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Essays on health insurance

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ESSAYS ON HEALTH INSURANCE

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Amanda C. Cook

In Partial Fulfillment of the

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For my dad, who inspired my love of mathematics and who filled childhood hikes with discussions of the imperfections of health insurance markets.

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ABSTRACT

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Uninsured in Maryland:

Uninsured individuals receive fewer health care services for at least three reasons: higher prices, responsibility for the entire bill, and potential provider reductions for concern of non-payment. This study isolates differences in service levels between insured and uninsured individuals that are attributed to different effective prices; the uninsured pay the bill without a contribution from an insurance company. I capitalize on Maryland's highly regulated health care system, where prices are set by the state, are uniform across all patients, and hospitals are compensated for free care and bad debt, to isolate the difference in quantity demanded by the uninsured. While the Oregon study compares Medicaid individuals and their low-income uninsured counterparts, this paper considers income variation among the uninsured, quantifies the difference in demand in an environment with uniform prices, and evaluates health outcomes in light of these reductions. A Blinder-Oaxaca decomposition estimates uninsured individuals receive 8.4% fewer services after accounting for differences in characteristics. Compared to insured patients, the uninsured are 74% as likely to be readmitted. This difference in service level and readmission rates is larger for patients residing in low-income zip codes and smaller in wealthy zip codes. This suggests that income is a substantial constraint for uninsured patients, and as this constraint relaxes, more services are demanded. For illnesses with a high risk of mortality, both services demanded and readmission rates are not statistically different for insured and uninsured individuals. Mortality rates are similar for insured and uninsured individuals living in the bottom 75% of average income by zip code. Differences in

the top 25% seem to be attributable to small numbers of uninsured individuals. While this paper analyses Maryland, it provides insight into demand for insured individuals with high-deductible plans country wide. Prior to meeting their deductible, these insured patients face similar conditions to uninsured patients in Maryland — they have access to negotiated rates but are solely paying the bill.

Hospital Insurance bargaining:
In addition to risk-sharing, U.S. health insurance companies negotiate rates for services with hospitals. The price of service can vary depending on which entity, if any, is insuring the patient. Insurers (and possibly their customers) benefit from negotiating through lower prices, while hospitals benefit through higher patient volume.

Using Massachusetts' Center for Health Information and Analysis (CHIA) data, we use hospital and insurer characteristics to estimate negotiated prices specific to hospital-insurer pairs. We investigate the relationship between two important quantities: (i) the charged amount that hospitals bill for their services, and (ii) the amount that hospitals are paid for insured patients. These numbers differ because the former is a function only of the services provided and the hospital's "chargemaster" prices, while the latter is the result of negotiation.

We find that payments for privately insured patients are on average 38% of charges when payments are made on a fee-for-service basis. However this ratio varies greatly by hospital and insurer. Compared to community hospitals without an emergency room, academic medical centers are compensated 15% more for their services, and hospitals with an emergency room are compensated 7% more than those without.

1. UNINSURED? A STUDY OF DIFFERENTIAL SERVICES, RATES OF HOSPITAL READMISSION, AND RISK OF MORTALITY IN MARYLAND.

1.1 Introduction

In most of the United States, prices for health care services are unregulated. Therefore, if two identical individuals go to the same hospital, with the same illness, at the same time, and receive the same services, but have different insurance coverage, their total payments to the hospital are likely to differ (Reinhardt (2011); White et al. (2013)). This is because insurance companies, both private and governmental, contract with hospitals to set prices for their enrollees. For uninsured patients, it is not unusual for the hospital's prices to be two to three times negotiated rates of insured (White et al., 2013).

In the American health insurance industry, insurance serves two distinct functions. The first is that of typical insurance: to reduce the financial risk to potential patients by aggregating risk. The second function of American health insurance is to negotiate rates for services received. With numerous insurance plans that have varying amounts of market power, there is substantial variability in prices for the same services, even among insured individuals. Uninsured individuals — with no bargaining power — pay far more. Because of the tremendous variation in prices for a single service, and with a great number of services provided at a hospital, one cannot look at a hospital's revenue and 'back out' the quantity of services provided in an attempt to estimate demand. Differential pricing makes it difficult to determine if having health insurance changes demand for health services. By capitalizing on an environment with equal prices for all patients — Maryland's health system — this research determines if there is a difference in the quantity of services received, the rates of readmission, and the rates of mortality for insured and uninsured individuals for inpatient hospital visits in Maryland from 2011 to 2013.

The paper is organized as follows. In Section 1.2, I review the studies of insurance status and health care demand, readmissions, and mortality that are most closely related to this work. In Section 1.3, I describe the unique approach to health care regulation in the State of Maryland and explain how data generated in this environment can shed new light on the insurance status-health market performance relationship. In Section 1.4, I document the characteristics of the uninsured population in Maryland. Section 1.5.1 presents the results of my statistical analysis, and Section 1.6 concludes.

1.2 Literature Review

1.2.1 Health Care Demand and Insurance Status

Previous studies have produced conflicting results on the relationship between insurance status and quantity of services received. Within the medical literature, White et al. (2007) investigate an emergency room's treatment of traumatic brain injury in Rochester, NY and find limited evidence that insurance status affects patient care. Bruen et al. (2013) find no differences in the average time spent with a primary care provider based on insurance status. In the economics literature, Keeler and Rolph (1988) use the RAND Health Insurance Experiment to highlight two dimensions to the insurance-demand problem: while less-insured individuals sought less care, once they did seek out care, their cost per episode was the same. While Keeler and Rolph (1988) use different co-insurance rates to estimate sensitivity to price, the plans they analyze have low out -of-pocket caps, so they don't generalize to the experience of an uninsured individual who is out of pocket for tens of thousands of dollars. These works highlight the sensitivity of results to the measure of demand one is examining: total volume per year, or services per episode of illness. This paper will focus on the latter, specifically, patients who are sufficiently ill that they are admitted overnight at a hospital for more than one night.

There are also a number of papers which suggest insurance status does affect demand. In the medical literature, Weissman and Epstein (1993) study the effect of insurance on descriptive, self-reported health outcomes and find that "source of payment has a substantial effect on the amount, location, and even quality of care received".

In the economics literature, Manning et al. (1987) use the RAND Health Insurance Experiment to calculate the demand elasticity for medical care and finds it to be non-zero. Baicker et al. (2013) capitalize on a natural experiment in Oregon where there were more individuals eligible for Medicaid than the state could fund. A lottery was implemented. This provided a control group of uninsured persons, and a treated group of insured persons with similar characteristics. They find that the treatment group had substantially and statistically significantly higher health care utilization but they did not find significant changes in visits to emergency department or hospital admissions. Here, the increased service volume is a function of subsidized (near zero) prices from having Medicaid. The uninsured, however, have no bargaining power and, since Oregon is a state without price regulation, uninsured individuals stand to pay very high amounts for service. In contrast, in this paper, by looking at an environment with price controls, and where hospitals are compensated equally for all patients, I can isolate the patient-driven reductions in demand and compare these reductions between insured and uninsured individuals. I link different levels of service to differences in long term health outcomes, namely readmissions and mortality.

1.2.2 Readmissions and Insurance Status

Due to patient confidentiality, readmissions have, historically, been difficult for researchers to study. Within the medical literature, Philbin et al. (2001) examined the relationship between income and readmission for heart failure. They found that having a low income was a positive predictor for readmission. Hasan et al. (2010) look at hospital readmission for general medical patients, and find that insurance status is a predictor of early readmission. However, in the economics literature Finkelstein et al. (2011) use the Medicaid lottery in Oregon to compare low income insured and uninsured patients and find for the very poor that there is no difference in rates of readmission between the two groups.

Gorodeski et al. (2010) study heart failure and suggests that readmissions may be preventing mortality. While historically, readmissions have been viewed as a signal of prior low quality care, Gorodeski et al. (2010) suggests that higher readmissions may be a substitute for death, and thus associated with lower mortality.

In the economics literature, Bartel et al. (2014) and Carey (2014) also look at the connection between readmissions and mortality by investigating longer hospital stays versus outpatient interventions. Zhang et al. (2013) analyze the Hospital Readmission Reduction Program— part of the Affordable Care Act(ACA)— and using a game theoretic approach show that competition between hospitals can both reduce readmissions for some hospitals and increase the number of 'worst offenders' who would rather pay a readmission penalty than reduce readmissions.

1.2.3 Mortality and Insurance Status

Much like the literature on demand, the literature on mortality and health insurance is sensitive to the type of analyses and populations examined. Looking at working-age individuals, Kronick (2009) uses a Cox proportional survival analysis, and when he controls for demographic characteristics, health status, and behaviors, finds that there is no effect of insurance coverage on mortality for uninsured individuals. In the economics literature, Finkelstein and McKnight (2008) look at the impact of the establishment of Medicare on mortality rates of the elderly and find no discernible impact of insurance on mortality. Recently, Sommers et al. (2014) capitalized on the quasi-experiment that occurred in Massachusetts when the state dramatically expanded health insurance coverage in 2006. They found no evidence of a change in mortality for a 3 to 8 percentage-point increase in insurance rates.

There are however, a number of studies which do find that lack of insurance increases the risk of mortality. Sommers et al. (2012) use a difference-in-difference strategy and capitalize on the substantial expansion of Medicaid in New York, Maine, and Arizona to quantify the effect of expanded coverage on mortality. They found that expanding coverage by 2.2 percentage points decreased deaths by 19.6 per 100,000 adults, for a reduction of 6.1%. Wilper et al. (2009) used a survival analysis of non-elderly adults and estimates that uninsured individuals are 1.4 times as likely to die as their insured counterparts.

1.2.4 My Contribution

While the above literature has explored the questions of reduced services, rates of readmission, and risk of mortality, this study links all three. More importantly, it quantifies the disparities in demand for health services based on insurance status, and investigates how those reductions in demand for uninsured patients influence health outcomes.

Typically, there are three forces which reduce the demand of uninsured individuals for medical care. First, they pay the entire bill — i.e. they have no co-insurance. Second, the uninsured face much higher prices in a unregulated environment. Third, providers may offer fewer services for fear of non-payment. Capitalizing on price regulation in Maryland, this study is the first to isolate the patient-driven reductions in quantity demanded for uninsured individuals who face the same prices as their insured counterparts. One can conceptualize this as the effect of 'paying the entire bill'. Therefore, this paper provides insight into the level of service insured individuals in an unregulated state would select if they were required to pay the whole bill, i.e. for patients before they had hit their yearly deductible. Given that high-deductible plans have blossomed in popularity under the Affordable Care Act, this paper provides insight into pre-deductible consumption.

1.3 Maryland

1.3.1 Regulatory Framework

Maryland is often excluded from national health studies because of its unique insurance structure. Maryland has a state commission, the Health Systems Cost Review Commission (HSCRC), that regulates prices in the health care industry (Murray, 2009). The first type of regulation imposes prices on each type of service (called 'rate centers'), such as minutes in surgery, days in the ICU, etc. A patient's bill then adds up quantity times price in each rate center. For the purposes of illustration, suppose that the only service a Maryland patient receives is time with a physician. If patient j spends 20 minutes with a doctor and receives a bill of 100, patient k, who spent 40 minutes would receive a bill of 200. In most states, since prices are a function of negotiated contracts, one cannot 'back out' from price an estimate of how much care was received. If one looked at two bills of \$100 and \$200 which were not from Maryland, a researcher would need to know which insurance (if any) the patients had, about the market power of the insurance companies in the specific area, etc. Even knowing these features, it would be very difficult to say with certainty the duration of service the two patients had received. In Maryland, when comparing bills from the same hospital, charges are directly tied to services received, and thus provide a good measure of the quantity of services received.

Typically, Medicare sets its own rates and reimbursement structures for all hospitals in the country. Upon occasion, a state is granted a wavier to the Medicare reimbursement system to showcase a new approach to health care reimbursement. The waivers provide the federal government a chance to determine on a small scale the strengths and drawbacks of an alternative payment arrangement. Maryland has a waiver that allows it to charge patients uniformly.

1.3.2 Health Pricing in General and Health Pricing in Maryland

In a typical, non-waiver state, the Medicare/Medicaid reimbursements rates are low. When considering Medicare nationally, in 2010 Medicare reimbursement is approximately 94.5 % of average costs and was projected to reach 93% by 2012 (MedPac, 2012). By comparison, uninsured individuals pay prices far above costs. According to the Centers for Medicare & Medicaid Services, for the 100 most common Diagnosis-Related Groups (DRGs), hospitals charged 3.77 times Medicare's reimbursement rates (Park, 2013). To compare charges to costs, then, we would observe Medicare paid 91.4 of costs in 2011 (Association(AHA), 2015). The ratio of charges to costs is then $3.77 * .914 = 3.45$. Thus, charges average 3.45 costs. Therefore in a non-regulated state, we would expect uninsured individuals to face prices that are 3.45 times costs. There is a great deal of variation from state to state in terms of how Medicaid is implemented, but to get a sense Medicaid might pay 85 percent of average costs (Association(AHA), 2015), with charges again being approximately 3.45 times costs. We think of many hospitals as having market power, and thus having the ability to set prices. However, we can think of the current governmental reimbursement system as creating a lower bound for a hospital's private insurance rates for the hospital to remain financially solvent. As a result, in a typical state, hospitals will look for substantial markups when they negotiate with private insurance companies. We can see this in Figure 1, as governmental reimbursement rates drop, private insurance rates increase (Association, 2015). Possibly, as government programs expand, the residual, private-insurance, part of the market is made up of individuals with a lower price-elasticity of demand. Hospitals are able to charge them higher prices, and insurance rates rise accordingly.This relationship between governmental and private insurance rates is one I observe in the data, and one I will explore in future work.

Market segmentation allows hospitals to price discriminate between privately-insured, government-insured, and uninsured individuals. As hospitals have an obligation to provide services to all patients in the emergency department, knowing that

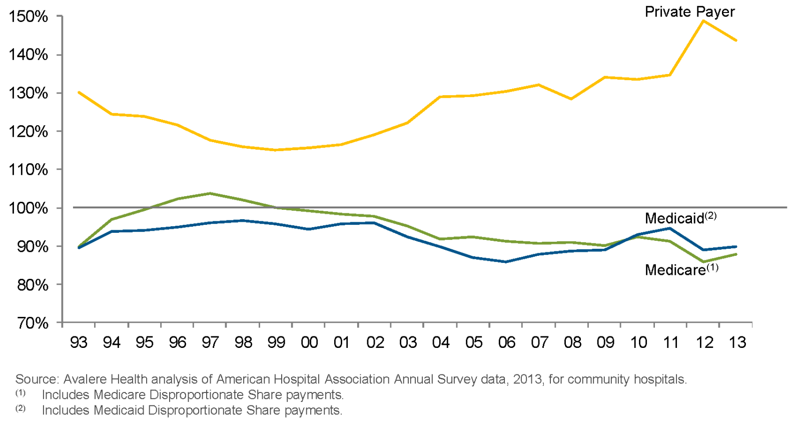

Fig. 1.1. Cost Shifting from American Hospital Association

uninsured individuals may have difficulty paying for some or all of the services provided, profit-maximizing hospitals may provide fewer services to uninsured individuals.

The payment structure in Maryland, however, eliminates both differential pricing and concerns of non-payment. In Maryland, Medicare and Medicaid pay 94 percent of **charges**, which, in 2008 were 1.22 times costs (Commission, 2008). This implies Maryland hospitals are compensated above costs by government payers ($1.22 * .94 = 1.15$), which is unusual. Compared to traditional states, hospitals in Maryland receive equal payment for uninsured, privately insured, or Medicare/Medicaid patients. Maryland hospitals have no capacity to set rates (prices).[1]

In a non-waiver state, the gap between privately-insured and government payers is large. The American Hospital Association graph in Figure 1 illustrates that currently, this gap in the reimbursement rate is close to 40%. Additionally, since individuals have no bargaining power, hospitals set prices for the uninsured at an average of

[1]For government payers there is, at most, a 6 percent difference between Medicare/ Medicaid and non-Medicare/Medicaid patients. This doesn't create an incentive to provide fewer services to government payers, however, because when a hospital's base rate is established, the fraction of government patients is considered and built into the base rate. If a hospital serves more government payers, its base rate increases the next year, if it serves fewer, it declines. As such, a hospital has no financial incentive to provide a differential service mix to different payers. Details of how the base rate is established can be found in Appendix A

3.45 times costs, or nearly 2.5 times the rate for insured patients. Since rate-setting is done at the state level in Maryland, all patients pay the same rates for services, instead of the typical, less transparent system where some patients pay dramatically more than others. One of the major contributions of this work is that by capitalizing on the lack of incentives for hospitals to provide differential service to different payer classes, I can quantify the patient-driven reductions in services for the uninsured and the resulting health outcomes of those receiving reduced services.

1.3.3 Free Care and Bad Debt

One additional important feature of the rate-setting system in Maryland is the Uncompensated Care pool, which encompasses both free care and bad debts. When a hospital's base rates are established, the average amount of free care and bad debt provision—a little under 7%—is built into each hospital's rates (HSCRC, 2013). At the end of each year, hospitals reconcile their uncompensated care with the state average. Hospitals which provided less uncompensated care than average pay into the free care and bad debt pool. Hospitals which provided more such services than average withdraw from the free care pool (HSCRC, 2013). In this way, hospitals do not have an incentive to provide fewer services to uninsured individuals for fear that they will not receive compensation for their services. From the point of view of the hospital, the uncertainty over payment has been resolved and there is no financial reason to provide a differential mix of services based on insurance status.

1.3.4 APRDRG: an illness severity measure

Patients are heterogeneous in the types and severity of their illnesses. As a result, when comparing demand for services across patient classes, we need to have a measure of 'how sick' each patient is. 3M Health Information Systems developed a classification system, which categorizes each patient into an All-Patient-Refined-Diagnosis-Related-Group (APRDRG). This classification of patients is defined in two dimensions. A patient is categorized into a listing of diagnosis or procedure. This initial categorization is the root Diagnosis Related Group (DRG). There are 314 root DRGs in Maryland. Once the root DRG has been established, secondary diagnosis and other factors (obesity, other illnesses) are then considered and the patient is assigned a severity class (1-4). For severity, the 1-4 scale runs from low to high. The combination of the root DRG and the level of severity form the APRDRG (Systems, 2013). The APRDRG system is used in 30 states for payment or reporting. APRDRGs are given weights according to their relative difficulty to treat. I will use charges/APRDRG weight as a normalized measure of quantity of medical services received and denote it by q_N.

1.3.5 CMAD: a hospital volume of services

To measure the total volume of services a hospital provides, looking at charges–per–patient would not be meaningful because of the heterogeneity in illness and severity. To deal with this issue, we use a standardized measure of the number of patients, adjusted for type and severity of illness, treated at each hospital. This variable, the Case Mix Adjusted Discharge (CMAD), is developed by the HSCRC. The construction of the CMAD is explained in Appendix B. Here I simply note that it can be used as a measure of quantity of output that is normalized to be comparable across hospitals.

1.3.6 Allowances

In Maryland, hospitals get an allowance for services per standard patient (APRDRG weight of 1). This allowance is multiplied by the patient's APRDRG weight to adjust for illness heterogeneity. Therefore, if in a particular year a hospital sees more patients or more ill patients, their allowance reflects those changes. This allowance puts financial pressure on the hospital to provide all necessary services, but not to 'over serve' patients. In aggregate, a hospital is penalized if it charges above its allowance for the year. Typically a hospital is given 2% leeway, where if it is within 2% of total charges, the hospital pays back the excess charges plus interest in the subsequent year. For violations above 2%, it pays a penalty proportional to the overage.

1.3.7 Readmissions

In 2011, the HSCRC established a new policy to motivate hospitals to reduce levels of readmitted patients. The idea was to create a clear financial incentive to coordinate care so that patients would receive higher quality care initially and thereby reduce readmissions. Prior to 2011, hospitals did not have a strong incentive to reduce readmissions, as each time a patient returned to the hospital, they would have a new APRDRG and add to the aggregate allowance for the hospital. In 2011, under the Admission-Readmission Revenue (ARR) policy, for each readmission there was no new allowance for treatment. Additionally, hospitals with high rates of readmission got a reduced allowance per APRDRG the subsequent year, while hospitals that reduced readmission got an increase to their allowance.

1.4 Who is Uninsured in Maryland?

1.4.1 Financially constrained

There are two primary reasons why individuals do not have health insurance: an income constraint or a belief they don't need insurance because they are young and invincible.[2] Insurance is costly, and prior to the health insurance exchanges set

[2] The second reason some individuals may chose to be uninsured is because they believe their private health signal is very good and they don't think they will get sick or injured, or that if they do, it will be cheaper to pay out of pocket than to have insurance. One might be concerned that individuals with good private health information may be healthier than average. However, in the data, I am only looking at individuals who needed to stay at a hospital overnight. Even if one had a history of good health, for there to be a presumption that there is a difference between the insured and uninsured, one would need to believe that after the bad health shock I observe, the numerous categories for classifying severity, risk of mortality, and other patient characteristics were insufficient controls. Put

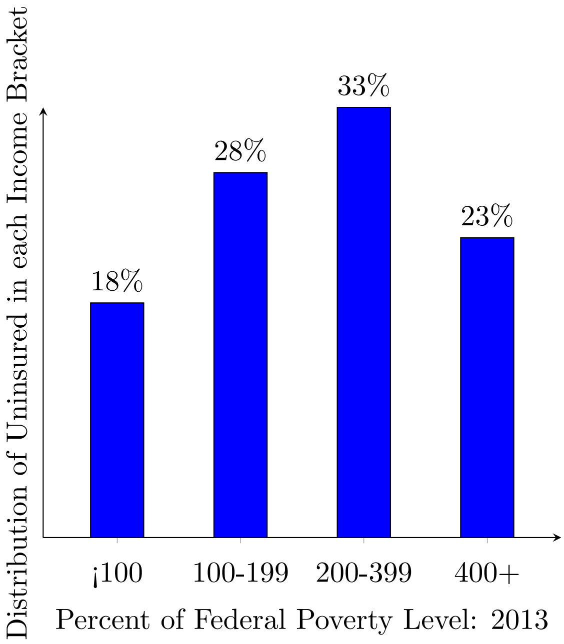

Fig. 1.2. Distribution of all Uninsured in MD by Federal Poverty Level

up by the Affordable Care Act, individuals who were not offered insurance as part of an employment package faced relatively high prices on the private market. The logic behind high individual prices is that if an individual is seeking out individual insurance that they are either very risk averse or have a bad private health signal. Poor qualified individuals are eligible for Medicaid, but many low-income uninsured individuals don't qualify or make more than the Medicaid threshold.[3] The histogram in Figure 2 details who is uninsured in Maryland as a fraction of the Federal Poverty level. Data is from the Kaiser Family Foundation (2013). In general, the uninsured in Maryland are low-income individuals. Even in the top bracket, at 400+ percent of the poverty level, families may be unable to afford insurance. In 2013, 400 percent of

another way, even if you have been very healthy, if you get acutely ill, would you be 'less sick' than someone else who had similar characteristics?
I will run a number of specifications of my demand analysis to control for different patient characteristics an potential selection effects. While 'young invincibles' are a documented phenomena (Smith, 2014), the remainder of this analysis will focus on an income constraint as being the driving motivation for remaining uninsured.

[3]To be eligible for Medicaid in Maryland, one must be over 65 years of age, disabled, blind, under 21, pregnant, or a parent of an unmarried child under 21.

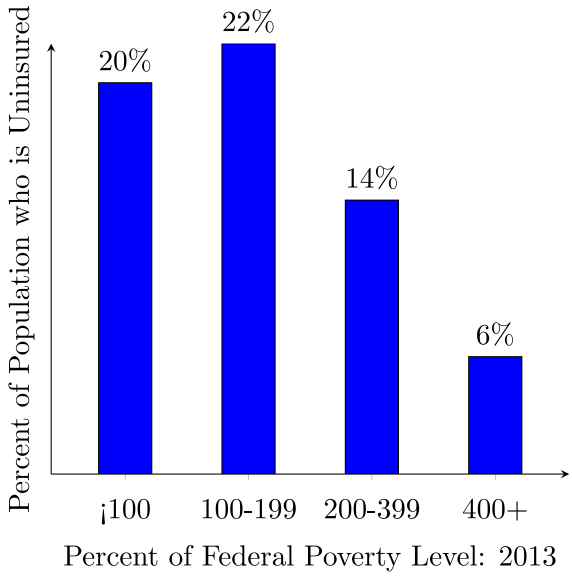

Fig. 1.3. Percent of Population Uninsured in MD by Federal Poverty Level

the poverty line would mean a family of 3 would make about \$75,000. Prior to ACA, premiums for a moderate policy for such a family could cost \$750/month. \$9,000 a year would constitute 12% of such a family's pre-tax income. That may not be affordable.

While Figure 2 looks at income distributions of those who are uninsured, it is also informative to look at who is uninsured compared to the total population of Maryland.

Data for Figure 3 is from the Kaiser Family Foundation (2013). We see in Figure 3 that more than 1 in 5 households that make less than 200 percent of the poverty line are uninsured. At higher levels of family income, the probability of being uninsured declines. Given that in the population, only 6% of individuals who make more than 4 times the poverty limit are uninsured, this data seems to support the story of an income constraint. In the general population, most families or individuals who are above 4 times the poverty line choose to be insured.

1.4.2 Demand for Health Care in Maryland: Description

I think of the level of services received by a patient as the outcome of a bargaining process involving physician, hospital, and patient.[4] Descriptive statics for the Maryland health care market confirm that uninsured individuals receive lower levels of care.

One of the reasons people buy health insurance is that it reduces risk. Premium payments each month lead to lower payments if services are required. After any deductible has been met, individuals with insurance pay less out of pocket for services than uninsured individuals.

As argued above, individuals who chose not to be insured do so either because of a financial constraint or because they anticipate a low probability that they will need health care services. Therefore, when uninsured individuals have a bad health shock and require overnight hospitalization, they are likely to be more sensitive to prices than insured individuals, since they pay the full price of services. They should thus demand fewer services, all else equal.[5]

1.5 Empirical Results

1.5.1 Identification

I report below the results of econometric analyses of normalized level of services received, readmission rates, and mortality rates for patients under age 65. My strategy

[4] For an explicit model of the determination of the equilibrium level of services received, see Cook and Martin (2015).

[5] In 2005, Maryland created legislation that required hospitals to provide financial assistance for low income individuals (HSCRC, 2015). There is a voluntary guideline that hospitals should, at a minimum, provide free care to those below 150% of the Federal Poverty Line (FPL). In 2009, 15 hospitals used this standard and 23 used a higher level of income, ranging from 175% to 300% of the FPL, with 200% being the mode (HSCRC, 2009). If patients are aware of these aid programs, we might expect individuals living in poorer zip codes to be less price sensitive, since they know they will not have to pay their bills. We then might expect low-income uninsured individuals to receive more care, and high-income uninsured individuals to receive less care. However, while these financial aid programs exist, finding information on them outside of Commission documentation is quite challenging and it seems unlikely they were common knowledge. While the data will speak to this, my working assumption is that uninsured individuals face a 'higher' price than the insured.

for identification is as follows. I am conceptualizing this as a two-period model. In this first period, individuals choose if they would like to purchase insurance, either through their employer or non-group insurance on the private market. They can also choose to remain uninsured.

In the second period, after the insurance decision has been made, some individuals experience a bad health shock and are admitted to the hospital. Thus, at the time of admission, insurance status is exogenous.

One might have concerns that there are covariates that are correlated with the choice to purchase insurance in the first period. The response to this concern is two fold. First, there are a great number of demographic controls—sex, race, ethnicity, marital status, age category, zip code of residence—which are explicitly controlled for in my empirical work. So while young, white, married men are more likely to be uninsured, each of those characteristics is used as a control in my regressions, and therefore the effect of being uninsured is disentangled from characteristics.

Second, one might be concerned about a patient having private health information and that influencing their decision to purchase insurance. For example, if a patient is sicker, they may opt to purchase insurance. While this certainly occurs it is not a threat to identification for two reasons. My measure of services examines normalized charges. Normalized charges represent the number of services a patient would receive if they had an 'average' illness. It is scaled by 'illness level'(APRDRG weight). Therefore, sicker patients—as determined by their APRDRG weight— have their charges scaled down, and less ill patients have their charges scaled up, so I can compare average patients with a APRDRG weight of 1.

The second reason private information is not a threat to identification is that a patient's knowledge of potential illness might increase the probability that they would seek out care, but given that my data is conditional on admission, I am only looking at patients who were sick enough to seek out treatment. The services provided by the hospital are a function of the current bad health shock and the associated diagnoses. They are uncorrelated with prior beliefs about health.

Additionally, to address the concern that uninsured individual may be less likely to go to the hospital when ill, I exclude patients who are only admitted for one night. Thus excluding 'marginal' admissions. However, even if I did not exclude these patients staying for only one night, there would not be a threat to identification. My evaluation of services looks at charges normalized by level of illness. As such, very ill patients receive proportionally more services. While one still may be concerned that less ill uninsured patients select not to go to the hospital, this would not bias my results. The reason for this is that the level of illness(APRDRG weight) is not economically predictive of normalized charges, $q_N = \frac{total\ chg}{APRDRGweight}$. [6]It is not the case that less sick patients receive fewer *normalized* charges, so even if the 'marginal' uninsured selected not to go to the hospital, and removing the patients who stay for one night did not seem like a sufficient adjustment, patient illness level is not predictive of normalized charges. So there is not a threat to identification from selection of uninsured not to go to the hospital.

1.5.2 Level of Services

Regression

To determine if payer class has an effect on service volume, I run a regression on total charges per APRDRG weight with control variables would help correct for observable characteristics. I use the following specification:

$$q_N = \beta_0 + P\beta_1 + payer\ class\beta_2 + H\beta_3 + year\beta_4 + \epsilon, \tag{1.1}$$

where $q_N = \frac{total\ chg}{APRDRGweight}$, P is a vector of patient characteristics including sex, race, ethnicity, martial status, average income by zip code, and age category and H is a

[6]APRDRG weight predicts an increase of about 25 dollars of increased charges for every one unit increase of APRDRG weight. The mean and standard deviation of APRDRG weight are both about 1, so a one unit change in weight is very substantial. The $25 increase in charges is econometricaly significant, but not economically so.

vector of hospital variables including hospital dummies, severity, mortality. Results are found in Table 1.1.

Table 1.1.
Charges/ Weight by Payer Class

	(1)	
	Charges per weight (CPW)	
Medicare	-107.1**	(34.01)
Blue Cross	-609.2***	(39.62)
Non-Group Ins.	-629.7***	(35.42)
Workmen's Comp	-173.5	(108.4)
Uninsured	-1561.3***	(40.84)
Ave Income	0.00370***	(0.000495)
Black	122.9***	(17.33)
Married	-242.1***	(18.95)
Separated	-52.41	(49.27)
Divorced	94.29**	(29.27)
Widow/er	-122.0***	(27.51)
Observations	1805121	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

There is relatively little variation among insured individuals. Looking at column 1, charges per weight, we observe that Medicaid patients, the comparison group, use more services for adjusted illness than any other group—all the coefficients on payer classes are negative. Blue Cross and non-group insurance both use about $600 fewer services than Medicaid patients, which given average charges per weight of $13,075 is a 4.6% reduction in services. The reduction in services for uninsured individuals—$1561, is 2.6 times bigger than of Blue Cross and non-group insurance and is estimated as approximately 12% reduction in services. The type of insurance is far less important to predict services per weight than whether a patient has any insurance or no insurance. As such, the remainder of this paper will combine all insured individuals —both government payers and private— to create an 'insured' dummy variable.

In the United States, if one works for 10 years, s/he becomes eligible for Medicare. As a result, individuals who are over 65 and remain uninsured likely are different from their insured counterparts. The remainder of this paper will focus on individuals under 65.

Blinder-Oaxaca Decomposition for Patients Under 65 Years of Age

Patients who are uninsured may be different from those who are insured. Statistically, the uninsured are working, male, in a family, younger, and earn less income than their insured counterparts. In order to explicitly separate the effects of differences in characteristics and differences in insurance status, I employ a Blinder Oaxaca Decomposition to determine the effect of being uninsured on services received per APRDRG weight. I have grouped all insured payer classes together to create an insured/uninsured dummy variable. The specification is then

$$q_N = \beta_0 + P\beta_1 + payer\ class\beta_2 + H\beta_3 + year\beta_4 + \epsilon, \tag{1.2}$$

where P is a vector of patient characteristics including sex, race, ethnicity, martial status, average income by zip code, average income interacted with insurance, age category and H is a vector of hospital variables including a hospital dummy, severity, mortality.

To interpret the results in Table 1.2, note that uninsured individuals (Prediction_1) receive an average q_N of \$11,699 while insured individuals receive \$13188.1. The difference in the average charges per weight is \$1489.2. We decompose this difference into three components: the difference in observables, the difference in coefficients, and an interaction term, which recognizes that differences in endowments and coefficients exist simultaneously.

From the Blinder Oaxaca decomposition, we can see that, on average, uninsured individuals receive about 11.3% fewer services than their insured counterparts. The

Table 1.2.
Blinder Oaxaca Demposition by Insurance for Under 65

	(1)	
	chg_per_weight	
Differential		
Prediction_1	11699.0***	(28.65)
Prediction_2	13188.1***	(10.80)
Difference	-1489.2***	(30.48)
Decomposition		
Endowments	-247.1***	(15.04)
Coefficients	-1103.9***	(59.59)
Interaction	-138.1**	(51.22)
Observations	1172395	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Blinder-Oaxaca decomposition breaks down this difference into three components. The first is the 'Endowment' effect. It measures the difference in predictors between the insured and uninsured groups. Therefore, about 2 percentage points[7] of the difference ($\frac{\$-274}{13188.1}$) can be attributed to uninsured individuals having 'healthier' characteristics. While this suggests that uninsured and insured individuals have slightly different characteristics, these differences in observables are a small part of the overall difference between the two groups.

The differences in coefficients, however, is much larger in magnitude. The 'Coefficients' term measures the expected change in treatment if an insured individual had coefficients of an uninsured individual. About 8.4 percentage points[8] of the difference ($\frac{-\$1103.94}{13188.1}$) in service levels between insured and uninsured individuals is attributed to coefficients. We can think of this as the effect in treatment of being uninsured.[9]

Finally, the interaction term captures the simultaneous differences between endowments and coefficients. It represents 1% ($\frac{-138}{131881.1}$) of the differences in treatment levels.

Blinder Oaxaca: Dummy for Illnesses with High and Low Risk of Mortality

To better understand differences in demand, I now turn my attention to illnesses which have a high risk of mortality. Uninsured individuals are much more likely than their insured counterparts to die of a handful of diseases. These include: tracheostomy, liver disease, stroke, respiratory failure, pulmonary embolism, lung and colon cancer, heart attacks and pneumonia. To determine what effect these diseases have on different rates of mortality, I created a dummy variable for the 13 APRDRGs. One might imagine that if faced with a high risk of death, that a patient would be less price sensitive than if they had a low risk of mortality. As such, I expect demand for

[7] or 16.6%

[8] or about 75%

[9] Propensity score matching was also employed. The effect was about a 5.1% reduction in services for the uninsured.

services to be similar for insured and uninsured individuals when they have illnesses which have a high risk of mortality and larger differences in services for diseases with low mortality. I run the following specification twice, once for high risk illnesses once for low risk illnesses.

$$q_N = \beta_0 + P\beta_1 + payer\ class\beta_2 + H\beta_3 + year\beta_4 + \epsilon \tag{1.3}$$

P is a vector of patient characteristics including sex, race, ethnicity, martial status, average income by zip code, average income interacted with insurance, age category and H is a vector of hospital variables including a hospital dummy, severity, mortality. Results can be seen in Table 1.3

Table 1.3.
Blinder Oaxaca Demposition by Insurance with High and Low Risk Illnesses

	(1) high risk		(2) low risk	
Differential				
Prediction_1	13353.3***	(174.3)	11618.7***	(28.69)
Prediction_2	14131.0***	(61.55)	13154.3***	(10.88)
Difference	-777.7***	(184.1)	-1535.6***	(30.55)
Decomposition				
Endowments	-783.1***	(90.51)	-238.6***	(15.29)
Coefficients	320.6	(435.0)	-1135.9***	(60.45)
Interaction	-315.2	(388.7)	-161.1**	(52.03)
Observations	41674		1130721	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 1.3, column 1 shows the coefficients for the Blinder Oaxaca decomposition for individuals who have a diagnosis related group with a high risk of mortality. We see that insured individuals (Prediction 2) receive $14,131 of charges per average patient. Uninsured individuals (Prediction 1), receive $777.70 fewer services per average patient. However, this difference is attributable to differences in endowments, i.e. the insured have 'worse' health characteristics and is not attributable to insurance status. What this suggests is that when faced with death, there is no difference in service provision based on insurance status.

This is not the case in column 2, which show coefficients for patients who have a low risk of mortality. Here we see insured patients (Prediction 2) receive \$1535.6 more services than uninsured patients, but for these low risk DRGs the vast majority of the difference \$1136 is attributable to being uninsured. The \$1136 represents the reduction in services an insured person would receive if his insurance status were changed to uninsured.

Blinder Oaxaca by Average Income Quantiles

To assess if income is the driving force for differences in patient-driven differences in services, I run a separate Blinder-Oaxaca Decomposition for each of the eight average income quantiles to determine if patient-driven demand varies by the average income of their residential zip code.

$$q_N = \beta_0 + P\beta_1 + payer\ class\beta_2 + H\beta_3 + year\beta_4 + \epsilon \tag{1.4}$$

P is a vector of patient characteristics including sex, race, ethnicity, martial status, average income by zip code, average income interacted with insurance, age category and H is a vector of hospital variables including a hospital dummy, severity, mortality.

This regression was run eight separate times, each time taking data from one of the eight average income quantiles. Results for quantiles 1 through 4 were recorded in Table 1.4 and results for quantiles 5 through 8 were recorded in Table 1.5.

As one might expect, as income rises, the gap between Insured (Prediction˙2) and Uninsured (Prediction 1) decreases dramatically as we look from Quantile 1 (column 1 in Table 1.5) to Quantile 8 (Column 4 in Table 1.6). In Quantile 1, individuals who live in the bottom $\frac{1}{8}$ of average income by zip code receive \$2619.9 fewer services than their insured counterparts. In Quantile 8, individuals who live in the top $\frac{1}{8}$ of average income by zip code, that gap drops to \$851.9 fewer services than their

Table 1.4.
Blinder Oaxaca Demposition by Insurance and Ave. Income

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	11937.8***	(63.95)	11840.6***	(72.31)	11742.3***	(74.19)	11684.5***	(78.01)
Prediction_2	14557.7***	(32.12)	13669.0***	(30.05)	13593.4***	(31.87)	13130.8***	(29.04)
Difference	-2619.9***	(71.18)	-1828.3***	(77.99)	-1851.1***	(80.29)	-1446.3***	(82.91)
Decomposition								
Endowments	-856.4***	(39.64)	-507.2***	(39.75)	-238.3***	(42.28)	-306.0***	(41.41)
Coefficients	-2001.9***	(138.7)	-1142.6***	(160.6)	-1468.6***	(151.8)	-969.3***	(160.0)
Interaction	238.4	(122.0)	-178.6	(140.8)	-144.3	(127.7)	-171.0	(137.8)
Observations	164434		155520		140085		152137	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.5.
Blinder Oaxaca Demposition by Insurance and Ave. Income

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	11554.3***	(85.42)	11575.7***	(93.06)	11474.0***	(93.84)	11520.9***	(100.5)
Prediction_2	12685.7***	(29.11)	12612.0***	(28.58)	12673.5***	(28.72)	12372.8***	(29.75)
Difference	-1131.4***	(89.93)	-1036.2***	(97.12)	-1199.5***	(97.94)	-851.9***	(104.6)
Decomposition								
Endowments	-181.4***	(39.76)	-172.9***	(46.79)	-216.0***	(45.00)	-249.5***	(48.18)
Coefficients	-968.6***	(163.2)	-774.9***	(188.1)	-392.3*	(198.0)	-833.6***	(153.6)
Interaction	18.62	(140.0)	-88.43	(167.2)	-591.2***	(178.7)	231.2	(133.8)
Observations	135367		151842		136466		136544	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

insured counterparts. These numbers account for both differences in endowments and differences associated with being uninsured. The 'Coefficients' term tells us how many fewer services an insured person would receive if they were uninsured. We see significant and substantial changes in the effect of being uninsured as one moves up the income quantiles. For the individuals in quantile 1, an insured person who 'switched' to being uninsured would receive $2002 fewer services. In the top quantile, this difference drops to $834 fewer services per average patient. This suggests that income is playing a significant role in patients' demand for services. Patients with lower incomes are more sensitive to price, and as a result, uninsured patients in the bottom quantile of average income demand a smaller quantity of services than both their wealthier uninsured and low-income insured counterparts. To further explore this question of an income constraint, I now examine an interaction of the high and low risk of mortality dummy with income quantiles.

Blinder Oaxaca by Average Income Quantiles with High/Low Risk Interactions

Next, I examine how average income by zip code and high and low risk of mortality work together. Using the same specification

$$q_N = \beta_0 + P\beta_1 + payer\ class\beta_2 + H\beta_3 + year\beta_4 + \epsilon, \tag{1.5}$$

I cut the data both by income quantile and high/ low risk. As such there are 16 separate regressions. Results for the low risk diagnoses and all income quantiles can be found in Tables 6 & 7. High risk across all quantiles is in Tables 8 & 9.

For individuals with diagnoses with low risk of mortality, we observe that the effect of being uninsured (Coefficients) varies by income and is largest for individuals who live in the bottom quantile of average income by zip code at just over $2050 fewer dollars of treatment. The amount of service reduction for uninsured patients is fairly

Table 1.6.
Blinder Oaxaca Demposition with Ave. Income(1-4) and Low Risk

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	11884.8***	(64.47)	11792.4***	(73.12)	11685.6***	(74.80)	11577.8***	(77.32)
Prediction_2	14541.9***	(32.66)	13654.4***	(30.54)	13554.6***	(32.09)	13101.6***	(29.21)
Difference	-2657.1***	(71.87)	-1862.0***	(78.93)	-1869.0***	(80.95)	-1523.8***	(82.35)
Decomposition								
Endowments	-839.9***	(40.66)	-489.6***	(40.68)	-219.2***	(43.07)	-314.4***	(42.15)
Coefficients	-2054.2***	(139.7)	-1186.0***	(161.8)	-1444.9***	(155.7)	-915.2***	(159.8)
Interaction	237.0	(123.3)	-186.4	(141.4)	-204.9	(131.8)	-294.3*	(139.6)
Observations	158190		149328		134923		146563	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7.
Blinder Oaxaca Demposition with Ave. Income(5-8) and Low Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	11445.7***	(85.79)	11483.3***	(91.90)	11396.8***	(95.13)	11378.8***	(99.43)
Prediction_2	12644.1***	(29.36)	12574.7***	(28.49)	12640.7***	(28.83)	12323.2***	(29.71)
Difference	-1198.4***	(90.39)	-1091.4***	(96.00)	-1243.9***	(99.21)	-944.3***	(103.6)
Decomposition								
Endowments	-191.5***	(40.37)	-182.4***	(47.30)	-228.7***	(45.14)	-281.0***	(47.27)
Coefficients	-991.2***	(170.0)	-969.2***	(153.2)	-411.9*	(206.3)	-912.5***	(157.3)
Interaction	-15.75	(146.2)	60.27	(136.0)	-603.3**	(187.7)	249.2	(139.3)
Observations	130593		147253		131791		132080	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

constant for quantiles 4 through 8 at about \$900.[10] Again, I observe that when faced with uniform prices, patients living in low income zip codes demand fewer services.

Table 1.8.
Blinder Oaxaca Demposition with Ave. Income(1-4) and High Risk

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	13334.1***	(391.7)	12731.2***	(386.6)	12999.6***	(397.5)	13888.6***	(527.3)
Prediction_2	14955.9***	(142.8)	14029.6***	(132.1)	14626.6***	(183.4)	13917.0***	(177.2)
Difference	-1621.8***	(416.6)	-1298.4**	(408.2)	-1627.0***	(435.0)	-28.42	(551.0)
Decomposition								
Endowments	-1614.6***	(174.0)	-1186.9***	(162.6)	-1138.7***	(256.3)	-474.7	(270.0)
Coefficients	-36.33	(1433.2)	-72.29	(596.4)	-906.5	(584.1)	987.1*	(437.0)
Interaction	29.21	(1338.7)	-39.19	(589.6)	418.2	(503.9)	-540.9	(398.9)
Observations	6244		6192		5162		5574	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9.
Blinder Oaxaca Demposition with Ave. Income(5-8) and High Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	13704.1***	(462.6)	13423.2***	(653.8)	12817.9***	(446.3)	14229.6***	(657.8)
Prediction_2	13859.7***	(164.2)	13856.9***	(231.0)	13638.0***	(172.5)	13893.8***	(196.1)
Difference	-155.6	(490.7)	-433.7	(688.5)	-820.1	(477.4)	335.8	(684.6)
Decomposition								
Endowments	-228.3	(247.3)	-330.6	(432.9)	-204.8	(312.6)	-78.11	(415.0)
Coefficients	78.29	(529.3)	2719.4	(1787.4)	-409.8	(513.4)	229.8	(559.2)
Interaction	-5.539	(473.9)	-2822.4	(1616.5)	-205.5	(366.0)	184.1	(561.9)
Observations	4774		4589		4675		4464	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For individuals with a high risk of mortality, for all but one quantile, there is no reduction in services attributable to insurance status. For quantile 4, the aggregate difference for insured and uninsured is small, and the effect of being uninsured is to receive more services.[11] This suggests that when faced with death, patients elect

[10]Notice quantile 7 has a smaller reduction (-411.9) but has a large standard error (206.3) and has a large interactions term, meaning a fair amount of the variation in charges couldn't be disentangled between endowments and insurance status.

[11]This result is no longer significant if two high charge-per-weight uninsured outliers are removed. There are 573 uninsured individuals in quantile 4 of income with illnesses that put them at a high risk of mortality.

to receive the same amount of service, regardless of insurance status. Assuming that Maryland hospitals are optimally providing both the right type and quantity of service, an assumption that seems reasonable given that hospitals have financial pressure not to over serve and also prevent readmissions, this suggests all patients receive optimal service provision levels when faced with death.[12]

1.5.3 Readmission

Readmission Rates for Patients Under 65 Years of Age

Blinder-Oaxaca estimates uninsured patients receive 8% fewer services than their insured counterparts, and that these differences are magnified for a few categories of patients: low income, low-risk of mortality, and black patients (or any combination of those groups). The next two sections investigate the link between uninsured patients receiving fewer services and worse health outcomes in the form of higher rates of readmission or higher rates of mortality.

In Maryland, readmission is defined as a patient returning to the hospital within thirty days of an initial admission. I am interested in the link between a reduction in services for uninsured patients and an increase in subsequent readmission rates to the hospital. In order to get at this, I look at initial patient records and determine if there was a subsequent readmission. For visits where there was a subsequent visit, the initial visit was identified as a 'readmit later'. This is the variable of interest in this section.[13]

[12]I have also run Blinder Oaxaca with Average Income, High/Low Risk, and a Black White Race Dummy. Results follow a similar pattern to the results with high/low risk and income quantiles, however, the differences in service level is between insured and uninsured individuals is larger for Blacks than Whites. Full regressions results can be found in Appendix E and F.

[13]For robustness, the regressions for readmissions were also run using the readmission—as opposed to the first visit which had a subsequent readmission— results are nearly identical. However, by looking only at initial admissions, every visit has the opportunity to become a readmission.

Below there is the first specification for the logistic regression on readmission.

$$\begin{aligned} logit(readmission) = \beta_0 + uninsured\beta_{uninsur.} + P\beta_p \\ + H\beta_{hosp} + year\beta_{yr} + \epsilon \end{aligned} \tag{1.6}$$

Here P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality.

Results are reported in Table 1.10 as an odds ratio.

Table 1.10.
Logit: Readmission of Uninsured Dummy with Average Income –Under 65

	(1)	
	readmitlater	
readmitlater		
uninsured==1	0.719***	(0.0123)
Ave Income	1.000	(0.000000323)
Black	0.963***	(0.0110)
Married	0.888***	(0.0104)
Separated	1.114***	(0.0286)
Divorced	1.111***	(0.0189)
Widow/er	1.149***	(0.0308)
Observations	1089602	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 1.10, we see uninsured individuals are 71.9% as likely to be readmitted as their insured counterparts. We see that black patients are 3.7% percent less likely to be readmitted than whites, and that married individuals are readmitted a bit under 10% less than single patients, while separated, divorced, or widowed patients are readmitted over 10% more than single patients. In the next specification, we will examine if readmission rates vary with diagnoses with high and low risk of mortality.

Readmissions with Uninsured and High and Low Risk of Mortality Dummy

We saw in section 5.1.3 that uninsured individuals who faced a high risk of death received the same level of service as insured patients, whereas uninsured individuals who had a low risk of mortality received fewer services than their insured counterparts. In this section, we investigate if there is a difference in readmission rates for these same groups of patients using the following specification.

$$\begin{aligned} logit(readmission) &= \beta_0 + uninsured * high\ risk\beta_{unhig.} \\ +uninsured * low\ risk\beta_{unlow.} &+ insured * high\ risk\beta_{inhigh.} \\ &+ P\beta_p + H\beta_{hosp} + year\beta_{yr} + \epsilon \end{aligned} \tag{1.7}$$

Where P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality. Results can be found in Table 1.11.

Table 1.11.
Logit: Readmission of Uninsured Dummy with High/Low Risk Interactions

	(1) readmitlater	
readmitlater		
Insured_highrisk	1.260	(0.261)
Uninsured_lowrisk	0.717***	(0.0126)
Uninsured_highrisk	0.941	(0.203)
Ave Income	1.000	(0.000000323)
Observations	1089602	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 1.11, the comparison group for the odds ratios found is insured low-risk individuals. We can see that insured high-risk individuals and insured low-risk individuals have the same rates of readmission. When faced with death, uninsured individuals return to the hospital and receive equivalent services.

However, uninsured low-risk individuals are much less likely to be readmitted than insured low risk individuals. Recall from section 5.1.3, that uninsured low-risk individuals received 11.7% fewer services than their insured counterparts and nearly 75% of that difference is not attributable to characteristics (8.6%). This suggests that the reduction in services that affects uninsured low-risk individuals does not translate into a bad health outcome, namely higher rates of readmission. This reduction in readmissions for low-risk illnesses is consistent with a patient-driven reduction in demand for services among the uninsured. Uninsured individuals, facing responsibility for the entire bill, demand less service and that includes returning to the hospital.

Readmission Rates by Income Quantiles

In the next specification, I allow the effect of my income proxy, average income by zip code, to assume a nonlinear form by diving average income into 8 quantiles.

$$\begin{aligned} logit(readmission) = \beta_0 + Unins. * Inc.\ Quantiles\beta_{uninc.} \\ + P\beta_p + H\beta_{hosp} + year\beta_{yr} + \epsilon \end{aligned} \tag{1.8}$$

Here P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality. Results can be found in Table 1.12

As we see in Table 1.12, the uninsured individuals are less likely than their insured counterparts to be readmitted to the hospital. Uninsured individuals living in the poorest quantile, are 62.5% as likely to be readmitted as their insured counterparts.[14] A discussion of insured and uninsured individuals is facilitated by coefficient plots.

[14]Also notice that readmission rates vary by marital status. Married individuals are 2% less likely than single individuals to be readmitted. Separated individuals are 13% more likely than single individuals to be readmitted. One might attribute this to worse health as the result of the stress of separation, although divorced individuals are about 11% more likely to be readmitted than single patients.

Table 1.12.
Logit: Readmission of Insured Dummy with Income Interactions –Under 65

	(1)	
	readmitlater	
readmitlater		
uninsured==1	0.625***	(0.0248)
Insured_income2	0.979	(0.0175)
Insured_income3	0.982	(0.0187)
Insured_income4	1.020	(0.0204)
Insured_income5	0.988	(0.0203)
Insured_income6	0.960*	(0.0197)
Insured_income7	0.975	(0.0206)
Insured_income8	0.936**	(0.0207)
Uninsured_income2	1.119*	(0.0642)
Uninsured_income3	1.052	(0.0620)
Uninsured_income4	1.137*	(0.0670)
Uninsured_income5	1.309***	(0.0788)
Uninsured_income6	1.265***	(0.0810)
Uninsured_income7	1.220**	(0.0780)
Uninsured_income8	1.344***	(0.0894)
Observations	1089602	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

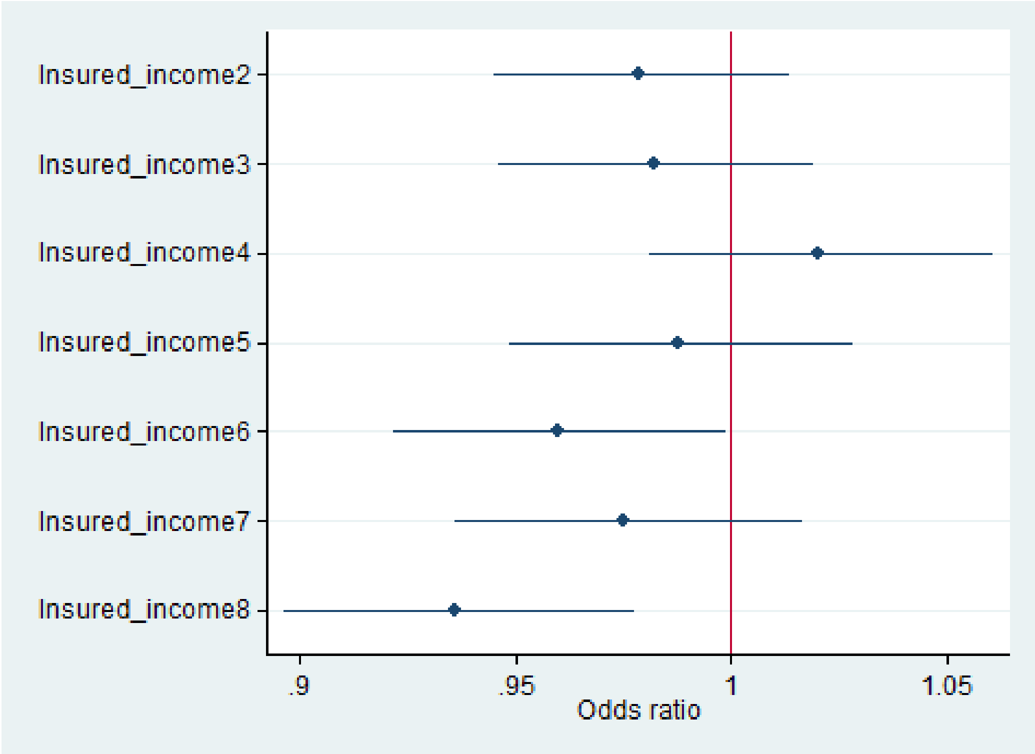

Fig. 1.4. Readmission Rates for Insured Individuals Under 65

In Figure 4, the basis for comparison is insured individuals who live in the poorest (1st quantile) zip codes. Observe that there is almost no variation in readmission rates for insured individuals in all quantiles of average income by zip code. The exception is the top income quantile, which has a statistically significant lower rate of readmission, at 6.4% less likely. This effect is reasonably small in magnitude and one might imagine the decline in readmission to be attributed to a wealth effect. Individuals who are quite wealthy may hire home care and recover better from initial admissions, may be better able to take time off from work to recover from their initial admission, and may have access to better food, additional treatments, etc.

When we compare these readmission rates to levels of service, we do not find a similar pattern. Insured individuals in the highest quantile do not receive more services. For insured individuals, there does not seem to be a link between service provision and readmission rates.

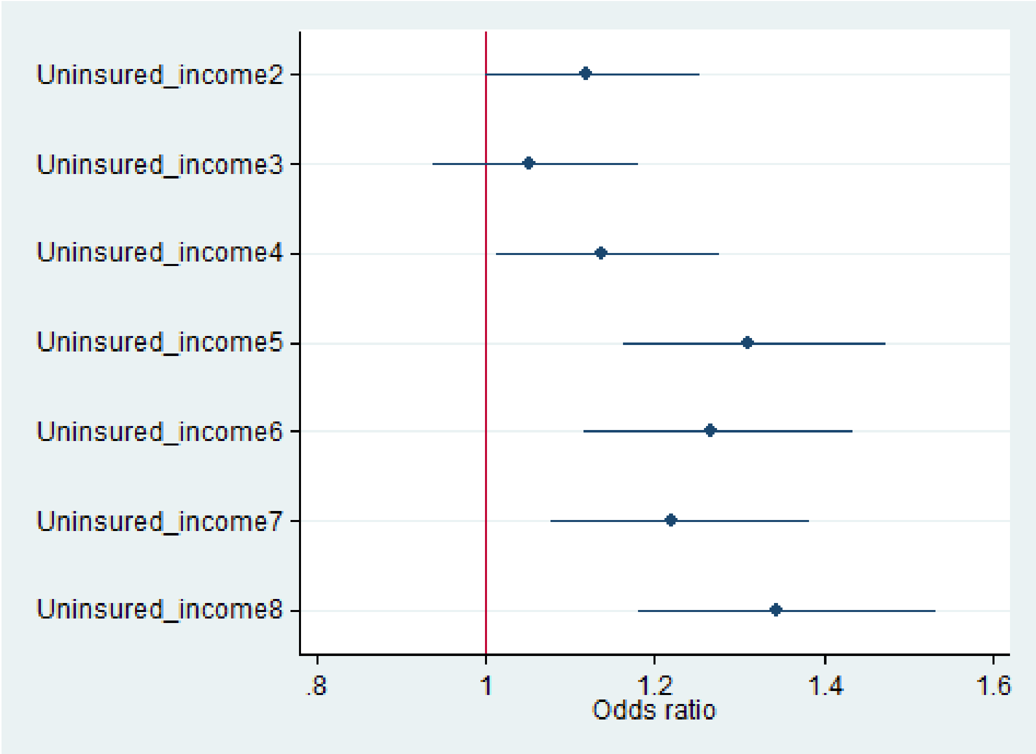

Fig. 1.5. Readmission Rates for Uninsured Individuals Under 65

Figure 5 plots coefficients from Table 1.12 for uninsured individuals interacted with average income by quantile. We see a substantial increase in readmission rates for uninsured individuals in the top half of average income by zip codes compared to those uninsured individuals in the bottom eighth. In quantiles 5, 6, 7, and 8, we see a 22 to 34% increase in readmission rates. Income appears to be a substantial factor in an uninsured person being readmitted. One could explain this result with an income-constraint argument. Uninsured individuals who live in wealthier zip codes are more likely to have more money and thus are more likely to return to the hospital when they are ill for additional treatment compared to their poor counterparts.

Comparing the uninsured individuals living in the top quantile of average income to insured individuals in the same segment, one would look at the product of the odds ratios. In this case, $.625 * 1.344 = .84$. The uninsured individuals living in the top quantile of income, who are the most likely among the uninsured to be readmitted are still only 84% as likely to readmitted as insured individuals in the bottom quantile of average income.[15]

When we consider these readmission rates in conjunction with service levels from Section 5.1.4, again we find limited evidence of reduced services translating into poor health outcomes. Uninsured individuals from the bottom quantile received the fewest services compared to their insured counterparts, but were the *least* likely to be readmitted. If low provision of services were causing poor health outcomes, one would expect uninsured individuals in the bottom quantile to be the most likely to be readmitted. Similarly, uninsured individuals in the top half of average income by zip code have much higher rates of readmission, but have closer service provision to their insured counterparts. Based on their levels of service, we would expect uninsured individuals in the top half of the average income distribution to have the lowest rates of readmission, not the highest.[16]

These findings are consistent with a patient-driven reduction in demand story. The uninsured from the lowest average income zip codes prefer fewer services at the given price. As the proxy for income rises, the uninsured demand more services. Uninsured patients in the bottom quantile of income receive both the fewest services in initial admissions and are much less likely to be readmitted. They demand fewer services, very possibly because of income constraints. As one looks looks at progressively wealthier zip codes of residence, I observe that the level of service from initial admissions rises—although not to the same level as the insured— and the rates of readmission rise as well. As the income constraint is relaxed, uninsured patients demand more services. For insured patients, who are responsible for a fraction of the bill—their coinsurance rate— we see nearly identical rates of readmission across all

[15]In comparing length of stay in the hospital and time between visits, there was no significant difference among privately insured, Medicaid and uninsured individuals. Uninsured individuals are neither staying in the hospital less time nor postponing care.

[16]I have also investigated if un/insured individuals have differences in their length of stay at a hospital or if the time between readmissions varies. Neither length of stay nor time between visits explains the difference in patterns of readmission, but a full discussion can be found in the Appendix in section A.8.

income quantiles. When services are less costly, as to a patient with insurance, the optimal level of readmission is unrelated to income.

Readmission Rates by Income Quantiles and High/ Low Risk of Mortality Dummy

In the next specification, I examine the interaction between risk of mortality (high and low) and 8 income quantiles. I use the following specification:

$$\begin{aligned}logit(readmission) = Uninsured\beta_{Uninsured} + Unins\ Low * Income\ Quantiles\beta_{unlow}\\ + Unins\ High * Income\ Quantiles\beta_{unhigh} + Ins\ High * Income\ Quantiles\beta_{inhigh}\\ + Income\ Quantiles\beta_{inc} + P\beta_p + H\beta_{hosp} + year\beta_{yr} + \epsilon.\end{aligned} \tag{1.9}$$

Here P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality. Results can be found in Table 1.13.

Note that the comparison group for Table 1.13 is low-risk insured individuals who are in the bottom quantile of income. Again, in the bottom quantile of income, we see no difference in readmission between insured individuals with a low or high risk of mortality. Uninsured high-risk individuals residing in the bottom $\frac{1}{8}$ of average income by zip code get readmitted at the same rate as their insured counterparts. However, uninsured low-risk individuals living in the bottom quantile of average income have much lower rates of readmission, at only 62% of their insured counterparts.

Insured and uninsured individuals with a high risk of mortality all are readmitted at the same rates, and at nearly identical rates to insured low-risk individuals. The exception is the slightly lower rates of readmission among the 'high-income' low-risk insured group, with 6% reduction in readmission.

Table 1.13.
Logit: Readmission of Uninsured Dummy with Income Interactions

	(1)	
	readmitlater	
readmitlater		
Insured_highrisk	1.292	(0.273)
Uninsured_lowrisk	0.621***	(0.0253)
Uninsured_highrisk	0.903	(0.233)
Ins_low_income2	0.976	(0.0179)
Ins_low_income3	0.981	(0.0191)
Ins_low_income4	1.025	(0.0209)
Ins_low_income5	0.986	(0.0208)
Ins_low_income6	0.963	(0.0202)
Ins_low_income7	0.981	(0.0211)
Ins_low_income8	0.941**	(0.0213)
ins_high_income2	1.048	(0.0675)
ins_high_income3	1.020	(0.0717)
ins_high_income4	0.928	(0.0644)
ins_high_income5	1.030	(0.0727)
ins_high_income6	0.942	(0.0685)
ins_high_income7	0.899	(0.0654)
ins_high_income8	0.911	(0.0681)
Unin_low_income2	1.129*	(0.0666)
Unin_low_income3	1.059	(0.0641)
Unin_low_income4	1.147*	(0.0694)
Unin_low_income5	1.298***	(0.0810)
Unin_low_income6	1.260***	(0.0836)
Unin_low_income7	1.229**	(0.0810)
Unin_low_income8	1.366***	(0.0932)
Unin_high_income2	1.005	(0.216)
Unin_high_income3	0.946	(0.218)
Unin_high_income4	0.900	(0.209)
Unin_high_income5	1.438	(0.312)
Unin_high_income6	1.239	(0.283)
Unin_high_income7	0.976	(0.228)
Unin_high_income8	0.942	(0.245)
Observations	1089602	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The uninsured low-risk individuals show a fair amount of variation in their readmission rates, with much higher readmission rates in the top half of average income. However, uninsured low-risk individuals in the top quantile of average income still receive fewer services than all insured patients. Multiplying the two coefficients for 'uninsured' and 'uninsured˙income8', I find even the most likely uninsured low-risk individuals are only 84.8% as likely to be readmitted as an insured patient.[17]

Again, there is no link between a reduction in service and an increase in readmission rates and a fairly strong link between uninsured patients' reduction in demand for services and readmission for low risk illnesses. For high risk illnesses, all patients have equivalent rates of both services and readmission.[18] Next, I will investigate if there is a relationship between a reduction in service and increased rates of mortality.

1.5.4 Mortality

Mortality Rates for Patients Under 65

After examining the question of how readmission rates are affected by insurance status, I now turn to another measure of health, mortality. This next section addresses how insurance status for those under 65 years of age changes a patient's likelihood of death.

Table 1.14 contains the results of the following regression:

$$\begin{aligned} logit(death) = \beta_0 + P\beta_p + insurance\ dummy\beta_{ins} + Average\ Income\ by\ Zip\beta aibz \\ + H\beta_{hosp} + year\beta_{yr} + \epsilon. \end{aligned} \tag{1.10}$$

[17].621x1.366 is .848

[18]I have also done this analysis using the Agency for Healthcare Research and Quality's Inpatient Quality Indicators and have found similar results. Please see the Appendix in section A.7 for a complete discussion.

Here P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality.

Table 1.14.
Logit: Mortality of Uninsured Dummy with Income Interactions

	(1)	
	death	
death		
uninsured==1	1.228***	(0.0599)
Ave Income	1.000	(0.000000919)
Divorced	1.016	(0.0460)
Widow/er	1.004	(0.0690)
Observations	1103074	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Here we can see that overall, uninsured individuals are 23% more likely to die than their insured counterparts. I next investigate if there is a differential rate of mortality for uninsured individuals with a high and low risk of mortality.

Mortality Rates by High/ Low Risk

To investigate which uninsured patients are experiencing high rates of mortality, I interact an uninsured dummy with a high/ low risk of mortality dummy using the following specification:

$$\begin{aligned} logit(death) = \beta_0 + uninsured * high\ risk\beta_{unhig.} \\ + uninsured * low\ risk\beta_{unlow.} \\ + insured * high\ risk\beta_{inhigh.} \\ + P\beta_p + H\beta_{hosp} + year\beta_{yr} + \epsilon \end{aligned} \tag{1.11}$$

P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality. Results can be found in Table 1.15.

Table 1.15.
Logit: Mortality Rates of Uninsured Dummy with High/Low Risk Interactions

		(1) death
death		
_Iuninhigh_1	14.13***	(5.125)
_Iuninhigh_10	1.123*	(0.0645)
_Iuninhigh_11	22.11***	(8.242)
Ave Income	1.000	(0.000000930)
Observations	1103074	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note that the comparison group in Table 1.15 is insured, low risk of mortality patients. When we compare insured low-risk patients to uninsured low-risk patients, we see that the uninsured have a 12.3% increase in their rate of mortality. We see sizable coefficients for both the high-risk uninsured and high-risk insured individuals. This is not surprising, as the high-risk dummy identifies those illnesses which have a high risk of mortality. To better compare the two high risk groups, I rerun the above specification, changing the comparison group to high-risk insured individuals. The results are in Table 1.16.

The comparison group for Table 1.16 is insured high-risk individuals. Here, the uninsured high-risk patients are 56.5% more likely than the insured high-risk patients to die. When we compare these rates of mortality to quantity of service demanded in section 5.1.2, I observe that even though uninsured patients received the same level of service for high risk diseases, their rates of mortality are much higher. I will next examine mortality rates by income quantile

Table 1.16.
Logit: Mortality Rates of Uninsured Dummy with High/Low Risk Interactions

	(1)	
	death	
death		
Insured_lowrisk	0.0708***	(0.0257)
Uninsured_lowrisk	0.0795***	(0.0292)
Uninsured_highrisk	1.565***	(0.144)
Ave Income	1.000	(0.000000930)
Observations	1103074	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Mortality Rates by Income Quantiles

In order to determine if income is a predictor for mortality rates, I add average income by zip code interactions with insurance to the specification below:

$$logit(death) = \beta_0 + P\beta_p + Insurance\ dummy\beta_{insurance}\ + Income\ groups\beta income \\ +Insurance * Income\ groups\beta_i + H\beta_{hosp} + year\beta_{yr} + \epsilon \tag{1.12}$$

P is matrix of patient characteristics: age category, race, average income by zip code, marital status, sex, and H is a matrix of patient characteristics at the hospital: ID, APRDRG, severity, mortality. Results can be found in Table 1.17.

In Table 1.17, where we observe that there is no statistically significant difference in mortality rates for insured and uninsured individuals who live in the poorest zip codes. In fact, for all insured individuals, there is no significant variation in rates of mortality based on the wealth of the zip code. For uninsured individuals, too, there is no statistically significant variation in the bottom 6 quantiles, but individuals in the top two quantiles are 2 and 1.8 times as likely to die as uninsured individuals living in the 1st quantile of zip codes. While we typically associate wealth with good health, for uninsured individuals the risk of mortality is doubled for those residing in the wealthiest zip codes. Comparing mortality to readmission and demand results, we saw that these uninsured, high-average-income individuals received more services than uninsured counterparts from the bottom quantile of income, and were more likely to be readmitted than both their insured counterparts or uninsured individuals living in the poorest zip codes. Therefore, it does not seem that an initial reduction in service or deferred readmission is causing these high rates of mortality. The next subsection examines income and high/low risk interactions to explain these differences by examining specific diagnoses.

Table 1.17.
Logit: Mortality of Uninsured Dummy with Income Interactions

	(1)	
	death	
death		
Uninsured	1.036	(0.123)
income_groups8==2	1.061	(0.0536)
income_groups8==3	0.991	(0.0526)
income_groups8==4	0.978	(0.0542)
income_groups8==5	0.968	(0.0570)
income_groups8==6	0.928	(0.0542)
income_groups8==7	0.930	(0.0565)
income_groups8==8	0.970	(0.0610)
Uninsured_income2	0.762	(0.136)
Uninsured_income3	1.080	(0.196)
Uninsured_income4	1.137	(0.196)
Uninsured_income5	1.030	(0.191)
Uninsured_income6	1.240	(0.235)
Uninsured_income7	2.062***	(0.366)
Uninsured_income8	1.817**	(0.339)
Black	0.938*	(0.0293)
Married	1.034	(0.0318)
Seperated	0.832*	(0.0644)
Divorced	1.016	(0.0462)
Widow/er	1.001	(0.0691)
Observations	1103074	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Mortality Rates by Income Quantiles and High/Low Risk of Mortality

In the next specification, I examine the interaction between risk of mortality (high and low) and 8 income quantiles.

In the next specification, I examine the interaction between risk of mortality (high and low) and 8 income quantiles. As the specification below shows, I interacted this 'high risk' variable with uninsured status and income groups.

$$\begin{aligned}logit(death) = \beta_0 + P\beta_p + insurance\ dummy\beta_{ins} + Income\ groups\beta_{income}\\ +insurance * income\ groups\beta_{ii} + insurance * high\ risk\beta_i h\\ +insurance * high\ risk * income\ groups\beta_{ihi} + hospital\ id\beta_{hosp} + \beta_{drg} * drg\\ +severity\beta_{severity} + mortality\beta_{mort} + year\beta_{yr} + \epsilon\end{aligned} \tag{1.13}$$

Notice that in Table 1.18, both insured and uninsured individuals in the 'high risk group' have much higher rates of mortality. Insured individuals in the high risk group are nearly 15 times as likely to die as insured individuals with APRDRGs that are not in the high risk group. Uninsured individuals with high risk diagnosis are nearly 15.5 times as likely to die as insured individuals in the low risk group, though this slight increase over the mortality rates of the insured is not significant.[19]

When one looks at uninsured individuals with high-risk APRDRGs in the top two average income groups, we see triple the rates of mortality when compared to similarly diagnosed uninsured individuals living in low income zip codes. Furthermore, there is no difference in mortality rates by income group for any of the insured individuals, and with the exception of weak significance for uninsured, low risk, income group 7, we see no variation in mortality rates by income for uninsured individuals.

This result of high mortality among uninsured, high-risk individuals who reside in the top quarter of average income by zip code is unexpected, as typically we think

[19] I have also done this analysis using the Agency for Healthcare Research and Quality's Inpatient Quality Indicators and have found similar results. Please see the Appendix in section A.9 for a complete discussion.

Table 1.18.
Logit: Mortality of Uninsured Dummy with Income Interactions

	(1)	
	death	
death		
Insured_highrisk	14.90***	(5.329)
Uninsured_lowrisk	1.034	(0.148)
Uninsured_highrisk	15.48***	(6.760)
Ins_low_income2	1.080	(0.0600)
Ins_low_income3	1.006	(0.0594)
Ins_low_income4	0.974	(0.0588)
Ins_low_income5	0.950	(0.0614)
Ins_low_income6	0.944	(0.0604)
Ins_low_income7	0.947	(0.0627)
Ins_low_income8	0.991	(0.0677)
Ins_high_income2	0.924	(0.100)
Ins_high_income3	0.930	(0.109)
Ins_high_income4	1.015	(0.116)
Ins_high_income5	1.078	(0.130)
Ins_high_income6	0.927	(0.112)
Ins_high_income7	0.919	(0.112)
Ins_high_income8	0.911	(0.112)
Unin_low_income2	0.726	(0.157)
Unin_low_income3	1.090	(0.233)
Unin_low_income4	1.169	(0.235)
Unin_low_income5	1.055	(0.231)
Unin_low_income6	1.034	(0.230)
Unin_low_income7	1.597*	(0.344)
Unin_low_income8	1.381	(0.310)
Unin_high_income2	0.809	(0.295)
Unin_high_income3	0.976	(0.381)
Unin_high_income4	1.057	(0.381)
Unin_high_income5	1.024	(0.391)
Unin_high_income6	1.842	(0.662)
Unin_high_income7	3.361***	(1.134)
Unin_high_income8	2.883**	(0.984)
Black	0.937*	(0.0289)
Observations	1103074	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of income as being a positive predictor of health. This increase in mortality is not associated with initial lower provisions of services or lower rates of readmissions. It also is not consistent with a demand story, where the uninsured individuals who are very credit constrained should be more likely to die. It is the individuals who, based on previous demand, should be the *least* likely to die who have this high rate of mortality. The focus of this work is on the relationship between service provision and bad health outcomes. To that end, there is no evidence that this anomalous result is related to prior levels of service or readmission rates. However, it is interesting, and so I will make a few comments about it.

When one takes equation 1.13 and adds an additional interaction with Race, Black have much worse health outcomes. Being in the 'high risk' group and Black gave 12 times the rates of mortality for uninsured individuals and 13 times the rates of mortality for insured individuals. In this same specification, high-risk, uninsured whites had no increase in mortality in the top two quantiles of income, while these same black individuals had 3.3 to 3.5 times the rates of mortality. It seems that this result is driven by Black patients.

A word of caution, however, these results are based off extremely small samples. For example, in income quantile 7, there were 13 individuals who died who were black, uninsured, and high risk. This unusual pattern of high mortality may be attributable to small number of uninsured patients in the high income quantiles. Complete regression results with race interactions can be found in Appendix I.

The nature of these high-risk diseases is suggestive as to why these particular diseases may disproportionately affect uninsured individuals from wealthier zip codes. These diseases (tracheostomy, liver disease, stroke, respiratory failure, pulmonary embolism, lung and colon cancer, heart attacks and pneumonia) drive the vast majority of the difference in mortality rates between insured and uninsured individuals. After consulting with physicians, I offer some preliminary explanations as to why these particular diseases seem to be so problematic.

These diseases can be classified into three categories: timing, prevention, and behavioral. Diseases of timing are those where earlier treatment has a dramatic effect on mortality. This category includes pneumonia, hemorrhagic and non-hemorrhagic strokes, pulmonary embolisms (blood clots in one's legs that travel to the lung), and tracheostomy (a procedure for individuals who will be on a ventilator for over a month). For each of these diseases a delay in treatment leads to a higher risk of mortality.

Diseases of prevention are those where frequent preventative care, screening, or monitoring make a substantial difference for mortality rates. These diseases include pulmonary edema and respiratory failure (which is caused by congestive heart failure), heart attacks, and colon cancer. In the first two cases, worse primary care leads to worse heart disease and more death, while with colon cancer, later detection leads to higher rates of mortality.

Diseases of behavior are those where individual choices have a substantial effect on likelihood of contracting the illness. These illnesses include lung cancer, alcoholic liver disease and liver disease which starts as hepatitis C. Smoking and drinking increase one's risk for lung cancer and alcoholic liver disease, while hepatitis C is more prevalent among IV drug users. Future work should determine if this result is robust across additional years or if it is a phenomena of small samples.

Given that demand for medical services for high-risk illnesses was the same for insured and uninsured patients once differences in patient characteristics were taken into account, that readmission rates did not vary by income quantile for high-risk illnesses, and that mortality rates were identical with the exception of Black uninsured patients in the top two income quantiles, it seems reasonable to conclude that uninsured individuals do not have adverse health effects from being uninsured when they have a a high risk illness.

1.6 Conclusions

This paper investigated if uninsured individuals receive less care, if they have different rates of readmission to hospitals, and if they have different rates of mortality than their insured counterparts. Using a Blinder-Oaxaca decomposition, I find uninsured individuals receive 8.3% fewer services than their insured counterparts. Assuming that income was a limiting factor for procuring insurance, I ran Blinder-Oaxaca decompositions for 8 quantiles of average income by zip code; the most affected individuals were uninsured individuals living in the poorest $\frac{1}{8}$ of zip codes (by average income). There was nearly a 14% reduction in services not attributable to patient characteristics for uninsured individuals in poor zip codes compared to their insured counterparts. Looking at uninsured individuals who lived in the wealthiest zip codes, the gap in the level of services not attributable to characteristics narrowed to about 7%. This provides evidence that uninsured individuals reduce their level of medical services due to concerns about prices. As we look from one quantile of income to the next— looking at increases in average income by zip code—we see a pattern of increased levels of service demanded.

However, when I also include an interaction of income quantiles with a high/low risk of mortality dummy variable, I find that for high risk illnesses, insurance status does not predict the quantity of services demanded. When uninsured patients face a high risk of death, they don't elect to forgo services. For patients with a low risk of mortality, we see the most reductions in quantity of services demanded for individuals in the lowest quantile of income.

The next question this paper addresses is if this reduction in services for uninsured individuals has an impact on other health outcomes. I will first discuss readmission rates. Overall, uninsured patients were 72% as likely to be readmitted as their insured counterparts. When I include a high-risk dummy interaction, I find that for high-risk illnesses, there is no difference in rates of readmission.

To determine if income is a predictive factor in readmission rates, I interacted an uninsured dummy variable with the 8 income quantiles. I find uninsured individuals in the bottom quantile of zip codes are 62.5% as likely to be readmitted as their insured counterparts. Uninsured individuals were increasingly likely to be readmitted as their income increased, with the top income quantile being 1.34 times as likely to be readmitted as uninsured individuals in the bottom quantile. This provides evidence that uninsured individuals living in poorer zip codes return to the hospital less frequently due to income constraints. Among insured individuals, there was minimal variation in admission rates by income. Uninsured individuals in every quantile had lower rates of readmission than insured individuals in the same quantile of income. The gap in readmission rates between uninsured and insured individuals fell from 62% in the bottom quantile to 85% in the top quantile. Here, as income rises, uninsured individuals chose more services and higher rates of readmission.

Next, I consider if illnesses with a high or low risk of mortality have differing patterns of readmissions by income quantile. For diseases with a low risk of mortality, individuals from lower quantiles have lower rates of readmission. As average income increases, readmission rates rise, though never to the rates of insured patients. Insured patients with both high and low risk illnesses have approximately identical rates of readmission. Uninsured individuals in the high risk group are admitted at an equal rate across income quantiles. Again we find that when faced with a grave illness, uninsured individuals do not elect fewer services than their insured counterparts, but when the illness has a low risk of mortality, they chose to return to the hospital less frequently.

Finally, I will discuss differences in mortality rates by insurance status. Overall, uninsured individuals are 23% more likely to die than their uninsured counterparts. When I interact an uninsured dummy with a low and high risk dummy, I find that for low risk patients, the uninsured are 12% more likely to die. For the high risk illnesses, the uninsured are 57% more likely to die. When I consider income as a predictor of mortality, income is largely a poor predictor except for uninsured individuals in the top two income quantiles who have double the rate of mortality of their insured counterparts, though this seems likely to be an issue of a small sample.

For low risk illnesses, uninsured individuals received less care, and had lower rates of readmission, and this translated into a 12% increase in rates of mortality. Uninsured low income individuals saw the biggest reductions in services and the lowest rates of readmissions, suggesting that at the current prices, they preferred to demand fewer services. As the income constraint was relaxed—by examining more affluent income quantiles— uninsured individuals sought out more services and were more likely to be readmitted to the hospital.

While Maryland has debt forgiveness to 150% of the poverty line—making care costless to the poorest individuals— I do not find a response to this 'low price' in the data. While the lowest income quantile includes families up to about $41,000 dollars a year, and therefore should include a large number of the individuals eligible for free care, these patients demand the fewest services, and have the lowest rates of readmission compared with their insured counterparts. Given that the gap in services between uninsured and insured patients drops as income quantile increases, income is constraining the quantity of services demanded.

This work is broadly applicable under the implementation of the ACA. With financial penalties for not holding health insurance, many individuals are opting for care with a high deductible plan. Prior to meeting the deductible, insured individuals are much like uninsured individuals in Maryland: they pay the whole bill, but have access to negotiated rates. Future work should conduct this analysis at a disease-specific level, to determine if preventative services or substance abuse cessation programs should be covered prior to a deductible being met. At a state level, this work could inform estimates of the increased use of services, particularly for low-risk illnesses, as individuals with high deducible plans consume like the uninsured in Maryland.

2. HOSPITAL-INSURER BARGAINING POWER AND NEGOTIATED RATES

with James Bland

Abstract: In addition to risk-sharing, U.S. health insurance companies negotiate rates for services with hosptials. The price of service can vary depending on which entity, if any, is insuring the patient. Insurers (and possibly their customers) benefit from negotiating through lower prices, while hospitals benefit through higher patient volume.

Using Massachusetts' Center for Health Information and Analysis (CHIA) data, we use hospital and insurer characteristics to estimate negotiated prices specific to hospital-insurer pairs. We investigate the relationship between two important quantities: (i) the charged amount that hospitals bill for their services, and (ii) the amount that hospitals are paid for insured patients. These numbers differ because the former is a function only of the services provided and the hospital's "chargemaster" prices, while the latter is the result of negotiation.

We find that payments for privately insured patients are on average 38% of charges when payments are made on a fee-for-service basis. However this ratio varies greatly by hospital and insurer. Compared to community hospitals without an emergency room, academic medical centers are compensated 15% more for their services, and hospitals with an emergency room are compensated 7% more than those without.

2.1 Introduction

Health insurance in the US performs two functions for consumers. The first is the traditional function of transferring wealth from good to bad states of the world. The other is the result of the increased bargaining power that follows from having an insurance company act (in part) on behalf of a large number of customers. Insurers can, and do, negotiate prices with hospitals so that, for the same services provided, the hospital is paid less for the insured patients than it would otherwise charge an uninsured patient. The benefit to insurers of this ex-ante negotiation is that their costs are lower. Some of this discount may also be passed on to consumers in the form of lower premiums.[1] For hospitals, negotiation can ensure higher volumes of admissions, because insurers can direct their customers away from hospitals that fail to reach an agreement, typically by having a higher co-insurance rate for "out-of-network" hospitals compared to those that are in network.

Using data from Massachusetts Center for Health Information Analysis (CHIA), we estimate these negotiated rates from patient-level insurance claims and hospital discharge data. We find considerable variation in the amount paid for (normalized) services. This variation comes from three sources. (i) At any given hospital, the payment made for services depends on the patient's insurer. This variation can be interpreted as insurers having different bargaining powers with the hospital. (ii) Holding the insurer constant, the payment for services depends on the hospital at which the patient was treated. We interpret this as evidence of hospitals having different bargaining power over insurers. (iii) Considerable variation in these payments is left over, even after controlling for the patient's hospital and insurer. The existence of this residual variation is testimony to the imperfectly-competitive, and imperfectly understood nature, of health care markets.

[1]Once insurance companies have negotiated a lower payment. They may either rent-seek or pass the savings on to consumers. While it is not clear which of these actions the insurance company will take, from the point of view of social welfare, we would be interested in the latter.

The contribution of this paper is that we (1) calculate variation within a hospital-insurance pair, (2) examine how this within-pair variation compares to the variation of prices between different hospital-insurer pairs. In doing so, we contribute to the literature studying competition in health care and insurance markets, by adding a patient-specific level of observation whereas previous studies such as Cooper et al. (2015) and Ho and Lee (2015) have used a hospital as the level of observation.

2.2 Literature Review

Features of hospital-insurer negotiations: Gaynor et al. (2015) outline four elements that characterize negotiation between hospitals and insurers, and the incentives faced by insured individuals:

1. Insurers can encourage patients to go to particular hospitals over others through differential co-insurance rates. Hospitals with which the insurer has negotiated a favorable price have a low "in-network" rate. Hospitals with which the insurer has not negotiated have a higher "out-of-network" rate.

2. Except for co-insurance, patients do not pay directly for their care.[2]

3. At the time inpatient care is needed, the patient is generally locked-in to their insurance plan, and so cannot change plans to access the negotiated rate of another insurance product that would (ex-post) be better to treat their illness.

4. Insurers negotiate with hospitals over network status (patients pay lower co-insurance rates at in-network hospitals),and how the hospital will be compensated for services. In our dataset, the reimbursement structure is mostly on a fee-for-service basis (e.g.: the insurer pays a fraction of the amount charged by the hospital), or a DRG basis (e.g.: the insurer pays the hospital a flat rate determined by the patient's diagnosis and severity of illness).

[2]While deductibles are common in the US health insurance industry, it is not the focus of Gaynor's study, nor does it affect hospital-insurance negotiations as it is focused on the spitting of the payment between insured individuals and insurance companies.

Reinhardt (2006) documents some of the features of how payments are made between hospitals and insurers. Each hospital has a "charge master", a list of prices for each procedure performed in the hospital. Charges reported by the hospital are the sum of the prices from this list of all services performed on a patient. For insured patients, charges typically differ from the amount the hospital is compensated (by the insurer and patient together), Compensation is based on a negotiated rate agreed upon between the hospital and insurer. An implication of this, and the focus of our study, is that a hospital's compensation for a particular patient depends on the patient's insurer, and by extension the relative bargaining power of the hospital and the insurer during the negotiation.

Market power: Gaynor et al. (2015) document significant and increasing concentration of both hospitals and insurers. Data on insurers suggests that they are not price-takers either when dealing with employers, or with health care providers. Dafny (2008) provides evidence that insurers have market power over employers in that they can extract some surplus from more profitable firms through higher premiums. If the insurance market were competitive, premiums for the same health plan would be the same across firms. Dafny et al. (2009) also show that premiums increase when insurers merge. On the provider side of insurers' operations, they also find a decline in physicians' compensation and employment when insurers merge. There is also evidence of varying negotiating power on the hospital side of the market. For example, Ho (2008) estimates that "star" hospitals and capacity-constrained hospitals can command markups of about 25% of revenues. Other estimated markups were much lower. Our analysis generally agrees with this markup: we estimate that academic medical centers with an emergency room are compensated approximately 23% more than community hospitals without an emergency room.

Cooper et al. (2015) use insurance claims data of individuals with private employer-sponsored insurance to document variation in prices paid to hospitals. They estimate prices paid for privately insured individuals that vary by a factor of three over the

Hospital Referral Regions. These prices are not strongly correlated (0.14) with similar compensations for Medicare beneficiaries, but are associated with measures of market power, Herfindahl indexes and counts of hospitals within a market, suggesting that hospitals' compensation for the privately insured is not driven by cost. Prices for specific procedures vary by even greater factors. Our analysis complements that of Cooper et al. (2015) by exploiting a more detailed data set, albeit only including observations from Massachusetts.

If variation in negotiated prices is driven by varying levels of competition, then prices should be lower in markets with more competitive hospitals. Ho and Lee (2015) use exposure to Kaiser Permanente, a large vertically integrated insurer, as a measure of competition in a health care market. Hospitals in more competitive markets typically have lower prices, however attractive hospitals are able to negotiate higher rates.

Welfare implications for insured individuals: Negotiated prices could affect patients' welfare for several reasons. Firstly, since insured patients typically pay a fixed fraction of the medical bill (the co-insurance rate), a lower negotiated rate means lower out-of-pocket expenses.This effect may be somewhat mitigated by hospitals' response to lower prices. Using an exogenous change in Medicare pricing, Dafny (2003) shows that hospitals respond to lower prices by "upcoding" patients to diagnosis codes that attract higher reimbursement, although she finds no evidence of an increase in the intensity of care. Secondly, depending on their market power, insurers may pass some of the savings on to consumers in the form of lower premiums. However Dafny et al. (2015) show that premiums are typically lower in markets with more insurers. At least by this measure, it seems that the between-insurer competition effect on premiums is stronger than any passed-through costs of higher negotiated prices in more competitive markets.[3] Ho and Lee (2015) find consolidation of insurers increases

[3]If we make the assumption that patient illnesses are spread evenly across insurance companies, then the actuarially fair price of insurance should be constant. If this were the case, one could compare premiums to determine measures of surplus. In a perfect world we would know both actuarially fair prices and premiums, and look at the difference between the two.

premiums and find a heterogeneous effect on negotiated prices. Another concern for the welfare of consumers could be through the restricted choice set imposed by an insurer's network. Assuming no price effect, Ho (2006) estimates a welfare loss of about $1 billion per year in the markets studied due to restricted choice sets. As Ho notes, this loss may be mitigated by price reductions at the hospitals remaining in the insurer's network. Using a natural experiment, Gruber and McKnight (2016) find that consumers are highly price sensitive to limited-network insurance plans, and that those who switch to them had almost 40% lower medical expenses than those who did not. This reduction in expenditure is attributable to reductions in both demand and price for services, especially for specialist and hospital care. They found substitution effects in the direction of primary care.

2.3 Data Description

We use two datasets produced by the Massachusetts Center for Health Information and Analysis (CHIA). The first of these is the All Payer Claims Database (henceforth APCD), the set of records submitted by insurance companies to the state of Massachusetts, and provides detailed information about charges, the amount paid by the insurance company, the patient's out-of-pocket amount, details on deductibles. The second is the Massachusetts Acute Hospital Case Mix Database (henceforth Case Mix), the set of medical records submitted by the medical providers to the state. While the data set is rich, including outpatient care, we restrict ourselves for this study to inpatient hospital services only. These inpatient records include demographic information as well as detailed information about diagnosis, procedures, etc.

We capitalize on the rich information about payments (in APCD) and patients (Case Mix) through an aggregated merge of the two datasets. The inpatient records in both Case Mix and APCD are a census of hospital admissions of privately insured patients for the state of Massachusetts. The two datasets are distributed yearly, but since reporting periods differ overlap for nine months of the year. Therefore we observe every admission of a privately insured patient in Massachusetts between January and September of 2013 (inclusive). To this end, we first collapse the APCD by patient episode (multiple line items are associated with each patient episode),[4] then use episode-specific characteristics documented in both datasets to merge the two files. These include patient age, gender, residential zip code, hospital zip code, and at least one of the following: diagnosis code, principal procedure code and total charges within \$1000. For the overlapping 9-month period of the two datasets, we match approximately 65% of privately insured patients. Of the patients we do match, over a third of them match on all three criteria (principal diagnosis, principal procedure, and total charges within \$1000), about 40% match on two criteria.

2.3.1 Some important variables

Table 1 shows summary statistics of some variables in the merged dataset. Summary statistics are calculated separately for two different payment methodologies, Fee For Service (FFS) and Diagnosis Related Group (DRG), which are discussed in more detail below. Of particular interest are the first three variables summarized in this table, `allowed` `charged` and `paid`, which capture different ways of accounting for hospital services.

[4]For example, a patient may go to the hospital and have separate charges from radiology and surgery. These would show up as separate line items in APCD. Since we are interested in all charges associated with a single patient episode, we sum charges from each line item for each patient episode.

	(1)		(2)	
	FFS		DRG	
	mean	sd	mean	sd
allowed	6902	12481	10076	12645
charged	19171	21954	20281	23210
paid	6771	11064	10810	13956
weight_imp	1.126	1.124	1.369	1.484
aoverwi	6095	7456	8066	6719
poverwi	6051	7472	8992	8337
coverwi	16860	8320	15356	7684
Observations	47739		35855	

Table 2.1.
Summary statistics

The first variable, `allowed`, documents the maximum amount to be paid to the hospital for a particular illness or procedure. Specifically, the CHIA Submission Guide instructs:

> Report the maximum amount contractually allowed, and that a carrier will pay to a provider for a particular procedure or service. This will vary by provider contract and most often it is less than or equal to the fee charged by the provider.
>
> APCD Medical Claims File Submission Guide, p 38.

If patients were homogeneous, the mean of the `allowed` variable would represent negotiated rates between the hospital and the insurance company.

The second variable `charged` is the amount the hospital charged for the services received by a patient for a particular visit. The documentation for this variable suggests it is independent of insurance type and payment methodology. One could view this as the 'sticker price' for services, or, following the language used in Reinhardt (2006), we could think of these as the 'charge master' prices. It is worth observing that the charges are very similar between the two payment methodologies: DRG and FFS.

The `paid` variable is the total amount paid to the hospital. There are, however, a few different methodologies to determine payments, the most frequent of which is fee-for-service. As the name suggests, charges are accrued for each service. For example, for each x-ray the insurance company pays $150. This methodology for payments accounts for about 40% of our inpatient records.

The next largest payment methodology in our data set is a Diagnosis Related Group (DRG) system. DRG systems pay based on the patient illness, not on services received. For example, a patient comes in and is admitted with pneumonia. Once the diagnosis is determined (in this example, pneumonia), the patient is assigned to a DRG and based on that DRG the insurance company pays the hospital a flat fee (say $7000). This payment is invariant if the patient receives a great deal of services or a very few services. DRG payments account for about 35% of our data. While there are a few other payment systems, no other single system accounts for a large fraction of our data. As these two payment methodologies are quite different, summary statistics are provided separately for both.

It is important to note that for some patients `paid` is larger than `charged`. At first, this is quite counter-intuitive. Why would one pay more than one is charged for services? However, it is precisely because of the variation in payment methodologies that the paid to charged ratio can be greater than 1. Take a patient who is admitted under a DRG system. This patient's payments are determined by the DRG classification, not by the services they receive. As such, their payment may exceed their charges, which is a function of the services they actually receive in the hospital.

As not all illnesses require the same level of service provision, a weighting system was developed by Medicare and Medicaid. These weights, which are based on illness classification, allow us to compare average service provision for numerous illnesses. We had DRG illness classifications for approximately 40% of our data.

The next variable `weight imp` ("Imputed Weight") is a derived variable equal to patient's charges relative to the casemix-adjusted average charges at the patient's hospital. The reason for this normalization is that we wish to attribute differences in our estimates of negotiated rates to differences in aspects of the bargaining process, rather than hospitals having different charge-master prices.[5] We interpret this variable as an aggregation of the quantity of services received, relative to the services a patient at that hospital would receive if they had a DRG weight of 1. Therefore, a patient with an imputed weight of 2 receives twice the services (measured in charges) than a patient with an imputed weight of 1. It is worth noting that the average weight of fee-for-service patients is lower than that for diagnosis related group patients. We would interpret this to mean that our DRG patients are 'sicker' and require about $1.37/1.13 - 1 \approx 21\%$ more services than out FFS patients.

[5]We motivate this normalization in more detail in Appendix B.1, and describe the procedure for calculating imputed weight in Appendix B.2.

We have also included the variables `aoverwi` (allowed over weight) and `poverwi` (paid over weight) to be able to better compare across payment types. When we look at an illness adjusted measure of allowable services, the two values \$6,100 (for FFS) and \$8,065 (for DRGs) are far closer than when we consider the raw means \$6,933 (for FFS) and \$10,104 (for DRGs). Similarly, when we compare `poverwi` (paid over weight), we see that the difference in payment for equally ill patients between FFS and DRG has dropped (\$6052 vs \$8991), compared to their per-patient averages without accounting for illness levels(\$6791 vs \$10843). The goal of this paper is to understand the 'markdown' of charges for normalized patients.

2.4 Results

We begin this section by testing our assumption that FFS payments are a fraction of charges. Table 2.2 shows the result of regressing log payments against log(imputed weight) for FFS payments, with various controls. If FFS payments are truly a fraction of charges, then we would expect a coefficient of 1 on log(imputed weight) in a

	(1)	(2)	(3)	(4)	(5)	(6)
log(weight imp)	1.040	1.029	1.009	0.740	0.737	0.723
	(0.0106)	(0.0106)	(0.0104)	(0.00922)	(0.00909)	(0.00908)
N	47278	47278	47278	47278	47278	47278
R^2	0.168	0.182	0.226	0.417	0.441	0.467
AIC	191793.2	191004.3	188456.6	175050.1	173110.9	172188.6
BIC	191810.7	191056.9	188947.4	175260.4	173794.4	178630.0
H0: fixed markdown	0	0.00600	0.364	0	0	0
Controls						
EMS region	-	Y	-	-	-	-
Hospital	-	-	Y	-	Y	Y
Insurer	-	-	-	Y	Y	Y
Interactions	-	-	-	-	-	H $\times$ I
No. of controls	0	4	54	22	76	733

Standard errors in parentheses

Table 2.2.
OLS regressions with FFS log payments against log(charges), with various controls. Significance stars are suppressed. The row labeled "H0: fixed markdown" reports the p-value for the test that the coefficient on log(weigh imp) is equal to 1 (i.e., a linear relationship between payments and imputed weight).

regression of log(payments) on log(imputed weight) and control variables.[6] That is, letting c_i denote the controls used, the relationship would be:

$$\log(\text{paid}_i) = \log(\text{weight}_i) + \tilde{\rho} c_i \tag{2.1}$$

The row labeled "H0: fixed markdown" reports the p-value for this test. While we reject the hypothesis that the coefficient is 1 for all but model (3), we note that in models (1), (2), and (3) that the coefficients are close to one, indicating a close to linear relationship. Looking at the coefficient on log(weight_imp) in columns (4) (5) and (6), we see some variation between 0.723 and 0.740. Given our understanding of FFS payments, we have run the OLS regressions from columns 5 (which includes hospital and insurer fixed effects) and have plotted the coefficients for the general model and one in which we impose that the coefficient on log(imputed weight) is 1. These coefficient plots can be found in Appendix B.4. What we see in these plots is that while the slope coefficients differ significantly from 1, our estimates of negotiated rates do not vary much between these two specifications: the ranking and approximate levels are very close.

We also investigate the relationship between (log) imputed weight and (log) payments for patients under the DRG payment systems. Table 2.3 shows the result of regressing log(payments) against log(imputed weight) for DRG payments, with various controls. In the DRG system, the hospital is reimbursed for treating a patient with a particular disease, and this payment is independent of the services the patient actually receives. We observe that while the coefficient on log(imputed weight) is somewhat more consistent across the different specifications, that the predictive power of the models is lower. This is consistent with our understanding of how reimbursement works for patients under a DRG system.

[6]If we assume charges are a linear combination of services and charge master prices, then we expect insurance companies to pay a fixed fraction of these prices. In a log specification, then, for a 10% increase in charges we would expect a 10% increase in payments, which is why we assert that this coefficient should be equal to 1.

	(1)	(2)	(3)	(4)	(5)	(6)
log(weight imp)	0.929	0.929	0.892	0.924	0.884	0.884
	(0.00987)	(0.00983)	(0.00930)	(0.00992)	(0.00934)	(0.00934)
N	35631	35631	35631	35631	35631	35631
R^2	0.199	0.206	0.301	0.200	0.303	0.309
AIC	136066.6	135761.5	131319.7	136049.1	131259.9	131168.5
BIC	136083.6	135812.4	131794.6	136116.9	131785.7	132635.7
H0: fixed markdown	0	0	0	0	0	0
Controls						
EMS region	-	Y	-	-	-	-
Hospital	-	-	Y	-	Y	Y
Insurer	-	-	-	Y	Y	Y
Interactions	-	-	-	-	-	H $\times$ I
No. of controls	0	4	54	6	60	171

Standard errors in parentheses

Table 2.3.
OLS regressions with DRG log payments against log(inputed weight), with various controls. Significance stars are suppressed. The row labeled "H0: fixed markdown" reports the p-value for the test that the coefficient on log(weigh imp) is equal to 1 (i.e., a linear relationship between payments and imputed weight).

Next, we investigate the explanatory power of individual hospitals and insurers, and their interactions, in explaining the ratio of payments to charges.[7] This ratio is of interest because it represents the fraction of charges for which the hospital is compensated. In a fee-for-service environment, this ratio provides preliminary insight into the rate negotiated between hospitals and insurance companies. We look at a number of specifications using different controls, and evaluate the predictive power of different models using both frequentest and Bayesian criteria. We consider both linear and log specifications.

Table 2.4 reports various measures of goodness-of-fit for regressions of the paid to charge ratio against controls for emergency medical service (EMS) regions, hospitals, and insurers. Each column restricts the sample to a single payment type. Columns 1 and 2 report results when restricting the sample to fee-for-service (FFS) payments with linear and log specifications. Since FFS payments are typically negotiated as a fraction of charges, we would expect these regressions to have better fit than those with DRG payment types. Looking at Columns (3) and (4), we see the same regressions (both linear and log) for DRG payments. The better fit of the FFS model is observed in the systematically higher R^2 values reported in the first two columns, corresponding to FFS payments. We also observe that in both FFS and DRG payment methods, the log specification fits the data better than the linear counterpart. This is consistent with our understanding of how the industry handles reimbursement.

The bottom two panels report the Bayesian and Akaike information criteria for the estimated models. For FFS payments, the BIC selects Model 4, which controls for hospitals and insurers, but without interactions.[8] The AIC selects Model 7, which includes hospital-insurer interactions. This is due to the AIC and BIC differing in the penalty function for adding more variables. For the BIC it is $k \log(N)$, where k and N are the number of controls and the number of observations respectively. For the

[7]Looking at the ratio of payments to charges is a special case of regressing log(charges) against log(payments), in which we are forcing the coefficient on log(charges) to be 1.

[8]Note in Table 2 the value for Model 4 is the lowest. As the BIC is a penalty function, lower numbers indicate better performance.

	(1)	(2)	(3)	(4)
	poverc	log_poverc	poverc	log_poverc
Mean value	0.383***	-1.962***	0.659***	-1.129***
	(172.99)	(-234.16)	(212.78)	(-127.90)
N	47739	47739	35855	35855
Payment type	FFS	FFS	DRG	DRG
Number of controls				
1 - EMS region (E)	4	4	4	4
2 - Hospital (H)	61	61	61	61
3 - Insurer (I)	22	22	6	6
4 - H & I (uninteracted)	83	83	67	67
5 - H, I, & E (uninteracted)	85	85	68	68
6 - H & (I & E interacted)	154	154	84	84
7 - H & I (interacted)	779	779	179	179
R^2				
1 - EMS region (E)	0.00416	0.00682	0.00319	0.00436
2 - Hospital (H)	0.0565	0.0613	0.157	0.165
3 - Insurer (I)	0.139	0.258	0.00103	0.000808
4 - H & I (uninteracted)	0.191	0.310	0.158	0.166
5 - H, I, & E (uninteracted)	0.191	0.310	0.158	0.166
6 - H & (I & E interacted)	0.197	0.314	0.159	0.166
7 - H & I (interacted)	0.234	0.342	0.163	0.173
Bayesian information criterion				
0 - Constant only	66093	193233	63456	138603
1 - EMS region (E)	65937	192950	63384	138488
2 - Hospital (H)	63974	190868	57981	132792
3 - Insurer (I)	59164	179220	63482	138637
4 - H & I (uninteracted)	56850	176394	58003	132801
5 - H, I, & E (uninteracted)	56866	176401	58012	132808
6 - H & (I & E interacted)	57286	176922	58149	132961
7 - H & I (interacted)	61786	181668	58971	133663
Model selected	4	4	2	2
Akaike information criterion				
0 - Constant only	66093	193233	63456	138603
1 - EMS region (E)	65902	192915	63350	138454
2 - Hospital (H)	63438	190333	57463	132274
3 - Insurer (I)	58971	179027	63431	138586
4 - H & I (uninteracted)	56122	175666	57435	132233
5 - H, I, & E (uninteracted)	56120	175656	57435	132231
6 - H & (I & E interacted)	55934	175571	57436	132248
7 - H & I (interacted)	54951	174833	57452	132144
Model selected	7	7	4	7

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4.
Regressions of the ratio of payments to charges, controlling for EMS region, hospitals, insurers, and interactions thereof.

AIC the penalty is $2k$. As N is relatively large in our sample, these two criteria place greatly different weight on the number of controls. We interpret these selections as hospitals and insurers having varying bargaining power, which is supported by both criteria. We interpret the AIC's selection as hospital-insurance pairs being the level of observation that best explains the variation in price.

For DRG payments, the BIC selects Model 2, which controls for hospitals. The AIC selects Model 4 with a linear specification for the ratio of payments to charges, which includes all hospitals and insurance companies without interactions. The AIC selects Model 7 in the log specification, which includes all interactions. We now turn our attention to understanding the variation in negotiated rates at the hospital-insurance level.

2.4.1 Estimates of negotiated rates for FFS payments

In this section, we estimate negotiated rates for FFS payments, and document the variation in rates across hospitals and insurers. We investigate negotiated rates using payments per imputed weight as the relevant metric. Figures 2.1 and 2.2 show coefficient plots from a regression of the (log) paid per imputed weight ratio against indicators for hospitals and insurers respectively, suppressing the constant term. Differences in these coefficients represent fractional negotiated rate differences. That is, if hospital A has a coefficient of 8.5, and hospital B has a coefficient of 9.0, then hospital B's negotiated rates are estimated to be on average $\exp(9.8-8.5) \approx 1.65$ times greater than hospital B's. These figures document much variation in mean compensation per weight by both hospital and insurer. For hospitals (Figure 2.1) we see variation in negotiated rates by a factor of approximately $\exp(10.4 - 8.4) \approx 7.4$ (comparing New England Baptist to Anna Jacques). For insurers (Figure 2.2) Blue Cross negotiates rates that are on average approximately one tenth ($\exp(-2.4 - 0) \approx 0.1$) that of Aetna and Tufts, and one third that of Fallon ($\exp(-2.4-(-1.4)) \approx 0.37$).

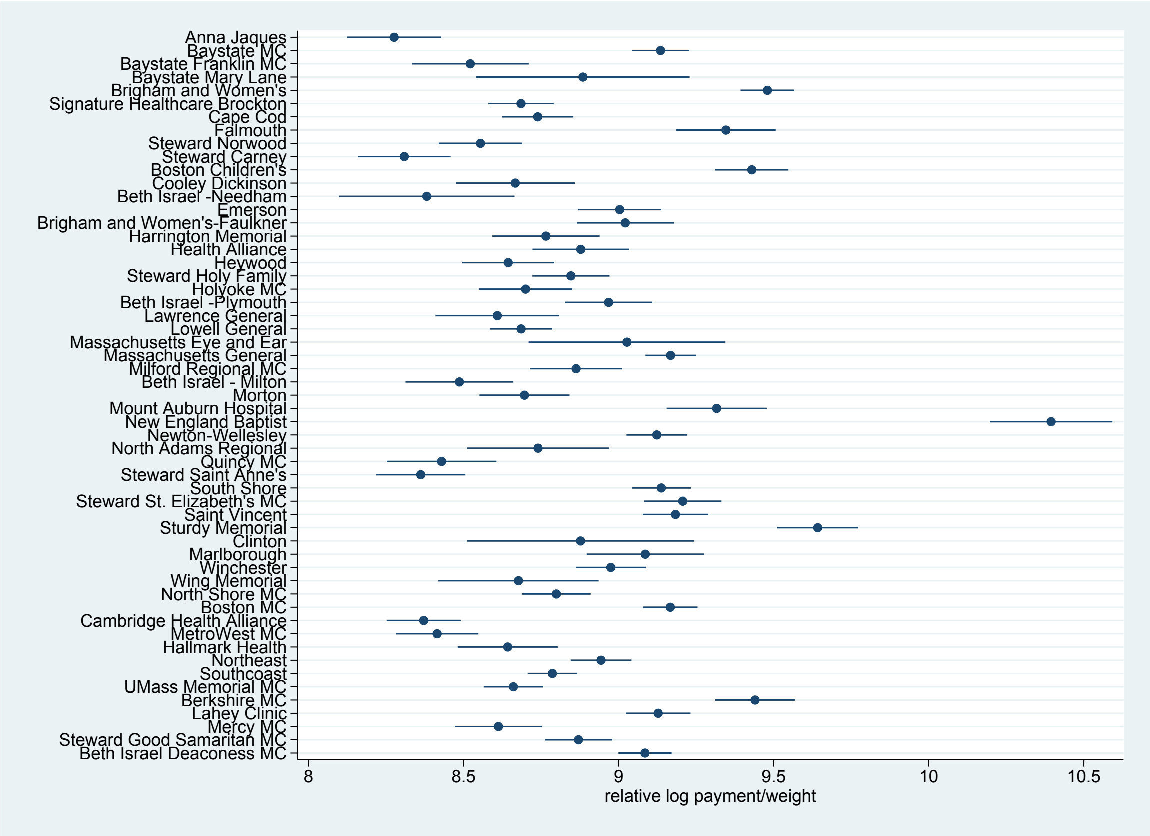

Fig. 2.1. Coefficients on hospital indicators estimated from regressing log(payment per imputed weight) against indicators for hospitals and insurers, suppressing the constant term.

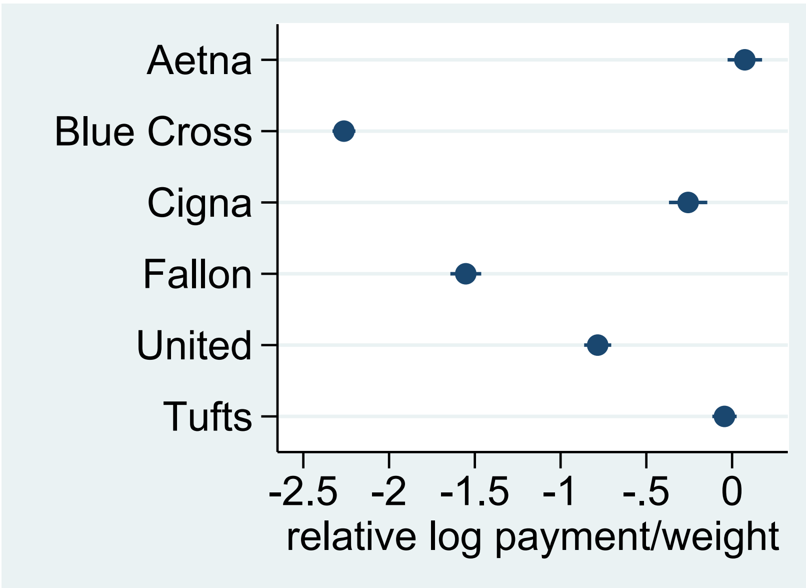

Fig. 2.2. Coefficients on insurer indicators estimated from regressing log(Payment per imputed weight) against indicators for hospitals and insurers, suppressing the constant term.

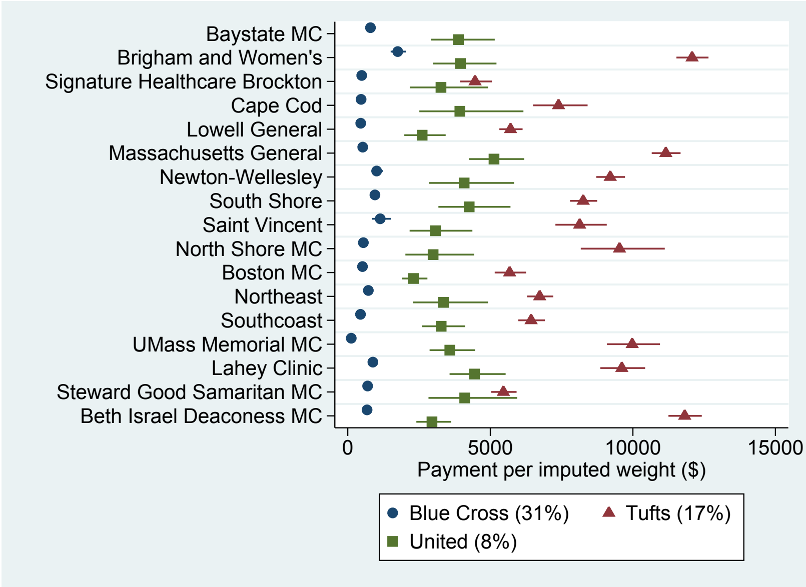

Fig. 2.3. Estimates of negotiated rates for the largest hospital-insurer pairs. Market shares are shown in parentheses (fraction of FFS admissions). The full list of negotiated rates is shown in Appendix B.3.

Appendix B.3 shows estimates of payments per imputed weight for each hospital-insurer pair with at least 30 admissions. We show these estimates for the three largest insurers in Figure 2.3. Each value in this table reports the mean payment made by an insurer for an imputed weight of 1, which we construct to be equivalent to a DRG weight of 1. Column (7) of this table highlights great variation between hospitals. For example, Berkshire Medical Center on average receives about $10,150 per imputed weight for insured individuals. This value is one of the highest in column (7), and reflects this hospital's geographic isolation: there are few substitute hospitals, so insurers are less able to direct patients living in that area elsewhere. Overall, Figure 2.3 shows that there is much more variation in compensation across insurers than across hospitals.

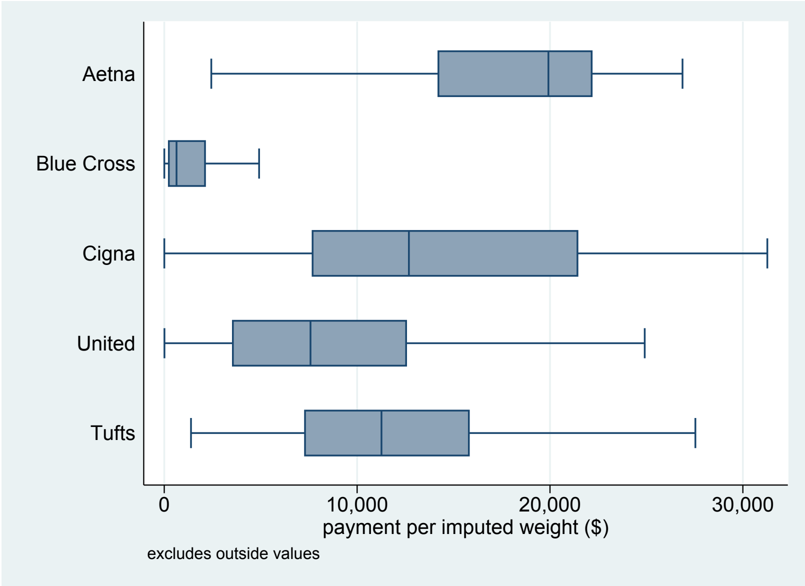

Fig. 2.4. Payment per imputed weight at Massachusetts General Hospital.

2.4.2 Within-pair variation

While previous literature has looked at hospitals as the level of observation, the patient-level data used here allows us to examine the variation within a hospital-insurer pair. In order to better understand the variation of the amount paid by both the hospital and insurance company in relation to the amount charged by the hospital, we look at the ratio of the total paid to imputed weight for each patient at a particular hospital with a particular type of insurance. Figure 2.4 shows boxplots of the ratio of payments to imputed weights for FFS payments at Massachusetts General Hospital (the largest hospital by number of FFS payments). While this figure illustrates that there is great variation in median payments for an imputed weight by insurer, there is much left to be explained. We consider the interquartile ranges shown in this figure to be economically significant, and wish to further understand this variation.

Table 2.5 investigates possible drivers of this variation by regressing the log ratio of payments per imputed weight against log negotiated rates and some patient characteristics. Column 1 shows the constant-only model, and column 2 introduces the

	(1)	(2)	(3)	(4)	(5)
	log_poverwi	log_poverwi	log_poverwi	log_poverwi	log_poverwi
log(negotiated rate)		1.609***	1.593***	1.397***	1.471***
		(0.0134)	(0.0136)	(0.0242)	(0.0227)
female			0.198***	0.0331	0.0350
			(0.0187)	(0.0250)	(0.0251)
5-18 years			-0.603***	-0.575***	-0.568***
			(0.0528)	(0.0840)	(0.0842)
17-24 years			-0.428***	-0.408***	-0.366***
			(0.0497)	(0.0750)	(0.0751)
24-44 years			-0.192***	-0.249***	-0.194***
			(0.0372)	(0.0540)	(0.0539)
44-64 years			-0.409***	-0.485***	-0.439***
			(0.0364)	(0.0528)	(0.0526)
over 64 years			-0.651***	-0.671***	-0.694***
			(0.0390)	(0.0658)	(0.0521)
Other Non-Federal Programs				-1.745***	
				(0.425)	
Preferred Provider organization				0.922***	
				(0.0871)	
Point of Service				0.731***	
				(0.0856)	
Exclusive Provider Organization				0.921***	
				(0.0921)	
Indemnity Insurance				0.859***	
				(0.125)	
Health Mainienance Organization				0.712***	
				(0.0942)	
Constant	7.676***	-6.047***	-6.192***	-4.940***	-4.779***
	(0.0109)	(0.115)	(0.615)	(0.717)	(0.717)
Observations	30206	30206	30206	12396	12396
R^2	0.000	0.323	0.339	0.329	0.320
AIC	124580.6	112789.6	112144.7	41894.8	42054.3
BIC	124588.9	112806.2	112535.5	42288.3	42403.3
Race and ethnicity controls?			Y	Y	Y

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5.

Regression of log payment per imputed weight against log negotiated rates estimates and patient characteristics. Column 5 restricts the dataset to only use observations that have no omitted values for the regression in Column 4.

log(negotiated rate) term. The R^2 suggests that negotiated rates account for about 32% of the variation in this ratio. Within the merged dataset we have two candidates for explaining at least some of the remaining 68%. Column 3 introduces patient demographics: age, sex, race, and ethnicity. including these characteristics improves slightly on the Column 2 regression. Of particular interest here is the positive and significant coefficient on the female indicator variable, suggesting that insurers compensate hospitals on average approximately 20% more than men for the same imputed weight. This is explored further in Column 1 of Table 2.6, which interacts sex with age categories. Here the effect goes away for all groups except for women aged between 17 and 44 years.[9] It may be that insurers negotiate differently for maternity care than for other services. However these demographic characteristics on their own account for very little variation in the paid to imputed weight ratio. In Column (2) we use only these demographics as explanatory variables, and achieve account for only 5.2% of the variation.

Another possibility is that insurers negotiate with hospitals for each of their plans, not for all of their customers together. If this was the case, then further slicing of the data by plans should provide more predictive power for payments. In the APCD we observe a variable categorizing the type of insurance plan a patient has. We use these as additional explanatory variables in Column 4 of Table 2.5. These buy marginally more explanatory power than controlling for patient demographics alone. Together, we interpret Tables 2.5 and 2.6 as suggestive evidence that a large fraction of hospitals' compensation of insured patients is explained by negotiated rates at the hospital-insurer level, but there still remains a large fraction of unexplained variation. Some of this variation may be the result of hospitals and insurers negotiating a fraction of charges for *most* services, but then negotiating other rates for some specific services, such as those provided in a maternity ward, or in a specialized care unit.

[9] Approximately 30% of women admitted in this age range are admitted for maternity care.

	(1)	(2)
	log_poverwi	log_poverwi
log(negotiated rate)	1.577***	
	(0.0136)	
female=1	-0.0495	-0.124
	(0.0629)	(0.0756)
5-18 years	-0.639***	-0.876***
	(0.0742)	(0.0892)
17-24 years	-0.800***	-0.977***
	(0.0770)	(0.0926)
24-44 years	-0.663***	-0.902***
	(0.0564)	(0.0678)
44-64 years	-0.450***	-0.424***
	(0.0490)	(0.0590)
over 64 years	-0.688***	-0.553***
	(0.0533)	(0.0641)
female=1 × 5-18 years	0.0840	0.0726
	(0.105)	(0.126)
female=1 × 17-24 years	0.632***	0.737***
	(0.100)	(0.121)
female=1 × 24-44 years	0.707***	1.262***
	(0.0748)	(0.0898)
female=1 × 44-64 years	0.0936	0.157
	(0.0697)	(0.0838)
female=1 × over 64 years	0.0981	0.236**
	(0.0751)	(0.0903)
Constant	-5.955***	8.343***
	(0.613)	(0.722)
Observations	30206	30206
R^2	0.344	0.052
AIC	111943.2	123074.5
BIC	112375.6	123498.6
Race and ethnicity controls?	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6.
Regression of log payment per imputed weight against log negotiated rates estimates and patient characteristics.

2.5 Conclusion

Hospitals and insurers both have significant market power in the market for health care. Exploiting that they can influence their customers' hospital choices, insurers negotiate lower prices for services. In return, hospitals are able to boost their admissions from that insurer. The resulting negotiated rates mean that the price paid for the same services at the same hospital varies by insurer.

This paper estimates these negotiated rates, and documents the variation in negotiated rates between hospitals and insurance companies. We look at this variation within hospital-insurer pairs, with a single hospital and many insurers, with a single insurer and many hospitals and across the state of Massachusetts. We find great variation in amounts paid for services across these three dimensions. Negotiated rates appear to vary more by insurer than by hospital, suggesting that insurers' bargaining power is more heterogeneous than hospitals'. Our analysis shows that using charges as a proxy for insured patients' out-of-pocket expenses (i.e. co-insurance) may be inaccurate if the sample includes more than one insurer.

This paper builds on existing studies with the use of the Massachusetts CHIA APCD and Case Mix datasets. These allow us to analyze payments at the patient level, with rich information about both illnesses and transactions. While negotiated rates organize our data well, there remain unexplained differences in payments within a hospital-insurer pair: within any hospital-insurer pair making FFS payments, the relationship between payments and charges is not deterministic. Given our understanding of FFS payment arrangements, we conclude that negotiations happen over finer measures of service than simply a fraction of charges. Possible candidates could be (i) the most extreme case of negotiating prices for each and every service the hospital offers (e.g. minutes in the operating room, nights stayed, etc.), and (ii) negotiating differential prices over types of service, for example patients in the maternity ward could face different negotiated rates to patients in the emergency room. Controlling for patient demographics suggests that at least the latter explanation is plausible.

Further work in this area could approach this bargaining problem from a more theoretical angle. In this paper we discuss negotiation while remaining agnostic as to the bargaining game underlying the process. Our estimates of negotiated rates could be used, along with estimated models of hospital demand, to structurally estimate parameters in bargaining games. Such analysis would be useful in analyzing counterfactual claims about the market for health insurance. As both sides of the market are large, hospitals merging may increase prices, and insurers merging may lower prices. The magnitude of these changes could be predicted with such a model. Additionally, the impact of price regulation, such as those in place in Maryland, could be simulated.

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APPENDICES

A. APPENDICES FOR UNISURED IN MARYLAND

A.1 Appendix A: Details of Base Rate Adjustments

The first thing to consider is the total prospective charges. Not all charges from the hospital are included in this calculation. Specifically, patients who stay for only one night are thrown out of allowable charges, as are some patients that are deemed to be outliers. These adjustments determine a hospital's previous year's approved charges. To determine the total prospective charges a few adjustments are made to the approved charges from the previous year. The first adjustment is for inflation and productivity using Global Insight's index, which measures the effect of general inflation in the economy on health care expenses. The second adjustment is a volume adjustment, which relies upon a historically made assumption about variable costs. The adjustment works as follows. If a hospital's service volume increased 10 percent in a year, in calculating the following years allowable revenue, only 85 percent of the increase would be considered as admissible charges. This is assumed to be the variable cost portion of the increased revenue of the hospital. The remaining adjustments are small in comparison to the two above, but for the sake of completeness are detailed below.The third adjustment considers any changes in the proportion of Medicare/Medicaid patients to the hospital. This adjustment exists because Medicare and Medicaid only pay 94% of charges. If there is growth in Medicare/Medicaid then it could be disadvantageous to a hospital's bottom line. For illustration, consider the following example of a hospital with 200 million in charges and 100 million of those charges belonging to Medicare and Medicaid patients. The discount from the hospital to the government is 6 million: $(1-.94)*100$ million. The existing \$6 million discount is taken into account in the charge structure. An adjustment would be made only on the basis of growth in the amount of Medicare and Medicaid patients. If the total charges of the hospital remained at 200 million, but now 150 million was attributable to Medicare and Medicaid, this growth in government-insured individuals induces a volume adjustment to this hospital. With 150 million in charges attribute to governmental insurance, this hospital would have a 9 million dollar shortfall, but 6 million was already accounted for in the initial cost structure. The volume adjustment covers this 3 million of additional discounts to the government. When half of the hospital's charges were governmental, the hospital was getting 3 million of revenue. To not disadvantage the hospital when its governmental charges rise to 150, Maryland's adjustment takes the 3 million 'discount' that previously was revenue, and simply increases the its initial charges by this amount. Now this hospital would be credited with 203 million in aggregate charges, its initial 200 million plus the 3 million discount for the government. The fourth adjustment pertains to capital investment, certificate-of-need project adjustments. If a hospital has major renovations, a portion of those costs can be covered by an increased base rate. The fifth adjustment is an adjustment for medical education. There are two types of medical education expenses, direct medical education expenses (DME) and indirect medical education expenses (IME). Both of these expenses are built into the base rate in levels. Thus, any adjustment to the base rate would be because of growth in DME or IME. For example, if a program added two more residents, their salaries would be an increase in DME. Finally, there is an adjustment for changes in the rate of bad debt (uncompensated care). To calculate future uncompensated care, an average is taken of previous rates of uncompensated care and a prediction of uncompensated care based on a regression. Again, only changes in uncompensated care require an adjustment; levels are built into the base rate.

A.2 Appendix B: CMAD

To understand how it is calculated, we must first describe how weights are established for each APRDRG. The Maryland commission has used two methodologies for calculation of weights. The current method adopted in 2006, though developed by Lave J (1981), the Hospital Specific Relative Value (HSRV) method establishes weights through an iterative process designed to reflect the clinical service expenditure of each APRDRG. HSRV weights removes charges associated with medical education. Complete technical details can be found in Udom (2013). The previous methodology, which is currently used by Medicare nationally, is the charge- based weight method and is described below. The two methodologies produce very similar weights. According to Rogowski and Byrne (1990) in over 95% of cases, the weights differed by no more than 5%. The older methodology, charge based weights, is far more intuitive and a brief description is below. Weights for each APRDRG are derived from a standard rate calculation. The standard rate calculation is a ratio of the average charges of all patients in the APRDRG and the average cost of everyone in the sample.

Let w_i denote the weight of APRDRG i, for $i = 1, ..., A$. Let the subscripts ij indicate patient j in APRDRG i, with $j = 1, ..., n_i$ and n_i the total number of patients in APRDRG i. Let C_{ij} be the charges, the amount billed, in connection with the services received by patient j in APRDRG i — to the patient if uninsured, to the patient's insurance entity otherwise.

$$w_i = \frac{((1/n_i)\sum_{j=1}^{n_i} C_{ij})}{\frac{(((\sum_{i=1}^{A}\sum_{j=1}^{n_i} C_{ij})}{(\sum_{i=1}^{A} n_i))))}} = \frac{\frac{\sum_{j=1}^{n_i} C_{ij}}{\sum_{i=1}^{A}\sum j=1^{n_i} C_{ij}}}{\frac{(n_i)}{\sum_{i=1}^{A} n_i}}. \tag{A.1}$$

If charge per patient is the same for all APRDRGs, then all weights equal 1.

The numerator is the share of the charges to APRDRG i patients in total charges. The denominator is the share of the number of patients in APRDRG i in the total number of patients. So an APRDRG gets a weight greater than 1 if its share of total charges is greater than its share of patients. An APRDRG gets a weight less than 1 if its share of total charges is less than its share of patients. Since charges are a measure of the cost of providing the services then the weights might be interpreted as a measure of the quantity of medical service provided to patients in an APRDRG.

In this way, patients who are expected to consume more services 'count more' than patients who receive fewer services. When a single patient is discharged, we talk about the 'weight' of their APRDRG. When we are describing a hospital's level of service, we have multiple patients with different diagnoses, so we sum the weights of the individual patients APRDRGs as a measure of total hospital services. This sum is the CMAD, a weighted value which conveys the difficulty of treating all the patients at a hospital.

$$CMAD_h = \sum_{j=1}^{n_h} w_i, \tag{A.2}$$

where n_h is the number of patients treated in the hospital in a given year.

Another way of understanding a CMAD is if there were no heterogeneity in illness, i.e. in a world with homogeneous patients with one type of illness and risk factors, the CMAD would simply count the number of people treated. CMAD is a measure of how many 'average' patients were treated. In our heterogeneous world however, a particularly service-intensive patient might have a weight of two, conveying that they require twice as many services as the average patient. Thus, they 'count' as two average patients when calculating CMAD.

When comparing charges per APRDRG weight, then, a constant level of charges/ APRDRG weight across insurance payer classes would suggest that patients require the same level of services, weighted by illness and severity. This measure of charges per weight will be used to compare relative demand across payer classes.

A.3 Appendix C: Summary Statistics for 2011-2013

Table A.1.
Summary Statistics from 2013

	Self Responsible and Charity	Medicare	Medicaid	Private	Dual Enrolled
Minimum	$ 8,523	$9,340	$9,153	$9,621	$8,820
Max	$28,265	$25,336	$23,288	$21,761	$24,063
Mean	$11,468	$12,319	$12,129	$12,320	$12,192
Median	$10,387	$11,615	$11,047	$11,352	$11,367
Standard deviation	3381.64	2847.27	2774.31	2690.84	2909.48

Table A.2.
Summary Statistics from 2012

	Self Responsible and Charity	Medicare	Medicaid	Private	Dual Enrolled
Minimum	\$ 8,909	\$ 9,870	\$ 9,639	\$ 9,870	\$ 9,521
Max	\$ 22,042	\$19,726	\$ 20,136	\$18,652	\$ 22,518
Mean	\$11,526	\$ 12,277	\$12,024	\$ 12,026	\$12,168
Median	\$ 10,954	\$ 11,511	\$11,195	\$ 11,260	\$ 11,522
Standard deviation	2259.73	2175.21	2277.60	2115.73	2597.57

Table A.3.
Summary Statistics from 2011

	Self Responsible and Charity	Medicare	Medicaid	Private	Dual Enrolled
Minimum	\$6,303	\$9,420	\$9,061	\$9,240	\$8,937
Maximum	\$ 19,084	\$ 21,078	\$ 20,345	\$ 19,898	\$ 20,609
Mean	\$ 10,764	\$ 11,763	\$ 11,542	\$ 11,413	\$ 11,577
Median	\$ 10,406	\$ 11,122	\$ 10,900	\$ 10,646	\$ 10,994
Standard deviation	2261.84	2195.68	2286.49	2144.70	2331.42

A.4 Appendix D: Charges by weights for patients Under 65 with interactions

Table A.4.
Charges/Weight by Payer Class

	(1) Charges per weight(CPW)
Medicare	-35.67
	(38.57)
Blue Cross	-690.8***
	(41.60)
Non-Group Ins.	-719.4***
	(37.40)
Workmen's Comp	-193.3
	(114.2)
Uninsured	-1482.8***
	(42.35)
Ave Income	0.00514***
	(0.000611)
Black	101.1***
	(20.90)
Married	-238.8***
	(22.32)
Separated	-73.47
	(55.71)
Divorced	50.06
	(36.36)
Widow/er	133.8*
	(60.15)
Observations	1203218

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Appendix E: Blinder Oaxaca with Average Income, White, High Low Risk Dummy Interactions

Table A.5.
Blinder Oaxaca Demposition with Ave. Income(1-4), White, and Low Risk

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	11786.2***	(126.4)	11672.3***	(100.3)	11771.7***	(108.8)	11777.9***	(117.6)
Prediction_2	13849.8***	(63.53)	13384.9***	(44.05)	13566.0***	(47.54)	13087.4***	(39.74)
Difference	-2063.6***	(140.4)	-1712.7***	(109.3)	-1794.3***	(118.4)	-1309.6***	(123.9)
Decomposition								
Endowments	-597.3***	(77.92)	-386.5***	(55.65)	-113.1	(64.63)	-259.5***	(61.49)
Coefficients	-1632.4***	(273.2)	-1240.6***	(184.5)	-1518.9***	(287.9)	-878.5***	(221.9)
Interaction	166.1	(234.6)	-85.58	(160.3)	-162.3	(257.4)	-171.5	(202.1)
Observations	38946		68447		65229		75335	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6.
Blinder Oaxaca Demposition with Ave. Income(5-8), White, and Low Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	11659.4***	(133.5)	11571.6***	(130.6)	11646.1***	(139.5)	11573.3***	(135.7)
Prediction_2	12622.5***	(39.32)	12573.5***	(38.19)	12610.6***	(37.43)	12348.8***	(37.15)
Difference	-963.1***	(138.8)	-1001.9***	(135.9)	-964.5***	(144.1)	-775.5***	(140.5)
Decomposition								
Endowments	-214.7***	(58.29)	-143.8	(85.22)	-167.1*	(65.96)	-258.0***	(61.93)
Coefficients	-977.3***	(296.4)	-944.9***	(249.5)	-582.2	(373.3)	-861.0***	(219.5)
Interaction	228.9	(259.5)	86.80	(230.5)	-215.2	(346.6)	343.5	(188.9)
Observations	71857		86350		79221		87091	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.6 Appendix F: Blinder Oaxaca with Average Income, Black, High low risk Dummy interactions

Table A.7.
Blinder Oaxaca Demposition with Ave. Income(1-4), White, and High Risk

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	13391.5***	(661.1)	12233.2***	(441.5)	12130.2***	(471.2)	12961.3***	(490.5)
Prediction_2	14067.3***	(282.4)	13633.4***	(184.0)	14653.3***	(268.1)	13231.2***	(196.7)
Difference	-675.8	(719.2)	-1400.3**	(477.8)	-2523.1***	(540.3)	-269.9	(527.8)
Decomposition								
Endowments	-1378.3***	(353.6)	-1205.9***	(233.8)	-1263.7***	(331.3)	-431.7	(266.4)
Coefficients	-1931.3*	(782.4)	-309.2	(741.5)	-2016.4**	(649.3)	1269.5*	(542.2)
Interaction	2633.8***	(678.9)	114.8	(668.2)	757.0	(551.7)	-1107.7*	(443.5)
Observations	1577		3142		2795		3050	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8.
Blinder Oaxaca Demposition with Ave. Income(5-8), White, and High Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	13355.0***	(652.4)	13753.1***	(978.2)	12594.1***	(674.2)	13215.9***	(762.9)
Prediction_2	13460.6***	(209.3)	13372.8***	(218.4)	13294.4***	(197.7)	13500.2***	(202.9)
Difference	-105.7	(684.5)	380.2	(1001.8)	-700.4	(700.8)	-284.3	(789.0)
Decomposition								
Endowments	-189.6	(317.6)	-250.1	(363.5)	-343.2	(303.3)	-294.0	(463.0)
Coefficients	-216.7	(622.9)	3956.8*	(1886.5)	-39.97	(568.1)	368.3	(679.2)
Interaction	300.7	(657.8)	-3326.5	(1709.6)	-317.2	(591.4)	-358.6	(828.3)
Observations	2800		2658		2781		3102	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9.
Blinder Oaxaca Demposition with Ave. Income(1-4), Black, and Low Risk

	(1) Quantile 1		(2) Quantile 2		(3) Quantile 3		(4) Quantile 4	
Differential								
Prediction_1	11870.5***	(75.70)	11822.6***	(109.7)	11546.5***	(122.8)	11235.6***	(117.6)
Prediction_2	14789.4***	(38.82)	13949.2***	(45.67)	13626.1***	(50.88)	13279.0***	(52.83)
Difference	-2918.9***	(84.67)	-2126.6***	(118.1)	-2079.6***	(132.4)	-2043.5***	(128.3)
Decomposition								
Endowments	-1004.4***	(50.94)	-718.8***	(64.94)	-600.1***	(66.21)	-622.5***	(71.75)
Coefficients	-2262.9***	(168.9)	-1301.4***	(272.2)	-1333.4***	(233.4)	-1420.4***	(181.0)
Interaction	348.4*	(153.1)	-106.3	(238.8)	-146.2	(202.4)	-0.620	(152.1)
Observations	114564		72210		54012		51691	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10.
Blinder Oaxaca Demposition with Ave. Income(5-8), Black, and Low Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	11271.3***	(135.9)	11445.0***	(156.3)	11173.4***	(155.1)	11531.1***	(209.2)
Prediction_2	12932.2***	(55.86)	12926.7***	(56.83)	12779.7***	(53.28)	12638.6***	(72.04)
Difference	-1660.9***	(146.5)	-1481.7***	(165.7)	-1606.4***	(163.7)	-1107.5***	(220.9)
Decomposition								
Endowments	-470.0***	(66.83)	-475.5***	(97.83)	-403.8***	(70.61)	-514.6***	(96.04)
Coefficients	-1166.1***	(256.0)	-1237.1***	(190.9)	-866.1***	(240.0)	-1053.4***	(258.8)
Interaction	-24.87	(217.7)	230.9	(168.0)	-336.5	(211.5)	460.5*	(185.7)
Observations	39768		38765		39114		22155	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11.
Blinder Oaxaca Demposition with Ave. Income(5-8), Black, and High Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	14446.0***	(889.9)	12371.4***	(607.2)	13216.8***	(722.4)	16711.8***	(1544.1)
Prediction_2	14482.9***	(287.1)	14191.4***	(343.0)	13814.5***	(301.9)	14298.4***	(554.1)
Difference	-36.91	(935.3)	-1820.0**	(695.6)	-597.6	(782.5)	2413.4	(1621.6)
Decomposition								
Endowments	-569.6	(480.2)	-1635.6***	(438.8)	599.2	(698.3)	-869.0	(756.3)
Coefficients	598.5	(1378.1)	-898.4	(872.3)	-3249.9**	(1148.9)	3666.3**	(1385.5)
Interaction	-65.86	(1214.7)	714.0	(861.5)	2053.0	(1200.6)	-384.0	(1454.7)
Observations	1545		1460		1560		800	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.12.
Blinder Oaxaca Demposition with Ave. Income(5-8), Black, and High Risk

	(1) Quantile 5		(2) Quantile 6		(3) Quantile 7		(4) Quantile 8	
Differential								
Prediction_1	14446.0***	(889.9)	12371.4***	(607.2)	13216.8***	(722.4)	16711.8***	(1544.1)
Prediction_2	14482.9***	(287.1)	14191.4***	(343.0)	13814.5***	(301.9)	14298.4***	(554.1)
Difference	-36.91	(935.3)	-1820.0**	(695.6)	-597.6	(782.5)	2413.4	(1621.6)
Decomposition								
Endowments	-569.6	(480.2)	-1635.6***	(438.8)	599.2	(698.3)	-869.0	(756.3)
Coefficients	598.5	(1378.1)	-898.4	(872.3)	-3249.9**	(1148.9)	3666.3**	(1385.5)
Interaction	-65.86	(1214.7)	714.0	(861.5)	2053.0	(1200.6)	-384.0	(1454.7)
Observations	1545		1460		1560		800	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.7 Appendix G: Sensitivity to Treatment: Readmission Inpatient Quality Indicators

Some diagnoses are more sensitive to treatment than others. The Agency for Healthcare Research and Quality (AHRQ) has identified Inpatient Quality Indicators (IQI). These indicators "include conditions for which mortality has been shown to vary substantially across institutions and for which evidence suggests that high mortality rates may be associated with deficiencies in the quality of care." (AHRQ and Quality, 2014)

Selecting patients with these diagnoses highlighted by the IQI, using ICD-9-CM diagnostic codes, I restrict my sample to those patients who suffer from an illness identified as sensitive to treatment. While these categories have been identified as sensitive for mortally, I also investigate their effects on readmission for individuals under 65. A priori, one would expect that uninsured IQI individuals receiving less services would be readmitted at higher rates than uninsured non-IQI individuals.

In Table 8, column 1 shows the regression results for IQI readmissions with an uninsured dummy and average income by zip code.

The first thing to observe is that coefficient on 'uninsured' in column 1 (.683) is about 6 percentage points less than in the full sample (.743). This means that uninsured individuals who have IQI diagnoses are less likely to get readmitted than all patients (under 65).

Column 2 of Table 8 shows results of readmission for patients with IQI diagnoses by average income quantile. The most notable result is the coefficient on 'uninsured'. In this specification, this coefficient is measuring the difference in readmission rates for insured versus uninsured individuals who reside in zip codes in the bottom $\frac{1}{8}$ of average income. Uninsured individuals from these low income zip codes are readmitted 63.6% as often as insured. The second major result is the relative lack of variation among all insured individuals and all uninsured individuals. It seems like the critical

Table A.13.
Logit: Readmission for IQI Under 65 with income interactions

	(1)		(2)	
	Uninsured		Income interactions	
readmit				
_Iuninsured_1	0.683***	(0.0208)	0.636***	(0.0457)
ave_income_by_zip	1.000*	(0.000000567)		
_Iincome_gr_2			0.940*	(0.0267)
_Iincome_gr_3			0.989	(0.0286)
_Iincome_gr_4			1.039	(0.0325)
_Iincome_gr_5			1.008	(0.0327)
_Iincome_gr_6			0.944	(0.0318)
_Iincome_gr_7			0.976	(0.0338)
_Iincome_gr_8			0.912*	(0.0341)
_IuniXinc_1_2			1.093	(0.117)
_IuniXinc_1_3			1.036	(0.115)
_IuniXinc_1_4			0.960	(0.101)
_IuniXinc_1_5			1.138	(0.125)
_IuniXinc_1_6			1.146	(0.136)
_IuniXinc_1_7			1.102	(0.128)
_IuniXinc_1_8			1.278*	(0.157)
N	233570		233570	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

factor is the presence of insurance, and income is much less important. Insured IQI individuals in the top income quantile tend to be readmitted at lower rates than other insured individuals, while uninsured individuals in the top quantile are readmitted more frequently than uninsured patients in lower quantile.[1]

Similarly, I investigate the likelihood of readmissions on non-IQI patients. We would assume these patients would be less sensitive to treatment, and as such, would expect more muted results than for the IQI patients.

Table A.14.
Logit: Readmission for Non-IQI Under 65 with income interactions

	(1)		(2)	
	Uninsured		Income interactions	
readmit				
_Iuninsured_1	0.772***	(0.0137)	0.615***	(0.0281)
ave_income_by_zip	1.000	(0.000000329)		
_Iincome_gr_2			0.982	(0.0187)
_Iincome_gr_3			1.018	(0.0195)
_Iincome_gr_4			1.006	(0.0208)
_Iincome_gr_5			1.052*	(0.0218)
_Iincome_gr_6			1.001	(0.0209)
_Iincome_gr_7			1.005	(0.0215)
_Iincome_gr_8			0.978	(0.0218)
_IuniXinc_1_2			1.319***	(0.0833)
_IuniXinc_1_3			1.060	(0.0706)
_IuniXinc_1_4			1.287***	(0.0806)
_IuniXinc_1_5			1.331***	(0.0873)
_IuniXinc_1_6			1.367***	(0.0946)
_IuniXinc_1_7			1.349***	(0.0917)
_IuniXinc_1_8			1.526***	(0.104)
N	934024		934024	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1]Given that IQI diagnoses were identified as those that were sensitive to treatment, it is surprising to find that for these diagnoses, readmission rates were lower than readmission rates for all diagnoses. If uninsured patients received fewer services, one would imagine they would have higher rates of readmission for the diseases that are very sensitive to treatment. Detailed analysis of which services were provided and at what levels is left to subsequent work.

In column 1 of Table 9, the coefficient on 'Uninsured' is .772; uninsured individuals without IQI diagnoses are 77% as likely as insured individuals to be readmitted. In column 2, with income interactions, uninsured individuals with non-IQI diagnoses who live in the bottom quantile of income are as 61.5% as likely to be readmitted. As with the insured individuals with an IQI diagnosis in Table 8, there is very little variation in readmission rates for any level of average income among insured individuals. Uninsured individuals without an IQI diagnosis have a different pattern of readmission. The coefficients and errors for uninsured, non IQI patients are plotted in Figure 6.

Among the uninsured non IQI patients, individuals in the 2nd, 4th, 5th, 6th and 7th quantiles are all about 30% more likely to get readmitted than those uninsured individuals in the bottom income quantile. As in the full sample, uninsured individuals living in the wealthiest zip codes are more likely to be readmitted than those in less affluent zip codes.

A.8 Appendix F: Length of Stay and Time Between Admissions

Robustness checks for readmission results: Time between visits In Table 10, we saw uninsured individuals under 65 were 72% as likely to be readmitted to the hospital as their insured counterparts. One might imagine that even though these are acute illnesses requiring overnight hospitalization, that individuals have some capacity to 'time' their readmission to the hospital. If that were the case, perhaps what is driving the result that uninsured individuals are less likely to be readmitted is that uninsured patients are postponing care beyond the 30-day window that defines a readmission. If we saw support for the theory that uninsured individuals were delaying care, we would expect to see a distribution of readmission times with a higher mean than for the uninsured individuals. Summary statistics can be seen below. Note all individuals below are under 65. In the summary statistics, there is no evidence that uninsured individuals wait longer to seek readmission. To look if this ability of

Table A.15.
Time between readmission by payer type

Insurance Class	Mean	Standard Deviation
Medicaid	13.9	8.2
Private Insurance	13.4	8.0
Uninsured	12.5	8.4

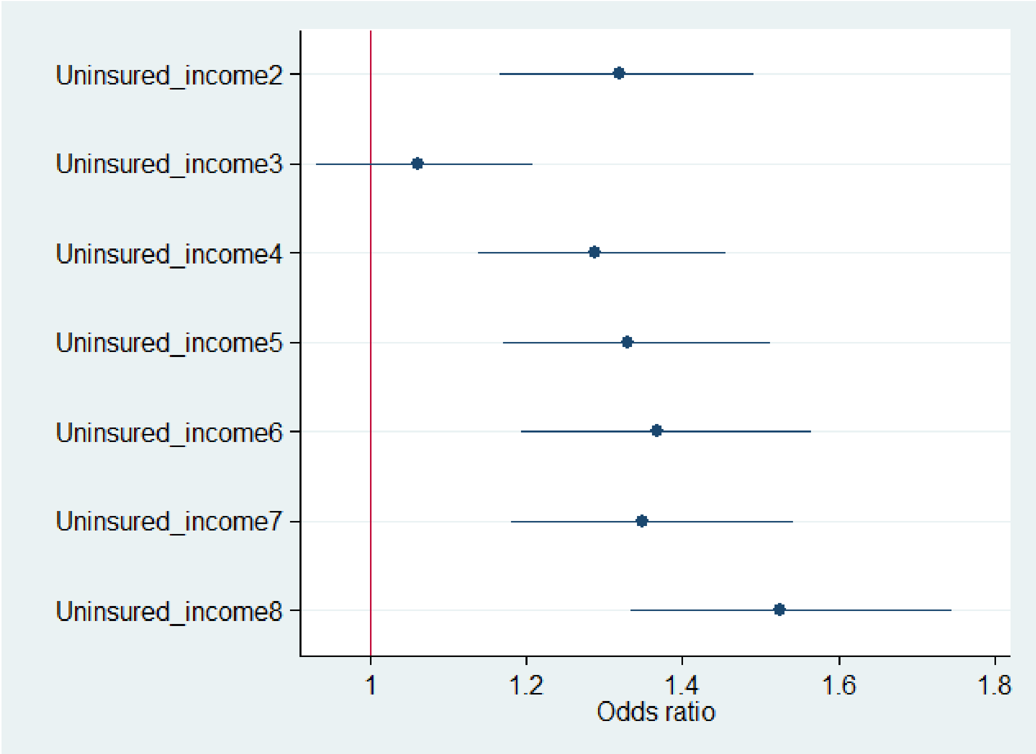

Fig. A.1. Logit: Readmission for Non-IQI Under 65 with income interactions

patients to influence their date of readmission was what was driving the result, I have created a distribution of times between discharge and readmission to the hospital by payer class. For the purposes of illustration, I have graphed Uninsured patients, Medicaid, Private insurance, and all patients (Total). The following histograms show the time that has elapsed between the last admission and the next visit to the hospital.

From these distributions it seems that uninsured individuals have a different pattern of readmission than their insured counterparts in the very early period after being released from the hospital. For the first five days or so, uninsured individuals return to the hospital at double the rates of their uninsured counterparts.

To better understand what factors influence the time between subsequent admissions (up to 60 days), I run a regression on time between admissions and control for types of disease, age, etc.

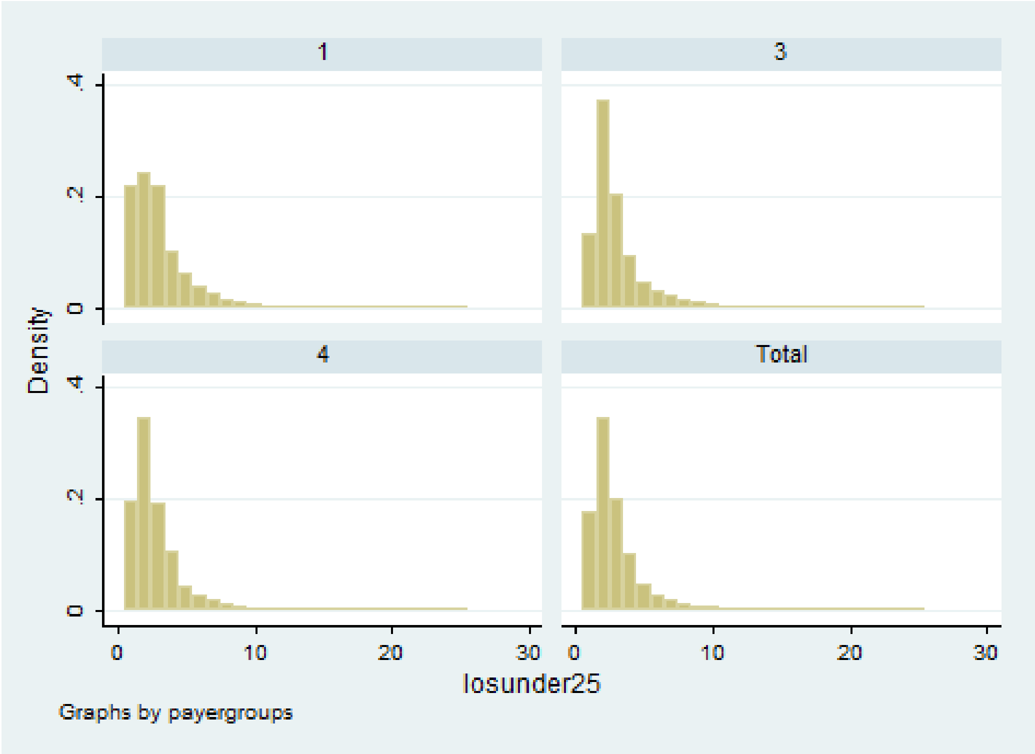

Fig. A.2. Time between Visits: Uninsured, Medicaid, Private Ins.

Notice that in the Table, the coefficient on Uninsured in column 2 is both very small and insignificant. For individuals living in zip codes in the bottom $\frac{1}{8}$ of the average income distribution, insurance status does not predict time between consecutive admissions. In fact, when one looks at insured individuals across income categories, there is little variation in the time between visits. At most it is about .7 days or less than 17 hours. Given that the average time away is about 22.5 days, this variation is fairly insignificant. For uninsured individuals there is about a 1 day reduction in time between visits for the lowest income quantile, but then little variation for the next 4 quantiles (2,3,4,5). The highest three income quantiles have substantial reductions in time between visits with 2 days less for quantile 6, 3.5 days less for quantile 7 and 4.75 days less for the highest income uninsured.

The question remains, though, why do uninsured individuals have an initial spike in readmissions. One theory is that uninsured individuals who need a major procedure

Table A.16.
Time Between visists: Uninsured and Ave Income Interactions

	(1)		(2)	
	Time		Interactions	
uninsured==1	-1.6143825***	(0.1708867)	-0.006401854	(0.3874471)
Black	0.8748875***	(0.08255084)	0.8592704***	(0.08356232)
Married	-0.2327008**	(0.08935114)	-0.2362986**	(0.08937809)
Seperated	0.1755054	(0.2084138)	0.1677914	(0.2083951)
Divorced	0.1931207	(0.1251261)	0.2045250	(0.1251409)
Widow/er	0.3278824**	(0.1171288)	0.3335622**	(0.1171310)
income_groups8==2			-0.1734736	(0.1370761)
income_groups8==3			-0.3484314*	(0.1404526)
income_groups8==4			-0.4589804**	(0.1470338)
income_groups8==5			-0.6945232***	(0.1490466)
income_groups8==6			-0.5730408***	(0.1505829)
income_groups8==7			-0.4022986*	(0.1568301)
income_groups8==8			-0.5989535***	(0.1650503)
Uninsured_income2			-0.9579977	(0.6083940)
Uninsured_income3			-0.7941942	(0.5918455)
Uninsured_income4			-1.1863758	(0.6139970)
Uninsured_income5			-0.9413719	(0.6077268)
Uninsured_income6			-2.0080148**	(0.6338382)
Uninsured_income7			-3.5046939***	(0.6104041)
Uninsured_income8			-4.7424810***	(0.6328836)
Observations	221576		221576	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

might return home for a night to save the expense of staying in the hospital. To investigate this empirically, running a regression on length of stay would inform if insurance status and average income were a good predictor of length of stay. As a robustness check, I excluded readmissions in the first three days after leaving the hospital. Results did not change appreciably.

Table A.17.
Length of Stay: Uninsured and Ave Income Interactions

	(1) Length of Stay		(2) Length of stay interactions	
uninsured==1	-0.04443884*	(0.01837747)	-0.1362901***	(0.04104730)
Black	0.09581459***	(0.01017150)	0.1088681***	(0.01029887)
Married	-0.2328788***	(0.01098457)	-0.2354867***	(0.01098885)
Seperated	-0.03537612	(0.03030945)	-0.03565102	(0.03030956)
Divorced	0.009114482	(0.01784573)	0.005833278	(0.01784938)
Widow/er	-0.06241945***	(0.01672531)	-0.06474998***	(0.01672731)
income_groups8==2			0.09213176***	(0.01783987)
income_groups8==3			0.1005392***	(0.01785896)
income_groups8==4			0.1236147***	(0.01850741)
income_groups8==5			0.09634154***	(0.01863656)
income_groups8==6			0.08567305***	(0.01854327)
income_groups8==7			0.08142438***	(0.01917792)
income_groups8==8			0.03670833	(0.01974922)
Uninsured_income2			0.01290092	(0.06285501)
Uninsured_income3			0.07256237	(0.05993899)
Uninsured_income4			0.07797528	(0.06325025)
Uninsured_income5			0.1752733**	(0.06339308)
Uninsured_income6			0.1328046*	(0.06640591)
Uninsured_income7			0.1209582	(0.06644391)
Uninsured_income8			0.2189164**	(0.06904879)
Observations	1454215		1454215	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When we consider the full interaction between income quantiles by zip code and insurance status, we see that for insured individuals, length of stay decreases with income, but that all estimates, while econometrically significant are not particularly

economically significant. The range of coefficients is less than .13 days or about three hours. The average length of stay is 4.3 days.
We also observe that uninsured individuals from the bottom quantile of the average income distribution have lengths of stay that are about .136 days shorter than their insured counterparts. While highly statistically significant, economically, this is fairly inconsequential, as it translated to a four hour shorter stay or a reduction of time in the hospital of 3%. There is more variation in length of stay among the uninsured by average income quantiles. Uninsured individuals from the wealthiest zip codes stay about 8.5 hours longer than uninsured individuals from the poorest zip codes.

A.9 Appendix H: Sensitive to Treatment: Mortality IQI

A.9 In Table 13, for individuals under 65 who have an IQI diagnosis, there is no statistical difference in the rates of mortality for insured or uninsured individuals. This is surprising, as IQI diagnoses were specifically identified as those which were sensitive to treatment, but this does not translate into a differential effect on mortality.

Table 14, we have results for the non˙IQI patients. Selected coefficients are plotted in Figure 8. We see increased mortality for uninsured individuals under 65 living in wealthy zip codes compared to all other groups. The mortality rate for uninsured individuals living in the top $\frac{3}{8}$ of zip codes rises to about 3 times that of uninsured individuals living in the poorest zip codes. For illnesses that were identified as non-IQI, or less sensitive to treatment, there seems to be a sizable, statistically significant increase in mortality for uninsured individuals who live in zip codes in the top $\frac{3}{8}$ of average income. This is particularly surprising given that for individuals who have diagnoses identified as sensitive to treatment (IQI), there is no difference in mortality between insured and uninsured, for all income zip code quantiles.

A.10 Appendix I: Readmission and Mortality Rates with Income, High/Low, and Race Interactions.

Table A.18.
Logit: U65 IQI Mortality of Uninsured with Income Interactions

	(1)	
	death	
death		
uninsured==1	1.228	(0.189)
income_groups8==2	1.052	(0.0664)
income_groups8==3	1.115	(0.0737)
income_groups8==4	0.985	(0.0681)
income_groups8==5	1.032	(0.0762)
income_groups8==6	0.940	(0.0696)
income_groups8==7	0.933	(0.0725)
income_groups8==8	1.015	(0.0813)
Unisured_income2	0.638	(0.147)
Unisured_income3	1.092	(0.248)
Unisured_income4	1.078	(0.233)
Unisured_income5	0.733	(0.178)
Unisured_income6	0.750	(0.186)
Unisured_income7	1.296	(0.305)
Unisured_income8	1.062	(0.264)
Observations	218088	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.19.
Under 65 Non-IQI Mortality

	(1)	
	death	
death		
uninsured==1	0.776	(0.178)
income_groups8==2	1.070	(0.0866)
income_groups8==3	0.810*	(0.0724)
income_groups8==4	0.947	(0.0830)
income_groups8==5	0.903	(0.0844)
income_groups8==6	0.934	(0.0838)
income_groups8==7	0.916	(0.0869)
income_groups8==8	0.913	(0.0898)
Unisured_income2	1.078	(0.347)
Unisured_income3	0.956	(0.342)
Unisured_income4	1.175	(0.372)
Unisured_income5	1.665	(0.523)
Unisured_income6	2.255**	(0.682)
Unisured_income7	3.719***	(1.094)
Unisured_income8	3.401***	(1.005)
Black	0.952	(0.0465)
Married	1.010	(0.0501)
Seperated	0.747*	(0.103)
Divorced	0.961	(0.0723)
Widow/er	1.213	(0.133)
Observations	835850	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

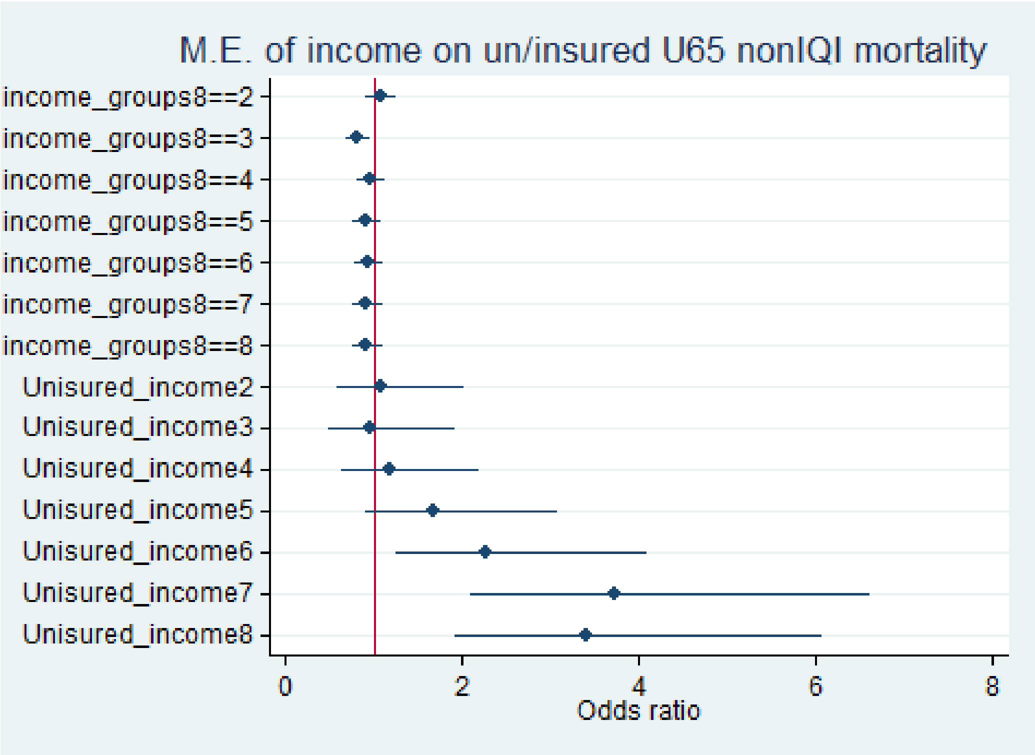

Fig. A.3. Marginal Effect of income on un/insured U65 nonIQI mortality

Table A.20.
Logit: Readmission and Mortality of Uninsured Dummy with Income Interactions

	(1)		(2)	
	readmitlater		death	
main				
Ins_low_black	0.941*	(0.0235)	0.915	(0.0835)
Insured_highrisk	1.320	(0.278)	14.38***	(5.613)
Ins_high_black	1.304	(0.256)	13.37***	(4.901)
Uninsured_lowrisk	0.721***	(0.0511)	0.724	(0.226)
Unins_low_black	0.521***	(0.0257)	1.064	(0.198)
Uninsured_highrisk	1.500	(0.472)	27.60***	(15.78)
Unins_high_black	0.766	(0.209)	12.22***	(5.973)
Unin_low_income2	1.230*	(0.105)	1.291	(0.484)
Unin_low_income3	0.956	(0.0835)	1.724	(0.643)
Unin_low_income4	1.038	(0.0894)	1.619	(0.574)
Unin_low_income5	1.173	(0.102)	1.544	(0.573)
Unin_low_income6	1.169	(0.104)	1.312	(0.491)
Unin_low_income7	1.157	(0.105)	1.894	(0.710)
Unin_low_income8	1.261**	(0.112)	2.093*	(0.766)
Unins_low_B_inc2	1.084	(0.0895)	0.538	(0.188)
Unins_low_B_inc3	1.045	(0.0948)	0.676	(0.249)
Unins_low_B_inc4	1.335***	(0.106)	1.119	(0.315)
Unins_low_B_inc5	1.329**	(0.115)	0.880	(0.301)
Unins_low_B_inc6	1.311*	(0.141)	1.048	(0.393)
Unins_low_B_inc7	1.228*	(0.116)	2.294**	(0.678)
Unins_low_B_inc8	1.412**	(0.154)	0.922	(0.394)
Unin_high_income2	0.832	(0.252)	0.455	(0.259)
Unin_high_income3	0.528	(0.174)	0.481	(0.286)
Unin_high_income4	0.720	(0.222)	0.629	(0.334)
Unin_high_income5	0.806	(0.253)	0.706	(0.403)
Unin_high_income6	0.763	(0.241)	0.779	(0.411)
Unin_high_income7	0.604	(0.198)	2.195	(1.135)
Unin_high_income8	0.664	(0.216)	1.679	(0.869)
Unin_high_B_income2	0.841	(0.293)	0.668	(0.404)
Unin_high_B_income3	1.462	(0.492)	2.366	(1.307)
Unin_high_B_income4	0.904	(0.301)	0.820	(0.475)
Unin_high_B_income5	1.411	(0.458)	0.941	(0.535)
Unin_high_B_income6	1.314	(0.508)	2.226	(1.386)
Unin_high_B_income7	1.657	(0.538)	3.525*	(1.760)
Unin_high_B_income8	0.618	(0.340)	3.298*	(1.738)
Observations	1172205		1103714	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. APPENDIX FOR: HOSPITAL-INSURER BARGAINING POWER AND NEGOTIATED RATES

B.1 Understanding Variation in Fee For Service Payments

In this section, we explore the variation in FFS payments, and some of the issues with using charge master prices as a measure of services. We assume that FFS payments are negotiated as a fraction of charges. If all variation in FFS payments were explained by this negotiated fraction, then a regression of log(payments) against log(charges) should result in a coefficient of 1 on log(charges), and and R^2 of 1. Specifically, estimating the model:

$$\log(\text{paid}_j) = \beta_0 + \beta_1 \log(\text{charged}_j) + \epsilon_j \tag{B.1}$$

for all patients j who were admitted at hospital h with insurance i should result in estimates of $\hat{\beta}_1 = 1$ and $R^2 = 1$. Setting $\epsilon_j = 0\ \forall j$ yields:

$$\log\left(\frac{\text{paid}_j}{\text{charged}_j}\right) = \beta_0 \tag{B.2}$$

$$\rho_{hi} = \exp(\beta_0) \tag{B.3}$$

These ρ_{hi}s tell us the fraction of charges that a homogenized patient would pay for a particular hospital-insurer combination. As such they allow us to compare relative prices between hospital-insurer pairs.

We begin with Table B.1 by exploring the variation in FFS payments and charges due to characteristics such as hospital type, location, and insurance and hospital market share. These regressions are used to motivate our analysis based on a normalization of charges, rather than charges themselves.

Before interpreting the coefficients on these regressions, it is worthwhile noting that, given a long enough time horizon, all of these market characteristics are endogenous. While we expect hospital location, teaching status, and the presence of an emergency room to be choice variables for the hospital only in the *very* long run, and hence fixed for the purposes of a particular negotiation, market share clearly varies directly with the negotiation process. We therefore invite the reader to be cautious in interpreting the coefficients on market shares as causal.[1]

We have four specifications. The first specification examines payments and charges on a per-patient basis. The second specification explains payments considering illness heterogeneity by interacting illness weight and hospital type. The third specification explains charges again by considering illness heterogeneity by interacting illness weight and hospital type. The final specification uses normalized charges to explain payments.

In Table B.1 column (1), we regress log(payments) against log(charges), hospital type indicators, region indicators, and measures of market share of hospitals and insurers. For FFS payments, we expect the coefficient on log(charges) to be equal to one. While we reject this hypothesis at the 5% level, the coefficient of 0.940 indicates a close to linear relationship between payments and charges.[2]

We next turn our attention to hospital type. Of some concern in column (1) is the negative and significant coefficient on the academic medical center (AMC) indicator. The comparison group of hospital type is community hospitals, which we think of as being highly substitutable. We predicted community hospitals would have limited bargaining power. AMCs are high-quality specialized hospitals, so we expected this

[1]Specifically, we expect hospital (insurer) market share to be correlated with unobservable hospital quality (insurance policy) characteristics that are important in the negotiating process. For example, we expect higher quality hospitals to command both (i) greater market shares and (ii) greater negotiated rates. As quality is unobserved and therefore an omitted variable, this would mean that the estimated coefficient on market share would over-state the effect of having a greater market share. Hence the estimates are an upper bound of the causal affect of a hospital or insurer commanding a greater market share in the negotiation.

[2]One thing to observe is that this suggests that patients with higher charges may pay a slightly smaller fraction of the bill than patients with lower charges. This may be attributable to budget constraints. If patients pay 10% of their bills through coinsurance, patients with bills in the upper tail of the distribution may struggle to pay even the coinsurance fraction of their bill.

	(1)	(2)	(3)	(4)
	log(paid)	log(paid)	log(charged)	log(paid)
log(charged)	0.937***			
	(0.0109)			
Academic MC	-0.481***	0.460***	0.696***	0.148***
	(0.0342)	(0.0365)	(0.0277)	(0.0332)
Community DSH	0.0793*	0.122**	0.0361	0.160***
	(0.0352)	(0.0391)	(0.0297)	(0.0357)
Teaching	-0.0182	0.183***	0.0323	0.0719*
	(0.0293)	(0.0331)	(0.0251)	(0.0292)
TraumaCenters	0.161***	0.135***	0.0400	0.0702*
	(0.0316)	(0.0298)	(0.0226)	(0.0316)
Central Mass	-0.0568	-0.237***	-0.145***	-0.250***
	(0.0423)	(0.0473)	(0.0359)	(0.0425)
North East Mass	-0.211***	-0.104*	-0.00933	-0.145***
	(0.0397)	(0.0426)	(0.0323)	(0.0399)
Metro Boston	0.497***	0.0328	-0.0483	0.528***
	(0.0382)	(0.0381)	(0.0289)	(0.0388)
South Eastern Mass	0.163***	0.00504	-0.220***	-0.126**
	(0.0424)	(0.0460)	(0.0349)	(0.0428)
Log hospital market share (DRG weight)	0.143***			0.256***
	(0.0116)			(0.0119)
Log insurer market share (DRG weight)	-0.131***			-0.124***
	(0.00451)			(0.00451)
Academic MC × log(DRGweight)		0.266***	0.373***	
		(0.0251)	(0.0190)	
Community × log(DRGweight)		0.294***	0.382***	
		(0.0296)	(0.0225)	
Community DSH × log(DRGweight)		0.269***	0.401***	
		(0.0301)	(0.0228)	
Teaching × log(DRGweight)		0.358***	0.414***	
		(0.0335)	(0.0254)	
log(Imputed weight)				1.044***
				(0.0118)
Constant	-0.705	7.557***	8.116***	8.514***
	(0.520)	(0.465)	(0.352)	(0.526)
Observations	43889	9797	9797	43462
R^2	0.220	0.167	0.403	0.228

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.1.
Relationship between payments and charges for Fee For Service payments. All regressions control for sex, race, ethnicity, and age (polynomial). Hospitals classified as "other specialty" have been omitted from these regressions.

coefficient to be positive. The reason for this unexpected sign is investigated in columns (2) and (3).

Column (2) in Table B.1 regresses log payments against various controls for market characteristics, and investigates the relationship between DRG weights (which capture illness heterogeneity) and payments.[3] One can interpret the coefficients on the hospital type indicators as (approximately) the fraction markup over a community hospital for a DRG weight of one. Note here that academic medical centers are estimated to receive $1.57 = \exp(0.454)$ times the payment compared to a community hospital for a patient with a DRG weight of 1. This coefficient, unlike the corresponding coefficient in column (1), *is* in line with our expectations that AMCs are the high-quality hospitals, and hence command higher prices.

The coefficient `AMC` $\times$ `Log weight` of .267 should be interpreted as follows. For an increase in DRG weight of 1, payments would increase by a factor of $\exp(0.267) = 1.306$, or 30.6%.

Column (3) changes the dependent variable in the regression, and regresses log(charges) against the same regressors as column (2). This estimation highlights the discrepancy noted in column (1) where the AMC indicator's coefficient was expected to have a positive sign. The coefficient on AMC in column (3) is significantly positive, indicating that AMC's *charges* are uniformly higher. Therefore, an insurer with the same negotiated rate (as a fraction of charges) at a community hospital and an AMC would be charged more at the AMC.

Notice, though, when we compare columns (2) and (3), that `AMC` have much higher charges than the community hospitals. AMCs have much higher prices than their community counterparts, but they only get payments that are a fraction higher.

This observation motivates the normalization of charges. We normalize hospital charges by creating a hospital charge index which compares each patient's charges to estimated charges at that hospital for a DRG of 1. This procedure is described in detail in Section B.2.2.

We call this variable `log(Imputed Weight)` and use it instead of raw charges in the same specification as column (1). The results of this are reported in column (4) of

[3] Here we include $\log(\text{weight}_j)$ interacted with all hospital type indicators to allow for more flexibility in this relationship. Typically in specifications with interactions, one includes a 'linear' term for the interacted variable alone. In this specification, however, since we interact weight with every hospital type, to include weight (uninteracted), we would have to omit the effect of an increase in weight on a particular hospital type.

Table B.1. Here we see that AMCs command payments of about $1.155 = \exp(0.143)$ times higher than community hospitals, and an additional 7% if they have a trauma center. When we compare our results to Ho (2008), who estimates 'star' hospitals to have markups of 25%, we find similar results (about 23%). We also include log market share by DRG weight, and estimate that a 1% increase in market share of a hospital is associated with a 0.257% increase in negotiated payments, and a 1% increase in market share of an insurer is associated with a 0.127% decline in negotiated payments. Again, due to suspected correlation with unobservable quality attributes, we consider these value to be upper bounds on the causal effects of these variables in the negotiation process.

B.2 Procedure for calculating negotiated rates

Our goal is to estimate the negotiated rates between hospitals and insurers in the market for health care. To this end, we must estimate:

1. An index of relative hospital charges. Specifically, for each hospital we estimate the amount that a patient with a DRG weight of 1 would be charged.
2. Negotiated rates for each hospital-insurer pair (i.e. how much is paid for services for a normalized patient[4], and how this varies for each hospital-insurer pair?)

The remainder of this section outlines the procedure.

B.2.1 Index of relative hospital charges

In Section B.1,we find a patient's charges varies greatly by hospital, even after normalizing differences in DRG weight.[5] As we aim to estimate negotiated rates as a fraction of charges, we wish to control for this variation so that a normalized

[4]Normalized in this context means for a patient with a DRG weight of 1

[5]For example, we would imagine hospitals at the top of the referral network to treat sicker patients. When we say we are controlling for DRG weights, what we mean is that we are comparing charges per DRG weight. Thus we can compare charges as if patients were homogeneous and each had an average illness.

"charge" buys the same quantity of services at each hospital.[6] As a motivation for this normalization, consider two hospitals, one with low costs and charges and one with high costs and high charges. \$5,000 of charges at Hospital L(ow) would buy more services than \$5,000 at Hospital H(igh). Our normalization allows us to look at percentage changes in service provision relative to a standard unit of service.[7]

We first calculate an index of hospital charges that is equal to the estimated (log) charges that a patient with a DRG weight of 1 would receive. To achieve this, we estimate the following equation for every hospital twice, once for FFS and once for DRG payments:

$$\log(\text{charged}_j) = \beta_{0,h} + \beta_{1,h}\log(\text{weight}_j) + \epsilon_j \tag{B.4}$$

where weight_j is patient j's DRG weight. Taking the conditional expectation of (B.4) for a weight of 1 yields:

$$E\left[\log(\text{charged}_j) \mid \text{weight}_j = 1\right] = \beta_{0,h} \tag{B.5}$$

Using the estimated intercept from (B.4), we then construct:

$$\log(\text{normalized\_charges}_j) = \log(\text{charged}_j) - \hat{\beta}_{0,h} \tag{B.6}$$

That is, if two patients at different hospitals have the same normalized charges, (say 1.5) we expect that they each receive 1.5 times as many services as a normalized patient at their hospital. the same quantity of services, but their (un-normalized) charges could be different.[8] Furthermore in expectation, $\log(\text{normalized\_charges}_j) = 0$

[6]One can roughly think of this as the ratio of actual charges to the charges a patient would receive if they had a weight of 1 (i.e., charges for an average patient) at that hospital. Precise details on our methodology for constructing these normalized charges are below

[7]A standard unit of service is one with a DRG weight of 1, and is not dependent on patient case mix.

[8]Because this specification is in logs, this is more clear if you consider 2 patients both of who receive 2 times the average service provision at two different hospitals. Both would have a normalized charge of 2. At hospital A, average charges may be \$8,000. At hospital B, average charges may be \$10,000. The patient at Hospital A would receive \$16,000 of services and at Hospital b would

corresponds to the quantity of services that would be provided for a DRG weight of 1.[9]

B.2.2 Procedure for estimating negotiated rates for FFS payments

Fee-for-service (FFS) payment arrangements are negotiated payments between a hospital and an insurer specifying either amounts to be paid for each service provided by the hospital, or the fraction of the hospital's charges that will be paid. Due to the availability of data, we make the simplifying assumption that all FFS contracts are a negotiated fraction of charges, noting that the alternative would be a negotiated price vector for services, say $\mathbf{p}_{hi}$. If $\mathbf{p}_{hi} = \rho_{hi}\mathbf{c}_h$ for some $\rho_{hi} \in (0,1)$, where $\mathbf{c}_h$ is hospital h's charge master prices, then these types of arrangements are identical.

We seek to estimate the fraction of charges that each insurer pays to each hospital. Additionally, noting that charges for the same services vary greatly between hospitals, we also estimate the amount paid by an insurer for one unit of normalized payments.

For a FFS arrangement, the relationship between charges and payments should be:

$$\text{paid}_j = \rho_{hi}\text{charged}_j, \quad \iff \quad \log(\text{paid}_j) = \log(\rho_{hi}) + \log(\text{charged}_j) \tag{B.7}$$

where ρ_{hi} is the fraction of charges paid by insurer i at hospital h. We estimate (B.7) by regressing log(payments) against log(charges) for all patients in a hospital-insurer pair:

$$\log(\text{paid}_j) = \beta_{0,hi} + \beta_{1,hi}\log(\text{charged}_j) + \epsilon_j \tag{B.8}$$

receive \$20,000, but each receives twice the average, so they each have a normalized charge of 2. In this way, normalized charges tells us the relative amount of service consumption at each hospital without explicitly comparing dollar values.

[9] and for small x, $\log(\text{normalized\_charges}_j) = x$ corresponds to a DRG weight of approximately $1+x$.

Hence, our estimated for negotiated rates as a fraction of services are:

$$\hat{\rho}_{hi} = \exp(\hat{\beta}_{0,hi}) \tag{B.9}$$

Note that between (B.7) and (B.8) we allow for $\beta_{1,hi} \neq 1$, that payments are not directly proportional to charges.

We also estimate the amount paid for normalized charges using the regression equation:

$$\log(\text{paid}_j) = \beta_{0,hi} + \beta_{1,hi} \log(\text{normalized\_charges}_j) + \epsilon_j \tag{B.10}$$

again, allowing for a nonlinear relationship between payments and normalized charges through estimating (rather than imposing a value on) $\beta_{1,hi}$. Our estimate of the amount paid for a unit of normalized charges is therefore:

$$\hat{\gamma}_{hi} = \exp(\beta_{0,hi}) \tag{B.11}$$

Note that the units of $\hat{\gamma}_{hi}$ are in US dollars, while $\hat{\rho}_{hi}$ is unit-free.

B.3 Estimates of negotiated rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Aetna	Blue Cross	Cigna	Fallon	United	Tufts	ALL
Anna Jaques	0	1539.2	0	0	4072.7	0	2158.2
	(.)	(312.2)	(.)	(.)	(1424.0)	(.)	(400.4)
Baystate MC	0	3320.1	7786.1	4853.6	7792.0	0	4794.6
	(.)	(210.6)	(906.8)	(617.0)	(1052.4)	(.)	(245.9)
Baystate Franklin MC	0	2264.1	0	0	0	0	4061.5
	(.)	(486.9)	(.)	(.)	(.)	(.)	(574.0)
Baystate Mary Lane	0	2639.7	0	0	0	0	4301.0
	(.)	(883.1)	(.)	(.)	(.)	(.)	(979.3)
Brigham and Women's	22001.1	7559.8	19721.4	10682.3	11954.0	13640.7	13279.2
	(296.5)	(193.2)	(813.6)	(958.8)	(1003.1)	(245.6)	(163.9)
Signature Healthcare Brockton	0	2186.7	0	0	5639.6	7102.1	3248.0
	(.)	(215.4)	(.)	(.)	(1446.4)	(652.9)	(274.4)
Cape Cod	10620.6	3770.7	0	0	9507.6	9897.4	6300.0
	(887.0)	(298.7)	(.)	(.)	(1657.1)	(666.1)	(337.7)
Falmouth	0	4130.9	0	0	0	12880.7	7385.6
	(.)	(499.2)	(.)	(.)	(.)	(1029.8)	(540.3)
Steward Norwood	0	0	0	0	5107.2	7106.3	5924.0
	(.)	(.)	(.)	(.)	(1362.5)	(455.0)	(392.3)
Steward Carney	0	1247.1	0	0	5972.2	5910.0	3529.9
	(.)	(452.6)	(.)	(.)	(1413.2)	(942.0)	(469.2)
Boston Children's	14984.2	4115.8	13830.8	0	0	16476.6	7753.3
	(648.9)	(234.4)	(1191.8)	(.)	(.)	(746.6)	(276.6)
Cooley Dickinson	0	0	0	2672.1	0	6189.5	4331.9
	(.)	(.)	(.)	(647.1)	(.)	(737.2)	(557.2)
Beth Israel -Needham	0	1332.6	0	0	0	0	3510.8
	(.)	(709.7)	(.)	(.)	(.)	(.)	(819.3)
Emerson	0	3645.1	0	0	5333.5	8707.9	5640.4
	(.)	(318.1)	(.)	(.)	(1548.1)	(504.2)	(328.7)
Brigham and Women's-Faulkner	0	3258.9	0	0	8358.4	8408.0	5785.9
	(.)	(360.5)	(.)	(.)	(1838.4)	(680.1)	(392.8)
Harrington Memorial	0	2071.9	0	3743.8	0	0	3609.1
	(.)	(448.9)	(.)	(575.0)	(.)	(.)	(438.0)
Health Alliance	0	0	0	3560.8	7307.0	0	4487.0
	(.)	(.)	(.)	(520.7)	(1711.4)	(.)	(495.2)
Heywood	0	1933.4	0	2725.0	0	6122.7	3018.7
	(.)	(333.0)	(.)	(633.2)	(.)	(793.8)	(364.6)
Steward Holy Family	0	2380.4	0	0	7229.3	7645.2	5250.3
	(.)	(352.1)	(.)	(.)	(960.1)	(557.3)	(324.5)
Holyoke MC	0	2003.5	0	0	6521.8	0	3415.8
	(.)	(421.6)	(.)	(.)	(1815.3)	(.)	(489.6)

Beth Israel -Plymouth	0	2906.4	0	0	5173.5	7347.6	4219.3
	(.)	(291.3)	(.)	(.)	(1862.4)	(620.3)	(344.7)
Lawrence General	0	0	0	1702.6	0	7638.9	5907.0
	(.)	(.)	(.)	(886.1)	(.)	(580.6)	(523.5)
Lowell General	0	2908.2	0	0	5985.2	7898.8	4998.2
	(.)	(215.4)	(.)	(.)	(963.4)	(376.3)	(230.6)
Massachusetts Eye and Ear	0	0	0	0	0	5013.7	4743.4
	(.)	(.)	(.)	(.)	(.)	(1165.6)	(857.7)
Massachusetts General	17153.6	2823.5	14790.3	0	9857.6	12197.0	8859.3
	(323.9)	(157.6)	(892.8)	(.)	(692.3)	(233.0)	(148.4)
Milford Regional MC	0	2541.9	0	3900.3	5065.3	8892.4	4184.2
	(.)	(366.5)	(.)	(690.7)	(1771.5)	(824.2)	(372.0)
Beth Israel - Milton	0	1964.2	0	0	4480.5	5127.1	3493.5
	(.)	(445.2)	(.)	(.)	(1862.4)	(695.1)	(458.9)
Morton	0	1839.7	0	0	5710.9	5596.8	3059.0
	(.)	(316.7)	(.)	(.)	(1674.6)	(873.4)	(375.0)
Mount Auburn Hospital	0	4995.8	0	0	7668.5	0	5558.3
	(.)	(360.5)	(.)	(.)	(1771.5)	(.)	(456.2)
New England Baptist	0	24610.1	0	0	22275.1	17304.6	20279.9
	(.)	(553.2)	(.)	(.)	(2029.5)	(1005.6)	(541.7)
Newton-Wellesley	8682.5	3677.5	9894.2	0	7754.0	10388.0	7505.2
	(433.6)	(225.4)	(1249.9)	(.)	(1308.3)	(287.2)	(203.0)
North Adams Regional	0	2543.9	0	0	0	0	4013.2
	(.)	(501.8)	(.)	(.)	(.)	(.)	(663.5)
Quincy MC	0	1551.2	0	0	0	5672.4	3597.0
	(.)	(553.2)	(.)	(.)	(.)	(799.6)	(549.3)
Steward Saint Anne's	0	1241.2	0	0	6848.0	8204.4	4860.8
	(.)	(491.7)	(.)	(.)	(1260.2)	(858.5)	(451.9)
South Shore	8577.8	3135.5	7649.7	0	7374.2	10134.7	6404.5
	(724.2)	(196.8)	(1332.4)	(.)	(1084.8)	(304.8)	(201.1)
Steward St. Elizabeth's MC	0	4354.7	0	0	8885.8	10427.9	8241.3
	(.)	(417.1)	(.)	(.)	(1362.5)	(408.9)	(328.4)
Saint Vincent	4973.1	2871.1	0	5172.7	5929.9	9631.6	5396.6
	(668.0)	(358.6)	(.)	(240.4)	(1291.7)	(553.3)	(217.9)
Sturdy Memorial	0	5628.2	0	0	5156.2	7138.8	5864.2
	(.)	(257.7)	(.)	(.)	(1507.5)	(805.6)	(318.9)
Clinton	0	0	0	0	0	0	3927.5
	(.)	(.)	(.)	(.)	(.)	(.)	(954.1)
Marlborough	0	2120.3	0	3007.6	8731.3	8507.0	4458.5
	(.)	(515.4)	(.)	(1023.2)	(2029.5)	(1184.3)	(528.9)
Winchester	0	3010.9	6241.1	0	4903.9	10028.8	6278.8
	(.)	(249.9)	(1613.6)	(.)	(1592.1)	(347.0)	(253.3)
Wing Memorial	0	1710.9	0	0	0	0	4050.9

	(.)	(819.5)	(.)	(.)	(.)	(.)	(785.7)
North Shore MC	10410.2	2964.4	0	0	7242.5	10180.5	5577.3
	(499.1)	(241.9)	(.)	(.)	(1413.2)	(766.5)	(276.4)
Boston MC	0	2828.3	0	0	5593.4	7310.2	4384.8
	(.)	(217.7)	(.)	(.)	(703.9)	(511.8)	(236.3)
Cambridge Health Alliance	0	1471.7	0	0	3048.7	5714.7	2274.3
	(.)	(255.3)	(.)	(.)	(1862.4)	(746.6)	(331.7)
MetroWest MC	0	1924.7	0	1568.5	5374.7	0	2393.0
	(.)	(250.3)	(.)	(905.2)	(1482.1)	(.)	(323.6)
Hallmark Health	0	2493.4	0	0	5204.6	9299.1	5339.6
	(.)	(591.9)	(.)	(.)	(1446.4)	(932.5)	(505.7)
Northeast	0	3438.0	0	3569.3	5297.2	9438.8	5466.6
	(.)	(199.7)	(.)	(877.1)	(1372.2)	(360.3)	(220.1)
Southcoast	7766.9	2317.5	7651.3	3144.4	8808.1	7674.9	4748.2
	(607.5)	(175.7)	(1493.9)	(995.9)	(848.7)	(381.3)	(194.5)
UMass Memorial MC	0	1100.5	11978.5	4698.0	7385.2	12213.5	6551.8
	(.)	(567.8)	(1363.8)	(256.9)	(820.0)	(491.5)	(223.7)
Berkshire MC	11209.2	0	0	0	9862.0	11012.2	10150.3
	(781.1)	(.)	(.)	(.)	(1136.8)	(881.1)	(460.7)
Lahey Clinic	0	4419.4	0	7065.2	9412.1	11588.1	7275.7
	(.)	(213.2)	(.)	(1085.3)	(813.8)	(415.4)	(227.6)
Mercy MC	0	1787.4	0	3485.0	0	6019.0	2965.1
	(.)	(310.4)	(.)	(792.6)	(.)	(914.4)	(374.5)
Steward Good Samaritan MC	0	2348.3	0	0	6416.5	7031.2	4392.8
	(.)	(249.0)	(.)	(.)	(1362.5)	(422.1)	(268.1)
Beth Israel Deaconess MC	0	3317.7	9080.4	0	7741.2	14187.4	8010.5
	(.)	(168.9)	(1007.2)	(.)	(755.4)	(261.5)	(171.6)
Observations	1267	14563	644	2188	3650	7894	31719

Standard errors in parentheses

B.4 OLS Robustness

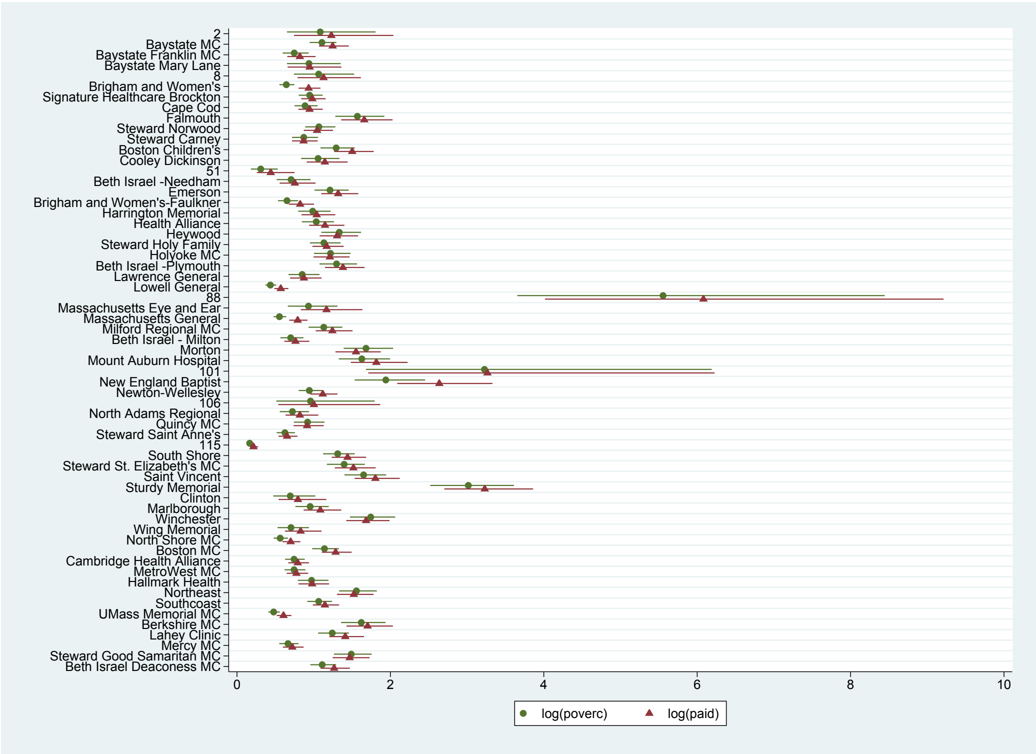

Fig. B.1. Restricted and unrestricted exponentiated coefficient plot for estimates of coefficients on hospital indicators. The green dots show the exponentiated coefficients of the restricted model, which regresses the log paid to charged ratio against hospital and insurer indicators (uninteracted). The red triangles show the exponentiated coefficients of the unrestricted model, which regresses log payments against log charges, hospital indicators, and insurer indicators (uninteracted). As the omitted hospital is Anna Jacques, the value of the exponentiated coefficient should be interpreted as the ratio of payments to charges relative to Anna Jacques. E.g.: a hospital with a coefficient equal to 0.7 has an average paid to charged ratio that is 70% of the same ratio at Anna Jacques.

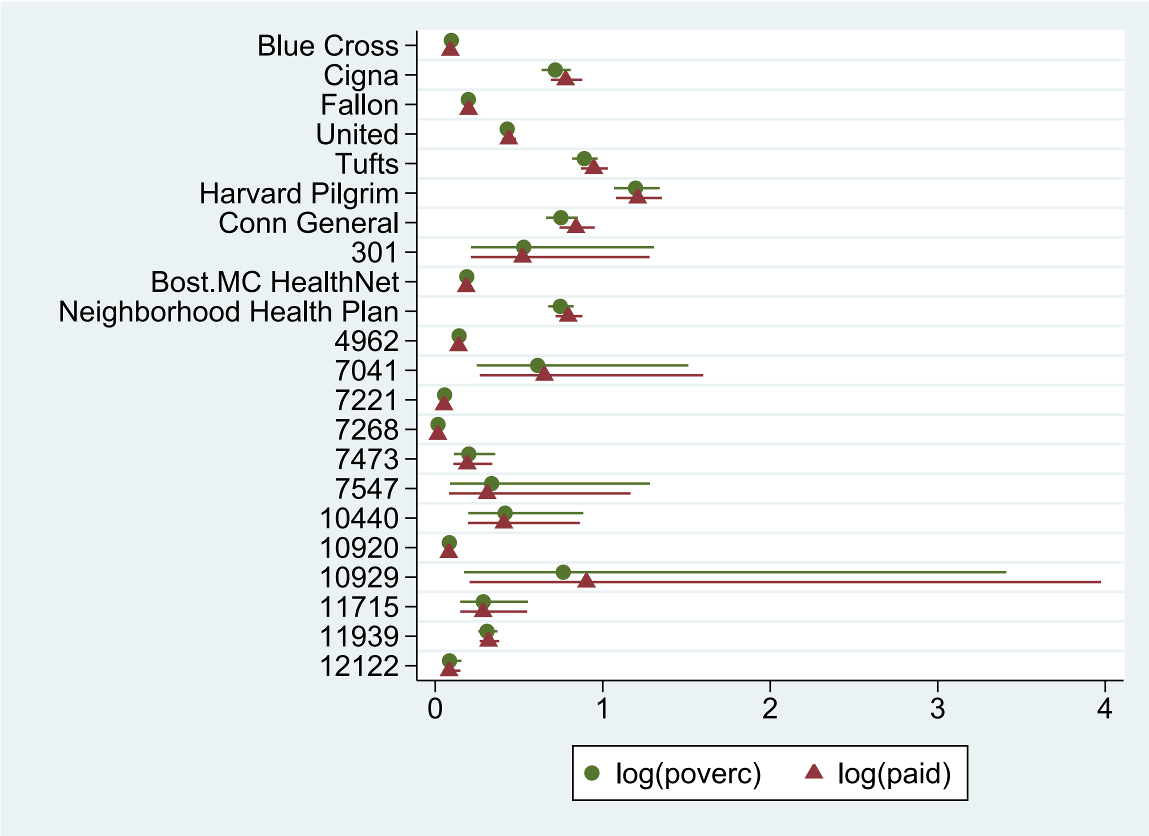

Fig. B.2. Restricted and unrestricted exponentiated coefficient plot for estimates of coefficients on insurer indicators. The green dots show the exponentiated coefficients of the restricted model, which regresses the log paid to charged ratio against hospital and insurer indicators (uninteracted). The red triangles show the exponentiated coefficients of the unrestricted model, which regresses log payments against log charges, hospital indicators, and insurer indicators (uninteracted). As the omitted insurer is Aetna, the value of the exponentiated coefficient should be interpreted as the ratio of payments to charges relative to those paid by Aetna. E.g.: an insurer with a coefficient equal to 0.7 has an average paid to charged ratio that is 70% of the same ratio for Aetna.

VITA

VITA

Amanda C Cook

RESEARCH INTERESTS

Health Economics, Health Insurance, Industrial Organization, Applied Microeconomics

EDUCATION

In progress	Economics Ph.D., Purdue University, Krannert School of Management Adviser: Stephen Martin
2011	Master of Economics -Graduate Program in Economic Development, Vanderbilt University
2003	Bachelors in Mathematics, Grinnell College

HONORS AND AWARDS

2015	Purdues Award for Distinguished Teaching
2014	Ph.D. Student Service Award - Krannert Deans Office
2014	Purdues Award for Distinguished Teaching
2014	Purdues Award for Distinguished Teaching
2014	Purdues Award for Outstanding Teaching
2014	Purdue University Graduate School Summer Research Grant
2013	Purdues Award for Distinguished Teaching
2013	Purdues Award for Distinguished Teaching
2011-12	Ross Fellowship Purdue University

RESEARCH

Uninsured? Less Service, Fewer Readmission, More Death. A Study of Maryland's Hospitals
Healthcare as a Platform market: A theoretical approach (with Steve Martin)
Hospital-Insurer Bargaining Power and Negotiated Rates (with Amanda Cook)

CONFERENCES, WORKSHOPS, AND SEMINARS

2016

- American Society of Health Economists conference
- Midwest Economic Association Meeting 2016

2015

- Southern Economic Association Meeting 2015
- Grinnell College, Department of Economics Seminar
- Purdue University, Interdisciplinary Health Seminar
- Towson University, Department of Economics Seminar
- Midwest Conference in Applied Economics, Regional and Urban Studies, W. Lafayette, IN

TEACHING Purdue University

- Intermediate Macroeconomics – Instructor: Summer 2014, Fall 2014, Summer 2015
- Introductory Microeconomics – Instructor: Summer 2013, Fall 2013, Spring 2014

AFFILIATIONS

American Economic Association, American Society of Health Economists, Southern Economic Association, Midwest Economics Association