Do the Poor Benefit From More Generous Medicaid Physician Payments?

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Abstract

This paper examines how changes in Medicaid physician payments affect provision of care to the poor. I find that when payments increase, time spent treating Medicaid patients increases but time spent treating the uninsured falls by a more than offsetting amount. I additionally show that physicians are more likely to encourage their uninsured patients to enroll in Medicaid. Finally, I demonstrate that when Medicaid eligibility is high, physicians are less likely to substitute between Medicaid and uninsured patients. My results suggest that payment increases should be coupled with eligibility expansions in order to improve access to care among the poor. JEL: I11, I12, I18

The Patient Protection and Affordable Care Act (ACA) simultaneously extended health coverage to millions of uninsured Americans and increased the Medicaid reimbursement rates for some physicians. However we lack a holistic understanding of how these policies affect provision of care. How does access to care change among those who remain uninsured? Moreover, what is the interaction between concurrent changes in payment and eligibility? In this paper, I address these questions by identifying both supply and demand responses to state-level changes in Medicaid payments, Medicaid eligibility, and their interaction.

Understanding how Medicaid policies affect the breadth of physician behavior, and not just the target market, is particularly important because the ACA changes the entire distribution of insurance enrollments. The Congressional Budget Office (CBO) forecasts that by 2022, an additional 11 million will have enrolled in Medicaid, 25 million will be covered by the health insurance exchanges, and 30 million will remain uninsured (CBO, 2012).[2] If physicians are

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[2]The remaining uninsured will consist of undocumented workers and the poor in states which have declined to expand Medicaid. In those states, people with income above the Medicaid federal poverty limit (FPL) but below the FPL to receive exchange subsidies will continue to have limited, if any, options for health coverage.

unwilling to treat patients with a particular type of insurance, then obtaining coverage may not improve access to care. This concern has already manifested itself among Medicaid patients. As illustrated in Figure 1, the percentage of practices offering any care to Medicaid patients has fallen from 87% in 1996 to 81% in 2008.[3]

I begin by presenting a simple stylized model of physician behavior. Extending the Sloan model to allow for charity care, I find that the impact of Medicaid payment changes on the provision of charity care is ambiguous (Sloan, Mitchell and Cromwell, 1978).[4] Higher reimbursements make physicians richer, so they are more willing to provide charity care. At the same time, higher reimbursements raise the effective cost of charity care, so physicians are less willing to provide charity care. Although my model does not offer clear predictions for how payment changes affect charity care, it does predict that Medicaid eligibility expansions will magnify the effect of payment changes on Medicaid supply and reduce the effect of payment changes on charity care supply. The basic intuition behind this conjecture is that there will be less substitution between Medicaid and charity care patients.

Turning to the data, I find that a 10% increase in Medicaid reimbursement rates is associated with 0.6% more physicians participating in Medicaid and 1.2% more physicians accepting all new Medicaid patients. I further show that the cross-price elasticity of Medicare participation is 0.06 to 0.08, willingness to treat the privately insured does not change, and the percentage of time spent on charity care falls by 3.8%. Because physicians *reduce* their total hours of care, these results imply that charity-care supply falls by more than the increase in Medicaid supply. I support this claim by demonstrating that the aggregate time spent treating Medicaid and charity care patients falls.

I then consider the demand responses to a change in Medicaid reimbursements. I find that a 10% increase in Medicaid reimbursements leads to a 2.3% increase in Medicaid enrollments. This increase comes primarily from reductions to the uninsured population. To shed light on why payment changes affect insurance enrollment, I use the Amazon Mechanical Turk (mTurk) platform to administer a survey identifying factors that influence insurance enrollment.[5] Results show that respondents in states with increasing Medicaid reimbursement rates are more likely to have received encouragement from a doctor or hospital to enroll in Medicaid. This finding provides suggestive evidence of supplier-induced Medicaid demand: physicians

[3] A growing number of national and state specific studies have concluded that the US physician workforce is facing current or future shortages (AAMC, 2012).

[4] In this paper, charity care refers to care supplied to the uninsured. It is different from uncompensated care because it excludes bad debts, incurred when patients do not apply for charity care or are unwilling to pay their bills (American Hospital Association, 2013).

[5] mTurk has become a growing platform for social science experiments, and researchers have found that the quality of responses compare well to other, more expensive survey platforms (Horton, Rand and Zeckhauser, 2011; Kuziemko et al., 2013; Paolacci, Chandler and Ipeirotis, 2010).

encourage their uninsured patients to enroll in Medicaid.

The net effect of these supply and demand responses can be identified from changes in access to care. I show that increasing Medicaid reimbursement rates leads to more efficient health care utilization: hospital emergency room (ER) admissions fall by 3% and preventable hospitalizations fall by 0.7%. These benefits accrue mainly from improved access to care for Medicaid patients.

Finally, I consider how expansions in eligibility affect the impact of Medicaid payment changes. Consistent with the predictions of my model, I find that the higher the fraction eligible for Medicaid, the bigger the effect of payment increases on Medicaid provision and the smaller the reductions in charity care. This result suggests that payment increases should be coupled with eligibility expansions in order to improve access to care among the poor, comprised of both Medicaid enrollees and the uninsured.

This paper makes several contributions to the literature. First, I expand on existing studies by considering the impact of Medicaid payment on non-Medicaid supply decisions. Ex ante an empirical analysis, it is unclear whether Medicaid and charity care are supply complements or substitutes, so the impact of Medicaid-policies on access to care for the poor is unknown. Furthermore, because health care comprises of private and public markets, changes in the public market can create unintended effects in the private market. For example, raising Medicaid prices can crowd-out supply of private care, or it can reduce cost-shifting where private payers are charged more in response to shortfalls in public payments (Cutler, 1998; Dafny, 2005; Dranove and White, 1998; Ginsburg, 2003; Mayes and Lee, 2004; Morrisey, 2003). These intricate connections highlight the importance of having a more complete understanding of physician supply.

Second, my estimates improve upon the handful of existing Medicaid supply elasticity estimates. Earlier papers examining the relationship between Medicaid payment and supply rely on a single cross-section of national data while omitting state fixed effects (Sloan, Mitchell and Cromwell, 1978; Mitchell, 1991; and Cohen, 1993). Because substantial geographic variations in health access and spending can explain much of the observed correlation between physician pay and supply, these estimates are likely biased. Studies using more robust empirical specifications focus on a subset of the Medicaid population, such as the Medicaid supply in one specific state or the Medicaid supply for pregnant women seeking obstetric services (Currie, Gruber and Fischer, 1995; Gray, 2001; Gruber, Kim and Mayzlin, 1999; Hadley, 1979). Many of these papers also rely on an inseparable Medicaid to Medicare fee ratio, which masks the differential responses between Medicaid and Medicare price changes (Adams, 1994; Decker, 2007, 2009; Gray, 2001; Shen and Zuckerman, 2005). In this paper, I construct an expenditure-weighted Medicaid price index from data covering over 200 procedural codes to isolate the

impact of Medicaid price changes on overall Medicaid supply.[6]

Third, this paper extends the literature on physician reimbursement rates by examining the demand-side response to increased payments. Although "supplier-induced demand" has traditionally referred to physicians increasing their own income by manipulating their patients into receiving more services than they would want, I identify a variant of supplier-induced demand in which physicians encourage their Medicaid-eligible uninsured patients to enroll in Medicaid. This practice can be beneficial for both the patient and the physician.

Finally, to my knowledge, this paper is the first to consider the interaction between payment increases and eligibility expansions.[7] While these policies traditionally constitute two separate bodies of literature, the ACA increases both payments and eligibility simultaneously, so understanding the interacted effect of these policies yields important policy implications.

The rest of the paper is organized as follows. Section I. provides a brief background on Medicaid rate-setting and eligibility policies. Section II. outlines a model and delineates the empirical strategy. Section III. describes the data. Section IV. discusses the impact of payment changes, eligibility changes, and their interaction. Section V. presents results on health behaviors and outcomes. Section VI. provides robustness checks. Section VII. concludes.

I. Brief Overview of Medicaid Policies

Medicaid is the nation's largest health insurance program, insuring over 62 million Americans. In this paper, I use changes in the Medicaid state-administered fee-for-service reimbursement rate to identify the impacts of a price change. I also rely on state-level changes in insurance coverage to identify how changes in Medicaid eligibility affect the impact of payment changes. To assess whether these two sources of variation are plausibly exogenous, it is necessary to understand the legislation governing Medicaid payment and eligibility.

A. Medicaid Rate-Setting Policies

Because federal regulations on state-specific Medicaid payment policies are lax, states have set their fee schedules using several different methods.[8] Some states base original rates on physicians' actual charges for services or negotiations with various provider groups. Others use a rate-setting system comparable to Medicare's: each procedure has an associated weight that

[6] These studies are outlined in greater detail in Appendix A.

[7] Currie, Gruber and Fischer (1995) is one of the few studies that compares payment changes with eligibility expansions, but their study does not examine the interaction effect.

[8] See Merlis (2004) for details on the regulation governing state Medicaid policies.

takes into account physician work, practice expenses, and malpractice costs. These weights are then multiplied by a fixed unit value to create a fee schedule. The different rate-setting methods cause Medicaid reimbursements to vary dramatically from state to state. For example, in 2010, a cardiac catheterization costs $140 in Pennsylvania but $746 in neighboring New Jersey (AAP, 2011).

Regardless of the rate-setting method, the Congressional Research Service reports that "basic rates and/or inflation increases are fixed by the state and may bear no relation to what physicians ordinarily charge or what they are paid by Medicare or private insurers" (Merlis, 2004). Although the apparent randomness in rate-setting policies supports an assumption of exogeneity, one might argue that observable factors which are endogenous to physician supply, such as the demand for services or changes in a state's economic condition, can impact reimbursement policy changes. I consider several potential predictors of Medicaid price in Section A. and show that none of these predictors significantly predict Medicaid prices.

B. Medicaid Eligibility Policies

To participate in Medicaid, states are federally required to cover certain population groups, and they have the power to extend coverage to other groups.[9] I argue that in the late 1990s and 2000s, states enacted eligibility changes primarily in response to federal legislation. Established in 1997, the State Children's Health Insurance Program (CHIP) set aside $40 billion in federal funds for states to expand their existing Medicaid programs or establish new state CHIP programs.[10] While there were no initial restrictions on the generosity of CHIP expansions, in 2007, CMS issued a directive restricting states from using CHIP funds to cover families with gross incomes above 250% of the FPL. This directive affected 23 states, many of which had income thresholds at 300% of the FPL or higher. The passing of the Children's Health Insurance Program Reauthorization Act (CHIPRA) in 2009 and the infusion of fiscal relief from the American Recovery and Reinvestment Act (ARRA) then revived state interest in expanding Medicaid (Ross et al., 2009).

In addition to children-specific expansions, extensions in Medicaid eligibility to low-income adults have been enacted in response to the 2001 Health Insurance Flexibility and Accountability (HIFA) Demonstration Program. HIFA streamlined the approval process for states to enact Section 1115 waivers, which allow states to run experimental or pilot projects to expand Medicaid coverage.[11] Because Medicaid expansions in the period I examine are driven by responses

[9] For details on eligibility criteria, see Feder, Rowland and Holahan (1993) and Klemm (2000).

[10] For detailed information on CHIP, see Allen (2007).

[11] For detailed information on Section 1115 waivers, see Kaiser Family Foundation (2012).

to changes in federal legislation, state-to-state variation in Medicaid eligibility expansions are likely independent of other policies that influenced provision of and demand for care.

II. Empirical Model

A. Conceptual Framework

Virtually all studies of physician behavior in Medicaid follow a simple framework developed by Sloan, Mitchell and Cromwell (1978).[12] Although their model yields clear implications for the tradeoffs between Medicaid and privately-insured care, it is insufficient for explaining the tradeoffs between Medicaid and charity care, and it provides an incomplete understanding of how physicians adjust total hours of care.

I expand on the Sloan model by incorporating charity care into a physician's decision-making process. Assume physicians maximize a two-argument utility function $U = U(\pi,\ F)$, where π are profits and F is charity care.[13] Happiness from charity care come from altruistic motivations such as the satisfaction from meeting unmet needs or providing societal goodwill. Utility is increasing in both arguments, so $U_\pi > 0$ and $U_F > 0$.

The revenue from providing services is $p(Q)Q + p_m M + p_c(F)F$, where Q, M, and F are the number of private, Medicaid, and uninsured patients treated, respectively, and $p(Q)$, p_m, and $p_c(F)$ are prices for private, Medicaid, and uninsured services, respectively. The physician's cost function is given by $C = C(Q,M,F)$, so profits are defined as $\pi = p(Q)Q + p_m M + p_c(F)F - C(Q,M,F)$. Constraining physician supply to be non-negative, the Lagrangian and first-order conditions are:

$$\mathscr{L} = U\left(p(Q)Q + p_m M + p_c(F)F - C(Q,M,F),\ F\right) + \lambda_1 Q + \lambda_2 M + \lambda_3 F, \tag{1}$$

$$[Q]:\ U_\pi\left(p + p'(Q)Q - C_Q\right) = \lambda_1 \tag{2}$$

$$[M]:\ U_\pi\left(p_m - C_M\right) = \lambda_2 \tag{3}$$

$$[F]:\ U_\pi\left(p_c + p_c'(F)F - C_F\right) + U_F = \lambda_3. \tag{4}$$

When all constraints are non-binding, equations (2) and (3) indicate that physicians supply private and Medicaid care up to the point where price equals marginal cost. Equation (4) shows that physicians provide charity care up to the point where the marginal cost C_F equaand ls the

[12] For example, see Baker and Royalty (2000) or Garthwaite (2012).

[13] This setup is similar to the model presented in Frank and Salkever (1991), who consider the objective function for private non-profit hospitals. In their model, unmet needs provide a disutility that is affected by competition from other private and public hospitals.

marginal return in utility terms $(p_c F + p_c'(F) + (U_F/U_\pi))$. Note the second-order condition for a maximization $(U_{\pi\pi} < 0)$ guarantees diminishing marginal utility from money, so marginal returns to charity care increase when physicians have more income (U_π falls) or when physicians are more altruistic (U_F increases).

We should consider seven other Karush-Kuhn-Tucker conditions, but assuming physicians provide a positive amount of care to the privately insured, only three cases remain: (1) no Medicaid and no charity care, (2) some Medicaid and no charity care, and (3) no Medicaid and some charity care. In my data, 5% of physicians fall in category (1), 27% fall in category (2), and 10% belong to category (3).

B. Physician Response to a Payment Change

Figures 2(a) and 2(b) depict the marginal revenue curve (ABCD) for physicians who provide some Medicaid care before providing any charity care. The first portion of the curve (AB) is the marginal revenue a physician receives from privately insured patients. It is downward sloping because I assume physicians have some market power and face a downward-sloping demand curve from private patients.[14] The flat segment of the curve (BC) arises because Medicaid pays a flat fee (p^m) per visit. The last segment (CD) represents the marginal revenue a physician receives from providing charity care.[15] Supply of charity care begins when a physician's marginal return from charity care in utility terms exceeds the marginal return from Medicaid. Despite the lower monetary return, CD represents the quantities at which the physician's utility from charity care counteracts the financial loss. In Figure 2(a), I depict two candidate marginal cost curves: MC and MC'. Physicians with marginal cost curve MC see only privately-insured patients. Those with marginal cost curve MC' see all three types of patients: privately-insured, Medicaid, and charity care patients.[16]

Consider how an increase in Medicaid prices from p^{m1} to p^{m2} changes the physician's marginal revenue curve. The new marginal revenue curve is depicted by the dashed-red line. Physicians will be willing to supply Medicaid at lower quantities, but the effect of higher Medicaid payments on a physician's willingness to provide charity care is unclear. On the one hand, physicians become less altruistic because the opportunity cost of charity are is higher. This situation is depicted by the outward shift of line CD shown in Figure 2(a). Physicians with marginal cost curve MC will begin participating in Medicaid and make no changes to charity

[14] Implications from the model do not change if a step-wise marginal revenue curve is assumed.

[15] I assume Medicaid demand outstrips supply, so CD is not constrained by the number of Medicaid patients seeking care.

[16] Note that 58% of physicians in the CTSPS provide health care to all three types of patients, so marginal cost curves around MC' may be the norm.

care supply, whereas physicians with marginal cost curve MC' will increase their existing supply of Medicaid and reduce their charity care supply. Regardless of where the MC curve lies, in this case, higher Medicaid payments will increase total supply.

On the other hand, physicians might become more altruistic because higher Medicaid payments make physicians richer. This situation is represented by an inward shift of line CD shown in Figure 2(b). Physicians with marginal cost curve MC" will increase their supply of charity care. Depending on the size of the altruism effect, Medicaid supply will either increase or decrease: when the line CD shifts in by a small amount, Medicaid supply can increase. Notice that when physicians become more altruistic, it is possible for total supply to *fall*. Assuming physicians use their income for consumption and leisure, a decrease in total supply suggests that the income effect–which predicts fewer hours worked due to increased demand for leisure–dominates the substitution effect, which predicts more hours worked due to higher costs of leisure.

Figures 2(c) and 2(d) show the marginal revenue curve for physicians who provide some charity care before offering any Medicaid care. Here, the marginal return from charity care (BC) exceeds the marginal return from Medicaid (CD). Similarly predictions arise. If physicians become less altruistic (Figure 2c), total supply will increase. If physicians become more altruistic (Figure 2d), total supply can fall.

An analysis that ignores the provision of charity care definitively predicts increases in Medicaid supply and total supply. However, as the graphs in Figure2 illustrate, allowing for charity care makes supply-response predictions more ambiguous. The change in Medicaid, charity care, and total supply will depend on (1) the distribution of physician marginal cost curves, and (2) the relationship between Medicaid payments and altruism. Finding that higher Medicaid payments reduce total supply would be consistent with earlier research suggesting that physicians face a backward bending labor supply curve (Feldstein, 1970; Hughes and Yule, 1992; Mitchell, 1984; Sloan, 1974; Vahovich, 1977).[17]

C. The Interaction Between Payment and Eligibility Changes

To identify the interacted effects between payment and eligibility changes, consider how the number of people eligible for Medicaid affects a physician's supply decisions, prior to any changes in pay. Higher eligibility rates can reduce the entry costs into Medicaid because fixed costs fall with each additional Medicaid patient treated. Thus physicians will be more like to

[17] Appendix B discusses the implications from my model for how physicians respond to Medicaid eligibility expansions.

see Medicaid patients, instead of charity care patients. This claim is supported by a large theoretical and non-health empirical literature concluding that government provision of a public good crowds-out private contributions (Andreoni, 1989; Bergstrom, Blume and Varian, 1986; Brooks, 2003; Payne, 1998).

If physicians see more Medicaid patients when the fraction eligible for Medicaid is high, then the income effect from a payment increase will be larger because the income growth from a payment change is proportional to the number of Medicaid patients being seen. At the same time, the substitution effect from a payment increase will be smaller because there are fewer uninsured people. Thus, my model predicts that when the fraction eligible for Medicaid is high, increases in the Medicaid reimbursement rate will result in greater increases in Medicaid supply and smaller reductions in charity care.

D. Estimation Strategy

The main empirical approach is to run regressions of the form:

$$\begin{aligned} Y_{ist} &= \beta_1 log\left(Medicaid\ Pay\right)_{st} + \beta_2 \left(Fraction\ Eligible\right)_{st} \\ &\quad + \Gamma X_{ist} + \xi D_{st} + \gamma_s + \alpha_t + \varepsilon_{ist} \end{aligned} \tag{5}$$

When analyzing physician supply, Y_{ist} is a measure of supply for physician i living in state s at time t. The specific Y_{ist} variables I examine include physician participation in Medicaid, Medicare, and charity care; indicators for physicians accepting any new Medicaid, Medicare, or private care patients; and the distribution of practice revenues by payer type. When considering patient insurance enrollment, I utilize only state and year variation, so I run a variant of equation (5) that focuses on Y_{st}. The main dependent variables include the log population in state s at year t enrolled in Medicaid, Medicare, direct insurance, or employer-sponsored insurance.

$log\left(Medicaid\,Pay\right)_{st}$ is a measure of the Medicaid payment rate in state s and year t.[18] *Fraction Eligible* measures the fraction eligible for Medicaid in a given state and year. X_{ist} is a vector of individual-specific controls and D_{st} are state-specific controls. γ_s are state fixed effects that account for variation across states in the rate-setting methods. α_t are year fixed effects, capturing time-specific economic shocks that may influence Medicaid rates. ε_{ist} is an idiosyncratic error term. Throughout this analysis, all errors are robust and clustered at the state level. In regressions for physician supply, X_{ist} includes physician's sex, race dummies, age, years as a practicing doctor, income, and specialty. It also includes descriptions of the

[18] Construction of this variable is discussed in detail in Section III..

physician's main practice location and indicators for whether the physician is a full or part owner of the practice.

The validity of β_1 relies on the fact that no omitted variables affect both payment changes and Medicaid demand or supply decisions. To reduce potential bias, I include several state-level covariates in D_{st}. All regressions control for log Medicare and private prices; a vector of insurance demand variables proxied by the log of the number of people with Medicaid, Medicare, employer-based insurance, private-insurance, or no insurance; measures for a state's financial health, such as the unemployment rate, log median household income, log total population, federal medical assistance percentage, and log population for those in poverty ages 0-4, 5-17, and 18 and greater; and a division-specific time trend.

Similarly, estimates of β_2 can be biased for two reasons. The first is omitted variable bias. To address this concern, in regressions on insurance enrollment, D_{st} additionally includes four indicators for average state education, percentage of families with a single female parent, percentage of families with a single male parent, percentage of two-parent families with an unemployed head of the family, average family size, number of full-time workers in the average family, number of children in the average family, number of children under two in the average family, and number of children under age six in the average family.

Second, unobserved economic shocks may affect both the fraction of people eligible for Medicaid and insurance enrollment. Following Currie and Gruber (1996), I construct a simulated variable to serve as an instrument for the actual fraction eligible. Simulated eligibility is calculated using a nationally drawn 20% sample of households in the 2000 CPS data. I apply each state's eligibility rules to that sample and adjust income variables only by the appropriate CPI index for each year. By using the same population in each state simulation, I isolate the variation in eligibility from only state rules, as opposed to state-level omitted variables.

III. Data

The data used in this paper rely on several sources. I provide a overview of the main datasets. Remaining details and complete summary statistics are presented in Appendix C.

A. Main Data Sources

To measure changes in Medicaid prices, I construct state-level price estimates using the American Academy of Pediatrics (AAP) Medicaid Reimbursement Surveys, administered from 1998-1999, 2001, 2004-2005, 2007-2008, and 2009-2010.[19] These surveys, mailed to each state's Medicaid Director, gather Medicaid and Medicare fee-for-service payment data on approximately 200 Current Procedural Terminology (CPT) codes spanning 20 specialties.[20] Even

[19] All prices are converted to year 2000 dollars.

[20] Tennessee is excluded because it not have a fee-for-service Medicaid program. In 2004, Alaska, Delaware,

though the codes focus on commonly reported pediatric procedures, several adult procedures are included as well. To obtain price indices, I use the Medical Expenditures Panel Survey (MEPS) to calculate procedure-specific Medicaid and Medicare expenditure weights.[21]

A large number of studies in the literature measure prices by using a Medicaid-Medicare fee ratio collected by the Urban Institute (UI).[22] Approximately every five years beginning in 1993, the UI administered state surveys asking for Medicaid rates on 19 to 32 services which spanned six specialties. The AAP prices I construct offers several advantages over the UI rate. First, AAP's survey captures a more comprehensive measure of Medicaid prices relative to UI's. Medicaid fees vary widely across specialties, so relying on too few service codes may result in mis-measured state price changes. Second, Medicaid rates in the UI data are available only as a Medicaid-Medicare ratio, making it impossible to separate Medicaid payments from Medicare payments. Finally, the AAP collects data at more frequent intervals, allowing me to utilize more years of data. Because of these benefits, I rely on AAP prices in my main analysis and highlight the differences between AAP estimates and the UI estimates in Section C..

One drawback of both the AAP and UI rates is that they do not capture provider-level differences in Medicaid reimbursements. Several states may adjust Medicaid rates depending on the type of physician performing the procedure or the geographic location of the physician patient (Norton and Zuckerman, 2000). The use of state-level aggregates masks the variation in rates across providers, which can account for heterogeneity in physician behavior within a state.

The fraction eligible for Medicaid is calculated by state, year, age, and race using the 1998-2012 March Current Population Surveys (CPS) and income eligibility thresholds reported in Kaiser Family Foundation (KFF) reports. KFF conducts annual telephone interviews from with state program administrators to identify the Medicaid federal poverty line (FPL) cutoffs by age group and employment and pregnancy status.[23] To calculate an upper-bound on eligibility, I use the income eligibility rules set in December of a given year or January of the following

Indiana, and Michigan did not provide payment rates. In 2010, Arizona, District of Columbia, Georgia, North Carolina and Oregon did not provide data. In 1998 and 2001, Medicare data is not included in the AAP reports. I supplement those years of data with fee-for-service rates reported by Center for Medicare and Medicaid Services (CMS).

[21] MEPS data utilizes ICD-9 procedural codes, so I use SuperCoder's ICD-9 to CPT crosswalk to generate ICD-9 equivalents. When the ICD-9 to CPT crosswalk is not a 1-to-1 match, I sum over the various ICD-9 codes associated with each CPT to calculate the expenditure weight. When the CPT cannot be matched to an ICD-9 code, the CPT price is dropped in the calculation of state average Medicaid and Medicare rates. Weights are calculated at the national level.

[22] See Appendix A.

[23] Because the March CPS does not identify pregnant women, I use birth data from the Centers for Disease Control and Prevention's National Center for Health Statistics (NCHS) and the Census' population estimates to calculate the annual birth rate for women ages 15-44 by state and race (white, black, others). I then randomly assign pregnancy to women ages 15-44 in the CPS by state and race.

year, except in 2004, when thresholds are collected in July. [24]

Physician data comes from the restricted-use version of the Community Tracking Study Physician Survey (CTS) and the Health System Change Health Tracking Physician Survey (HSC). The CTS was conducted in four rounds from 1996-97, 1998-99, 2000-01, and 2004-05, and the fifth round, known as the HSC, was conducted in 2008.[25] For convenience, I use the term "CTSPS" to refer to both the CTS and HSC survey rounds. In addition to a rich set of physician covariates, the CTSPS includes data on physician supply, such as the acceptance of new patients, revenue distribution by insurance type, and hours spent charity care.

Although the CTSPS is composed of a nationally representative sample of office- and hospital-based physicians involved in direct patient care, I restrict my analysis to only physicians who work in solo or group practices or free standing community clinics.[26] By excluding HMO and hospital-based physicians from my analysis, I can more accurately measure responses from physicians who face fee-for-service payments. Physicians in my restricted sample are also unlikely to be affected by the Emergency Medical Treatment and Active Labor Act, requiring hospitals to provide care to anyone needing emergency healthcare treatments.[27]

State-level Medicaid enrollment data comes from the CMS Medicaid Statistical Information System (MSIS), and it is based on the number of people enrolled in Medicaid or CHIP who are eligible for physician, clinic, laboratory, and radiological services. Non-Medicaid insurance counts come from the Census Bureau.[28] Since Medicaid eligibility expansions target the under-age-65 population, I focus on insurance enrollments for those under age 65.

Finally, for patient health, I rely on the Healthcare Cost and Utilization Project Nationwide Inpatient Sample (NIS). Administered annually since 1988, NIS is the largest all-payer inpatient-care database in the United States, containing more than 8 million hospital stays per year from over 1,000 community hospitals. It is designed to approximate a 20% sample of US community hospitals, but state coverage varies from 22 states in 1998 to 45 states in 2010. The

[24] KFF reports focus on income-related Medicaid eligibility (MCH, 1996; Ross and Cox, 2000; Ross and Cox, 2004; and Ross et al. (2009)). Although most Medicaid eligible individuals from 1998 onwards are captured by income-related rules, some individuals are Medicaid eligible only based on welfare-related rules. I thank Tal Gross and Matthew Notowidigdo for assistance in calculating welfare-related Medicaid eligibility.

[25] Respondents in the CTS are sampled from predominantly 60 communities, whereas the HSC survey relies on a national-sample design covering 10 geographic regions. Both the CTS and HSC samples focus on data from 12 specific communities. Sampling weights are used throughout the analysis to calculate nationally representative estimates in each year.

[26] The physician roster is taken from the American Medical Association and American Osteopathic Association master files. Federal physicians, residents, and fellows are excluded.

[27] Although the interpretation of estimates is less clear without this sample restriction, the magnitudes of the estimates are comparable.

[28] The Census also provides Medicaid insurance counts, but I rely on the MSIS Medicaid data because it likely suffers from less measurement error. Whereas MSIS tracks all Medicaid enrollees, Census estimates rely on several surveys (CPS, American Community Survey, and Survey of Income and Program Participation) that differ in the number of households sampled and the methodology used to collect and process the data.

NIS includes inpatient admission and health-severity data for all discharges from a sampled hospital. Hospital and discharge weights allow for nationally representative estimates.

B. Statistics on Medicaid Pay and Eligibility

Figure 3 plots the trend in average physician reimbursement rates per claim. Even though Medicaid reimbursements have been increasing over time, payments from both Medicare and private-insurance have been increasing at a faster rate. This graph highlights the value of accounting for prices separately when identifying the effects of Medicaid-specific policies; using a Medicaid-Medicare ratio may measure changes driven by fluctuations in Medicare prices instead of Medicaid prices. Figure 4 highlights the variation in the change in Medicaid payments prices, which can vary from -39% to 191% from 1998 to 2007.

The fraction eligible for Medicaid is shown in Figure 5. As discussed in Section B., changes in eligibility likely come from responses to federal policies, which supports the exogeneity of state legislation and use of simulated eligibility as an instrument.

Because I use changes in both payment and eligibility to identify physician response, one might be concerned that payment changes are simply policy responses to eligibility changes, or vice versa. For example, states that expand eligibility might raise payment rates to ensure sufficient supply. Alternatively, if expanding eligibility increases the financial burden of Medicaid, states might couple eligibility expansions with lower payment rates. For each year of data, I plot each state's percentage change in fraction eligible for Medicaid versus the percentage change in Medicaid pay. As Figure 6 illustrates, there are no discernible relationships between Medicaid pay and eligibility policies.[29]

IV. Results

A. Responses to Medicaid Payment Changes

1. Physician Response

Table 1 estimates the effect of increasing the Medicaid payment rate on physician supply of Medicaid, holding constant Medicaid eligibility. In row (1), I show that a 10% increase in the average Medicaid rate per claim leads to 0.6 of 100 additional physicians participating in Medicaid and 1.2 of 100 additional physicians accepting all new Medicaid patients. Note that the row (1) OLS estimates are essentially equivalent to the corresponding IV estimates, confirming that unobserved economic shocks affecting Medicaid eligibility and physician supply of Medicaid are uncorrelated with changes in the Medicaid reimbursement rate. In the remaining discussion, I focus on IV estimates.[30]

[29] Separate plots of each year of data yield similar cloud patterns.

[30] OLS estimates not shown in the paper can be provided upon request.

My estimates of the physician participation supply elasticity (0.07) and Medicaid supply elasticity (0.29) are small relative to existing estimates, which range from 0.2 to 1.7.[31] Table 2 shows why my estimates differ from the literature. Studies using data from a single state tend produce estimates that are very different from studies using national data. This disparity can be attributed to state-specific unobserved differences in a physician's ability to adjust supply.[32] For example, columns (1) and (4) show that the Medicaid supply elasticity in California is much higher than the national average, a result consistent with Hadley (1979). Columns (2) and (5) demonstrate that omitting state fixed effects yields higher elasticities, ranging from 0.17 to 0.58. These estimates are consistent with other studies that omit state fixed effects, such as Cohen (1993), Mitchell (1991) , Sloan, Mitchell and Cromwell (1978), and Showalter (1997). Finally, columns (3) and (6) show results from regressions that control for all individual- and state-level controls, except for the fraction eligible for Medicaid. These estimates are comparable to Table 1 estimates, which control for Medicaid eligibility.

Table 3 shows how physicians adjust their supply of non-Medicaid care when Medicaid payments increase. Estimates in row (1) indicate that when Medicaid payments increase by 10%, total hours of fall by a small but statistically significant 0.5%, implying a backward-bending physician labor supply curve.[33] Changes in Medicaid payments do not affect a physician's willingness to provide care to the privately-insured, but the percentage of time devoted to charity care falls by 3.84%.

Columns (5) and (6) show that increasing Medicaid reimbursements induces greater Medicare participation and provision. Several theories can explain the complementary relationship between Medicaid and Medicare. First, there can be diminishing marginal administrative costs. For example, the standard CMS-1500 form Medicare carriers use to file claims is also used by some Medicaid State Agencies for Medicaid billing. Thus as Medicaid provision increases, administrative costs of Medicare fall. Second, Medicare beneficiaries who have limited resources may may also be eligible for Medicaid. These dual eligibles account for 14% of Medicaid beneficiaries and 19.5% of Medicare beneficiaries (CMS, 2013*b*). Depending on a patient's income, Medicaid will cover some to all of the out-of-pocket Medicare costs. Thus, it is possible that increasing payments indirectly causes increased demand from dual-eligibles. Since physicians

[31] If it not surprising that these elasticities are small because entry costs are high. To become Medicaid-certified, physicians need to fill out a non-trivial application, learn about mandatory Medicaid services, and familiarize themselves with claim-filing procedures and deadlines.

[32] Physicians in neighborhoods that are highly segregated by income will have less flexibility to substitute between their Medicaid and privately-insured patients.

[33] The -0.05 estimate is close to measures of labor-supply elasticity amongst other populations. Gruber and Saez (2002) estimate a general labor elasticity of -0.07. Imbens, Rubin and Sacerdote (2001) estimate an elasticity of -0.11 to -0.05 among lottery winners. Camerer et al. (1997) find that taxi cab drivers have an elasticity of -0.2 to -0.5. In my data, the backward-bending curve is driven by physicians who derive a larger portion of their revenue from Medicaid and those with incomes above $250,000.

must accept Medicare assignments for all Medicaid patients, higher payments will generate a complementary rise in Medicare supply (CMS, 2013*a*).

Because Medicaid and Medicare participation increase while total hours of care falls, these results suggest that charity care supply falls by more than the increase in Medicaid supply. To establish this finding more definitively, it is necessary to examine not just Medicaid participation or willingness to accept new Medicaid patients, but also time spent treating Medicaid patients. Even though data on the total time spent with Medicaid, Medicare, and privately-insured patients are not available in the CTSPS survey, I back out a measure of time for these patients using last year's percent revenue by insurance type, average payment by insurance type, total hours of patient care in the last week, and weeks worked during the last year.[34]

To capture physicians who do not participate in Medicaid or charity care, I run an instrumental variables fixed-effects Poisson Quasi-Maximum Likelihood (QML) count model (Wooldridge, 1999).[35] The Poisson QML count model is robust to arbitrary distributional assumptions as long as the conditional mean is specified by

$$E\left[Hours_{ist}|P_{st}, E_{st}, X_{ist}, D_{st}, , \gamma_s, \alpha_t\right] = exp\left(\beta_1 P_{st} + \beta_2 E_{st} + \Gamma X_{ist} + \xi D_{st} + \gamma_s + \alpha_t\right)\varepsilon_{ist}$$

where P_{st} is the log of Medicaid Pay, E_{st} is the fraction eligible, and X_{ist}, D_{st}, γ_s, α_t, and ε_{ist} are defined in Equation (5).

Row (1) of Table 4 presents the results. Column (1) verifies that when Medicaid prices increase by 10%, the expected number of hours spent on both Medicaid and charity care patients falls by 13%. Thus, increasing the Medicaid payments reduces total care provided to the poor. This finding supports the conclusion that increasing public medical spending may not improve access to care for the poor (Duggan, 2000). The remaining columns indicate that the time spent treating Medicaid or Medicare patients increases, whereas time spent treating the privately insured falls. However, these estimates are imprecisely estimated.

2. Enrollment Response

If there are no changes in enrollment, the results thus far suggest that patients with Medicaid will have increased access to care while the uninsured will reduced access to care. However, Table 5 indicates that holding constant changes in Medicaid eligibility, changes in Medicaid reimbursements will also affect insurance enrollment. Row (1) demonstrates that a 10% increase in the average Medicaid payment rate is associated with a 2.3% increase in Medicaid

[34] Details are explained in Appendix C.

[35] Estimates from using 2SLS with a log dependent variable are qualitatively similar, suggesting that results are robust to alternate functional forms.

enrollment.

To identify who is enrolling in Medicaid, I consider how non-Medicaid insurance take-up changes. Columns (2) to (5) indicate that virtually all of the increased Medicaid enrollment comes from the former uninsured taking-up insurance. When physician reimbursement rates increase by 10%, the uninsured population falls by about 1%. Private insurance through direct-purchases or employer-sponsored insurance are not crowded out, and the under-65 in Medicare does not change.

Why would a supply shock cause the uninsured to enroll in Medicaid? One likely explanation is that physicians and hospitals encourage Medicaid enrollment because of the increased financial returns.[36] To evaluate whether this type of supplier-induced demand is present, I run a short survey on mTurk. The survey, limited to US residents, asks 1,537 respondents to identify who or what encouraged them to enroll in the insurance they currently have. To gather sufficient responses from Medicaid-insured respondents, I over-sample the Medicaid population: the number of mTurk respondents with Medicaid (20%) is higher than the actual US Medicaid share (15%), and the number of mTurk respondents with private insurance (55%) is lower than the actual US share (66%). Although I only capture those who use the internet as a way to earn extra money, any supplier-induced demand will be underestimated because the "internet-savvy" poor are more likely to enroll themselves into Medicaid relative to the poor without internet access.

Survey results are shown in Table 6. I split the sample between states with increasing and decreasing Medicaid physician payments from 2007 to 2010 and compute the difference in means for Medicaid and private respondents.[37] Column (1) shows that in states with increasing Medicaid payments, respondents are 2.13% to 5.53% more likely to have received encouragement from a doctor or hospital to enroll in Medicaid. Even though these estimates are not statistically significant, they do not simply reflect state trends: the difference in means in Column (2) indicates private respondents are less likely to receive insurance-enrollment advice from doctors or hospitals. In addition to providing suggestive evidence of supplier-induced demand, the mTurk survey suggests that information via television or internet and own-health problems do not motivate Medicaid enrollment.

B. Responses to Medicaid Eligibility Expansions

Row (2) of the aforementioned tables show the effects of Medicaid eligibility expansions

[36] This argument assumes physicians lose money by treating the uninsured. Gruber and Rodriguez (2007), however, find physicians earn more from their uninsured patients than their insured patients. Hospitals treating a large share of poor patients are also compensated by tax appropriations and a disproportionate share of hospital adjustments, offsetting the cost of uncompensated care (Hadley and Holahan, 2003).

[37] It would be better to examine payment rate changes from 2012 to 2013. Due to the limitation of Medicaid payment data, I use AAP data from 2007 and 2010 as a rough approximation.

on physician supply and insurance enrollment. Row (2) of Table 1 shows that a 10-percentage-point increase in the fraction eligible for Medicaid leads to 3.6% increase in the number of physicians participating in Medicaid. Note that the OLS estimates imply that physicians reduce their supply of Medicaid when Medicaid demand increases. This finding is not supported by theory and is likely a result of the correlation between eligibility changes and omitted factors affecting physician supply, an explanation supported by the IV estimates.

Row (2) of Table 3 further indicates that unlike payment increases, Medicaid eligibility expansions are associated with an increase in total hours of care supplied. The percent of hours spent on charity care falls by 20.2%, but a physician's willingness to accept privately-insured and Medicare patients does not change. Because total hours increase, these results suggest that when Medicaid eligibility becomes more generous, Medicaid supply increases by more than the decrease in charity care. As such, overall care to the indigent population increases. This conclusion is supported by the results in row (2) of Table 4.

Shown in row (2) of Table 5, a 10-percentage-point increase in the fraction eligible for Medicaid causes Medicaid enrollments to increase by 6.3%.[38] Instead of supplier-induced demand, the mTurk survey data in Table 6 suggests these enrollments are driven by increased TV or internet ads, and not from stronger physician or hospital influences. This finding is consistent with the fact that most states have relied on television, radio, and print ads to promote their CHIP and Medicaid programs (Perry et al., 2000).

C. Interaction Effects Between Payment and Eligibility Policies

To identify how the fraction eligible for Medicaid affects a physician's response to payment changes, or alternatively, how Medicaid reimbursement rates affect a physician's response to eligibility expansions, I add an interaction term between $log(Medicaid\ Pay)$ and $(Fraction\ Eligible)$ to equation 5. Following Aiken and West, 1991 and Judd, McClelland and Ryan (2008), I also center the $log(Medicaid\ Pay)$ and $(Fraction\ Eligible)$ variables by subtracting their respective means. Centering reduces multicollinearity and increases the interpretability of the regression coefficients. β_1 indicates the effect of increasing Medicaid reimbursements for physicians facing the average fraction eligible for Medicaid. β_2 indicates the effect of expanding Medicaid eligibility for physicians with the average Medicaid reimbursement rate. I eliminate bias from omitted variables by instrumenting not only the fraction eligible with simulated eligibility, but also the interaction term with log Medicaid pay times simulated eligibility. The validity of the interacted instrument rests on the assumption that payment rates are exogenous and simulated eligibility is a valid instrument for actual eligibility.

[38] The results in row (2) of Table 5 are generally consistent with the existing literature (Gruber and Simon, 2008; Thorpe and Florence, 1998; Lo Sasso and Buchmueller, 2004).

The first three columns of Table 7 show the interaction of payment changes and eligibility expansions on physician supply. When eligibility is high, Medicaid hours increase by an additional 31%. This result is consistent with the theory-based predictions discussed in Section D.. Because the interaction term for charity care is not statistically insignificant, I conclude that eligibility expansions do not have an added effect on charity care. In sum, eligibility expansion magnify the increase in Medicaid supply without adding reductions to charity care. This allows the sum of care to the poor to increase when eligibility expansions are coupled with payment increases. Shown in the column (3) of Table 7, the interaction effect on hours of care allocated to the poor is positive and large.

The last three columns show the interaction of payment changes and eligibility expansions on insurance enrollment. When eligibility is high, physician-induced supply is much smaller. This result makes sense since there are fewer uninsured when Medicaid eligibility is high, so the need to enroll uninsured patients into Medicaid is reduced.

V. Access to Health Care

To get a sense of the net effect of these supply and demand responses, I turn to data on hospital ER admissions. Because I cannot identify Medicaid eligibility at the individual level using NIS data, I collapse the data to state-year-age-race cells where age ranges from 0 to 65 and race groups are Black, White, or other. I run a regression similar to 5, except the fraction eligible for Medicaid is recalculated at the age-race-state-year level instead of the state-year level. Specifically, I estimate

$$\begin{aligned} Y_{arst} &= \beta_1 log\left(Medicaid\ Pay\right)_{st} + \beta_2 \left(Fraction\ Eligible\right)_{arst} \\ &\quad + \xi D_{st} + \eta_a + \phi_r + \gamma_s + \alpha_t + \varepsilon_{arst}, \end{aligned} \tag{6}$$

where a indexes age, r indexes race, s indexes state, and t indexes year; η_a, ϕ_r, γ_s, and α_t are dummy variables for age, race, state, and year, respectively. D_{st} includes division-year dummy interactions to control for both division-specific trends that can be correlated with Medicaid policy changes and regional differences in the NIS sampling frame. D_{st} also includes controls for the average share of females in the cell, hospital size and characteristics, state-insurance take-up, population in poverty, and unemployment rates over time. Standard errors are adjusted to allow for correlation within states.

IV regression results are shown in Table 8. Column (1) shows that a 10% increase in the Medicaid reimbursement rate reduces hospital admissions from the ER by 3.03%. Changes in the fraction eligible for Medicaid have a small and statistically insignificant effect on hospital admissions from the ER. These results are consistent with existing studies finding that

eligibility and payment changes have a zero to positive effect on access to care (Aizer, 2007; Baker and Royalty, 2000; Bermudez and Baker, 2005; Cohen, 1993; Currie, Decker and Lind, 2008; De La Mata, 2012; Gruber, Adams and Newhouse, 1997; Howell and Kenney, 2012). I also consider the impact of Medicaid policy changes on hospitalizations that medical experts have denoted as "avoidable."[39] Column (2) shows that preventable ER admissions decrease by about 0.7% when payment rates increase.

Despite the general reduction in ER admissions, Medicaid payment and eligibility changes differentially affect access to care by insurance type. When payments increase by 10%, a hospital's share of Medicaid ER admissions falls by 1.94% while the shares of uninsured and privately-insured ER admissions do not change. It is possible that the Medicaid-ER-admissions estimate is biased by unobserved health quality, which is endogenous with insurance enrollment. However, physicians are more likely to encourage their sicker patients to enroll in Medicaid due to the higher financial incentives. A lower overall Medicaid health level biases against finding reductions in Medicaid ER admissions.

In contrast to payment increases, a 10-percentage-point increase in eligibility is correlated with a 4% increase in the share of Medicaid ER admissions, 0.4% increase in the share of charity care ER admissions, and 3.3% reduction in share of privately-insured ER admissions. In this case, the direction of bias from unobserved health quality is not as clear: Medicaid enrollments come from both reductions in the uninsured, which likely lowers health status, and crowd-out of the privately insured, which possibly improves health status. Nevertheless, my Medicaid results are consistent with findings from the Oregon insurance experiment (Taubman et al., 2014). These results imply that when eligibility increases, increases in Medicaid demand outstrip Medicaid supply, so access to care for Medicaid patients falls. On the other hand, access to care for privately insured patients improves because demand for private care has been crowded-out by Medicaid while hours supplied to privately insured patients increases.

VI. Robustness Checks

A. Exogeneity of Medicaid Price Changes

There are several reasons why Medicaid price changes might be not be exogenous. First, the amount of federal funding for Medicaid that a state receives–known as the Federal Medical Assistance Percentage (FMAP)–can affect a state's reimbursement rates. Second, states might reduce Medicaid prices when they are unable to provide matching funds. Medicaid is a large program, accounting for 23.9% of state expenditures, so even small increases in spending can

[39] Avoidable hospitalizations are those which might not have occurred of patients had received effective, timely, and continuous outpatient medical care. The ICD-9 codes for these hospitalizations are shown in Appendix Table C.5.

be unsustainable (NASBO,2012).[40] Third, states might adjust payment rates in response to Medicaid demand and supply changes. If increased Medicaid eligibility causes there to be an insufficient number of providers, states will be in violation of the federal government's rate setting policies and will need to increase their Medicaid payments. Finally, the political climate in a state can affect Medicaid spending policies.

To test whether these observables can significantly predict Medicaid prices, I use state-level panel data to estimate OLS regressions of log Medicaid price on covariate groups, state fixed effects, and year fixed effects.[41] I test whether variables in each group of controls are jointly different from zero.

Table 9 shows the F-statistics and corresponding p-values. Column (1) controls for demand and supply variables such as the number of doctors, physician assistants, registered nurses, and individuals enrolled in each insurance group. Column (2) controls for measures of poverty, specfically the unemployment rate, population in poverty, and median household income. Column (3) controls for state finances, such as the FMAP, per capita tax revenue, state debt, and cash and holdings. Column (4) controls for the political climate, such as the differences in the number of Democrat and Republican representatives and the political affiliation of the state governor. I find that only state financial variables are significantly correlated with Medicaid prices, but once other groups of controls are included, none of these categories significantly predict Medicaid price changes.

B. Leads Analysis

If the conditional independence assumption holds–namely that conditional on observables, payment and eligibility policy variables are as good as randomly assigned, then future policy changes should not affect outcomes today. In Table 10, I test whether payment and eligibility rates three years in the future affect current supply and demand.[42] Columns (1) to (3) indicate the effects of future payment and eligibility changes on Medicaid supply, total hours supplied, and percent of time spent on charity care, respectively. Columns (4) to (6) indicate the effects of future payment and eligibility changes on insurance take-up. The coefficients on future policy changes are all small and statistically insignificant. Furthermore, controlling for future changes does not affect how payment and eligibility changes affect contemporaneous responses.[43] These results suggest that the main results of this paper are estimated off of fairly

[40] For comparison, K-12 education accounts for 19.8% of total state expenditures.

[41] Data sources are described in Section III. and Appendix Table C.1.

[42] I use data three years in the future because Medicaid reimbursement rate data is only available in three year increments.

[43] I also test whether policy changes three years in the past affect current demand and supply. I examine these separately because payment data is only available from 1998 to 2010. Thus, the lags analysis drops more than a third of the observations. I also find that past policy changes are not predictive of supply and demand today.

sharp changes in Medicaid payments and eligibility.

C. Using a Different Price Index

To shed light on the advantages of the AAP price index that I constructed, I test for changes in my results when I rely on the UI's Medicaid-Medicare fee index, a variable used in many existing studies of Medicaid (Adams, 1994; Decker, 2007, 2009; Gray, 2001; Shen and Zuckerman, 2005).[44] Table 11 presents the results. Although increases in the UI index are associated with increases in Medicaid supply and demand, I find that predictions on total hours supplied, supply of charity care, and the number of uninsured are different when using the UI index, instead of AAP prices. These differences can be attributed to the fact that increases in the UI index are not synonymous with Medicaid price increases. For example, if Medicare prices fall and if Medicare and charity care are supply substitutes, then increases in the UI index will be correlated with increased charity-care supply.

D. Medicaid Managed Care

The fraction of Medicaid patients enrolled in Medicaid managed care (MMC) plans have increased over time. Because physicians who treat MMC patients are not reimbursed based on the Medicaid fee-for-service (FFS) schedule, one might be concerned that physicians in high MMC penetration states will not react to changes in Medicaid FFS payments. In Table 12, I split the sample by states above and below the 50th percentile of MMC penetration in 2004.[45] Columns (4) to (6) show that physician responses to Medicaid payments are statistically significant, even in states with high MMC penetration. While the Medicaid supply responses is smaller, the response on total supply is larger. It may be important to note that some of these estimates may be driven by changes in the MMC payment rate because correlations between Medicaid FFS and MMC payment rates are not accounted for in the regressions.[46]

VII. Conclusion

A good deal of policy has focused on increasing reimbursement rates to address concerns about a growing physician shortage. I identify the impact of price changes on physicians' responses, insurance enrollment, and health outcomes. Using a carefully constructed Medicaid price index and a robust empirical model, I estimate a Medicaid physician participation elasticity of 0.07 and a Medicaid supply elasticity of 0.29. Even though Medicaid supply increases, I show total care supplied to the poor, measured by the sum of Medicaid and charity care hours,

[44] Data from the UI are available from 1998, 2003, and 2008. I use 2003 price data as proxy for 2004 to utilize three years of CTSPS data. See Norton and Zuckerman (2000), Zuckerman et al. (2004), and Zuckerman, Williams and Stockley (2009) for detailed information on the construction of the UI index.

[45] Splitting the sample by the MMC penetration rate in 1998 or 2008 yields similar results.

[46] Duggan and Hayford (2013) find that in states with high Medicaid reimbursements relative to commercial reimbursements, MMC will reduce expenditures, possibly through reduced payments or reduced utilization.

falls. I further show that higher Medicaid payments are associated with the uninsured enrolling in Medicaid and provide suggestive evidence of physician-induced demand. Although payment rate increases cause both Medicaid supply and demand to increase, I find that the supply response dominates the demand response: when Medicaid reimbursement rates increase by 10%, access to care improves, and Medicaid ER admissions falls by almost 2%.

The impact of eligibility expansions are very different from the effects of a payment increase. Medicaid enrollments increase, but increased enrollments come from both the uninsured and crowd-out of private insurance. Unlike the supply response to a payment increase, physicians increase their total hours of care supplied when the fraction eligible for Medicaid increases. Although charity care supply falls, overall care to the poor increases. Here, increases in Medicaid demand dominate increases in Medicaid supply, and Medicaid patients have reduced access to care, represented by a 3.87% increase in Medicaid ER admissions. Privately insured patients seem to benefit the most from eligibility expansions: the private care demand falls, but supply of private care increases marginally.

Finally, I demonstrate that when the fraction eligible for Medicaid is high, supply responses to a payment increase are amplified while demand responses are diminished: Medicaid supply increases by bigger amount, whereas Medicaid enrollments increase by a smaller amount. This result suggests that simultaneously increasing Medicaid payments and eligibility can yield the largest improvements in access to care for the poor.

While my paper sheds light on the substitution between Medicaid, charity care, and private care supply, many questions remain. For example, how does the profitability of a specific procedure affect supply adjustments among patients with differing insurances? To answer this question, detailed procedure-level price and quantity data is necessary. Future research identifying characteristics of the uninsured is also important. Are uninsured patients who enroll in Medicaid sicker than the average uninsured patient or the average Medicaid patient? Do reductions in charity care supply lead to increases in community health clinics or registered nurses? Answers to these questions can better inform policies directed at improving access to care.

References

Adams, Kathleen. 1994. "Effect of Increased Medicaid Fees on Physician Participation and Enrollee Service Utilization in Tennessee, 1985-1988." *Inquiry*, 31(2): 173–187.

Aiken, Leona, and Stephen West. 1991. *Multiple Regression: Testing and Interpreting Interactions.* Sage Publications.

Aizer, Anna. 2007. "Public Health Insurance, Program Take-up, and Child Health." *The Review of Economics and Statistics*, 89(3): 400–415.

Allen, Kathryn. 2007. "Children's Health Insurance: State Experiences in Implementing SCHIP and Considerations for Reauthorization." *United States Government Accountability Office*, 1–39.

American Academy of Pediatrics. 2011. "Medicaid Reimbursement Survey, 2010/11."

American Hospital Association. 2013. "Uncompensated Hospital Care Cost Fact Sheet."

Andreoni, James. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence." *The Journal of Political Economy*, 97(6): 1447–1458.

Association of American Medical Colleges. 2012. "Recent Studies and Reports on Physician Shortages in the US." *Center for Workforce Studies* https://www.aamc.org/download/100598/data/.

Baker, Laurence, and Anne Royalty. 2000. "Medicaid Policy, Physician Behavior, and Health Care for the Low-Income Population." *The Journal of Human Resources*, 35(3): 480–502.

Bergstrom, Theodore, Lawrence Blume, and Hal Varian. 1986. "On the Private Provision of Public Goods." *Journal of Public Economics*, 29: 25–49.

Bermudez, Dustin, and Laurence Baker. 2005. "The Relationship Between SCHIP Enrollment and Hospitalizations for Ambulatory Care Sensitive Conditions in California." *Journal of Health Care for the Poor and Underserved*, 16(1): 96–110.

Brooks, Arthur. 2003. "Do Government Subsidies To Nonprofits Crowd Out Donations or Donors?" *Public Finance Review*, 31(2): 166–179.

Camerer, Colin, Linda Bacock, George Loewenstein, and Richard Thaler. 1997. "Labor Supply of New York City Cabdrivers: One Day at a Time." *The Quarterly Journal of Economics*, 112(2): 407–441.

Center for Medicare and Medicaid Services. 2013*a*. "Medicaid Coverage of Medicare Beneficiaries (Dual Eligibles) At a Glance." *Medicare Learning Network*, ICN 006977: 1–6.

Center for Medicare and Medicaid Services. 2013*b*. "Medicare-Medicaid Dual Enrollment From 2006 Through 2011." *Data Analysis Brief.*

Cohen, Joel W. 1993. "Medicaid Physician Fees and Use of Physician and Hospital Services." *Inquiry*, 30(3): 281–292.

Congressional Budget Office. 2012. "Estimates for the Insurance Coverage Provisions of the Affordable Care Act Updated for the Recent Supreme Court Decision."

Currie, Janet, and Jonathan Gruber. 1996. "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women." *Journal of Political Economy*, 104(6): 1263–1296.

Currie, Janet, Jonathan Gruber, and Michael Fischer. 1995. "Physician Payments and Infant Mortality: Evidence from Medicaid Fee Policy." *American Economic Review*, 85(2): 106–111.

Currie, Janet, Sandra Decker, and Wanchuan Lind. 2008. "Has Public Health Insurance for Older Children Reduced Disparities in Access to Care and Health Outcomes?" *Journal of Health Economics*, 27: 1567–1581.

Cutler, David. 1998. "Cost Shifting or Cost Cutting? The Incidence of Reductions in Medicare Payments." *Tax Policy and the Economy*, 12: 1–27.

Dafny, Leemore. 2005. "How Do Hospitals Respond to Price Changes?" *American Economic Review*, 95(5): 1525–47.

Decker, Sandra. 2007. "Medicaid Physician Fees and the Quality of Medical Care of Medicaid Patients in the USA." *Review of Economics of the Household*, 5(1): 95–112.

Decker, Sandra. 2009. "Changes in Medicaid Physician Fees and Patterns of Ambulatory Care." *Inquiry*, 46: 291–304.

De La Mata, Dolores. 2012. "The Effect of Medicaid Eligibility on Coverage, Utilization, and Children's Health." *Health Economics*, 21: 1061–1079.

Dranove, David, and William White. 1998. "Medicaid-Dependent Hospitals and Their Patients: How Have They Fared?" *Health Services Research*, 33(2): 163–85.

Duggan, Mark. 2000. "Hospital Ownership and Public Medical Spending." *The Quarterly Journal of Economics*, 4: 1343–1373.

Duggan, Mark, and Tamara Hayford. 2013. "Has the Shift to Managed Care Reduced Medicaid Expenditures? Evidence from State and Local-Level Mandates."

Feder, Judith, Diane Rowland, and John Holahan. 1993. *The Medicaid Cost Explosion: Causes and consequences.* The Henry J. Kaiser Family Foundation.

Feldstein, Martin. 1970. "The Rising Price of Physician's Services." *The Review of Economics and Statistics*, 52(2): 121–133.

Frank, Richard, and David Salkever. 1991. "The Supply of Charity Services by Nonprofit Hospitals: Motives and Market Structure." *Rand Journal of Economics*, 22(3): 430–445.

Garthwaite, Craig. 2012. "The Doctor Might See You Now: The Supply Side Effects of Public Health Insurance Expansions." *American Economic Journal: Economic Policy*, 4(3): 190–215.

Ginsburg, Paul. 2003. "Can Hospitals And Physicians Shift The Effects Of Cuts In Medicare Reimbursement To Private Payers?" *Health Affairs*, w3: 472–479.

Gray, Bradley. 2001. "Do Medicaid Physician Fees for Prenatal Services Affect Birth Outcomes?" *Journal of Health Economics.*, 20(4): 571–590.

Gruber, Jon, and Emmanuel Saez. 2002. "The Elasticity of Taxable Income: Evidence and Implications." *Journal of Public Economics*, 84: 1–32.

Gruber, Jonathan, and David Rodriguez. 2007. "How Much Uncompensated Care do Doctors Provide?" *Journal of Health Economics*, 26(6): 1151–1169.

Gruber, Jonathan, and Kosali Simon. 2008. "Crowd Out 10 Years Later: have Recent Public Insurance Expansions Crowded Out Private Health Insurance?" *Journal of Health Economics*, 27(2): 201–217.

Gruber, Jonathan, Kathleen Adams, and Joseph Newhouse. 1997. "Physician Fee Policy and Medicaid Program Costs." *The Journal of Human Resources*, 32(4): 611–634.

Gruber, Jon, John Kim, and Dina Mayzlin. 1999. "Physician Fees and Procedure Intensity: The Case of Cesarean Delivery." *Journal of Health Economics*, 18(4): 473–490.

Hadley, Jack. 1979. "Physician Participation in Medicaid: Evidence from California." *Health Services Research*, 14: 266–280.

Hadley, Jack, and John Holahan. 2003. "How Much Medical Care Do The Uninsured Use, And Who Pays For It?" *Health Affairs*, w3: 66–81.

Horton, John, David Rand, and Richard Zeckhauser. 2011. "The Online Laboratory: Conducting Experiments in a Real Labor Market." *Experimental Economics*, 14(3): 399–425.

Howell, Embry, and Genevieve Kenney. 2012. "The Impact of the Medicaid/CHIP Expansions on Children: A Synthesis of the Evidence." *Medical Care Research and Review*, 69(4): 372–396.

Hughes, David, and Brian Yule. 1992. "The Effect of Per-item Fees On the Behavior of General Practitioners." *Journal of Health Economics*, 11: 413–437.

Imbens, Guido, Donald Rubin, and Bruce Sacerdote. 2001. "Estimating the Effect of Unearned Income on Labor Earnings." *American Economic Review*, 91(4): 778–794.

Judd, Charles, Gary McClelland, and Carey Ryan. 2008. *Data Analysis: A Model-Comparison Approach, Second Edition.* Routledge.

Kaiser Family Foundation. 2012. "An Overview of Recent Section 1115 Medicaid Demonstration Waiver Activity." *The Kaiser Commission on Medicaid and the Uninsured*, No. 8318: 1–15.

Klemm, John. 2000. "Medicaid Spending: A Brief History." *Health Care Financing Review*, 22(1): 105–112.

Kuziemko, Ilyana, Michael Norton, Emmanuel Saez, and Stefanie Stantcheva. 2013. "How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments." *NBER Working Paper*, No. 18865.

Lo Sasso, Anthony, and Thomas Buchmueller. 2004. "The Effect of the State Children's Health Insurance Program on Health Insurance Coverage." *Journal of Health Economics*, 23: 1059–1082.

Mayes, Rick, and Jason Lee. 2004. "Medicare Payment Policy and the Controversy over Hospital Cost Shifting." *Applied Health Economics and Health Policy*, 3(3): 153–159.

MCH Update: Medicaid Coverage of Pregnant Women and Children. 1996. *Issue Brief.*

Merlis, Mark. 2004. "Medicaid Reimbursement Policy." *Congressional Research Service Report for Congress.*

Mitchell, Janet. 1984. "Why Do Women Physicians Work Fewer Hours Than Men Physicians?" *Inquiry*, 21(4): 361–368.

Mitchell, Janet. 1991. "Physician Participation in Medicaid Revisited." *Medical Care*, 29(7): 645–653.

Morrisey, Michael. 2003. "Cost-Shifting: New Myths, Old Confusion, and Enduring Reality." *Health Affairs*, w3: 489–491.

National Association of State Budget Officers. 2012. "State Expenditure Report: Examining Fiscal 2010-2012 Spending."

Norton, Stephen, and Stephen Zuckerman. 2000. "Trends in Medicaid Physician Fees, 1993-1998." *Health Affairs*, 19(4): 222–232.

Paolacci, Gabriele, Jesse Chandler, and Panagiotis Ipeirotis. 2010. "Running Experiments on Amazon Mechanical Turk." *Judgment and Decision Making*, 5(5): 411–419.

Payne, Abigail. 1998. "Does the Government Crowd-Out Private Donations? New Evidence from a sample of non-profit firms." *Journal of Public Economics*, 69: 323–345.

Perry, Michael, Vernon Smith, Catherine Smith, and Christina Chang. 2000. "Marketing Medicaid and CHIP: A Study of State Advertising Campaigns." *The Kaiser Commission on Medicaid and the Uninsured*, 2213: 1–40.

Ross, Donna, and Laura Cox. 2000. "Making it Simple: Medicaid for Children and CHIP Income Eligibility Guidelines and Enrollment Procedures, Findings from a 50-State Survey." *The Kaiser Commission on Medicaid and the Uninsured*, 1–48.

Ross, Donna, and Laura Cox. 2004. "Beneath the Surface: Barriers Threaten to Slow Progress on Expanding Health Coverage of Children and Families." *The Kaiser Commission on Medicaid and the Uninsured*, 1–68.

Ross, Donna, Marian Jarlenski, Samantha Artiga, and Caryn Marks. 2009. "A Foundation for Health Reform: Findings of a 50 State Survey of Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and CHIP for Children and Parents During 2009." *The Kaiser Commission on Medicaid and the Uninsured*, 1–68.

Shen, Yu-Chu, and Stephen Zuckerman. 2005. "The Effect of Medicaid Payment Generosity on Access and Use Among Beneficiaries." *Health Services Research*, 40(3): 723–744.

Showalter, Mark H. 1997. "Physicians Cost Shifting Behavior: Medicaid Versus Other Patients." *Contemporary Economic Policy*, 15(2): 74–84.

Sloan, Frank. 1974. "A Microanalysis of Physicians' Hours of Work Decisions." In *The Economics of Health and Medical Care*. 302–325. John Wiley and Sons.

Sloan, Frank, Janet Mitchell, and Jerry Cromwell. 1978. "Physician Participation in State Medicaid Programs." *Journal of Human Resources*, 13: 211–245.

Taubman, Sarah, Heidi Allen, Bill Wright, Katherine Baicker, and Amy Finkelstein. 2014. "Medicaid Increases Emergency-Department Use: Evidence From Oregon's Health Insurance Experiment." *Science*, 343(6168): 263–268.

Thorpe, Kenneth, and Curtis Florence. 1998. "Health Insurance Among Children: The Role of Expanded Medicaid Coverage." *Inquiry*, 35(4): 369–379.

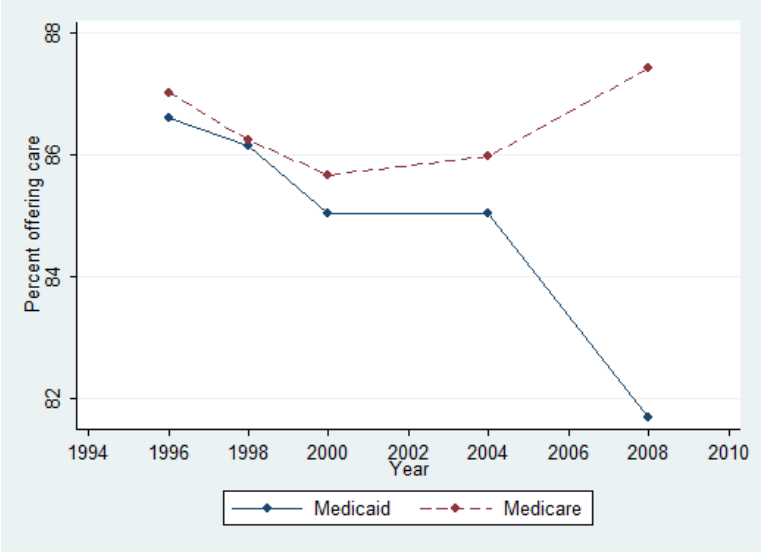
Vahovich, Stephen. 1977. "Physicians' Supply Decisions by Specialty: 2SLS Model." *Industrial Relations*, 16(1): 51–60.

Wooldridge, Jeffrey. 1999. "Distribution-free Estimation of Some Nonlinear Panel Data Models." *Journal of Econometrics*, 90: 77–97.

Zuckerman, Stephen, Aimee Williams, and Karen Stockley. 2009. "Trends In Medicaid Physician Fees, 2003-2008." *Health Affairs*, 28(3): w510–w519.

Zuckerman, Stephen, Joshua McFeeters, Peter Cunningham, and Len Nichols. 2004. "Changes in Medicaid Physician Fees, 1993-2003: Implications for Physician Participation." *Health Affairs*, w4: 374–384.

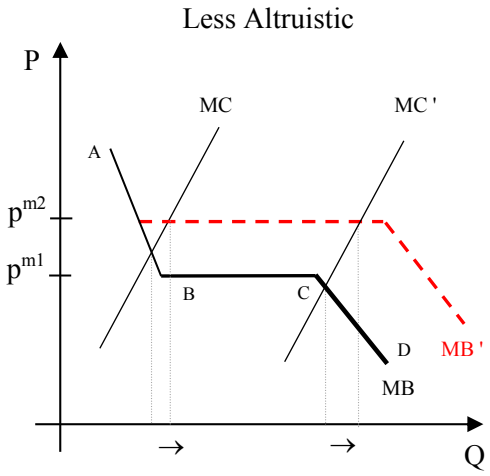
Figure 1: Share of Practice Seeing Medicaid or Medicare Patients



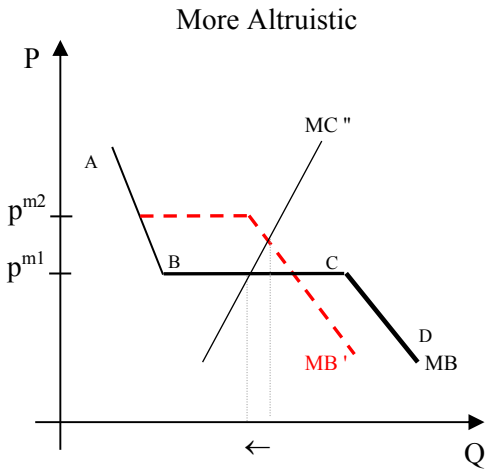
Notes: This figure shows that over time, the percent of practices seeing any Medicaid patients decreases over time while the percent of practice seeing Medicare patients increases slightly. Data from CTSPS.

Figure 2: Impact of Medicaid Payment Increase on Physician Supply

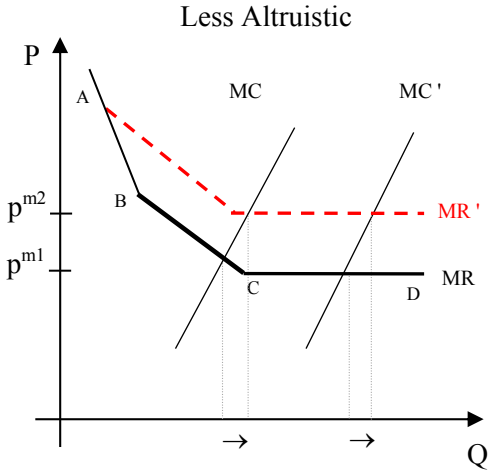
(a) Medicaid MR > Charity MR



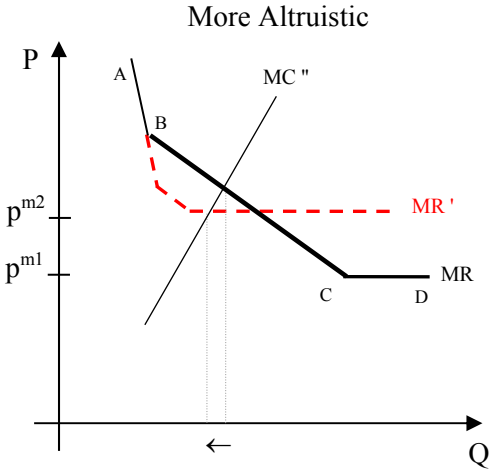
(b) Medicaid MR>Charity MR



(c) Charity MR > Medicaid MR

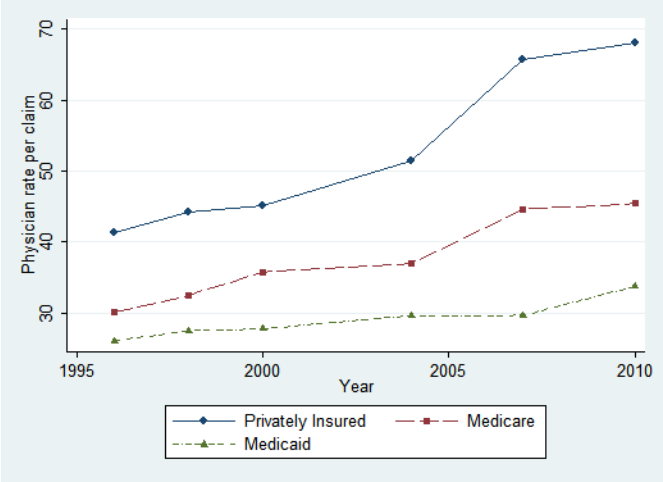


(d) Charity MR > Medicaid MR



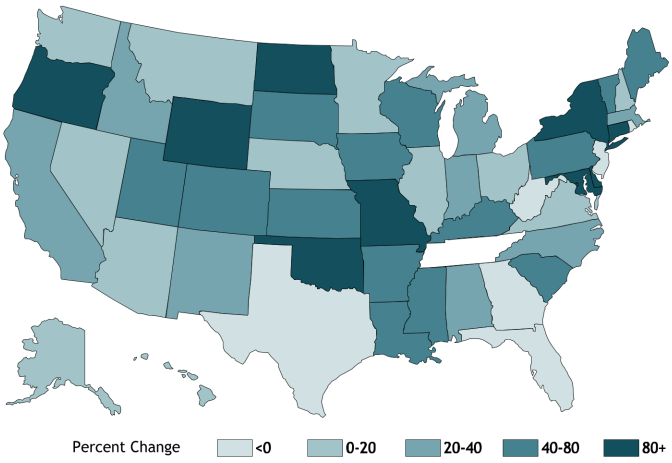
Notes: These graphs show how a physician adjusts supply when the Medicaid payment rate increases. A physician's marginal revenue curve is represented by ABCD. AB is the marginal revenue from privately insured patients. In plots (a) and (b), BC is the marginal revenue from Medicaid, and CD is the marginal revenue from charity care. These associations are reversed for plots (c) and (d), where physicians supply some charity care before any Medicaid. When the Medicaid reimbursement rate increases from p^{m1} to p^{m2}, the physician's new marginal revenue curve is depicted by the dashed, red line. If increased Medicaid payments make physicians more (less) altruistic, the marginal revenue from charity care will shift to the left (right). MC, MC', and MC" represent candidate marginal cost curves: a physician with marginal cost curve MC sees only privately insured patients, whereas a physicians with marginal cost curve MC' or MC" provides private, Medicaid, and charity care. These graphs demonstrate that a payment increase has an ambiguous effect on charity care, Medicaid, and, total supply.

Figure 3: Payment Rates, by Insurance Type



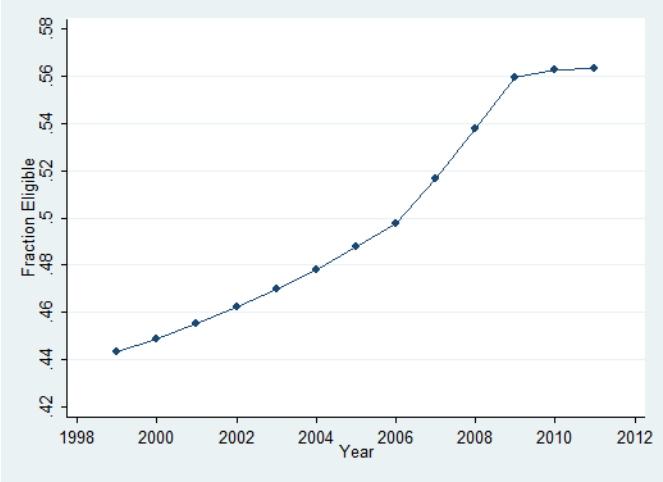
Notes: This figure shows physician reimbursements rates for privately insured, Medicaid, and Medicare patients. Rates calculated at the regional level using NHEA payments for physician and clinic services expressed in 2000 dollars divided by total claims per region from NAMCS.

Figure 4: Percent Change in Medicaid Payments, 1998-2007



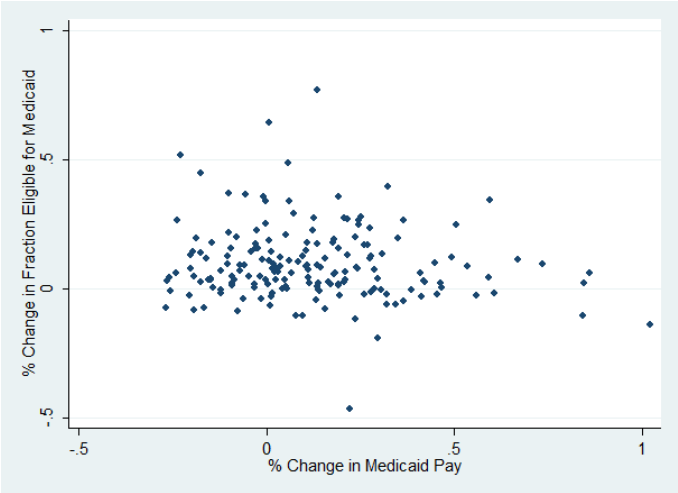
Notes: This map shows how real Medicaid payments have changed over time, which ranges from -39% to 191%. Data from AAP and MEPS. No data is available for Tennessee because it does not have Medicaid fee-for-service payments.

Figure 5: Medicaid Eligibility, Enrollment, and Usage Over Time



Notes: This figure shows the fraction of people eligible for Medicaid who are under age 65. Data is calculated using KFF reports on Medicaid eligibility and the March CPS from 1998-2010.

Figure 6: Relationship between Reimbursement and Eligibility Policy Changes



Notes: Each point in this figure represents a state and in a given year. A total of 45 states in years 2001, 2004, 2007, and 2010 are represented. The graph shows indicates there is no discernible relationships between the percent change in Medicaid price and the percent change in the fraction eligible for Medicaid.

Table 1: Medicaid Physician Response

		1(Any Medicaid)	1(All New Medicaid)	% Revenue Medicaid	1(Any Medicaid)	1(All New Medicaid)	% Revenue Medicaid
	Mean:	0.821	0.399	12.80	0.821	0.399	12.80
		OlS	OLS	OLS	IV	IV	IV
		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Log(Pay)	0.0752**	0.135***	5.321***	0.0592**	0.119***	4.102*
		(0.0371)	(0.0340)	(1.666)	(0.0300)	(0.0392)	(2.290)
(2)	Fraction	0.0993	-0.203	-9.592	0.359**	0.0342	8.235
	Eligible	(0.145)	(0.163)	(6.844)	(0.180)	(0.210)	(11.45)
	Obs.	22,382	22,382	22,382	22,382	22,382	22,382
	R^2	0.122	0.156	0.198	0.122	0.156	0.198

Notes: Physician level OLS (columns 1-3) and IV (columns 4-6) regressions are shown with robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include state and year fixed effects, a division year time trend, Medicare and private payment rates, physician covariates, practice characteristics, and demand-side controls. Physician covariates are age years as practicing doctor, dummies for DO degree, being educated abroad, sex, race (white, black), specialty (family practice, pediatrics, and surgery), and income (less than $150,000 and between $150,000 to $250,000). Practice characteristics include dummies for having a solo practice or being the full- or part- owner of the practice. Demand controls include percent of the state that is employer, direct, Medicaid, or Medicare insured, percent uninsured, county population in poverty, unemployment rate, and log population.

Table 2: Physician Participation in Medicaid, Comparison to Existing Estimates

	1(Any Medicaid)			1(All New Medicaid)		
	California	All States	All States	California	All States	All States
Mean:	0.731	0.821	0.821	0.280	0.399	0.399
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Pay)	1.448*	0.143***	0.0814**	2.484***	0.230***	0.0886*
	(0.770)	(0.0197)	(0.0378)	(0.738)	(0.0364)	(0.0464)
State FE			Y			Y
Demand		Y	Y		Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	2,472	22,382	22,382	2,472	22,382	22,382
R^2	0.066	0.107	0.122	0.065	0.131	0.153
Elasticity	1.98	0.17	0.10	8.87	0.58	0.22

Notes: Physician level OLS regressions with robust standard errors in parentheses. Standard errors clustered by state in all columns except (1) and (4). *** p<0.01, ** p<0.05, * p<0.1. All regressions control for Medicare and private reimbursement rates and the physician and practice-characteristic covariates described in Table 1. Demand controls are those described in Table 1.

Table 3: Non-Medicaid Physician Response

		Total	*Private*	*Charity Care*		*Medicare*	
		Log(Patient Hours)	1(All New Private)	1(Any Charity)	Log(% Hrs Free)	1(Any Medicare)	1(All New Medicare)
	Mean:	3.76	0.632	0.748	-3.52	0.868	0.584
		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Log(Pay)	-0.0521*	0.0165	-0.0266	-0.397***	0.0570***	0.0445
		(0.0272)	(0.0401)	(0.0405)	(0.0932)	(0.0189)	(0.0289)
(2)	Fraction	0.433***	-0.117	0.0865	-2.021***	-0.0684	0.0418
	Eligible	(0.141)	(0.180)	(0.184)	(0.339)	(0.0925)	(0.226)
	Obs.	22,382	22,382	22,382	16,709	22,382	22,382
	R^2	0.146	0.066	0.073	0.058	0.340	0.123

Notes: Physician level IV regressions shown with robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include the controls listed in Table 1 notes. *Log(Patient Hours)* is the log total hours of patient care per month. *1(All New Private)* equals 1 for physicians who accept all new privately insured patients. *1(Any Charity)* equals 1 for physicians providing some charity care. *Log(% Hrs Free)* is the log percent of hours spent on charity care. *1(Any Medicare)* equals 1 for physicians who see at least one Medicare patient. *1(All New Medicare)* equals 1 for physicians accepting all new Medicare patients.

Table 4: Physician Hours of Care

		Medicaid + Charity Hrs	Medicaid Hours	Charity Hours	Medicare Hours	Private Hours
	Mean:	415	333	82	718	1052
		(1)	(2)	(3)	(4)	(5)
(1)	Log(Pay)	-0.129**	0.253***	-0.267*	0.152**	-0.0657
		(0.0647)	(0.0973)	(0.153)	(0.0738)	(0.0436)
(2)	Fraction	1.350***	1.701***	0.359	-0.535	0.861***
	Eligible	(0.408)	(0.586)	(0.776)	(0.421)	(0.274)
	Obs.	22,045	22,045	22,045	22,045	22,045

Notes: Physician level IV Poisson QMLE regressions with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include the controls listed in Table 1 notes. Hours spent with each type of patient are backed out using total hours of patient care last week, weeks worked in the year, percent revenue by patient type, and average price by patient type. Observations dropped include those reporting charity care hours greater than total hours, those missing weeks worked, and those reporting percent revenue from Medicaid plus Medicare exceeding 100%.

Table 5: Enrollment Response

		Log (Medicaid)	Log (Uninsured)	Log (Direct)	Log (Employer)	Log (Medicare)
	Pop. Mean:	845,209	855,812	374,374	3,213,336	123,412
		(1)	(2)	(3)	(4)	(5)
(1)	Log(Pay)	0.231**	-0.108**	0.0215	0.0852	-0.143
		(0.0995)	(0.0486)	(0.112)	(0.0660)	(0.101)
(2)	Fraction	0.628*	-0.337*	-0.865**	0.209	0.609*
	Eligible	(0.351)	(0.201)	(0.399)	(0.190)	(0.348)
	Obs.	227	227	227	227	227
	R^2	0.979	0.995	0.993	0.992	0.982

Notes: State level IV regressions shown with robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample universe is population under age 65. All regressions include the Medicare and private reimbursement rates; log state population; log unemployment; three controls for the population in poverty ages 0-4, ages 5-17, and ages 18, four dummies for average education of a family within a state (less than high school, high school grad, some college, bachelor or associate's degree); two indicators for average number of single parent families by gender (female or male household head); average two-parent families with unemployed head of family; average family size; average number of full time workers in the family; average number of kids per family; average number of kids younger than 2 per family; average number of kids younger than 6 per family; and state, year, and division year trend fixed effects. See Appendix Table C.1 for more detail on data sources.

Table 6: Reported Reasons for Enrolling in Health Insurance

	Payment Difference (High-Low)		Eligibility Difference (High-Low)	
Who/what encouraged you to get insurance?	Medicaid (1)	Private (2)	Medicaid (3)	Private (4)
Doctor (%)	5.33	-3.03	0.01	-1.36
Hospital (%)	2.13	-1.29	1.89	0.09
Government worker (%)	0.41	-2.91	-4.59	0.33
TV ad or internet (%)	-2.14	-4.71	3.22	1.73
Own Health Problem (%)	-2.97	6.85	-7.71	2.79
Observations	338	903	338	903

Notes: Data on insurance enrollment from mTurk survey. The first two columns show the difference in means between respondents in states with positive nominal payment changes from 2010-2007 and those in states with negative nominal payment changes. The last two columns show the difference in means between respondents in states with increasing Medicaid eligibility from 2011-2010 and respondents in states with decreasing eligibility. Respondents are asked who/what encouraged you to get insurance and can select all that apply. The omitted category is "none of the above."

Table 7: Interacted Effects

	Physician Supply			*Insurance Enrollment*		
	Medicaid Hours	Charity Hours	Medicaid + Charity Hrs	Log (Medicaid)	Log (Uninusre)	Log (Direct)
Mean:	342	84	426	845,209	855,812	374,374
	Poisson	Poisson	Poisson	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Pay)	0.263***	-0.257*	-0.0657	0.221**	-0.124**	0.00569
	(0.0970)	(0.154)	(0.0640)	(0.0981)	(0.0491)	(0.110)
Eligible	2.492***	0.351	2.396***	0.939**	-0.122	-0.528
	(0.650)	(0.924)	(0.537)	(0.369)	(0.222)	(0.415)
Log(Pay) x	3.135**	-0.302	3.575***	-1.385**	-0.991**	-1.472**
Eligible	(1.270)	(2.133)	(0.920)	(0.605)	(0.473)	(0.723)
Obs.	21,890	21,890	21,890	227	227	227

Notes: Columns (1)-(3) show physician level IV Poisson QMLE regressions and include controls listed in Table 1 notes. Columns (4)-(6) show state-level 2SLS regressions with controls listed in able 5 notes. Robust standard errors, clustered by state for columns (4)-(6), shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Patient Access to Care

		% Admited From ER	Preventable ER Admits	% ER Admits Medicaid	% ER Admits Charity	% ER Admits Private
	Mean:	0.412	0.089	0.299	0.009	0.404
		(1)	(2)	(3)	(4)	(5)
(1)	Log(Pay)	-0.303**	-0.077***	-0.194***	0.006	0.017
		(0.119)	(0.030)	(0.059)	(0.014)	(0.084)
(2)	Fraction	-0.109	-0.008	0.387***	0.037*	-0.332***
	Eligible	(0.109)	(0.043)	(0.140)	(0.020)	(0.093)
	Obs.	16,969	16,968	16,134	16,134	16,134
	R^2	0.569	0.400	0.412	0.287	0.401

Notes: IV regressions at the state-year-age-race level using NIS data. Robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include covariates for female, hospital characteristics (teaching hospitals, small/medium hospital, rural/urban location); state, age, race, and year fixed effects; a division by year trend, log population with Medicaid, Medicare, employer-insurance, direct-insurance, or uninsured, log state population (total, those in poverty ages 0-4, in poverty ages 5-17, and in poverty ages 18 and older), log median household income, and the state unemployment rate. *Preventable ER Admits* are the share of hospitalizations which are preventable and occurred at the emergency room.

Table 9: Predicting Medicaid Prices

	H_0:Coefficients Equal Zero	F-statistic For Test of Joint Significance Dependent Variable: Log(Medicaid Pay), μ=3.55				
		(1)	(2)	(3)	(4)	(5)
(1)	Demand and Supply	1.45				1.15
		(0.214)				(0.351)
(2)	Measures of Poverty		1.45			0.93
			(0.214)			(0.485)
(3)	State Finances			3.51		1.97
				(0.014)		(0.114)
(4)	Political Climate				1.15	0.73
					(0.340)	(0.536)
	Obs.	233	233	233	233	233
	R^2	0.827	0.831	0.838	0.819	0.855

Notes: F-statistic are shown with p-values in parenthesis. Each column shows the test of joint statistical significance for a group of covariates in an OLS regression of log Medicaid prices on state and year fixed effects, and the covariates. See text Section A. for details on covariates included in each regression.

Table 10: The Effect of Future Policy Changes

	Physician Supply			*Insurance Enrollment*		
	1(Any Medicaid)	Log(Total Hours)	Log(% Hrs Free)	Log Medicaid	Log Direct	Log Uninsure
Mean:	0.841	3.76	-3.52	12.99	13.01	12.29
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Pay), t	0.0468	-0.0684**	-0.407***	0.276**	-0.0403	-0.0361
	(0.0363)	(0.0309)	(0.0890)	(0.116)	(0.158)	(0.0755)
Eligible, t	0.595***	0.405**	-1.770***	0.180	-1.233***	-0.519*
	(0.225)	(0.162)	(0.452)	(0.333)	(0.445)	(0.279)
Log(Pay), t+3	-0.0202	0.0280	-0.0194	-0.0476	-0.0758	0.0556
	(0.0322)	(0.0236)	(0.0702)	(0.0765)	(0.114)	(0.0576)
Eligible, t+3	-0.198	0.0628	0.139	-0.169	-0.156	-0.106
	(0.134)	(0.175)	(0.624)	(0.405)	(0.472)	(0.289)
Obs.	21,260	21,254	15,926	174	174	174
R^2	0.105	0.147	0.075	0.991	0.975	0.996

Notes: Columns (1)-(3) show physician-level IV regressions with controls listed in Table 1. Columns (4)-(6) show state-level IV regressions with controls listed in Table 5. Robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0.

Table 11: Using the UI Medicaid-Medicare Fee Index

	Physician Supply			Insurance Enrollment		
	1(Any Medicaid)	Log(Total Hours)	Log(% Hrs Free)	Log Medicaid	Log Direct	Log Uninsure
Mean:	0.848	3.728	-3.45	12.95	12.28	13.03
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Medicaid-)	0.0671	-0.0368	0.410*	0.575***	-0.397	0.212
Medicare Index)	(0.0895)	(0.0430)	(0.222)	(0.211)	(0.463)	(0.183)
Obs.	13,665	13,665	10,087	138	138	138
R^2	0.127	0.155	0.060	0.988	0.986	0.997

Notes: Columns (1)-(3) show physician-level IV regressions with all controls listed in Table 1, except for the Medicare AAP payment rate. Columns (4)-(6) show state-level IV regressions with all controls listed in Table 5, except for the Medicare AAP payment rate. Robust standard errors, clustered by state, in parentheses. *** p<0.01, ** p<0.05, * p<0. Main independent variable is from the Urban Institute.

Table 12: Changes in Supply, by Medicaid Managed Care Penetration

	Low MC Penetration (51.5%)			High MC Penetration (77.8%)		
	1(Any Medicaid)	Log(Total Hours)	Log(Charity Hours)	1(Any Medicaid)	Log(Total Hours)	Log(Charity Hours)
Mean:	0.82	3.76	1.66	0.82	3.76	1.64
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Pay)	0.0773*	-0.0448	-0.886***	0.0292	-0.534***	-0.549***
	(0.0400)	(0.0529)	(0.154)	(0.0506)	(0.0892)	(0.0876)
Obs.	11,336	11,336	8,475	11,056	8,165	8,270
R^2	0.127	0.150	0.054	0.122	0.066	0.069

Notes: Sample in columns (1)-(3) are clinic-based physicians living in states with 2004 Medicaid managed care penetration below the 50th percentile. Sample in columns (4)-(6) are those living in states with 2004 Medicaid managed care penetration above the 50th percentile. Splitting the sample by the penetration rate in 1998 or 2008 yields similar results.

Appendix A: Literature Summary

Table A.1: Literature on Medicaid Supply Responses to Price Changes

Paper	Main data	Payment data	Medicaid Supply Estimate	Notes
Sloan, Mitchell and Cromwell (1978)	NORC survey (1975-76)	Physician reported fees in NORC	10% increase in pay produces 2% increase in Medicaid participation	no state FE
Hadley (1979)	CA claims data (1972-75)	Average revenue per patient in claims	10% increase in pay produces a 17% increase in physician participation	single state with year FE
Mitchell (1991)	NORC survey (1975-76, 1984-85)	Physician reported fees in NORC	10% increase in fees related to 3.6% increase in physician participation	no state or year FE
Cohen (1993)	National Medical Expenditures Survey (1987)	Fees for one CPT code	10% increase in Medicaid index lowers seeing a physician by 1.6%	no state FE
Adams (1994)	TN claims data (1985-88)	Urban Institute fee ratio	10% increase in fee ratio increased the physicians serving at least 3 Medicaid enrollees by 2.5%	single state with year FE
Showalter (1997)	Physician survey (1983-85)	Physicians reported fees	$10 increase in pay increases physician's share of Medicaid patients by 1.6 ppt.	no state or year FE
Gruber, Kim and Mayzlin (1999)	HCUP, Medicaid claims (1988-92)	Fees from ACOG and PPRC	29% increase in pay increases c-sections performed by 3.7% points	state and year FE
Gray (2001)	NMIHS (1989)	Urban Institute fee ratio for obstetrical services	10% higher fee ratio results in 0.074% lower risk low birthweight infant	no state FE
Shen and Zuckerman (2005)	National Surveys of Families (1997, 99, 02)	Urban Institute Medicaid capitation rate	One-unit increase in scale increases probability of having a usual source of care by 1.5 ppt.	no state FE
Decker (2007)	NAMCS (1989, 1993 1998, 2003)	Urban Institute fee ratio	10% increase in fee ratio increases physician participation by 5% (statistically insignificant)	state and year FE
Decker (2009)	NHIS, NAMCS (1993, 98, 03)	Urban Institute fee ratio	Decreases in fee ratio from 1 to 0.64 Medicaid individuals with no doctor visits increases from 12.7% to 15.3%	state and year FE

Appendix B: Model of Physician Response to a Change in Eligibility

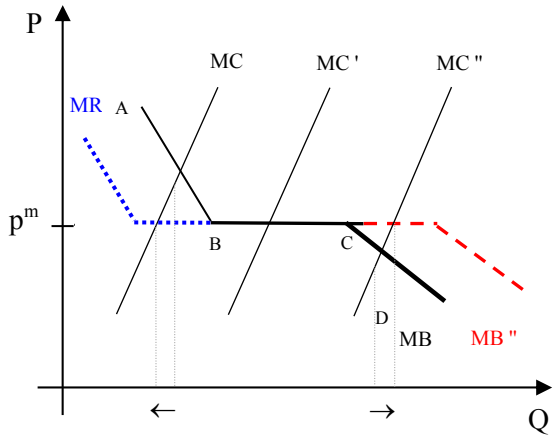
Figure B.1 shows the impact of eligibility changes on physician behavior. Plot (a) depicts the marginal revenue curve (ABCD) and marginal cost curves for physicians who provide some Medicaid before supplying any charity care. Plot (b) shows the marginal curves for physicians who provide some charity care before supplying any Medicaid.

To identify the effects of an eligibility expansion on physician response, consider two contrasting situations. Case one is when Medicaid eligibility expansions induce the formerly uninsured to enroll in Medicaid. Reductions in the amount of unmet need may cause physicians to be less altruistic, shifting the marginal returns from charity care outwards. The red, dashed line delineates the new marginal revenue curve. Physicians with marginal cost curves like MC' will have not change their supply decisions, whereas those with marginal cost curves like MC" will increase their supply of Medicaid and reduce charity care. Total supply will increase.

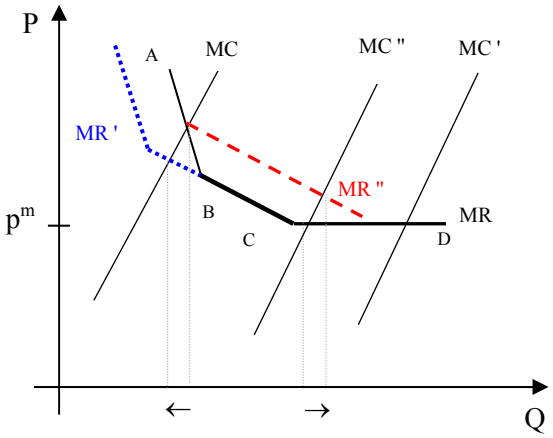
Case two is when eligibility expansions only crowd-out private insurance into Medicaid. That is, patients who previously had private coverage drop their insurance in favor of free Medicaid coverage, and the number of uninsured remains constant. In this case, the blue, dotted lines depicts the new marginal revenue curve. Physicians with relatively low returns to charity care (plot a) will reduce their provision of private care and begin participating in Medicaid. Physicians with high returns to charity care (plot b) will reduce their provision of charity care and make no changes to their Medicaid supply. With pure crowd-out, total supply decreases or remains constant.

Figure B.1: Impact of Eligibility Expansion

(a) Medicaid MR > Charity MR



(b) Charity MR > Medicaid MR



Notes: See notes to Figure 2. Here, the dotted and dashed lines represent the new marginal revenue curve when the fraction eligible for Medicaid increases. The graphs indicate that expanding Medicaid eligibility can both increase or decrease total supply.

Appendix C: Data

This section supplements the data discussion in Section III.. In addition to the main data sources, I use CMS' National Health Expenditures Accounts (NHEA) data to create a proxy for physician reimbursements from privately-insured patients. NHEA provides the official estimate of health care spending by state, type of provider, and type of insurance. I focus on non-public expenditures for physician and clinical services and divide those expenditures by the National Ambulatory Medical Care Survey (NAMCS) claims counts to calculate an average private payment per claim. Public-use NAMCS data only allows for estimate by region, so I convert regional claims counts to state claims counts by using the "number of physician visits in the last 12 months" for private claims in the Survey of Income and Program Participation (SIPP) data.

To back out hours of care by insurance type in the CTSPS data, I solve for four unknowns– time spent on Medicaid, time spent on Medicare, time spent on private care, and total income– using data on the percent revenue from each type of care. Although there is an income variable available, I do not use it because the variable reflects bonuses and other incentive payments not captured by Medicaid and Medicare prices. Furthermore, income in 2008 is only reported categorically. From the percent revenue variables, I write three equations. The fourth equation assumes that total hours spent on patient care is allocated across Medicaid, Medicare, private care, and charity care, where charity care hours are known. These equations allow me to create a proxy for time spent with patients by insurance type. Observations dropped include those reporting charity care hours greater than total hours, those missing weeks worked, and those reporting percent revenue from Medicaid plus Medicare exceeding 100%.

Table C.1 provides a dictionary of all data sources used in this paper. Tables C.2 - C.4 show detailed summary statistics for most variables used in the physician supply, patient enrollment, and health outcomes regressions. Table C.5 shows the ICD-9 codes used to identify preventable hospitalizations.

Table C.1: Data Sources

	Variables	Data Sources
Dependent Variables		
1.	Physician supply	CTSPS (1998-9, 2000-1, 2004-5, 2008)
2.	Medicaid enrollment	CMS MSIS (1998-2010)
	Non-Medicaid enrollment, number uninsured	Census, CPS, and Annual Social and Economic Supplements Table HIB-4 (1998-2010)
3.	Enrollment reasons	mTurk survey
4.	Patient health outcomes	NIS (1998-2010)
Payment		
5.	Medicaid and Medicare rates	AAP Medicaid Reimbursement Survey (1998-99, 2001, 2004-05, 2007-08, 2010-11); CMS for Medicare data in 1998 and 2001; MEPS for procedural weights (2002, 2004, 2007, 2010)
6.	Private rate	National Health Expenditure; reginal claims count from NAMCS and state claims weight from SIPP (1998-2010)
7.	Medicaid:Medicare index	Urban Institute (1998, 2003, 2008)
Eligibility		
8.	Fraction Eligible for Medicaid	Kaiser Family Foundation Reports (1998, 2000, 2002, 2004-2006, 2008-2013); CPS; Census poverty threshold cutoffs; HHS poverty limit cutoffs; Vital Statistics for birth rates by race for 15-44 (1998-2010)
Other Covariates		
9.	State population, population in poverty, median household income	Census State and County Intercensal Estimates, Small Area Income and Poverty Estimates (1998-2010)
10.	Unemployment	Bureau of Labor Statistics (1998-2010)
11.	FMAP	Federal Registrar notices from HHS (1998-2010)
Price Predictors		
12.	Total MDs and physician assistants	Area Health Resource File (1997, 2000, 2003, 2006, 2009)
13.	Number of registered nurses	Licensure and Examination Statitsics published by the National Council of State Boards of Nursing
13.	State financial data	Census' "State Government Finances" reports
14.	Political alliance of state governments	The Council of State Governments Reports

Table C.2: Summary Statistics for Variables in Physician Supply Regressions

Variable	Mean	Std. Dev.	Min.	Max.
Main Dependent Variables				
1(Seeing any Medicaid)	0.82	0.38	0	1
1(Accept all new Medicaid)	0.4	0.49	0	1
Revenue from Medicaid (%)	12.8	15.94	0	100
1(Seeing any Medicare)	0.87	0.34	0	1
1(Accept all new Medicare)	0.58	0.49	0	1
Revenue from Medicare (%)	30.77	23.03	0	100
1(Providing any charity care)	0.75	0.43	0	1
Percent hours to charity	4.25	16.28	0	100
Hours of patient care, last week	45.69	15.11	1	160
1(Accept all new private)	0.63	0.48	0	1
Main Independent Variables				
Medicaid rate	29.66	9.56	11.6	71.13
Medicare rate	46.24	6.53	23.19	59.99
Private rate	47.8	11.79	18.65	136.75
Actual fraction eligible	0.49	0.08	0.29	0.79
Simulated fraction eligible	0.5	0.1	0.29	0.75
Physician Characteristics				
MD degree	0.78	0.41	0	1
Educated abroad	0.22	0.42	0	1
1(Female)	0.22	0.42	0	1
1(White)	0.8	0.4	0	1
1(Black)	0.04	0.19	0	1
Age	48.71	10.66	28	103
Years as practicing doctor	16.3	10.75	0	65
1(Family practice)	0.21	0.41	0	1
1(Pediatrics)	0.13	0.34	0	1
1(Surgical specialty)	0.13	0.34	0	1
1(Income<$150,000)	0.52	0.5	0	1
1($150,000<$250,000)	0.3	0.46	0	1
Practice Characteristics				
1(Solo practice)	0.42	0.49	0	1
1(Full owner)	0.46	0.5	0	1
1(Part owner)	0.31	0.46	0	1
Other Covariates				
% County in poverty	11.71	4.44	1.7	38.9
Log(County population)	13.17	1.37	7.60	16.1
% State in Medicaid	11.24	3.27	4	21.6
% State in Medicare	13.7	2.36	8	20.2
% State uninsured	15.78	8.81	5	118
% State employer-insured	62.09	5.92	47	74.40
% State directly insured	9.47	1.81	6	18.4
% Unemployment rate	4.67	1.08	2.2	8.4
% FMAP	56.97	7.34	50	77.08
No. of Observations		22,382		

Table C.3: Summary Statistics for Variables in Insurance Enrollment Regressions

Variable	Mean	Std. Dev.	Min.	Max.
Population Counts, by Insurance				
Medicaid, all ages	1,012,116	1,507,042	45828	11027485
Medicaid, age<65	871,011	1,315,546	37476	9787499
Medicaid, age≥65	141,105	199,879	5812	1239986
Direct, age<65	385,704	489,614	23000	3697000
Employer, age<65	3,310,541	3,478,606	131000	18801000
Medicare, age<65	127,198	131,701	5000	783000
Main Independent Variables				
Medicaid rate	36.92	13.65	10.98	100.87
Medicare rate	50.66	9.12	21.95	84.38
Private rate	48.66	16.05	17.93	157.19
Actual fraction eligible	0.39	0.1	0.17	0.78
Simulated fraction eligible	0.38	0.12	0.18	0.73
Average Family Characteristics from CPS				
Share less high	0.94	0.12	0.58	1.35
Share high school Grad	0.54	0.07	0.34	0.77
Share some college	0.33	0.05	0.18	0.49
Share college grad	0.14	0.04	0.04	0.25
Single male parent family	0.2	0.03	0.13	0.31
Single female parent family	0.3	0.04	0.22	0.48
Two parents, unemployed head	0.13	0.02	0.06	0.21
Family size	2.36	0.15	1.75	3.03
Fulltime workers in family	1.02	0.08	0.78	1.22
Families w/kids	0.74	0.11	0.35	1.21
Families w/kids under 2	0.1	0.02	0.05	0.21
Families w/kids under 6	0.25	0.05	0.14	0.48
Other Covariates				
Log(State population)	8.14	1.04	6.19	10.53
Log(% in poverty, ages 0-4)	10.7	1.13	8.4	13.32
Log(% in poverty, ages 5-17)	11.42	1.16	9.04	14.15
Log(% in poverty, ages 18+)	12.53	1.08	10.41	15.15
Log(Unemployment rate)	1.62	0.34	0.92	2.7
Log(Median household income)	10.7	0.18	10.26	11.14
No. of Observations		227		

Table C.4: Summary Statistics for Variables in Health Access Regressions

Variable	Mean	Std. Dev.	Min.	Max.
Health Access				
Admitted from ER	0.412	0.205	0	1
% ER Admits, Medicaid	0.299	0.219	0	1
% ER Admits, Charity	0.009	0.039	0	1
% ER Admits, Private	0.404	0.214	0	1
% Preventable ER Visits	0.089	0.096	0	1
Main Independent Variables				
Medicaid rate	35.63	13.65	10.98	100.87
Medicare rate	52.93	9.54	21.95	84.38
Private rate	48.82	15.10	18.64	157.19
Actual fraction eligible	0.470	0.253	0	1
Simulated fraction eligible	0.461	0.223	0	1
Patient and Hospital Characteristics				
Female share	0.598	0.187	0	1
White share	0.344	0.475	0	1
Black share	0.314	0.464	0	1
Other race	0.342	0.474	0	1
Teaching hospitals	0.515	0.288	0	1
Small hospital	0.149	0.203	0	1
Medium-sized hospital	0.262	0.224	0	1
Urban hospital	0.814	0.262	0	1
Additional State Controls				
Log(State population)	8.496	0.917	6.250	10.527
Log(% in poverty, ages 0-4)	11.027	1.029	8.398	13.321
Log(% in poverty, ages 5-17	11.756	1.064	9.155	14.149
Log(% in poverty, ages 18+)	12.872	0.987	10.410	15.154
Log(Unemployment rate)	1.695	0.386	0.956	2.701
Log(Median household Income)	10.760	0.164	10.418	11.141
No. of Observations		21,184		

Table C.5: Detailed Summary Statistics: Health Outcomes

Condition		ICD-9 Code	Exceptions and Notes
1.	Angina	4111, 4118, 413x	not with procedures below 87000
2.	Asthma	493x	
3.	Bacterial Pneumonia	481x, 4822, 4823, 4829, 483x, 485x, 486x	with secondary diagnosis that is not 2826
4.	Cellulitis	681x, 682x, 683x, or 686x	not with procedures below 87000
5.	Chronic Obstructive Pulmonary	491x, 492x, 494x, 496x	
6.	Congenital Syphilis	V3x	infants (age<1), with secondary diagnosis 090x
7.	Congestive Heart Failure	428x, 40201, 40211, 40291, 5184	not with 3601, 3602, 3605, 3610-36199, 375x, 3770-37799
8.	Convulsions	7803	age<1
9.	Dehydration- Volume Depletion	2765	
10.	Dental Conditions	521x, 522x, 523x, 525x, 528x	
11.	Diabetes	2500-2503, 2508-2509	
12.	Ear, Nose, Throat Infections	382x, 462x, 463x, 465x, 4721	not a procedure of 2001
13.	Epilepsy	345x	
14.	Failure to Thrive	7834	age<1
15.	Gastroenteritis	5589	
16.	Hypertension	401x (but not 4010 or 4019), 40200, 40210, 40290	not with 3601, 3602, 3605, 3610-36199, 375x, 3770-37799
17.	Hypoglycemia	2512	
18.	Immunizations	033x, 390x, 391x, 037x, 045x, or 3200 for age<6	
19.	Kidney/Urinary Infection	590x, 5990, 5999	
20.	Nutritional Deficiencies	260x, 261x, 262x, 2680, 2681, or 2801, 2808, 2809 for age<6	
21.	Pelvic Inflammatory Disease	614x	not with 68300 through 68999, sex is female
22.	Tuberculosis-Pulmonary	011x 012x, 013x, 014x, 015x, 016x, 017x, 018x	

Notes: Taken from Missouri Health Department, available at <http://health.mo.gov/data/mica/PreventableMICA/Documentation.html>