	[0.189]	[0.228]	[0.189]	[0.188]

Notes: The main model on the first row repeats the results shown in Table 4.1. DV=Dependent Variable. HHI=Herfindahl-Hirschman Index. Regressions are weighted by the number of hospital beds and include hospital fixed effects. Standard errors are shown in brackets.
Statistical Significance: *** p<0.01, ** p<0.05, * p<0.10. + Indicates that coefficient is significantly different from comparison coefficient at the 0.05 level. The first row in each group is treated as the comparison (i.e., coefficients for hospital markets > 2,500 are tested against hospital markets < 2,500, and hospital and insurance markets > 2,500 are tested against hospital and insurance markets < 2,500.)

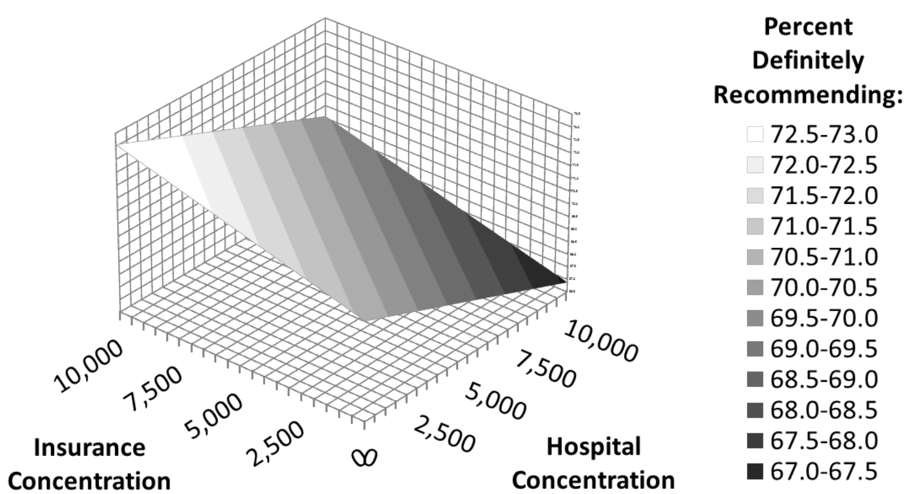
4.8 Figures

Figure 4.1: Predicted Patient Experience By Level of Insurance and Hospital Market Concentration

Panel A: Percent of Patients Rating the Hospital a 9 or 10



Panel B: Percent of Patients Definitely Recommending the Hospital



Notes: The predicted values are based on the results shown in Table 4.1.

4.9 Appendices

Appendix Table 4.1: Comparison of Characteristics between Included and Excluded Hospitals for 2008

	Included Hospitals (N=3,152)		Excluded Hospitals (N=1,441)		Included vs. Excluded Difference
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**P Value**
Percent Giving a Rating of 9 or 10	63.5	8.94	64.4	12.5	0.063
Percent Giving a Rating of 7+	89.5	5.15	89.4	6.61	0.841
Percent Definitely Recommending	67.2	9.9	67.8	13.42	0.261
Pct. Def./Probably Recommending	93.9	3.86	93.3	4.75	0.005
Market Concentration:					
Insurance HHI (1,000s)	3.10	1.29	3.56	1.51	<.001
Hospital HHI (1,000s)	2.43	1.52	2.46	1.54	0.493
Hospital Characteristics					
Type: Nonprofit Ind. (reference)	0.26	0.44	0.22	0.42	0.021
Type: Nonprofit System	0.41	0.49	0.23	0.42	<.001
Type: For-Profit	0.15	0.36	0.18	0.39	0.013
Type: Government (Non-Fed)	0.18	0.39	0.36	0.48	<.001
Size: 6-24 beds	0.03	0.18	0.22	0.41	<.001
Size: 25-49 beds	0.14	0.35	0.37	0.48	<.001
Size: 50-99 beds	0.16	0.37	0.21	0.41	<.001
Size: 100-199 beds	0.26	0.44	0.13	0.33	<.001
Size: 200-299 beds	0.17	0.37	0.04	0.18	<.001
Size: 300-399 beds	0.10	0.3	0.02	0.14	<.001
Size: 400-499 beds	0.05	0.22	0.01	0.10	<.001
Size: 500+ beds	0.08	0.27	0.01	0.09	<.001
Percent Medicare	0.53	0.14	0.61	0.19	<.001
Percent Medicaid	0.17	0.13	0.15	0.20	0.001
Graduate Medical Education	0.22	0.42	0.04	0.20	<.001
Average Length of Stay	4.61	2.63	6.35	8.84	<.001
County Characteristics					
Rural (vs. Non-Rural) County	0.14	0.04	0.16	0.04	<.001
Percent Age 65+	0.28	0.21	0.25	0.22	<.001
Percent Nonwhite	55.83	14.66	49.38	11.82	<.001
Median Income ($000s)	0.16	0.06	0.18	0.06	<.001
Percent Uninsured	0.06	0.02	0.06	0.02	0.018
Unemployment Rate	0.20	0.13	0.15	0.12	<.001
Medicare Advantage Penetration	0.27	0.16	0.21	0.16	<.001
HMO/POS Penetration	2.12	1.64	1.33	1.45	<.001
MDs per 1000	0.60	0.45	0.53	0.66	<.001
Inpatient Days per Capita	0.67	0.47	0.49	0.50	<.001
FQHC in County	0.14	0.04	0.16	0.04	<.001

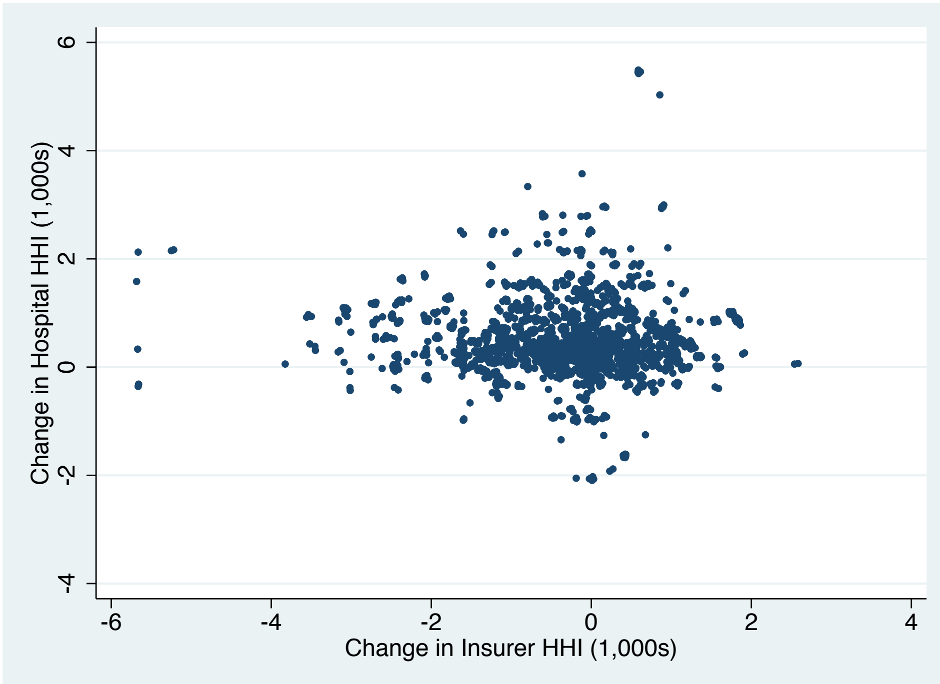
Notes: HHI=Herfindahl-Hirschman Index; FQHC=Federally Qualified Health Center.
Statistical Significance: *** p<0.01, ** p<0.05, * p<0.10

Appendix Table 4.2: Distribution of Patient Experience and Insurance and Hospital Market Concentration Across Hospital-Years

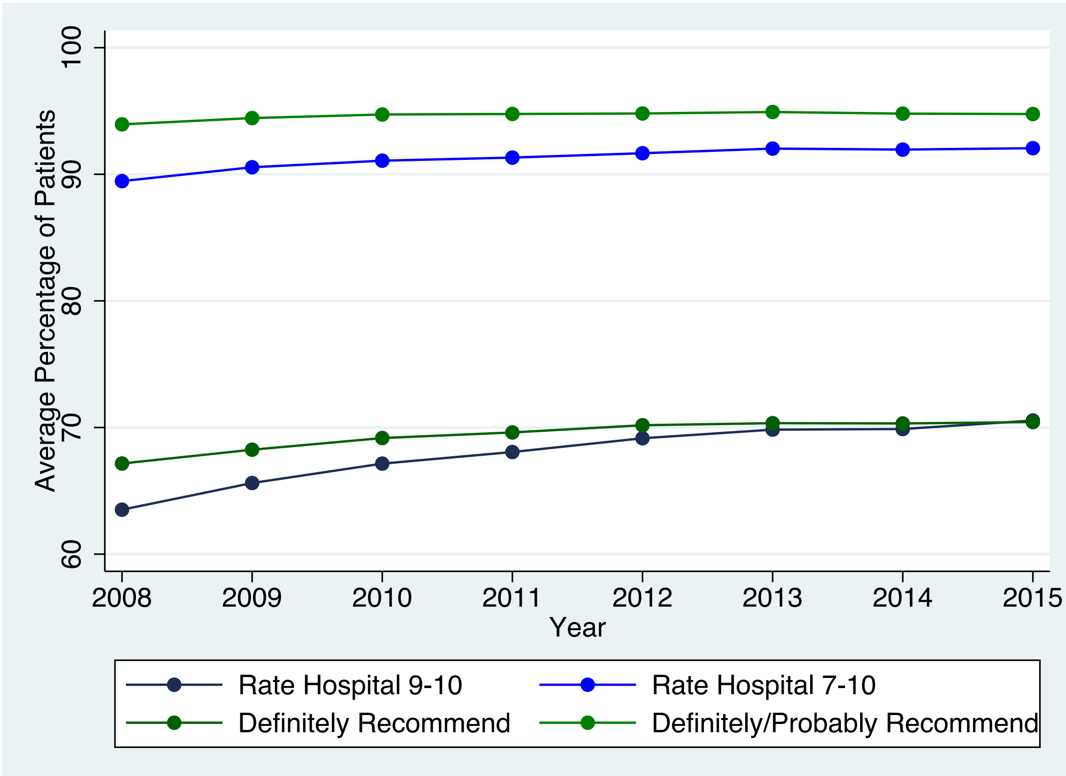
Percentile	Percentage Rating 9-10	Percentage Definitely Recommending	Insurance HHI (1,000s)	Hospital HHI (1,000s)
1st	45.0	46.0	1.388	0.706
5th	53.0	55.0	1.651	0.849
10th	57.0	59.0	1.820	1.093
20th	61.0	63.0	2.004	1.293
25th	63.0	65.0	2.090	1.395
50th	68.0	71.0	2.429	2.066
75th	73.0	77.0	3.118	3.009
80th	74.0	78.0	3.332	3.439
90th	77.0	81.0	3.967	4.618
95th	79.0	83.0	4.623	5.274
99th	83.0	86.0	6.397	8.605

Notes: HHI=Herfindahl-Hirschman Index. Observations are weighted by the number of hospital beds.

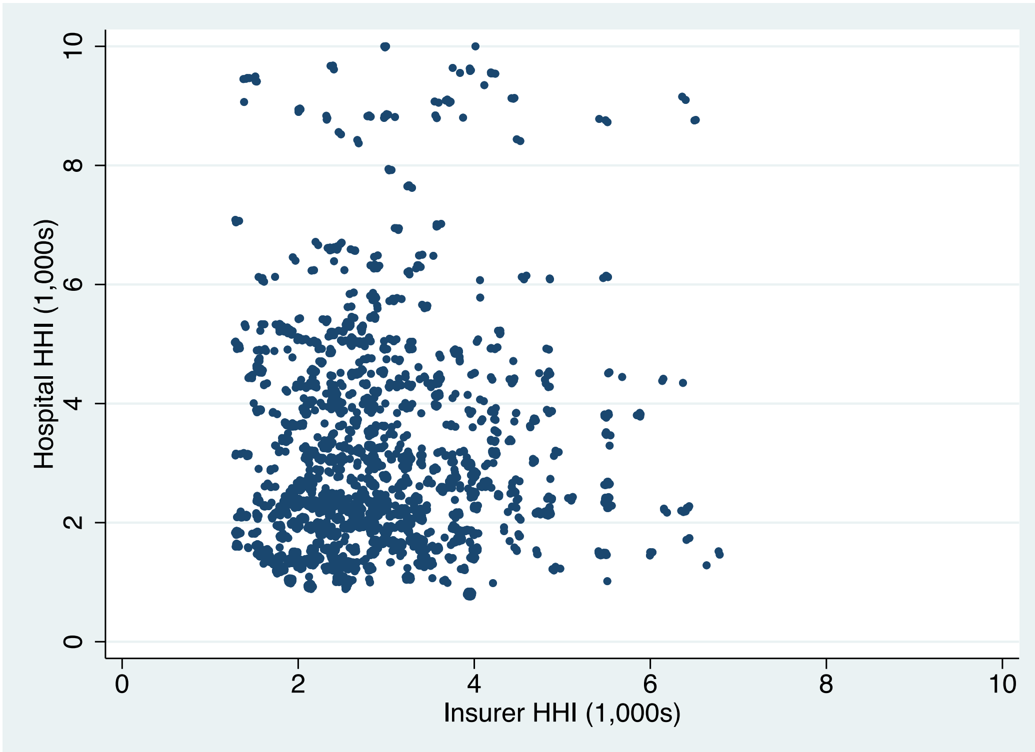
Appendix Figure 4.1: Scatter Plot of the Change in Insurance and Hospital Market Concentration Across Hospitals from 2008 to 2015



Appendix Figure 4.2: Unadjusted Trend in Average Patient Experience Scores from 2008 to 2015



Appendix Figure 4.3: Scatter Plot of Insurance and Hospital Market Concentration Across Hospitals in 2015



5. Conclusion

This work presents important evidence on the relationship between insurer concentration and utilization and quality, two outcomes of particular importance to patients. The first paper found that a 1,000-point increase in insurer concentration increases the likelihood of an inpatient admission by 0.09 percentage points and increases price-adjusted professional spending by $84.22, both around 2% of the unadjusted average level of utilization. Consistent with expectations linked to insurer negotiation of provider prices, insurer concentration did not affect treatment intensity of more price-inelastic acute admissions, but increased price-adjusted spending on more price-elastic planned admissions by $200.53, or 3.4% of the mean. This is suggestive evidence that conditional on having insurance, increases in insurer concentration on average increase access to care.

However, Paper 2 indicates that, at least in some contexts, a physician's financial incentives to provide more care contribute to higher utilization as insurance concentration increases. A 1,000-point increase in insurer concentration was predicted to increase the utilization of MRI imaging following a new patient visit with an orthopedist who bills for MRI by 11.9%, compared to 4% following a visit with an orthopedist who does not bill for MRI. Similarly, there was no detectable effect on back MRI following a new or established patient visit for back pain with an orthopedist who does not bill for MRI, compared to a 9.5% increase among patients who visited an orthopedist who bills for MRI. This dynamic may exacerbate overuse and contribute to inefficiently high healthcare utilization. Importantly, though the effect of insurer concentration is not positive in every model across the patients of owners and non-owners, it is positive in all the models in which the effect of insurance market concentration is statistically significant. This is important because it suggests that supplier-induced demand contributes to the positive relationship between insurer concentration and utilization in addition to patient-driven demand, rather than instead of it.

Papers 1 and 3 present mixed findings related to healthcare quality. This research found that insurer concentration did not significantly decrease the probably of an unplanned readmission in the primary sample, though the point estimate was negative and there was a significant negative effect in a more restricted sample. Insurer concentration was found to improve hospital patients' experience of care, with a 1,000-point increase in insurer HHI increasing the percentage of patients who rated the hospital a 9 or 10 by an estimated 0.273 percentage points and the percentage who would definitely recommend the hospital by 0.268 percentage points. The magnitudes of these results were comparable to the harmful effect of hospital concentration, with a 1,000-point increase in hospital concentration decreasing the respective scores by an estimated 0.291 percentage points and 0.350 percentage points.

Another key contribution of this research is to explore how these results depend on baseline levels of market concentration, an important question for regulators and policy-makers to consider as they estimate the likely impact of a proposed merger or pursue policies aimed at increasing market competition. While there were no meaningful differences in the effect of insurer concentration on the likelihood of an admission between low/moderate and high concentration physician or insurer markets, the effect of insurer concentration on intensive utilization was driven by markets that had relatively unconcentrated insurance markets. This finding might suggest that insurers in less concentrated insurance markets face more competitive pressure to pass on lower prices to patients and to limit the use of health plan tools that limit utilization, like claims review. Conversely, there were no large differences in the effect on hospital patients' experience of care between more and less concentrated insurance markets. One interpretation of this pair of findings is that, on the utilization side, the role of insurers as sellers of health plans modifies the extent to which patients benefit from the insurer's role as purchaser of health services; on the patient experience side, however, there is no issue of pass-through and patients can benefit directly from the pressure placed on providers to improve quality.

The findings related to baseline levels of provider market concentration are also interesting. Contrary to the expectation that the effect of increases in insurer concentration would be larger in more concentrated physician markets, where physicians would have more leverage to hold prices above competitive levels, the effect on intensive utilization was driven by relatively unconcentrated physician markets. This result may suggest that the effect of a marginal increase in insurer concentration does not meaningfully change the bargaining relationship if physicians and hospitals are highly concentrated. Conversely, the beneficial effect on patient experience was driven by more concentrated hospital markets, perhaps indicating that the effect of insurer concentration on quality plays a larger role when there is not already enough competition from other hospitals to achieve higher quality.

When synthesizing the results of this research, it is important to note that the underlying study population and time frame differed across the three papers. Papers 1 and 2 both focused on commercially-insured beneficiaries receiving employer sponsored insurance largely from self-insured firms. Paper 3 uses patient experience measures randomly sampled from hospital patients, across payer categories. While Paper 1 and Paper 3 focused on an inpatient setting, Paper 2 focused on an outpatient setting. Each paper also covered a different time period, with Paper 3 estimated over 2008-2015, Paper 1 estimated over 2013-2015, and Paper 2 over 2015. These differences in study setting may affect the interpretation of the results. For example, Paper 1 found no significant effect on readmissions, but Paper 3 found a beneficial effect on patient experience. This might be because improving clinical quality is simply more difficult than improving patient experience (which depends more on dimensions like communication and the comfort of the room), making hospitals less responsive to insurer pressure on measures of clinical quality. However, it also might be that insurer concentration and readmissions had a weaker relationship over 2013-2015 than they might have had over an earlier period, before the Hospital Readmissions Reduction Program placed more pressure on hospitals to reduce readmissions. Likewise, it is possible that insurer concentration and a less-publicized clinical quality measure may have a stronger relationship than insurer concentration and readmissions.

This work presents several opportunities for future research. One major area for further exploration is understanding the mechanisms underlying the different findings by baseline levels of market concentration. The interpretations outlined above are conceptually motivated, but not tested empirically. An understanding of why the level of insurer concentration modifies the effect of a change in insurer concentration would be strengthened by research on how insurer concentration affects underlying plan features, like the set of covered benefits, the out-of-pocket payment design, the size of the provider panel, and the likelihood of a claim being denied. An important question is how these relationships vary across fully-insured versus self-insured health plans, as some of these features may spill over from an insurer's fully-insured plans to plans where they provide administrative services, while others may not.

More work is also needed to understand whether increases in utilization related to increases in insurer concentration benefit the patient on any clinical dimension, or whether they increase inefficiency. Readmissions is an important but narrow measure of consumer welfare, and policy changes mentioned above may have weakened any existing relationship between insurer concentration and readmission. The hospital patient's experience of care is likewise an important measure of quality, but a measure that is only weakly related to clinical outcomes. There are many other metrics by which higher utilization may improve a patient's outcomes, and quality measurement continues to be an area of active research. Relatedly, while Paper 2 includes models predicting low-value imaging, this research largely focused on utilization, rather than overutilization. Testing for a relationship between insurer concentration and overuse in more settings would help clarify whether insurer concentration increases access among the insured or exacerbates overuse.

Additionally, more research is needed to understand why supply-side financial incentives significantly affected the relationship between insurer concentration and imaging utilization for orthopedics, but not urology or neurology. Perhaps orthopedics is a medical specialty where the physician's discretion plays a larger role, relative to urology or neurology. Relatedly, other work can explore how different types of supply-side financial incentives affect the relationship between insurer concentration and utilization, as the focus on imaging in this research is important but narrow.

Taken together, these three papers present evidence that insurer concentration is largely beneficial in its effect on utilization and quality, with the caveat that higher utilization is likely not entirely demand-driven and may not be clinically meaningful. These benefits must be weighed against the harms of insurer consolidation, predominantly higher administrative costs contributing to higher premiums, and perhaps an exacerbation of overuse. Regulators and policy-makers should consider ways to achieve the benefits of insurer concentration, while mitigating the harms.

6. Curriculum Vitae

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Education

Johns Hopkins Bloomberg School of Public Health, Baltimore, MD 2014-2019
Doctor of Philosophy (PhD), Department of Health Policy & Management
Concentration: Health Economics & Policy
Dissertation**:** The relationship between insurance market concentration and healthcare use and quality: An exploration of the role of market dynamics, patient demand, and physician incentives.
(Advisor: Dr. Bradley Herring)

Duke University, Durham, NC 2006 –2010
Bachelor of Science (BS), Economics
Second Major: Public Policy Minor: History
Senior Thesis**:** Heterogeneity in the Adverse Incentive Effect of Unemployment Insurance. (Advisor: Dr. V. Joseph Hotz)
Honors: Cum Laude; Six Semesters on Dean's List; Graduated with High Distinction

Scholarships and Fellowships

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National Research Service Award T32 Institutional Training Grant 2014 – 2016

Bill and Sue Gross Alumni Endowed Scholarship 2006 – 2010

Research

Published and Accepted for Publication

Hollin IL, Young C, **Hanson CS**, Bridges JFP, Peay H. Developing a patient-centered benefit-risk survey: a community-engaged approach. Value in Health. 2016; 19(6): 751-757.

Hanson CS, Herring BJ, Trish EE. Do health insurance and hospital market concentration influence hospital patients' experience of care? [Accepted for Publication at Health Services Research]

Nicholas LH, Segal JB, **Hanson CS**, Zhang K, Eisenberg MD. Understanding exposure to fraud and abuse among Medicare beneficiaries. [Accepted for Publication at Health Affairs]

Working Papers

Nicholas LH, Segal JB, **Hanson CS**, Zhang K, Eisenberg MD. Treatment by fraud and abuse perpetrators and mortality among Medicare beneficiaries.

Hanson CS. How does insurance market concentration affect inpatient utilization? Market interactions with physicians and the role of patient demand.

Hanson CS. Do Physician Financial Incentives Matter in the Relationship Between Insurance Market Concentration and Imaging Utilization?

Eisenberg MD, **Hanson CS**, McGinty EE, Stuart EA. A practical tutorial for using comparative interrupted time series models to evaluate public policy interventions.

Works in Progress

Hanson CS, Trish EE, Herring BJ. The relationship between hospital and insurer concentration and hospital markups.

Research Presentations

Office of the Actuary, Centers for Medicare & Medicaid Services — October 2018
"How Does Insurance Market Concentration Affect Inpatient Utilization? Market Interactions with Physicians and the Role of Patient Demand."

Center for Health Services and Outcomes Research, JHSPH — February 2018
"Does Health Insurance Market Concentration Affect Hospital Quality?"

Teaching

Adjunct Faculty, Johns Hopkins Carey Business School, Baltimore, MD
Applied and Behavioral Economics of Health Care — Summer 2018

Guest Lecturer, JHSPH, Baltimore, MD
Health Economics for Managers — Fall 2018
Health Economics II — Spring 2017

Teaching Assistant, Department of Health Policy & Management, JHSPH, Baltimore, MD
Introduction to the U.S. Healthcare System (Dr. Bradley Herring) — 2015 – 2019
The Research and Proposal Writing Process (Dr. Leiyu Shi) — 2017 – 2018
Health Economics II (Dr. Matthew Eisenberg) — 2017 – 2018
Introduction to Health Economics (Dr. Douglas Hough) — Fall 2015
Introduction to Economic Evaluation (Dr. Eric Roberts) — Spring 2015

Teaching Assistant, Department of International Health, JHSPH, Baltimore, MD
Econometric Methods (Dr. Antonio Trujillo) — 2017 – 2018

Professional Experience

Research Assistant, JHSPH, Baltimore, MD (10-15 hours/week)

- Dr. Lauren Nicholas: Exposure of Medicare beneficiaries to fraudulent and abusive providers — 2018 – Current
- Dr. Bradley Herring: The relationship between insurer and hospital market concentration and patient experience and hospital markups — 2015 – Current
- Dr. Antonio Trujillo: Economic analysis for The Access and Affordability Initiative — 2017 – 2018
- Dr. Matt Eisenberg: Stockpiling and anticipatory healthcare utilization under consumer-directed health plans — 2016 – 2017
- Dr. Sandra Newman: The role of the family setting in young adult outcome during economically turbulent times. — 2015 – 2017
- Dr. John FP Bridges: Assessing the value of pulmonary benefits in Duchenne muscular dystrophy. — 2015

Economists Incorporated, Washington, DC (40-50 hours/week)

- *Healthcare Analyst*: Conducted quantitative analysis of competitive issues in healthcare affiliations involving hospitals, physicians, and insurance networks — 2013 – 2014
- *Research Coordinator*: Supervised workflow, case staffing, skill development, and interoffice coordination for a team of 10 researchers working on roughly 20 cases at a time — 2012 – 2013
- *Research Associate:* Conducted statistical and economic analysis for economic litigation casework involving mergers and acquisitions, intellectual property, patent infringement and damage estimates — 2010 – 2012

Editorial Activities

Referee, Health Services Research — 2018

Core Coursework

Methods: Econometrics, Microeconometrics, Statistical Inference, Methods in Biostatistics, Methods in Health Services Research, Causal Inference in Medicine & Public Health, Multilevel Statistical Models in Public Health, Analysis of Longitudinal Data, Industrial Organization, Labor Economics, Economic Evaluation, Econometric Methods for Evaluation of Health Programs, Research & Evaluation Methods in Health Policy

Theory: Microeconomic Theory (General Equilibrium Theory, Consumer Theory, Game Theory, Economics of Information), Microeconomic Models in Public Health, Mathematical Microeconomics, Health Economics, Industrial Organization, Labor Economics

Policy: Seminar in Health Policy, Introduction to the U.S. Healthcare System

Technical Skills/Expertise

Statistical Programs: Stata, SAS, R

Data Sets:

Claims Data: Truven MarketScan Database of Commercial Claims, Research Identifiable Files (RIF) and Limited Data Set (LDS) Medicare Claims

Household Surveys: National Longitudinal Survey of Youth, Panel Study of Income Dynamics, Integrated Public Use Microdata Series, Survey of Income and Program Participation, American Community Survey

Publicly Available CMS Data: Hospital Compare, Physician Compare, Public Use File on Geographic Variation, Public Use File on Physician and Other Suppliers

Other: HealthLeaders-Interstudy, American Hospital Association Annual Survey

Work Authorization: U.S. Citizen