

# Do the Poor Benefit From More Generous Medicaid Physician Payments?\*

JOB MARKET PAPER

Alice Chen<sup>†</sup>  
University of Chicago

This draft: November 18th, 2013

## **Abstract**

This paper examines how changes in Medicaid physician payments affect provision of care to both Medicaid patients and the uninsured. I find that payment increases generate an increase in supply of care to Medicaid patients but a more than offsetting decrease in supply to the uninsured. Using survey data, I additionally show that physicians encourage their uninsured patients to enroll in Medicaid. Finally, I demonstrate that when Medicaid eligibility is high, physicians are less likely to substitute between caring for Medicaid patients and treating the uninsured. Because higher eligibility magnifies the Medicaid supply response to a payment change, my results suggest that payment increases should be coupled with eligibility expansions in order to improve access to care among the poor.

---

\*I am indebted to my advisers Marianne Bertrand, David Meltzer, Matthew Notowidigdo, and Emily Oster for their generous guidance. I also thank Steven Levitt, Willard Manning, Jessica Pan, Tomas Philipson, Matthew Plosser, Kosali Simon, and Heidi Williams for their helpful comments. Financial support from the Agency for Health Care Research and Quality T32 National Research Service Award Fellowship is gratefully acknowledged.

<sup>†</sup>Booth School of Business, University of Chicago, email: [alice.chen@uchicago.edu](mailto:alice.chen@uchicago.edu)

# 1 Introduction

The landmark 2010 Patient Protection and Affordable Care Act (ACA) will simultaneously extend health coverage to millions of uninsured Americans *and* increase the Medicaid reimbursement rates for some physicians. However we lack a holistic understanding of how these policies affect provision of care. How will access to care change among the privately insured or remaining uninsured? Moreover, what is the interaction between concurrent changes in payment and eligibility? In this paper, I address these questions by identifying the 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 will change the entire distribution of insurance enrollments. In addition to 11 million new Medicaid enrollees, 24 million people will enroll in private health insurance exchanges, and 30 million people will remain uninsured (Congressional Budget Office, 2012).<sup>1</sup> If physicians are 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. Even among practices seeing some Medicaid patients, nearly a third are not accepting new Medicaid patients (Decker, 2012). In contrast, Figure 2 shows that Medicaid enrollments have been increasing steadily over time. These opposing demand and supply trends offer suggestive evidence of worsening physician shortages.<sup>2</sup>

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 et al., 1978).<sup>3</sup> Higher Medicaid reimbursements will make

---

<sup>1</sup>The uninsured will consist of undocumented workers and the poor living 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.

<sup>2</sup>In addition to increasing media reports of physician shortages, a growing number of national and state specific studies have concluded that the US physician workforce is facing current or future shortages (AAMC, 2012).

<sup>3</sup>In this paper, charity care refers to care supplied to the uninsured. It is different from uncompensated care because

physicians richer, so they will be more willing to provide charity care. At the same time, higher reimbursements raise the effective cost of charity care, so physicians will be less willing to provide charity care. Although my model does not offer clear predictions for how payment changes affect charity care, it demonstrates that physicians face income trade-offs when deciding who to treat.

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.<sup>4</sup> 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 encourage their uninsured patients to enroll in Medicaid.

The net effect of these 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. Higher Medi-

---

it excludes bad debts, incurred when patients do not apply for charity care or are unwilling to pay their bills (American Hospital Association, 2013).

<sup>4</sup>Amazon's mTurk has become a growing platform for social science experiments, and researchers have found the quality of responses to compare well to other, more expensive survey platforms (Horton et al., 2011; Kuziemko et al., 2013; Paolacci et al., 2010).

caid payment rates have no statistically significant effect on the share of private or uninsured ER admissions.

Finally, I consider how eligibility expansions affect the impact of Medicaid payment changes. My stylized model predicts that when Medicaid eligibility is high, an increase in Medicaid payment should generate larger increases in Medicaid supply. The intuition behind this conjecture is that there will be less substitution between Medicaid and charity care patients. Consistent with the predictions of my model, I find that the higher the fraction eligible for Medicaid, the greater the effect of payment increases on Medicaid supply. This result suggests that payment increases should be coupled with eligibility expansions in order to improve access to care among the poor, composed of 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 policies that improve access to care for Medicaid patients can improve or worsen access to care for the uninsured. 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; Morrissey, 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 et al., 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 Med-

icaid population, such as the Medicaid supply in one state or the Medicaid supply for pregnant women seeking obstetric services (Adams, 1994; Currie et al., 1995; Gray, 2001; Gruber et al., 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.

Third, this paper further 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.<sup>5</sup> While these policies traditionally constitute two separate bodies of literature, the ACA will increase 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 2 provides a brief background on Medicaid rate-setting policies and eligibility criteria. Section 3 outlines a model and delineates the empirical strategy. Section 4 describes the data. Section 5 discusses the impact of payment changes, eligibility changes, and the interaction of payment and eligibility policies. Section 6 presents the results on health behaviors and outcomes. Section 7 provides robustness checks and discusses implications for the ACA. Section 8 concludes.

---

<sup>5</sup>Currie et al. (1995) is one of the few studies that compares payment changes with eligibility expansions, but their study does not examine the interaction effect.

## 2 Background on Medicaid

Medicaid is the nation's largest health insurance program, insuring over 62 million poor 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 expansion 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 criteria.

### 2.1 Medicaid Rate-Setting Policies

To receive federal matching funds for Medicaid, states need only adhere to three rules: (1) rates should be consistent with efficiency, economy, and quality of care, (2) rates should be sufficient to enlist enough providers so that care and services are available to the general population in the geographic area, and (3) providers must accept Medicaid reimbursement as payment in full, except for cost-sharing policies provided by the state.<sup>6</sup> To change their payment schedules, states must submit an amendment plan to the Centers for Medicare and Medicaid Services (CMS) for approval and must issue a public notice of the change.

Because Medicaid payment guidelines are so flexible, states have set their fee schedules in many different ways. 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 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.<sup>7</sup> The different rate-setting methods cause Medicaid reimbursements to vary dramati-

---

<sup>6</sup>States have much less leeway concerning covered services. All categorically needy Medicaid enrollees are mandatorily entitled to physicians' services, inpatient and outpatient services, other lab and x-ray services, and early and pediatric screening, diagnostics, and treatment services for individuals under age 21, among others. However, a wide range of optional services related to clinic services can be covered.

<sup>7</sup>For example, say a brief physician office visit has a value of 3 and an appendectomy has a value of 150. If a unit is valued at \$5, the state pays \$15 for the office visit and \$450 for the appendectomy (Merlis, 2004). Some states have adopted the exact Medicare scale weights while others have constructed a different set of weights.

cally 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 Medicaid services or changes in a state’s economic condition, can impact reimbursement policy changes. I consider several potential predictors of Medicaid price in Section 7.1 and show that none of these predictors significantly predict Medicaid prices.

## **2.2 Medicaid Eligibility Policies**

To receive funding from the federal government, states must offer Medicaid coverage to certain groups of low-income children, pregnant women, parents, seniors, and individuals with disabilities. For example, pregnant women and children under six with incomes below 133% of the federal poverty limit (FPL) are eligible for Medicaid in all states.<sup>8</sup> Beyond the federally mandated groups, states can extend coverage to various subgroups by raising the Medicaid income threshold (MCH 1996; Ross and Cox, 2000, 2004; Ross et al., 2008).

I argue that in the late 1990s and 2000s, states enacted changes in Medicaid eligibility primarily in response to federal legislation. Established by the Balanced Budget Act of 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.<sup>9</sup> Initially, there

---

<sup>8</sup>Other categorically needy groups include low-income families that meet the Aid to Families with Dependent Children (AFDC) requirements in place on July 16, 1996; all children born after September 30, 1983, from families with incomes up to 100% of the FPL; infants born to Medicaid-eligible women for the first year; aged, blind, and disabled individuals with Supplemental Security Income (SSI); and special protected groups (Gruber, 2003). These policies were established through the Deficit Reduction Act of 1984, Omnibus Reconciliation Acts (OBRA) of 1985, 1986, 1987, 1989 and 1990, and the Section 1931(b) of the Social Security Act. See Feder et al. (1993) and Klemm (2000) for policy details.

<sup>9</sup>For detailed information on CHIP, see Allen (2007).

were no restrictions on the generosity of CHIP expansions. However on August 17, 2007, CMS issued a directive restricting states from using CHIP funds to cover children in 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. Although the directive slowed Medicaid expansions, in 2009, the passing of the Children's Health Insurance Program Reauthorization Act (CHIPRA) and the infusion of fiscal relief from the American Recovery and Reinvestment Act (ARRA) revived state interest in expanding Medicaid (Ross et al. (2009)).

In addition to children-specific Medicaid expansions, extensions in Medicaid eligibility to low-income adults were established 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, pilot, or demonstration projects to expand Medicaid coverage.<sup>10</sup> Because Medicaid expansions in the period I examine are driven by responses 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.

## **3 Empirical Model**

### **3.1 Conceptual Framework**

Virtually all studies of physician behavior in Medicaid follow a simple framework developed by Sloan et al., 1978. In their model, physicians face demand for health care from both Medicaid patients and privately insured patients. Physicians first accept patients in the private market until the marginal revenue equals the Medicaid reimbursement rate set by the government. Then physicians accept Medicaid patients until the marginal cost of treating a Medicaid patient equals the government reimbursement rate. Although this model yields clear implications for the effects of payment changes and eligibility expansions, it is insufficient for explaining the tradeoffs between

---

<sup>10</sup>For detailed information on Section 1115 waivers, see Kaiser Family Foundation (2012).



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  $\pi$  are profits and  $F$  is charity care.<sup>11</sup> 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  $pQ + p^mM + p^cF$ , where  $Q$  is the number of privately-insured patients treated,  $M$  is the number of Medicaid patients treated,  $F$  is the number of uninsured treated, and  $p$ ,  $p^m$ , and  $p^c$  are prices paid 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  $\pi = pQ + p^mM + p^cF - C(Q + M + F)$ .

Constraining physician supply to private, Medicaid, and uninsured patients to be non-negative, the Lagrangian and first-order conditions are:

$$\mathcal{L} = U(pQ + p^mM + p^cF - C(Q + M + F), F) + \lambda_1 Q + \lambda_2 M + \lambda_3 F, \quad (1)$$

$$[Q] : \quad U_\pi (p - C_Q) = \lambda_1 \quad (2)$$

$$[M] : \quad U_\pi (p^m - C_M) = \lambda_2 \quad (3)$$

$$[F] : \quad U_\pi (p^c - C_F) + U_F = \lambda_3. \quad (4)$$

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  $C_F$  equals the marginal return in utility terms ( $p^c + (U_F/U_\pi)$ ). Note the second-order condition for a maximization ( $U_{\pi\pi} < 0$ ) guarantees diminishing marginal utility from money, so the marginal returns to charity care in-

<sup>11</sup>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.

crease when physicians have more income ( $U_\pi$  falls) or when physicians are more altruistic ( $U_F$  increases).

We should consider seven other Karush-Kuhn-Tucker conditions, but assuming that 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). Fifty-eight percent of physicians provide care to privately insured, Medicaid insured, and uninsured patients.

### 3.1.1 Physician Response to a Payment Change

Figures 3(a) and 3(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. 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. Charity-care supply begins when a physician's marginal return from charity care in utility terms exceeds the marginal return from Medicaid. Despite the lower monetary return, segment CD represents the quantities at which the physician's utility from charity care counteracts the financial loss. In Figure 3(a), I depict two candidate marginal cost curves: MC and MC'. A physician with marginal cost curve MC will see only privately-insured patients. Those with marginal cost curve MC' see all three types of patients: privately-insured, Medicaid, and charity care patients.<sup>12</sup>

Consider how an increase Medicaid prices from  $p^{m1}$  to  $p^{m2}$  changes the physician's marginal

---

<sup>12</sup>Studies examining the provision of just Medicaid and private care, such as Baker and Royalty (2000) and Garthwaite (2012), consider marginal revenue curves identical to the one depicted in Figure 3(a). However, in their model, the segment BC represents total Medicaid supply. Since Medicaid demand generally outstrips Medicaid supply, marginal cost curves around MC' are highly unlikely. In my model, point C is determined by the quantity where the marginal return from charity care equals  $p^m$ . Because a large majority of physicians provide health care to privately-insured, Medicaid, and uninsured patients, marginal cost curves around MC' may be the norm.

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, because the opportunity cost of charity care is higher, physicians might become less altruistic. This situation is depicted by the outward shift of line CD shown in Figure 3(a).<sup>13</sup> Physicians with marginal cost curve MC will begin participating in Medicaid and make no changes to charity 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 3(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 3(c) and 3(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). When Medicaid payments rise from  $p^{m1}$  to  $p^{m2}$ , the new marginal revenue curve is depicted by the dashed, red lines. If physicians become less altruistic, shown in Figure 3(c), total supply will increase. Physicians with marginal cost MC will reduce their supply of charity care, whereas physicians with marginal cost curve MC' will increase their supply of Medicaid. On the other hand, if physicians become more altruistic, shown in Figure 3(d), total supply can fall. Physicians with marginal cost curve MC'' will begin participating in

---

<sup>13</sup>I assume that Medicaid demand outstrips supply, so the position of segment CD is not constrained by the number of Medicaid patients seeking care.

Medicaid but reduce total supply.

An analysis that ignores the provision of charity care definitively predicts increases in Medicaid supply and total supply. However, as the graphs in Figure 3 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. If the supply response of physicians with different marginal cost curves or attitudes towards altruism are not analyzed separately, any combination of changes is possible. For example, higher Medicaid payment rates can increase Medicaid supply, reduce charity care, and reduce total supply. 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).

### **3.1.2 The Interaction of Payment and Eligibility Changes**

To identify the interacted effect of 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. High eligibility rates can reduce the entry costs into Medicaid because fixed costs fall with each additional Medicaid patient treated. Thus, physicians are more likely to 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.<sup>14</sup>

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. The reason for this claim is that 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

---

<sup>14</sup>For example, see Altonji et al., 1997; Andreoni, 1989; Bergstrom et al., 1986; Brooks, 2003; Payne, 1998.

is high, increases in the Medicaid reimbursement rate will result in greater increases in Medicaid supply and smaller reductions to charity care.

### 3.2 Estimation Strategy

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

$$Y_{ist} = \beta_1 \log(\text{Medicaid Pay})_{st} + \beta_2 (\text{Fraction Eligible})_{st} + \Gamma X_{ist} + \xi D_{st} + \gamma_s + \alpha_t + \varepsilon_{ist} \quad (5)$$

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.

$\log(\text{Medicaid Pay})_{st}$  is a measure of the Medicaid payment rate in state  $s$  and year  $t$ .<sup>15</sup> *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.  $\gamma_s$  are state fixed effects that account for variation across states in the rate-setting methods.  $\alpha_t$  are year fixed effects, capturing time-specific economic shocks that may influence Medicaid rates.  $\varepsilon_{ist}$  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 physician's main practice location and indicators for whether the physician is a full or part owner of the practice.

The validity of  $\beta_1$  relies on the fact that no omitted variables affect both payment changes

---

<sup>15</sup>Construction of this variable is discussed in detail in Section 4.

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  $\beta_2$  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 (less than high school, high school graduate, some college, and college graduate), 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, 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 still affect both the fraction of people eligible for Medicaid and the number of people enrolling in insurance. 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.

## 4 Data

### 4.1 Main Data Sources

The data used in this paper rely on several sources. I provide a brief overview of the main datasets here and discuss remaining details in Appendix C: Data.

#### Medicaid Payment and Eligibility

To measure changes in Medicaid prices, I construct state-level price estimates using five rounds of the American Academy of Pediatrics (AAP) Medicaid Reimbursement Survey: 1998-1999, 2001, 2004-2005, 2007-2008, and 2009-2010.<sup>16</sup> These surveys, mailed to each state's Medicaid Director, gather the Medicaid and Medicare fee-for-service payments data on approximately 200 Current Procedural Terminology (CPT) codes.<sup>17</sup> Even though these codes focus on commonly reported pediatric procedures, several adult procedures are included as well. To obtain a state-level estimate, I use the Medical Expenditures Panel Survey (MEPS) to calculate procedure-specific Medicaid and Medicare expenditure weights at the national level.<sup>18</sup>

As shown in Appendix Table A.1, a large number of studies in the literature use the Medicaid-Medicare fee ratio collected by the Urban Institute (UI) to measure prices. Approximately every five years beginning in 1993, the UI administered state surveys asking about Medicaid rates for 19 to 32 selected services, spanning primary care, obstetrics, hospital visits, surgery, lab tests, and radiology. The AAP prices I construct offers several advantages over the UI rate. First, the AAP

---

<sup>16</sup>All prices are converted to year 2000 dollars.

<sup>17</sup>Tennessee is excluded because it not have a fee-for-service Medicaid program. In 2004, Alaska, Delaware, 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).

<sup>18</sup>Due to lack of data access, I could not calculate expenditure weights at the state level. 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. Ideally, state-specific expenditure weights would be calculated; however,

captures a more comprehensive measure of Medicaid prices relative to the UI's fee ratio.<sup>19</sup> Medicaid fees vary widely across specialties, so relying on a few service codes within six specialties 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 estimates using AAP price data and the UI fee index in Section 7.3.

One drawback of both the AAP and UI rates is that they do not capture provider-level differences in Medicaid reimbursements. Several states report that Medicaid rates may be adjusted depending on the geographic location of the physician or patient or the type of physician performing the procedure (Norton and Zuckerman, 2000). The use of state-level aggregates masks the variation in rates across providers, which can account for heterogeneity in physician behaviors 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.<sup>20</sup> 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 year, except in 2004, when thresholds are collected in July.<sup>21</sup>

---

<sup>19</sup>In the AAP, the 200 CPT codes span allergy and immunology, cardiology, critical care, emergency care, evaluation and management, gastrointestinal, hospital care, hospital services, immunizations, newborn care, office and outpatient services, ophthalmology, otolaryngology surgery, preventative medicine services, pathology and laboratory, pulmonology, radiology, and urology and dialysis specialties.

<sup>20</sup>The categories are infants, children ages 1-5, ages 6-19, working parents, non-working parents, and pregnant women. 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.

<sup>21</sup>KFF reports focus on income-related Medicaid eligibility. Although most Medicaid eligible individuals from 1998 onwards are captured by income-related rules, some individuals become Medicaid eligible only when considering welfare-related rules. I thank Tal Gross and Matthew Notowidigdo for assistance in calculating welfare-related



## **Physician Data**

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.<sup>22</sup> For convenience, I use the term “CTSPS” to refer to both the CTS and HSC survey rounds. The CTSPS includes data on physician supply—such as the acceptance of new patients, revenue distribution by insurance type, and the hours spent on total versus charity care— and various physician covariates, including sex, age, race, years practicing medicine, approximate income, specialty, and type of practice.

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 at clinics.<sup>23</sup> 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.<sup>24</sup>

## **Patient Health Insurance Enrollment**

State-level Medicaid enrollment data comes from the CMS Medicaid Statistical Information System (MSIS). Since the Balanced Budget Act of 1997, states are required to submit to CMS files containing data on eligibility, usage, and demographic characteristics for each person enrolled in Medicaid. I estimate Medicaid enrollment by summing the number of people enrolled in Medicaid Medicaid eligibility.

---

<sup>22</sup>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.

<sup>23</sup>The physician roster is taken from the American Medical Association and American Osteopathic Association master files. Federal physicians, residents, and fellows are excluded from the sample.

<sup>24</sup>Results are comparable without the sample restriction.

or CHIP and eligible for physician, clinic, laboratory, and radiological services. Non-Medicaid health insurance comes from the Census Bureau. Since Medicaid eligibility expansions target the under-age-65 population, I use Census state-level estimates for the number of direct, private, Medicare, and uninsured population under age 65.<sup>25</sup>

## Health Access Data

For patient health, I rely on the Healthcare Cost and Utilization Project Nationwide Inpatient Sample (NIS). Administered annually since 1988, the 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.<sup>26</sup> 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 NIS includes inpatient admission and health-severity data for *all* discharges from a sampled hospital. Hospital and discharge weights allow for nationally representative estimates.

## 4.2 Statistics on Medicaid Pay and Eligibility

Figure 4 shows the trend in average physician reimbursement rate per claim. Even though the Medicaid reimbursement rates have been increasing over time, payments per Medicare claim have been increasing at a faster rate, and the growth in payments from privately insured patient, especially from 2004-2010, far exceeds the growth in Medicaid payments. 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.

The fraction eligible for Medicaid is plotted in Figure 5. As discussed in Section 2.2, the

---

<sup>25</sup>State-level Medicaid enrollment data are also available from the Census, but I rely on the MSIS Medicaid estimates because it likely suffers from less measurement error. 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, whereas MSIS tracks Medicaid enrollments in each state.

<sup>26</sup>Community hospitals include short-term, general, and other specialty hospitals. They exclude hospital units of institutions.

growth eligibility likely comes from responses to federal policies, which supports the exogeneity of state legislation and the 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. Furthermore, I compare the percentage change in eligibility among states with low, medium, and high changes in the Medicaid payment rate.<sup>27</sup> Shown in Table 1, the statistics indicate that eligibility changes are not systematically correlated with high or low changes in payment.

Detailed summary statistics for physicians, insurance enrollments, and health access are shown in Appendix Tables C.2-C.4.

## **5 Results**

### **5.1 Effects of Increasing the Medicaid Reimbursement Rate**

#### **5.1.1 Physician Response to Increased Pay**

Table 2 estimates the effect of increasing the Medicaid payment rate on physician supply of Medicaid, holding constant Medicaid eligibility. From 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

---

<sup>27</sup>The terciles of payment change are calculated for each year of data. Holding constant the tercile definition yields almost identical results.

(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 and provide the corresponding OLS estimates in Appendix D: Extra Tables.

My estimates suggest a physician participation supply elasticity of 0.07 and a Medicaid supply elasticity of 0.29. It is not surprising that physician participation in Medicaid is fairly price inelastic. To become state-certified Medicaid providers, physicians need to fill out a fairly long application form, learn about mandatory services covered under Medicaid, and familiarize themselves with claim-filing procedures and deadlines. The high fixed cost of entry needs to be offset by the Medicaid reimbursement rate to induce physician participation.

However, my estimates are small relative to existing estimates, which range from 0.2 to 1.7. Table 3 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.<sup>28</sup> 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 et al. (1978), and Showalter (1997). Finally, columns (3) and (6) show results from regressions controlling for all individual- and state-level controls, except for the fraction eligible for Medicaid. These estimates are comparable to Table 2 estimates, which control for Medicaid eligibility.

Table 4 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. Willingness to provide care to the privately-insured is not affected, whereas

---

<sup>28</sup>For example, physicians in neighborhoods that are highly segregated by income will have less flexibility to substitute between their Medicaid and privately-insured patients.

the percentage of time devoted to charity care falls by 3.84%.

Columns (5) and (6) show that increasing Medicaid reimbursements induces greater Medicaid 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 also be eligible for Medicaid. These dual eligibles account for 14% of Medicaid beneficiaries and 19.5% of Medicare beneficiaries (Young et al., 2011 and CMS, 2013b). Depending on the patient's income, Medicaid will cover some to all of the out-of-pocket Medicare costs.<sup>29</sup> Thus, it is possible that increasing the payments indirectly causes increased demand from dual-eligibles. Since physicians must accept Medicare assignments for all Medicaid patients, higher payments will generate a complementary rise in Medicare supply (CMS, 2013a).

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 definitively establish this finding, 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 time measurements are not in the physician CTSPS survey, I back out time spent with Medicaid, Medicare, and private care patients using last year's percent revenue by insurance type, average price by insurance type, total hours of patient care in the last week, and weeks worked during the last year.<sup>30</sup>

Rather than OLS or 2SLS with a log dependent variable, I run a instrumental variables fixed-effects Poisson Quasi-Maximum Likelihood (QML) count model to include physicians who do not participate in Medicaid or charity care (Wooldridge, 1999).<sup>31</sup> The Poisson QML count model is

---

<sup>29</sup>Those with income below 100% of FPL are entitled to have their Medicare Part A and B premiums, deductibles, coinsurance, and copayments all paid for by Medicaid. In contrast, those with incomes ranging from 100% to 135% of FPL are only eligible to have Medicare Part B premiums covered by Medicaid.

<sup>30</sup>I assume price received from charity care patients is zero. Details are explained in Appendix C: Data.

<sup>31</sup> Appendix Table D.3 shows the estimates from using 2SLS with a log dependent variable. The coefficients are

robust to arbitrary distributional assumptions as long as the conditional mean is specified by

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

where  $P_{st}$  is the log of Medicaid Pay,  $E_{st}$  is the fraction eligible, and  $X_{ist}$ ,  $D_{st}$ ,  $\gamma_s$ ,  $\alpha_t$ , and  $\varepsilon_{ist}$  are defined in Equation (5). Standard errors are bootstrapped.

Row (1) of Table 5 presents the results. Column (1) verifies that when Medicaid prices increase by 10%, the expected number of hours spent on Medicaid and charity care patients will fall by 13%. Thus, increasing the Medicaid payments reduces total care provided to the poor. The remaining columns indicate that hours spent on Medicaid and Medicare increase, whereas time spent treating the privately insured falls. However, these estimates are imprecisely estimated.

### 5.1.2 Enrollment Response to Increased Pay

If no changes occur in enrollment, the supply responses to a rise in Medicaid payments suggest that patients with Medicaid will have increased access to care, whereas the uninsured will particularly be disadvantaged. However, Table 6 indicates that holding constant changes in Medicaid eligibility, Medicaid payment increases 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 enrollment. Appendix Table D.4 shows that OLS estimates are equivalent to IV estimates.<sup>32</sup>

To identify who is enrolling in Medicaid, I consider how non-Medicaid health 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 

---

 qualitatively similar, suggesting that results are robust to alternate functional forms.

<sup>32</sup>Results using the insurance distribution of the entire population, as opposed to the under-65 population, are similar with slightly lower magnitudes.

does not change.

Why would a supply shock cause the uninsured to enroll in Medicaid? The uninsured who are eligible for Medicaid possibly recognize that Medicaid patients have increased access to care, so the increased awareness of Medicaid prompts the uninsured to enroll. However, this mechanism is a second-order effect. It is more likely that physicians and hospitals encourage enrollment in Medicaid because of the increased financial returns from treating Medicaid patients.<sup>33</sup>

By running a short survey on mTurk, I identify whether supplier-induced demand is present. The survey, limited to US residents, asks respondents to identify who or what encouraged them to enroll in the insurance they currently have. I collected data on 1,537 unique respondents. 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%).<sup>34</sup>

Survey results are shown in Table 7. 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.<sup>35</sup> The detailed breakdown of means is displayed in Appendix Table C.5. 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.

---

<sup>33</sup>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).

<sup>34</sup>I target Medicaid respondents by using the survey title “Have Medicaid? Take this Survey.” Upon selecting the survey, respondents indicate their insurance coverage. See Ross et al., 2010 for demographics on the Turker population.

<sup>35</sup>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.

## 5.2 Effects of Expanding Medicaid Eligibility

When Medicaid eligibility expands, more people will enroll in Medicaid. Row (2) of Table 6 shows a 10-percentage-point increase in the fraction eligible for Medicaid causes actual Medicaid enrollments to increase by 6.3%. However, unlike reimbursement rate changes, the increased enrollment in Medicaid from eligibility expansions comes from both a 3.37% reductions in the uninsured population and a 8.7% reduction in the privately-insured population.

The finding of private-insurance crowd-out is consistent with the existing literature, but I find that crowd-out comes from individuals purchasing direct insurance, as opposed to those with employer-provided insurance.<sup>36</sup> Few studies on crowd-out bifurcate private insurance into employer-sponsored versus direct (i.e. non-group) insurance. Among the papers that make this distinction, the evidence on the impact of Medicaid-eligibility expansions is mixed. Gruber and Simon (2008) and Thorpe and Florence (1998) find no statistically significant crowd-out effects among the non-group insured. Lo Sasso and Buchmueller (2004) identify an increase in non-group insurance and attribute it to increased misreporting of public coverage.

My results differ from the literature possibly because I consider eligibility changes in the 2000s, which experienced a period of low unemployment. If increasing eligibility is correlated with rising financial wealth, firms may face less-pressure to adjust their employer-sponsored health insurance policies. Differences may also be due to measurement error. Crowd-out estimates are known to be sensitive to the controls included, data set used, and treatment of people insured by both public and private insurance (Card and Shore-Sheppard, 2004; Gruber and Simon, 2008; Hudson et al., 2005; Lo Sasso and Buchmueller, 2004; Shore-Sheppard, 2008).

To identify what drives Medicaid enrollments, I split the mTurk survey sample between states with increasing eligibility versus decreasing eligibility from 2010 to 2011. The difference in means for Medicaid respondents are shown in Column (3) of Table 7. I find that increased Medicaid enrollments from an eligibility expansions stem from increased awareness through TV or internet

---

<sup>36</sup>Studies on crowd-out include Card and Shore-Sheppard (2004); Cutler and Gruber (1996); Dubay and Kenney (1996, 1997); Gruber and Simon (2008); Hudson et al. (2005); Shore-Sheppard (2008); Yazici and Kaestner (2000).



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).

Row (2) of Table 2 shows how physicians respond to increased Medicaid eligibility, holding Medicaid reimbursements constant. 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. Column (4) 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.

Row (2) of Table 4 further indicates a 10 percentage point increase in the fraction eligible is associated with a 4.33% 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 private and Medicare patients does not change. Because total hours increase, these results suggest that Medicaid supply increases by more than the decrease in charity care, so overall care to the indigent population increases. This conclusion is supported by the results in row (2) of Table 5. Unlike a payment increase, expanding Medicaid eligibility increases the sum of hours supplied to Medicaid and charity care patients.

Column (5) of Table 5 additionally indicates an increase in the hours supplied to the privately insured patients. This result can be explained by the fact that uninsured population falls when the fraction eligible for Medicaid increases. Because the need for charity care falls, physicians may become less altruistic. Those who offer some charity care patients before seeing any Medicaid patients will substitute away from charity care into private care. This mechanism is discussed in Appendix B: Model of Physician Response to an Eligibility Change.

### **5.3 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 eligi-

bility expansions, I estimate the following regression:

$$Y_{ist} = \beta_1 \log(\text{Medicaid Pay})_{st} + \beta_2 (\text{Fraction Eligible})_{st} + \beta_3 \log(\text{Medicaid Pay}) \times (\text{Fraction Eligible})_{st} + \Gamma X_{ist} + \xi D_{st} + \gamma_s + \alpha_t + \varepsilon_{ist}, \quad (6)$$

where  $X_{ist}$  and  $D_{st}$  are the covariates for physician  $i$  in state  $s$  in year  $t$  discussed in Section 3.2,  $\gamma_s$  are state fixed effects,  $\alpha_t$  are year fixed effects, and  $\varepsilon_{ist}$  is an idiosyncratic error term. Following Aiken and West, 1991 and Judd et al. (2008), I center the variables  $\log(\text{Medicaid Pay})$  and  $(\text{Fraction Eligible})$  by subtracting their respective means. Centering reduces multicollinearity and increases the interpretability of the regression coefficients.  $\beta_1$  indicates the effect of increasing Medicaid payments for physicians facing the average fraction eligible for Medicaid.  $\beta_2$  indicates the effect of expanding Medicaid eligibility for physicians with the average Medicaid reimbursement rate. I eliminate bias from omitted variables correlated with eligibility and physician or enrollment responses 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.

Table 8 shows the interaction of payment changes and eligibility expansions on physician supply. The first two columns show the interaction effect for Medicaid supply. When eligibility is high, Medicaid participation increases by an additional 12.2% and Medicaid hours increase by an additional 31%. This result is consistent with the theory-based predictions discussed in Section 3.2. The next two columns show the interaction effect for charity care supply. Because the interaction term 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 added 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 last column of Table 8, the interaction effect on hours of care allocated to the poor is positive and large.

Finally, Table 9 shows the interaction of payment changes and eligibility expansions on insurance enrollment. Column (1) shows that 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.

## 6 Access to Health Care

Because I cannot identify 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

$$\begin{aligned}
 Y_{arst} = & \beta_1 \log(\text{Medicaid Pay})_{st} + \beta_2 (\text{Fraction Eligible})_{arst} \\
 & + \xi D_{st} + \eta_a + \phi_r + \gamma_s + \alpha_t + \varepsilon_{arst},
 \end{aligned} \tag{7}$$

where  $a$  indexes age,  $r$  indexes race,  $s$  indexes state, and  $t$  indexes year;  $\eta_a$ ,  $\phi_r$ ,  $\gamma_s$ , and  $\alpha_t$  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 reimbursement or eligibility changes and regional differences in the NIS sampling frame that affect how a state is represented over time in the data.  $D_{st}$  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.<sup>37</sup> Standard errors are adjusted to allow for correlation within states.

IV regression results are shown in Table 10.<sup>38</sup> Column (1) shows that a 10% increase in the Medicaid reimbursement rate reduces hospital admissions from the ER by 3.03%. Changes in

<sup>37</sup>As discussed in Section 3.2, these covariates are the log population enrolled in Medicaid, Medicare, direct insurance, employer-sponsored insurance, or no insurance; log total population and population for those in poverty ages 0-4, 5-17, and 18 and greater; log median household income; and log unemployment.

<sup>38</sup>Corresponding OLS regressions in Appendix Table D.7.

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 et al., 2008; Currie and Gruber, 1996; De La Mata, 2012; Gruber et al., 1997; Howell et al., 2010; Howell and Kenney, 2012; Wherry, 2013). Extending Kaestner et al. (2001) and Dafny and Gruber (2005), I also consider the impact of Medicaid on hospitalizations that medical experts have denoted as “avoidable.” The ICD-9 codes for these hospitalizations, which might not have occurred if patients had received effective, timely, and continuous outpatient medical care, are shown in Appendix Table C.6. Column (2) shows that preventable ER admissions decrease by about 0.7% when payment rates increase.

Despite the general reductions in ER admissions, I additionally find that payment and eligibility increases differentially affect ER usage among Medicaid, charity care, and privately-insured patients. When payments increase by 10%, columns (3) to (5) show that a hospital’s share of Medicaid ER admissions falls by 1.94%, and the share of uninsured and privately insured ER admissions remain unchanged. One might argue that the coefficient on Medicaid ER admissions is biased by unobserved health quality, which is endogenous with insurance enrollment. However, this bias works against finding reductions in Medicaid ER admissions. Physicians receive higher financial returns from encouraging sicker patients to enroll in Medicaid, causing average Medicaid health quality to fall and Medicaid ER admissions to increase. Therefore, these results imply that increases in payment cause Medicaid supply to increase by more than physician-induced Medicaid demand, improving access to care for Medicaid patients.

In contrast to payment increases, a 10-percentage-point increase in eligibility is associated with Medicaid ER admissions increasing by almost 4%, charity care ER admissions increasing by 0.4%, and privately insured ER admissions falling by 3.3%. 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. The mTurk survey results on the enrollment impetus in columns

(3) and (4) of Table 7 suggest Medicaid patients are on average healthier post expansion, whereas private patients are less healthy. To the extent that these results are robust, the unobserved bias works against finding these results. Therefore, 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.

## 7 Robustness Checks and Extensions

### 7.1 Exogeneity of Medicaid Price Changes

There are several reasons why Medicaid price changes might not be exogenous. First, because Medicaid is jointly funded by federal and state governments, the amount of federal funding a state receives—known as the Federal Medical Assistance Percentage (FMAP)—can affect a state’s reimbursement rates.<sup>39</sup> FMAPs vary with state per capita income and range from 50%, where one state dollar equals one federal dollar, to 83%, where one state dollar equals \$4.88 federal dollars.<sup>40</sup> Despite the availability of federal support, states might also 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 be unsustainable (NASBO,2012).<sup>41</sup> 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

---

<sup>39</sup>The FMAP formula is  $1 - 0.45 \times \left( \frac{\text{state per capita income}}{\text{US per capita income}} \right)^2$ . Income variables are based on three-year rolling averages measured by the Department of Commerce’s Bureau of Economic Analysis. For example, the FMAP percentages for FY 2010 are published in 2008, go into effect October 2009, and are based on income from 2005-2007. During two economic recessions, the FMAP has been modified to increase aid to states. Refer to the Kaiser Family Foundation Report (2012) for details.

<sup>40</sup>Since the FMAP creates a spending multiplier, states with higher FMAPs induce larger payment cuts to providers when reducing state spending. For example, consider a service that is reimbursed at \$1000. In a 50% FMAP state, a \$100 cut in state spending reduces payment to providers to \$800, whereas in a 70% FMAP state, payment falls to \$667.

<sup>41</sup>For comparison, K-12 education accounts for 19.8% of total state expenditures.

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.<sup>42</sup> The detailed regression results are presented in Appendix Table D.1. I test whether variables in each group of controls are jointly different from zero. Table 11 shows the F-statistics and corresponding p-values.

Column (1) controls for demand and supply variables such as the number of physicians, physician assistants, and registered nurses; and the number of people with Medicaid, Medicare, private insurance, or uninsured. Column (2) controls for measures of poverty, such as 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 in the lower and upper houses 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.

## 7.2 Test of Causality

If the conditional independence assumption holds—namely that conditional on observables, the payment and eligibility policy variables are as good as randomly assigned, future policy changes should not affect outcomes today. In Table 12, I test whether payment and eligibility rates three years in the future affect current supply and demand responses.<sup>43</sup>

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. The coeffi-

---

<sup>42</sup>Data sources are described in Section 4 and Appendix Table C.1.

<sup>43</sup>I use data three years in the future because Medicaid reimbursement rate data is only available in three year increments.

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 supply: when payment (eligibility) increases, Medicaid supply increases, charity care falls, and total hours fall (increase).

Similarly, columns (4) to (6) indicate the effects of future payment and eligibility changes on insurance take-up. Again future policy changes are statistically insignificant, whereas the coefficients on contemporaneous policy changes are the same as previously discussed and statistically significant. These results support a causal interpretation of the regression results.

### 7.3 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). The UI index is calculated from the Medicaid and Medicare reimbursement rates for a small subset of services. Medicaid fees are combined into a single index using an expenditures weight calculated from 20 states, and Medicare fees are combined using a population-weighted average.<sup>44</sup>

Table 13 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.

---

<sup>44</sup>Refer to Norton and Zuckerman (2000), Zuckerman et al. (2004), and Zuckerman et al. (2009) for detailed information about the construction of these indices. 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.

## 7.4 Implications for the ACA

I use my results to forecast the effects of the ACA by performing calculations of the demand and supply responses to payment and eligibility changes. For tractability, I ignore potential changes from employment-sponsored health insurance and the health insurance exchange plans.

**Payment Changes** In 2014, the ACA will increase physician reimbursements for evaluation, management, and immunization services to at least 100% of Medicare plans. According to the American College of Physicians, this policy will increase payment rates by approximately 73% (ACP, 2013). If eligibility is held constant, a 73% increase in Medicaid payments, equivalent to raising average rate rising from \$50 to \$86.5, will induce 6,553 additional physicians to participate in Medicaid and an additional 44,377 physicians will begin accepting all new Medicaid patients.<sup>45</sup> Although Medicaid supply will increase, total hours of care supplied will fall by  $(73*0.05) = 3.65\%$  and the share of hours spent on charity care will fall by 28%. A 73% payment increase will also increase Medicaid enrollments by about 141,910 enrollees.<sup>46</sup>

**Eligibility Changes** However, the ACA does not hold eligibility constant. Instead, it mandates a national Medicaid minimum eligibility level of 133% of FPL for nearly all Americans under age 65. In 2012, this cutoff is equivalent to \$15,414 for individuals and \$31,809 for a family of four in 2012. Because 5% of income will be disregarded, the new threshold is effectively 138%. The largest beneficiaries of the ACA eligibility expansion will be poor parents and poor adults without children, a group that has been traditionally excluded from Medicaid coverage. Using CPS data from 2010, I find that this policy, which will be implemented in 25 states, increases the fraction of

---

<sup>45</sup>In 2010, the Federal State Medical Boards reported approximately 850,000 active licensed physicians in the US (Young et al., 2011). The CTSPS data indicates that 82.1% of physicians participated in Medicaid and 39.9% of physicians accepted all new Medicaid patients. A 10% increase in Medicaid increases participation by 0.59%, and acceptance of new Medicaid payments by 1.19%. Thus a 73% increase in Medicaid payments will result in  $850,000*(1-0.821)*0.0059*7.3 = 6,553$  additional physicians participating in Medicaid and  $850,000*(1-0.399)*0.0119*7.3 = 44,377$  accepting all new Medicaid patients.

<sup>46</sup>Average state enrollment in Medicaid of those under 65 in 2010 is 845,209. A 73% increase in payments leads to  $845,209*0.023*7.3 = 141,910$  more enrollees.



eligible for Medicaid by about 5 percentage points.<sup>47</sup>

To understand the effects of this change, begin by holding prices constant. My results suggest that a 5 percentage point increase in eligibility will increase Medicaid enrollments by 26,539 people within the average state. An additional 1,400 physicians will participate in Medicaid, and total supply will increase by about 2%, whereas the share of time spent on charity care will fall by 10%.<sup>48</sup> In reality, these changes are likely to be significantly larger because the penalty from not having insurance will induce most of the people who are eligible for Medicaid to enroll.

**Net Effect** Now summing the effect of both policies, we see that in the average state, Medicaid enrollments will increase by 167,729. Physician participation in Medicaid increases by 7,953 physicians nationwide, and the number of physicians accepting all new Medicaid patients increases by 44,377. The interaction between payment increases and eligibility expansions will generate an added increase in Medicaid supply and a reduction in Medicaid enrollments. Therefore, implementing both policies in tandem should mitigate concerns over a worsening physician shortage. Without data on the number of Medicaid enrollees seen per physician, I unfortunately cannot extrapolate my analysis to estimate the extent of a supply shortage.<sup>49</sup>

**Potential Savings** Studies estimating the cost of treating non-emergency conditions in the emergency department approximate a nationwide excess charge of \$4 to \$7 billion (Baker and Baker, 1994; Robin M. Weinick and Mehrotra, 2010). In 2008, there were 25.1 million Medicaid ER visits, and 4.5 per 100 visits were classified as non-urgent (Sommers et al., 2012). Using Baker and Baker's (1994) overall excess charge estimate of \$93.85 for use of the ER in a non-urgent situation,

---

<sup>47</sup>Even though this estimate seems low, the standardized definition of income reduces eligibility for some people in states with generous child care and work deductions.

<sup>48</sup>Similar to previous calculation. Change in physician participation =  $850,000 * (1 - 0.821) * 0.0359 * 0.5 = 1,400$ .

<sup>49</sup>Existing estimates of the physician shortage vary from 3,000 to 200,000 physicians (AAMC, 2010; Cooper et al., 2002; Dill and Salsberg, 2008; Lowrey and Pear, 2012; HHS, 2008; Lowrey and Pear (2012)).

I conclude that 3.03% reduction in ER use will result in savings of \$142 million.<sup>50</sup>

These savings come at the cost of higher payments for Medicaid services. For example, if the price for treating each Medicaid patient increases \$10, then ER savings will be balanced out when an additional 14.2 million Medicaid appointments are made. With 8.4 claims per Medicaid enrollee in 2010, this statement is equivalent to zero net savings once 1.7 million people are enrolled in Medicaid. A more accurate calculation should take into account increased administrative burdens from expanding Medicaid and loss in efficiency from private insurance crowd-out.

## 8 Conclusion

A good deal of policy has focused on increasing reimbursement rates to address concerns about a growing physician shortage (Pettersen et al., 2012 and Hofer et al., 2011). 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, 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

---

<sup>50</sup>Calculated from: 25.1 million \* 0.045 \* 93.85 \* 1.895 \* 0.0303 = \$142 million. The 1.895 is the CPI index converts the Baker and Baker (1994) estimate from 1987 dollars to 2008 dollars. The 3.03% comes from Column (1) of Table 10. Urgency depends on the number of minutes, determined by triage staff, that a patient can wait before receiving medical attention. Non-urgent is defined as being able to wait 2-24 hours.

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? How do physicians decide who to provide charity care to? 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**, “Effect of Increased Medicaid Fees on Physician Participation and Enrollee Service Utilization in Tennessee, 1985-1988,” *Inquiry*, 1994, 31(2), 173–187.
- Aiken, Leona and Stephen West**, *Multiple Regression: Testing and Interpreting Interactions*, Sage Publications, 1991.
- Aizer, Anna**, “Public Health Insurance, Program Take-up, and Child Health,” *The Review of Economics and Statistics*, 2007, 89(3), 400–415.
- Allen, Kathryn**, “Children’s Health Insurance: State Experiences in Implementing SCHIP and Considerations for Reauthorization,” *United States Government Accountability Office*, 2007, pp. 1–39.
- Altonji, Joseph, Fumio Hayashi, and Laurence Kotlikoff**, “Parental Altruism and Inter Vivos Transfers: Theory and Evidence,” *Journal of Political Economy*, 1997, 105(6), 1121–1166.
- American College of Physicians**, “Enhanced Medicaid Reimbursement Rates for Primary Care Services,” 2013.
- Andreoni, James**, “Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence,” *The Journal of Political Economy*, 1989, 97(6), 1447–1458.
- Association, American Hospital**, “Uncompensated Hospital Care Cost Fact Sheet,” January 2013.
- Association of American Medical Colleges**, “The Impact of Health Care Reform on the Future Supply and Demand for Physicians Updated Projections Through 2025,” AAMC Report [https://www.aamc.org/download/158076/data/updated\\_projections\\_through\\_2025.pdf](https://www.aamc.org/download/158076/data/updated_projections_through_2025.pdf) 2010.
- , “Recent Studies and Reports on Physician Shortages in the US,” Center for Workforce Studies <https://www.aamc.org/download/100598/data/> October 2012.
- Baker, Laurence and Anne Royalty**, “Medicaid Policy, Physician Behavior, and Health Care for the Low-Income Population,” *The Journal of Human Resources*, 2000, 35(3), 480–502.
- Baker, Laurence C. and Linda Schuurman Baker**, “Excess Cost of Emergency Department Visits for Nonurgent Care,” *Health Affairs*, 1994, 13(5), 162–171.
- Bergstrom, Theodore, Lawrence Blume, and Hal Varian**, “On the Private Provision of Public Goods,” *Journal of Public Economics*, 1986, 29, 25–49.
- Bermudez, Dustin and Laurence Claude Baker**, “The Relationship Between SCHIP Enrollment and Hospitalizations for Ambulatory Care Sensitive Conditions in California,” *Journal of Health Care for the Poor and Underserved*, 2005, 16(1), 96–110.
- Brooks, Arthur**, “Do Government Subsidies To Nonprofits Crowd Out Donations or Donors?,” *Public Finance Review*, 2003, 31(2), 166–179.

- Card, David and Lara D. Shore-Sheppard**, “Using Discontinuous Eligibility Rules to Identify the Effects of the Federal Medicaid Expansions on Low-Income Children,” *The Review of Economics and Statistics*, 2004, 86(3), 752–766.
- Center for Medicare and Medicaid Services**, “Medicaid Coverage of Medicare Beneficiaries (Dual Eligibles) At a Glance,” *Medicare Learning Network*, 2013, ICN 006977, 1–6.
- , “Medicare-Medicaid Dual Enrollment From 2006 Through 2011,” Data Analysis Brief February 2013.
- Cohen, Joel W.**, “Medicaid Physician Fees and Use of Physician and Hospital Services,” *Inquiry*, 1993, 30(3), 281–292.
- Congressional Budget Office**, “Estimates for the Insurance Coverage Provisions of the Affordable Care Act Updated for the Recent Supreme Court Decision,” CBO Report <http://www.cbo.gov/sites/default/files/cbofiles/attachments/43472-07-24-2012-CoverageEstimates.pdf> 2012.
- Cooper, Richard, Thomas Getzen, Heather McKee, and Prakash Laud**, “Economic and Demographic Trends Signal an Impending Physician Shortage,” *Health Affairs*, 2002, 21(1), 140–154.
- Currie, Janet and Jonathan Gruber**, “Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women,” *Journal of Political Economy*, 1996, 104(6), 1263–1296.
- , – , and **Michael Fischer**, “Physician Payments and Infant Mortality: Evidence from Medicaid Fee Policy,” *American Economic Review*, 1995, 85(2), 106–111.
- , **Sandra Decker, and Wanchuan Lind**, “Has Public Health Insurance for Older Children Reduced Disparities in Access to Care and Health Outcomes?,” *Journal of Health Economics*, 2008, 27, 1567–1581.
- Cutler, David**, “Cost Shifting or Cost Cutting? The Incidence of Reductions in Medicare Payments,” *Tax Policy and the Economy*, 1998, 12, 1–27.
- and **Jonathan Gruber**, “Does Public Insurance Crowd out Private Insurance?,” *The Quarterly Journal of Economics*, 1996, 111(2), 391–430.
- Dafny, Leemore**, “How Do Hospitals Respond to Price Changes?,” *American Economic Review*, 2005, 95(5), 1525–47.
- and **Jonathan Gruber**, “Public Insurance and Child Hospitalizations: Access and Efficiency Effects,” *Journal of Public Economics*, 2005, 89, 109–129.
- Decker, Sandra**, “Medicaid Physician Fees and the Quality of Medical Care of Medicaid Patients in the USA,” *Review of Economics of the Household*, 2007, 5(1), 95–112.
- , “Changes in Medicaid Physician Fees and Patterns of Ambulatory Care,” *Inquiry*, 2009, 46, 291–304.

- , “In 2011 Nearly One-Third Of Physicians Said They Would Not Accept New Medicaid Patients, But Rising Fees May Help,” *Health Affairs*, 2012, 31(8), 1673–1679.
- Dill, Michael and Edward Salsberg**, “The Complexities of Physician Supply and Demand: Projections Through 2025,” *AAMC Center for Workforce Studies*, 2008, pp. 1–90.
- Dranove, David and William White**, “Medicaid-Dependent Hospitals and Their Patients: How Have They Fared?,” *Health Services Research*, 1998, 33(2), 163–85.
- Dubay, Lisa and Genevieve Kenney**, “The Effects of Medicaid Expansions on Insurance Coverage of Children,” *The Future of Children*, 1996, 6(1), 152–161.
- and — , “Did Medicaid Expansions For Pregnant Women Crowd Out Private Coverage?,” *Health Affairs*, 1997, 16(1), 185–193.
- Feder, Judith, Diane Rowland, and John Holahan**, *The Medicaid Cost Explosion: Causes and consequences*, The Henry J. Kaiser Family Foundation, 1993.
- Feldstein, Martin**, “The Rising Price of Physician’s Services,” *The Review of Economics and Statistics*, 1970, 52(2), 121–133.
- Frank, Richard and David Salkever**, “The Supply of Charity Services by Nonprofit Hospitals: Motives and Market Structure,” *Rand Journal of Economics*, 1991, 22(3), 430–445.
- Garthwaite, Craig**, “The Doctor Might See You Now: The Supply Side Effects of Public Health Insurance Expansions,” *American Economic Journal: Economic Policy*, 2012, 4(3), 190–215.
- Ginsburg, Paul**, “Can Hospitals And Physicians Shift The Effects Of Cuts In Medicare Reimbursement To Private Payers?,” *Health Affairs*, 2003, w3, 472–479.
- Gray, Bradley**, “Do Medicaid Physician Fees for Prenatal Services Affect Birth Outcomes?,” *Journal of Health Economics*, 2001, 20(4), 571–590.
- Gruber, Jon, John Kim, and Dina Mayzlin**, “Physician Fees and Procedure Intensity: The Case of Cesarean Delivery,” *Journal of Health Economics*, 1999, 18(4), 473–490.
- Gruber, Jonathan**, *Means-Tested Transfer Programs in the United States*, University of Chicago Press,
- and **David Rodriguez**, “How Much Uncompensated Care do Doctors Provide?,” *Journal of Health Economics*, 2007, 26(6), 1151–1169.
- and **Kosali Simon**, “Crowd Out 10 Years Later: have Recent Public Insurance Expansions Crowded Out Private Health Insurance?,” *Journal of Health Economics*, 2008, 27(2), 201–217.
- , **Kathleen Adams, and Joseph Newhouse**, “Physician Fee Policy and Medicaid Program Costs,” *The Journal of Human Resources*, 1997, 32(4), 611–634.
- Hadley, Jack**, “Physician Participation in Medicaid: Evidence from California,” *Health Services Research*, 1979, 14, 266–280.

- **and John Holahan**, “How Much Medical Care Do The Uninsured Use, And Who Pays For It?,” *Health Affairs*, 2003, *w3*, 66–81.
- Hofer, Adam, Jean Marie Abraham, and Ira Moscovice**, “Expansion of Coverage under the Patient Protection and Affordable Care Act and Primary Care Utilization,” *The Milbank Quarterly*, 2011, *89(1)*, 69–89.
- Horton, John, David Rand, and Richard Zeckhauser**, “The Online Laboratory: Conducting Experiments in a Real Labor Market,” *Experimental Economics*, 2011, *14(3)*, 399–425.
- Howell, Embry and Genevieve Kenney**, “The Impact of the Medicaid/CHIP Expansions on Children: A Synthesis of the Evidence,” *Medical Care Research and Review*, 2012, *69(4)*, 372–396.
- , **Sandy Decker, Sara Hogan, Alshadye Yemane, and Jonay Foster**, “Declining Child Mortality and Continuing Racial Disparities in the Era of the Medicaid and SCHIP Insurance Coverage Expansions,” *American Journal of Public Health*, 2010, *100(12)*, 2500–2506.
- Hudson, Julie L., Thomas M. Selden, and Jessica S. Banthin**, “The Impact of SCHIP on Insurance Coverage of Children,” *Inquiry*, 2005, *42(3)*, 232–254.
- Hughes, David and Brian Yule**, “The Effect of Per-item Fees On the Behavior of General Practitioners,” *Journal of Health Economics*, 1992, *11*, 413–437.
- Judd, Charles, Gary McClelland, and Carey Ryan**, *Data Analysis: A Model-Comparison Approach, Second Edition*, Routledge, 2008.
- Kaestner, Robert, Ted Joyce, and Andrew Racine**, “Medicaid Eligibility and the Incidence of Ambulatory Care Sensitive Hospitalizations for Children,” *Social Science and Medicine*, 2001, *52*, 305–313.
- Kaiser Family Foundation**, “An Overview of Recent Section 1115 Medicaid Demonstration Waiver Activity,” *The Kaiser Commission on Medicaid and the Uninsured*, 2012, *No. 8318*, 1–15.
- Klemm, John**, “Medicaid Spending: A Brief History,” *Health Care Financing Review*, 2000, *22(1)*, 105–112.
- Kuziemko, Ilyana, Michael Norton, Emmanuel Saez, and Stefanie Stantcheva**, “How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments,” *NBER Working Paper*, 2013, *No. 18865*.
- Lo Sasso, Anthony and Thomas Buchmueller**, “The Effect of the State Children’s Health Insurance Program on Health Insurance Coverage,” *Journal of Health Economics*, 2004, *23*, 1059–1082.
- Lowrey, Annie and Robert Pear**, “Doctor Shortage Likely to Worsen with Health Law,” *The New York Times* <http://www.nytimes.com/2012/07/29/health/policy/too-few-doctors-in-many-us-communities.html> July 28 2012.

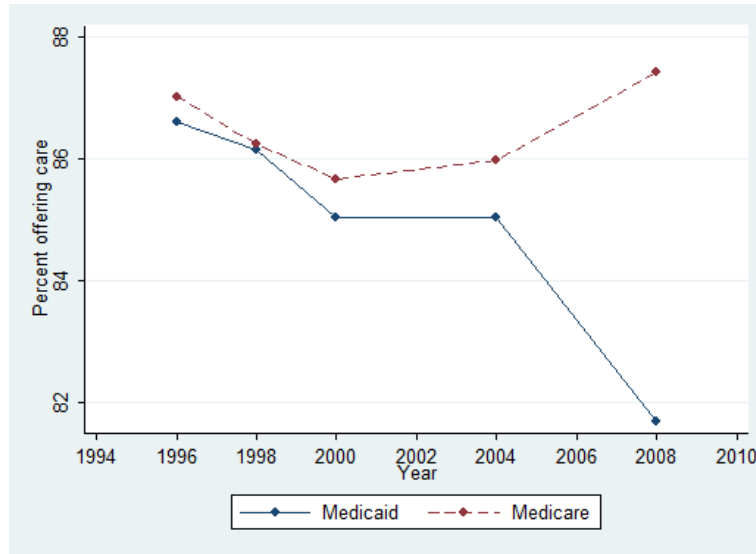
- Mata, Dolores De La**, “The Effect of Medicaid Eligibility on Coverage, Utilization, and Children’s Health,” *Health Economics*, 2012, 21, 1061–1079.
- Mayes, Rick and Jason Lee**, “Medicare Payment Policy and the Controversy over Hospital Cost Shifting,” *Applied Health Economics and Health Policy*, 2004, 3(3), 153–159.  
*MCH Update: Medicaid Coverage of Pregnant Women and Children*
- MCH Update: Medicaid Coverage of Pregnant Women and Children*, Issue Brief September 1996.
- Merlis, Mark**, “Medicaid Reimbursement Policy,” *Congressional Research Service Report for Congress October 2004*.
- Mitchell, Janet**, “Why Do Women Physicians Work Fewer Hours Than Men Physicians?,” *Inquiry*, 1984, 21(4), 361–368.
- , “Physician Participation in Medicaid Revisited,” *Medical Care*, 1991, 29(7), 645–653.
- Morrissey, Michael**, “Cost-Shifting: New Myths, Old Confusion, and Enduring Reality,” *Health Affairs*, 2003, w3, 489–491.
- National Association of State Budget Officers**, “State Expenditure Report: Examining Fiscal 2010-2012 Spending,” 2012.
- Norton, Stephen and Stephen Zuckerman**, “Trends in Medicaid Physician Fees, 1993-1998,” *Health Affairs*, 2000, 19(4), 222–232.
- Paolacci, Gabriele, Jesse Chandler, and Panagiotis Ipeirotis**, “Running Experiments on Amazon Mechanical Turk,” *Judgment and Decision Making*, 2010, 5(5), 411–419.
- Payne, Abigail**, “Does the Government Crowd-Out Private Donations? New Evidence from a sample of non-profit firms,” *Journal of Public Economics*, 1998, 69, 323–345.
- Perry, Michael, Vernon Smith, Catherine Smith, and Christina Chang**, “Marketing Medicaid and CHIP: A Study of State Advertising Campaigns,” *The Kaiser Commission on Medicaid and the Uninsured*, 2000, 2213, 1–40.
- Petterson, Stephen, Winston Liaw, Robert Phillips Jr, David Rabin, David Meyers, and Andrew Bazemore**, “Projecting US Primary Care Physician Workforce Needs: 2010-2025,” *Annals of Family Medicine*, 2012, 10(6), 503–509.
- Ross, Donna, Alyea Horn, and Caryn Marks**, “Health Coverage for Children and Families in Medicaid and SCHIP: State Efforts Face New Hurdles,” *The Kaiser Commission on Medicaid and the Uninsured*, 2008, pp. 1–75.
- **and Laura Cox**, “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*, 2000, pp. 1–48.



- **and** — , “*Beneath the Surface: Barriers Threaten to Slow Progress on Expanding Health Coverage of Children and Families*,” *The Kaiser Commission on Medicaid and the Uninsured*, 2004, pp. 1–68.
- , **Marian Jarlenski, Samantha Artiga, and Caryn Marks**, “*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*, 2009, pp. 1–68.
- Ross, Joel, Andrew Zaldivar, Lilly Irani, and Bill Tomlinson**, “*Who are the Turkers? Worker Demographics in Amazon Mechanical Turk*,” *CHI EA*, 2010, pp. 2863–2872.
- Shen, Yu-Chu and Stephen Zuckerman**, “*The Effect of Medicaid Payment Generosity on Access and Use Among Beneficiaries*,” *Health Services Research*, 2005, 40(3), 723–744.
- Shore-Sheppard, Lara D.**, “*Stemming the Tide? The Effect of Expanding Medicaid Eligibility On Health Insurance*,” *The B.E. Journal of Economic Analysis & Policy*, 2008, 8(2), 1–33.
- Showalter, Mark H.**, “*Physicians Cost Shifting Behavior: Medicaid Versus Other Patients*,” *Contemporary Economic Policy*, 1997, 15(2), 74–84.
- Sloan, Frank**, “*A Microanalysis of Physicians’ Hours of Work Decisions*,” in “*The Economics of Health and Medical Care*,” *John Wiley and Sons*, 1974, pp. 302–325.
- , **Janet Mitchell, and Jerry Cromwell**, “*Physician Participation in State Medicaid Programs*,” *Journal of Human Resources*, 1978, 13, 211–245.
- Sommers, Anna, Ellyn Boukus, and Emily Carrier**, “*Dispelling Myths About Emergency Department Use: Majority of Medicaid Visits Are for Urgent or More Serious Symptoms*,” *Health System Change Research Brief*, 2012, No. 23.
- The Kaiser Commission on Medicaid and Uninsured**, “*Medicaid Financing: An Overview of the Federal Medicaid Matching Rate (FMAP)*,” No. 8352 September 2012.
- Thorpe, Kenneth and Curtis Florence**, “*Health Insurance Among Children: The Role of Expanded Medicaid Coverage*,” *Inquiry*, 1998, 35(4), 369–379.
- U.S. Department of Health and Human Services**, “*The Physician Workforce: Projections and Research into Current Issues Affecting Supply and Demand*,” <http://bhpr.hrsa.gov/healthworkforce/reports/physwfiissues.pdf> December 2008.
- Vahovich, Stephen**, “*Physicians’ Supply Decisions by Specialty: 2SLS Model*,” *Industrial Relations*, 1977, 16(1), 51–60.
- Weinick, Rachel M. Burns Robin M. and Ateev Mehrotra**, “*Many Emergency Department Visits Could Be Managed At Urgent Care Centers And Retail Clinics*,” *Health Affairs*, 2010, 29(9), 1630–1636.
- Wherry, Laura**, “*The Impact of Medicaid Family Planning Expansions on preventive Services Utilization*,” *Population Studies Center Research Report*, 2013, 13-784.

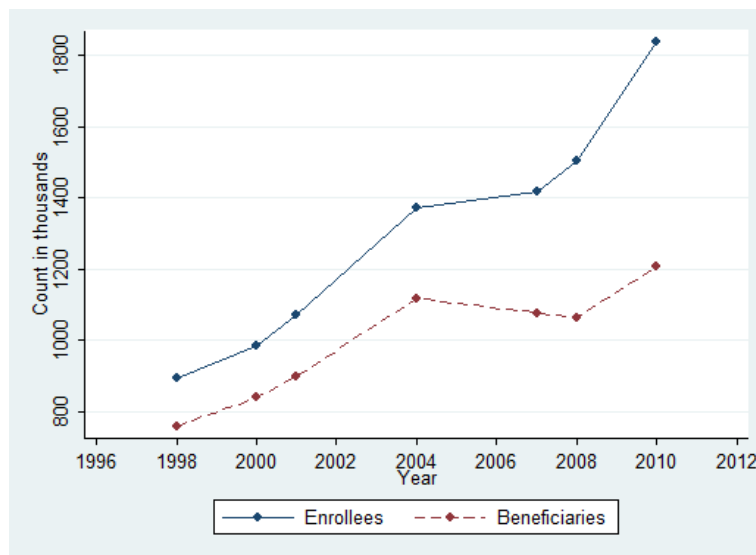
- Wooldridge, Jeffrey**, “*Distribution-free Estimation of Some Nonlinear Panel Data Models*,” *Journal of Econometrics*, 1999, 90, 77–97.
- Yazici, Esel and Robert Kaestner**, “*Medicaid Expansions and the Crowding Out of Private Health Insurance Among Children*,” *Inquiry*, 2000, 37(1), 23–32.
- Young, Aaron, Humayun Chaudhry, Janelle Rhyne, and Michael Dugan**, “*A Census of Actively Licensed Physicians in the United States, 2010*,” *Journal of Medical Regulation*, 2011, 96(4), 10–20.
- Zuckerman, Stephen, Aimee Williams, and Karen Stockley**, “*Trends In Medicaid Physician Fees, 2003-2008*,” *Health Affairs*, 2009, 28(3), w510–w519.
- , **Joshua McFeeters, Peter Cunningham, and Len Nichols**, “*Changes in Medicaid Physician Fees, 1993-2003: Implications for Physician Participation*,” *Health Affairs*, 2004, w4, 374–384.

Figure 1: Share of Practice Seeing Medicaid or Medicare Patients



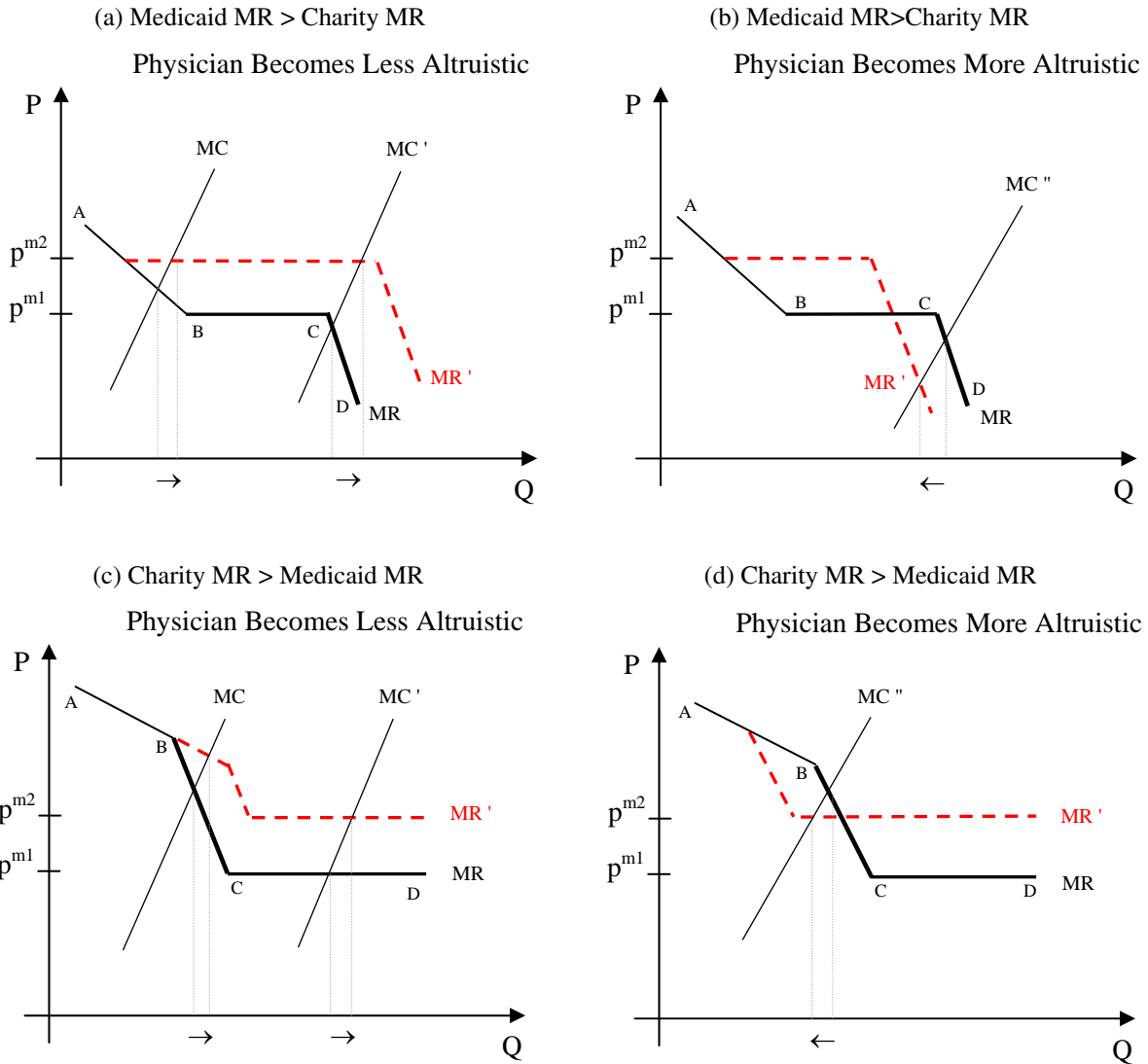
Notes: This figure shows that over time, the percent of practices seeing any Medicaid patients decreases over time while the percent of practice seeing Medicare patients increases slightly. Data from CTSPS.

Figure 2: Medicaid Enrollees and Beneficiaries



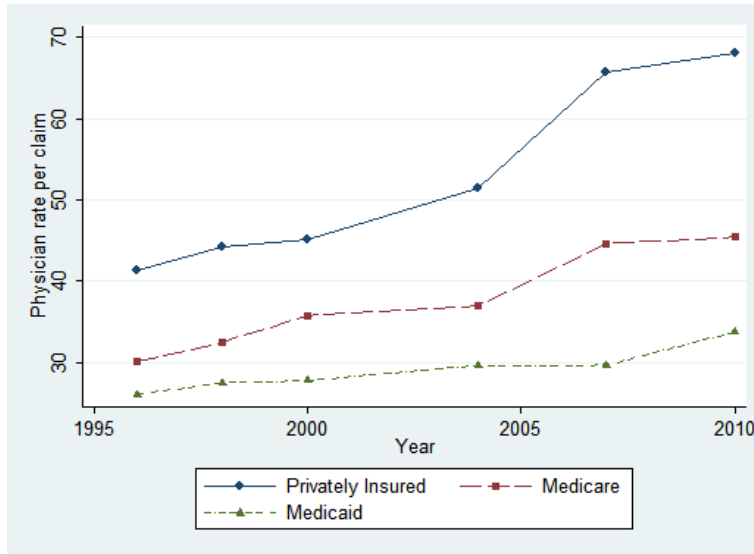
Notes: This figure shows that Medicaid enrollments have been increasing over time. However, the number of enrollees who have used Medicaid services (bottom line) are increasing at a much slower rate, suggesting that access to care for the average person with Medicaid is falling over time. Data from CMS MSIS.

Figure 3: Impact of Medicaid Payment Increase on Physician Supply



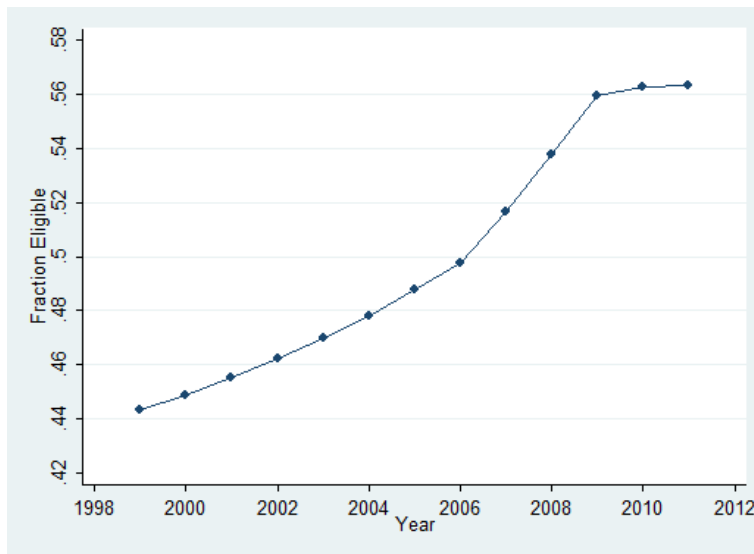
Notes: These graphs show how a physician adjusts supply when the Medicaid payment rate increases. A physician's marginal revenue curve is represented by ABCD. AB is the marginal revenue from privately insured patients. In plots (a) and (b), BC is the marginal revenue from Medicaid, and CD is the marginal 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 4: Payment Rates, by Insurance Type



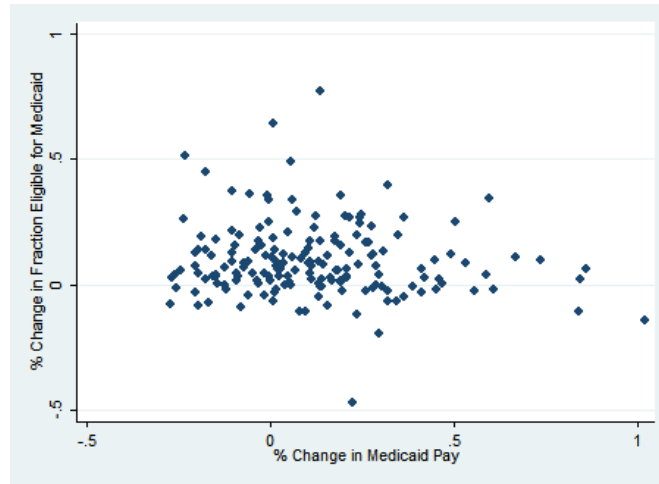
*Notes:* This figure shows physician reimbursements rates for privately insured, Medicaid, and Medicare patients. Reimbursement rates not only remain lower for publicly-insured patients, but they also grow at a slower rate than privately insured reimbursement fees. Rates calculated at the regional level using NHEA payments for physician and clinic services expressed in 2000 dollars divided by total claims per region from NAMCS.

Figure 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: The Relationship Between Payment and Eligibility Changes

%ΔMedicaid Pay, By Tercile	Percent Change in Fraction Eligible			
	1998-2001 (1)	2001-2004 (2)	2004-2007 (3)	2007-2010 (4)
(1) Tercile 1 (-11.4%)	11.83	7.28*	4.22	17.04*
(2) Tercile 2 (8.5%)	14.64*	7.09	9.02*	7.34
(3) Tercile 3 (2.62%)	11.73	6.99	6.90	8.58
Observations	46	44	44	45

Notes: Rows (1)-(3) show the average percent change in eligibility among states in the lowest, middle, and highest tercile of Medicaid payment change over time, respectively. The terciles are defined for each year (2001, 2004, 2007, and 2010). \* indicates the largest value in a column. This table shows that eligibility expansions are not necessarily accompanied by high or low payment changes.

Table 2: Medicaid Physician Response

Dependent Variable Mean:	1(Any Medicaid)	1(All New Medicaid)	% Revenue Medicaid	1(Any Medicaid)	1(All New Medicaid)	% Revenue Medicaid
	0.821	0.399	12.80	0.821	0.399	12.80
	OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)	IV (6)
(1) Log(Medicaid Pay)	0.0752** (0.0371)	0.135*** (0.0340)	5.321*** (1.666)	0.0592** (0.0300)	0.119*** (0.0392)	4.102* (2.290)
(2) Fraction Eligible	0.0993 (0.145)	-0.203 (0.163)	-9.592 (6.844)	0.359** (0.180)	0.0342 (0.210)	8.235 (11.45)
Observations	22,382	22,382	22,382	22,382	22,382	22,382
R-squared	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 of physician, years as a practicing doctor, dummy for having a DO degree, dummy for being educated abroad, sex, two race indicators (white, black), three specialty indicators (family practice, pediatrics, and surgery), and two income dummies (less than \$150,000 and between \$150,000 to \$250,000). Practice characteristics include a dummy for having a solo practice and indicators for being full- or part-owner of the practice. Demand controls include five variables measuring the percent of the state that is employer-insured, directly-insured, uninsured, Medicaid-insured, and Medicare-insured, county population in poverty, state unemployment rate, and log state population. See Appendix Table C.1 for data sources.

Table 3: Physician Medicaid Participation, Comparison to Existing Estimates

Dependent Variable Mean:	1(Any Medicaid)			1(All New Medicaid)		
	California	All States	All States	California	All States	All States
	0.731 (1)	0.821 (2)	0.821 (3)	0.280 (4)	0.399 (5)	0.399 (6)
Log(Medicaid Pay)	1.448* (0.770)	0.143*** (0.0197)	0.0814** (0.0378)	2.484*** (0.738)	0.230*** (0.0364)	0.0886* (0.0464)
State FE			Y			Y
Demand Covariates		Y	Y		Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	2,472	22,382	22,382	2,472	22,382	22,382
R-squared	0.066	0.107	0.122	0.065	0.131	0.153
Calculated 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 for (1). \*\*\* 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 2. Demand controls are population in poverty, state unemployment rate, and variables measuring insurance take-up: percent insured by Medicaid, Medicare, an employer, direct purchase, or uninsured.

Table 4: Non-Medicaid Physician Response

Dependent Variable Mean:	<i>Total</i>	<i>Private</i>	<i>Charity Care</i>		<i>Medicare</i>	
	Log(Patient Hours)	1(All New Private)	1(Any Charity)	Log(% Hrs Free)	1(Any Medicare)	1(All New Medicare)
	3.76 (1)	0.632 (2)	0.748 (3)	-3.52 (4)	0.868 (5)	0.584 (6)
(1) Log(Medicaid Pay)	-0.0521* (0.0272)	0.0165 (0.0401)	-0.0266 (0.0405)	-0.384*** (0.0932)	0.0570*** (0.0189)	0.0445 (0.0289)
(2) Fraction Eligible	0.433*** (0.141)	-0.117 (0.180)	0.0865 (0.184)	-2.021*** (0.339)	-0.0684 (0.0925)	0.0418 (0.226)
Observations	22,382	22,382	22,382	16,736	22,382	22,382
R-squared	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 2 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. OLS equivalents shown in Appendix Table D.2.

Table 5: Physician Hours of Care

Dependent Variable Mean:	Medicaid + Charity Hrs	Medicaid Hours	Charity Hours	Medicare Hours	Private Hours
	415 (1)	333 (2)	82 (3)	718 (4)	1052 (5)
(1) Log(Medicaid Pay)	-0.129** (0.0647)	0.253*** (0.0973)	-0.267* (0.153)	0.152** (0.0738)	-0.0657 (0.0436)
(2) Fraction Eligible	1.350*** (0.408)	1.701*** (0.586)	0.359 (0.776)	-0.535 (0.421)	0.861*** (0.274)
Observations	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 2 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%. The 2SLS equivalents with log dependent variables shown in Appendix Table D.3.



Table 6: Medicaid and Non-Medicaid Enrollment Response

	Log(Medicaid)	Log(Uninsure)	Log(Direct)	Log(Employer)	Log(Medicare)
Population Mean:	845,209 (1)	855,812 (2)	374,374 (3)	3,213,336 (4)	123,412 (5)
(1) Log(Medicaid Pay)	0.231** (0.0995)	-0.108** (0.0486)	0.0215 (0.112)	0.0852 (0.0660)	-0.143 (0.101)
(2) Fraction Eligible	0.628* (0.351)	-0.337* (0.201)	-0.865** (0.399)	0.209 (0.190)	0.609* (0.348)
Observations	227	227	227	227	227
R-squared	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 for dependent variables 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. OLS equivalents shown in Appendix Table D.4.

Table 7: Reported Reasons for Enrolling in Health Insurance

Who/what encouraged you to get insurance?	Payment Difference (High-Low)		Eligibility Difference (High-Low)	
	Medicaid	Private	Medicaid	Private
	(1)	(2)	(3)	(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
No. Observations	338	903	338	903

Notes: Data on insurance enrollment from mTurk survey. Physician reimbursement data and eligibility data from sources described in Section 4. 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.” Detailed means shown in Appendix Table C.5.

Table 8: Interacted Effects on Physician Supply

Dependent Variable Mean:	<i>Medicaid</i>		<i>Charity Care</i>		<i>Total Poor</i>
	1(Any Medicaid)	Medicaid Hours	Log(% Free Hours)	Charity Hours	Medicaid + Charity Hrs
	0.821	342	-3.52	84	426
	2SLS	Poisson	2SLS	Poisson	Poisson
	(1)	(2)	(3)	(4)	(5)
Log(Medicaid Pay)	0.0386 (0.0509)	0.263*** (0.0970)	-0.385*** (0.0930)	-0.257* (0.154)	-0.0657 (0.0640)
Fraction Eligible	0.725** (0.307)	2.492*** (0.650)	-1.938*** (0.432)	0.351 (0.924)	2.396*** (0.537)
Log(Medicaid Pay) x Fraction Eligible	1.222** (0.476)	3.135** (1.270)	0.457 (1.502)	-0.302 (2.133)	3.575*** (0.920)
Observations	22,382	21,890	16,736	21,890	21,890

Notes: Columns (1) and (3) show physician level 2SLS IV regressions. Columns (2), (4), and (5) show physician level IV Poisson QMLE regressions. Robust standard errors clustered by state shown in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. All regressions include the controls listed in Table 2 notes. OLS equivalents shown in Appendix Table D.5.

Table 9: Interacted Effect on Insurance Enrollment

Population Mean:	Log(Medicaid)	Log(Uninsure)	Log(Direct)	Log(Medicare)
	(1)	(2)	(3)	(4)
	845,209	855,812	374,374	123,412
Log(Medicaid Pay)	0.221** (0.0981)	-0.124** (0.0491)	0.00569 (0.110)	-0.137 (0.0985)
Fraction Eligible	0.939** (0.369)	-0.122 (0.222)	-0.528 (0.415)	0.467 (0.333)
Log(Medicaid Pay) x Fraction Eligible	-1.385** (0.605)	-0.991** (0.473)	-1.472** (0.723)	0.620 (0.486)
Observations	227	227	227	227
R-squared	0.979	0.995	0.975	0.982

Notes: State-level IV regressions shown with robust standard errors, clustered by state, shown in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. All regressions include controls described in Table 6 notes. Sample universe for dependent variables is population under age 65. OLS equivalents shown in Appendix Table D.6.

Table 10: Patient Access to Care

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

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. See Appendix Table D.7.

Table 11: Predicting Medicaid Prices

	H <sub>0</sub> :Coefficients Equal Zero	F-statistic For Test of Joint Significance				
		Dependent Variable: Log(Medicaid Pay), $\mu=3.55$				
		(1)	(2)	(3)	(4)	(5)
(1) Demand and Supply		1.45 (0.214)				1.15 (0.351)
(2) Measures of Poverty			1.45 (0.214)			0.93 (0.485)
(3) State Finances				3.51 (0.014)		1.97 (0.114)
(4) Political Climate					1.15 (0.340)	0.73 (0.536)
Observations		233	233	233	233	233
R-squared		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. Regression coefficients with robust standard errors clustered by state are shown in Appendix Table 11. The controls for (1) demand and supply include log of Medicaid enrollees, Medicare enrollees, privately-insured patients, and uninsured; log of active MDs, physician assistants, and registered nurses; (2) measures of poverty including minimum wage, and log of population in poverty, unemployment rate, and household income; (3) state finances including the FMAP, log of state income, debt, cash and holdings, tax revenue; and (4) political characteristics include the difference in Democrat minus Republican representatives in the lower and upper houses and an indicator for governor is a Democrat.

Table 12: The Effect of Future Policy Changes

Dependent Variable Mean:	Physician Supply			Insurance Enrollment		
	1(Any Medicaid)	Log(Total Hours)	Log(% Hrs Free)	Log Medicaid	Log Direct	Log Uninsure
	0.841 (1)	3.76 (2)	-3.52 (3)	12.99 (4)	13.01 (5)	12.29 (6)
Log(Pay), t	0.0468 (0.0363)	-0.0684** (0.0309)	-0.407*** (0.0890)	0.276** (0.116)	-0.0403 (0.158)	-0.0361 (0.0755)
Eligible, t	0.595*** (0.225)	0.405** (0.162)	-1.770*** (0.452)	0.180 (0.333)	-1.233*** (0.445)	-0.519* (0.279)
Log(Pay), t+3	-0.0202 (0.0322)	0.0280 (0.0236)	-0.0194 (0.0702)	-0.0476 (0.0765)	-0.0758 (0.114)	0.0556 (0.0576)
Eligible, t+3	-0.198 (0.134)	0.0628 (0.175)	0.139 (0.624)	-0.169 (0.405)	-0.156 (0.472)	-0.106 (0.289)
Observations	21,260	21,254	15,926	174	174	174
R-squared	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 2. Columns (4)-(6) show state-level IV regressions with controls listed in Table 6. Robust standard errors, clustered by state, in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0. I examine policy changes three years in the future because payment data is only available in three year increments.

Table 13: Using the UI Medicaid-Medicare Fee Index

Dependent Variable Mean:	Physician Supply			Insurance Enrollment		
	1(Any Medicaid)	Log(Total Hours)	Log(% Hrs Free)	Log Medicaid	Log Direct	Log Uninsure
	0.848 (1)	3.728 (2)	-3.45 (3)	12.95 (4)	12.28 (5)	13.03 (6)
Log(Medicaid-Medicare Index)	0.0671 (0.0895)	-0.0368 (0.0430)	0.410* (0.222)	0.575*** (0.211)	-0.397 (0.463)	0.212 (0.183)
Observations	13,665	13,665	10,087	138	138	138
R-squared	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 2, except for the Medicare AAP payment rate. Columns (4)-(6) show state-level IV regressions with all controls listed in Table 6, 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.

## Appendix A: Literature Summary

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

Paper	Main data	Payment data	Medicaid Supply Estimate	Notes
Sloan et al. (1978)	NORC survey (1975-76)	physician reported fees (Medicaid, private) in NORC survey	10% increase in Medicaid payment produces 2% increase in Medicaid participation	no state FE, single cross-section
Hadley (1979)	Sample of Medicare and Medicaid claims for CA physicians, 1972-1975	average revenue (Medicaid, private) per patient calculated from CA claims	10% increase in Medicaid payment produces a 17% increase in physician participation and 3% increase in patients per physician	single state with year FE
Mitchell (1991)	NORC survey (1975-76, 1984-85)	physician reported fees (Medicaid, private) in NORC survey	10% increase in Medicaid fees related to 3.6% increase in physician participation	no state FE, cross year comparison
Cohen (1993)	Medicaid beneficiaries in 1987 National Medical Expenditures Survey	Medicaid and Medicare fee measured by one CPT code	10% increase in Medicaid generosity index lowers seeing a physician by about 1.6%, but more likely to see physician in office rather than hospital	no state FE, single cross-section
Adams (1994)	All enrollment and claims for Tennessee 1985-88	Urban Institute, Medicaid:Medicare ratio	a 10% increase in fee ratio increased the number of physicians serving at least 3 Medicaid enrollees by 2.5%	single state with year FE
Showalter (1997)	Physicians' Practice Costs and Income Survey 1983-1985	Self-employed physicians reported Medicaid fees	\$10 increase in reimbursement increases physician's share of Medicaid patients by 1.6 percentage points	no state or year FE
Gruber et al. (1999)	HCUP 1988-1992: inpatient Medicaid claims for childbirth	Medicaid and private fees from ACOG and PPRC	If Medicaid raises its fee to private level (29%), cesarean deliver increases by 3.7% points	includes both state and year FE
Gray (2001)	NMIHS 1989	Urban Institute, Medicaid:Medicare fee for obstetrical services	10% higher Medicaid fee ratio results in 0.074% lower risk inf LBW	no state FE, single cross-section
Shen and Zuckerman (2005)	National Surveys of America's Families (1997, 1999, 2002)	Urban Institute and CMS, Medicaid capitation rate, Medicare rate	One-unit increase in Medicaid generosity scale increases probability of having a usual source of care by 1.5 percentage points	no state FE, single cross-section
Decker (2007)	NAMCS	Urban Institute, Medicaid:Medicare fee ratio (1989, 1993, 1998, 2003)	10% increase in fee ratio increases participation by about 5% (not significant), increase from 0.65 to 1 in fee ratio increases duration of visit by a minute	both state and year FE
Decker (2009)	NHIS, NAMCS (1993, 1994, 1998, 1999, 2003, 2004)	Urban Institute, Medicaid:Medicare fee ratio (1993, 1998, 2003)	If fee ratio decreases from 1 to 0.64, Medicaid individuals with no doctor visits increases from 12.7% to 15.3%	both state and year FE

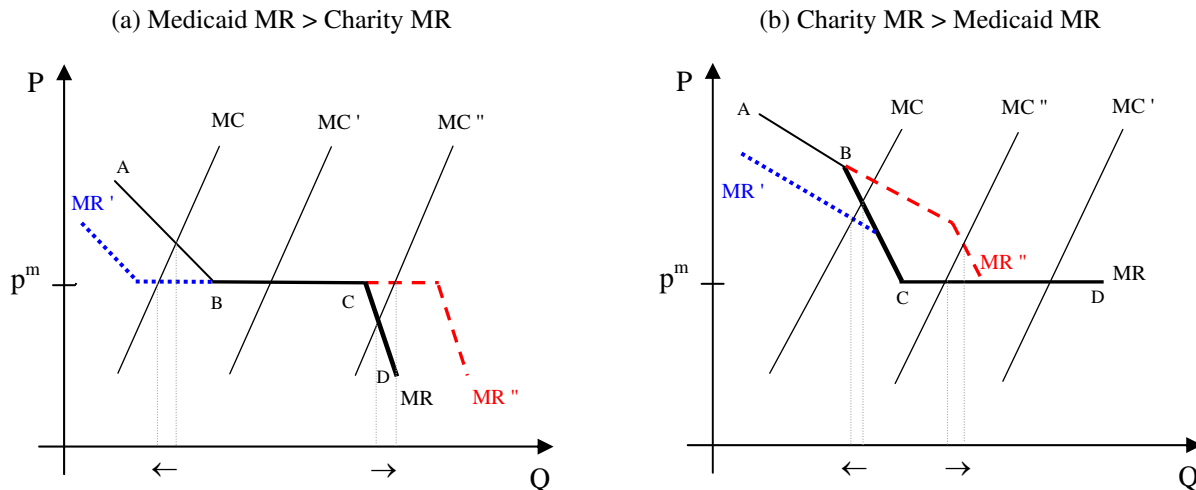
## Appendix B: Model of Physician Response to an Eligibility Change

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



Notes: See notes to Figure 3. 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 4. 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 sample means from the mTurk survey. These values are used to calculate the difference in means shown in Table 7. Finally, Table C.6 shows the ICD-9 codes used to identify preventable hospitalizations.

Table C.1: Data Sources

Variables	Data Sources
<b><u>Dependent Variables</u></b>	
1. Physician supply	CTSPS (1998-9, 2000-1, 2004-5, 2008)
2. Medicaid enrollment	CMS MSIS data (1998-2010)
Non-Medicaid enrollment, number uninsured	Census, CPS, and Annual Social and Economic Supplements Table HIB-4: Health Insurance Coverage Status and Type of Coverage by State All People (1998-2010)
3. Enrollment reasons	mTurk survey
4. Patient health outcomes	NIS (1998-2010)
<b><u>Payment</u></b>	
5. Medicaid and Medicare rates	AAP Medicaid Reimbursement Survey (1998-99, 2001, 2004-05, 2007-08, 2010-11); missing AAP Medicare data for 1998 and 2001 supplemented by CMS; MEPS to calculate procedure weights (2002, 2004, 2007, 2010)
6. Private rate	National Health Expenditure Data; claims count from regional NAMCS data and SIPP state claims weights (1998-2010)
7. Medicaid:Medicare index	Urban Institute (1998, 2003, 2008 )
<b><u>Eligibility</u></b>	
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)
<b><u>Other Covariates</u></b>	
9. State population, population in poverty by age, 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)
<b><u>Price Predictors</u></b>	
12. Total MDs and physician assistants	Area Health Resource File (1997, 2000, 2003, 2006, 2009)
13. Number of registered nurses	Licensure and Examination Statistics published by the National Council of State Boards of Nursing
13. State financial data (tax, debt, cash)	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.
<b>Main Dependent Variables</b>				
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	1875
Hours of patient care, last week	45.69	15.11	1	160
1(Accept all new private)	0.63	0.48	0	1
<b>Main Independent Variables</b>				
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
<b>Physician Characteristics</b>				
DO 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
<b>Practice Characteristics</b>				
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
<b>Other Covariates</b>				
% 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.
<b>Population Counts, by Insurance</b>				
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
<b>Main Independent Variables</b>				
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
<b>Average Family Characteristics from CPS</b>				
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
<b>Other Covariates</b>				
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.
<b>Health Access</b>				
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
<b>Main Independent Variables</b>				
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
<b>Patient and Hospital Characteristics</b>				
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
<b>Additional State Controls</b>				
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: Reasons for Enrolling in Health Insurance, Detailed Group Means

Who/what encouraged you to get insurance?	Payment Differences (2010-2007)				Eligibility Differences (2011-2010)			
	Medicaid		Private		Medicaid		Private	
	Decrease (1)	Increase (2)	Decrease (3)	Increase (4)	Decrease (5)	Increase (6)	Decrease (7)	Increase (8)
Doctor (%)	19.12	24.64	36.49	33.45	23.30	23.30	34.69	33.33
Hospital (%)	7.35	9.48	18.92	17.63	9.66	7.77	17.86	17.95
Government (%)	16.18	16.59	16.22	13.31	18.18	13.59	13.78	14.10
Internet (%)	7.35	5.21	16.22	11.51	4.55	7.77	11.73	13.46
Own-health problem (%)	32.35	29.38	39.19	46.04	32.95	25.24	43.37	46.15
Number of observations	82	256	178	725	215	123	500	403

Notes: Data on insurance enrollment from mTurk survey. Physician reimbursement data and eligibility data from sources described in Section 4. The means from columns (1) and (2) are used to calculate the values shown in column (1) of Table 7. Similarly, the means from columns (3) and (4) are used to calculate the statistics shown in column (2) of Table 7, and so on.

Table C.6: 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, age <sup>3</sup> 1
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 of 090x
7. Congestive Heart Failure	428x, 40201, 40211, 40291, 5184	not with procedures 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 procedures 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 procedures 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>

## Appendix D: Extra Tables

Table D.1: Predicting Medicaid Prices

	Log(Medicaid Payment)				
	(1)	(2)	(3)	(4)	(5)
<u>Physician Supply</u>					
Log(Active MDs)	-0.903 (0.737)				-0.243 (0.753)
Log(Physician Assistants)	-0.0873 (0.123)				0.00932 (0.110)
Log(Registered Nurse)	-0.00804 (0.151)				-0.0897 (0.147)
<u>Insurance Demand</u>					
Log(Medicaid)	0.0995 (0.120)				0.204 (0.138)
Log(Medicare)	0.102 (0.0815)				0.152* (0.0886)
Log(Private)	-0.178 (0.412)				-0.166 (0.455)
Log(Uninsured)	-0.0233 (0.110)				0.182 (0.134)
<u>Poverty Measures</u>					
Log(Poverty, 0-4)		0.159 (0.210)			0.0671 (0.259)
Log(Poverty, 5-17)		0.0550 (0.273)			-0.0815 (0.244)
Log(Poverty, 18+)		-0.745 (0.451)			-0.434 (0.448)
Log(Household Income)		0.294 (0.859)			0.404 (0.897)
Log(Unemployed)		-0.0138 (0.0960)			-0.0272 (0.114)
<u>State Finances</u>					
FMAP			-0.0156* (0.00795)		-0.0204** (0.00898)
Log(Debt per capita)			0.0736 (0.0919)		0.0221 (0.0993)
Log(Cash and Holdings)			0.227 (0.202)		0.183 (0.206)
Log(Tax per capita)			0.179 (0.163)		0.0134 (0.154)
<u>Political Characteristics</u>					
Lower House (Dem-Rep)				-0.00144 (0.000881)	-0.00105 (0.000998)
Upper House (Dem-Rep)				0.00480 (0.00442)	0.00445 (0.00428)
1(Governor is Democratic)				-0.00245 (0.0405)	-0.0223 (0.0359)
Observations	233	233	233	233	233
R-squared	0.827	0.829	0.837	0.819	0.853

Notes: Each column an OLS state-level regression. Robust standard errors, clustered by state, shown in parentheses.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1. All regressions include state and year fixed effects.

Table D.2: OLS Estimates for Table 4  
Non-Medicaid Physician Supply

	<i>Total</i>	<i>Private</i>	<i>Charity Care</i>		<i>Medicare</i>	
Dependent Variable Mean:	Log(Patient Hours)	1(All New Private)	1(Any Charity)	Log(% Free Hrs)	1(Any Medicare)	1(All New Medicare)
	3.76	0.632	0.748	-3.52	0.868	0.584
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Medicaid Pay)	-0.0406*	0.00942	-0.0182	-0.460***	0.0628***	0.0517**
	(0.0235)	(0.0417)	(0.0362)	(0.0701)	(0.0205)	(0.0251)
Fraction Eligible	0.246***	-0.0133	-0.0368	-0.869**	-0.153**	-0.0635
	(0.0819)	(0.120)	(0.133)	(0.333)	(0.0687)	(0.109)
Observations	22,382	22,382	22,382	16,736	22,382	22,382
R-squared	0.147	0.066	0.073	0.059	0.340	0.123

Notes: Each column an OLS physician-level regression. Robust standard errors, clustered by state, shown in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. See notes to Table 4.

Table D.3: IV 2SLS Regression for Table 5  
Physician Hours of Care

	Log(Mcaid + Charity Hours)	Log(Medicaid Hours)	Log(Charity Hours)	Log(Medicare Hours)	Log(Private Hours)
Mean Hours:	415	333	82	718	1052
	(1)	(2)	(3)	(4)	(5)
(1) Log(Medicaid Pay)	-0.174	0.135	-0.486***	0.0515	-0.130
	(0.134)	(0.0781)	(0.0848)	(0.0920)	
(2) Fraction Eligible	1.792**	2.162	-0.938**	-0.237	0.820
	(0.838)	(0.364)	(0.519)	(0.544)	
Observations	20,852	18,041	16,497	19,104	21,877
R-squared	0.161	0.225	0.058	0.142	0.079

Notes: Physician level IV regressions shown with robust standard errors, clustered by state, in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. See notes to Table 5.

Table D.4: OLS Estimates for Table 6  
Medicaid and non-Medicaid Health Insurance Enrollment

	Log(Medicaid) Under 65	Log(Uninsure) Under 65	Log(Direct) Under 65	Log(Employer) Under 65	Log(Medicare) Under 65
Population Mean:	845,209 (1)	855,812 (2)	374,374 (3)	3,213,336 (4)	123,412 (5)
Log(Medicaid Rate)	0.231* (0.114)	-0.113* (0.0637)	0.0287 (0.155)	0.0857 (0.0927)	-0.156 (0.137)
Actual Eligibility	0.373 (0.344)	-0.0811 (0.185)	-0.834** (0.383)	0.105 (0.197)	0.0811 (0.437)
Observations	227	227	227	227	227
R-squared	0.979	0.995	0.973	0.992	0.982

Notes: Each column an OLS physician-level regression. Robust standard errors, clustered by state, shown in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. See notes to Table 6.

Table D.5: OLS and Poisson Estimates for Table 8  
Interaction Effect on Physician Supply

Dependent Variable Mean:	<i>Medicaid</i>		<i>Charity Care</i>		<i>Total Poor</i>
	1(Any Medicaid)	Medicaid Hours	Log(% Free Hours)	Charity Hours	Medicaid + Charity Hrs
	OLS (1)	Poisson (2)	OLS (3)	Poisson (4)	Poisson (5)
Log(Medicaid Pay)	0.0790** (0.0357)	0.271*** (0.0894)	-0.457*** (0.0703)	-0.204 (0.151)	-0.0473 (0.0601)
Fraction Eligible	0.0306 (0.181)	0.830** (0.343)	-0.832** (0.340)	0.183 (0.543)	0.434 (0.272)
Log(Medicaid Pay) x Fraction Eligible	0.376 (0.315)	0.738*** (0.344)	0.511 (0.467)	-0.946 (1.024)	1.489*** (0.494)
Observations	22,382	21,890	16,736	21,890	21,890

Notes: Physician level OLS and non-instrumented Poisson QMLE regressions shown with robust standard errors, clustered by state, in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. See notes to Table 8.



Table D.6: OLS Equivalents for Table 9  
Interaction Effects on Insurance Enrollment

	Log(Medicaid)	Log(Uninsure)	Log(Direct)	Log(Medicare)
Population Mean:	845,209 (1)	855,812 (2)	374,374 (3)	123,412 (4)
Log(Medicaid Pay)	0.222** (0.0981)	-0.0633 (0.0486)	0.00978 (0.111)	-0.140 (0.0988)
Fraction Eligible	0.939** (0.369)	-0.139 (0.233)	-0.517 (0.396)	0.498 (0.309)
Log(Pay) x Eligible	-1.366** (0.631)	-0.747* (0.426)	-1.486** (0.708)	0.419 (0.485)
Observations	227	227	227	227
R-squared	0.979	0.995	0.975	0.982

Notes: State-level OLS regressions shown with robust standard errors, clustered by state, in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. See notes to Table 9.

Table D.7: OLS Equivalents for Table 10  
Patient Access to Care

	% Admitted From ER	Preventable ER Admits	% ER Admits Medicaid	% ER Admits Charity	% ER Admits Private
Dependent Var $\mu$	0.412 (1)	0.089 (2)	0.299 (3)	0.009 (4)	0.404 (5)
(1) Log(Medicaid Pay)	-0.298** (0.117)	-0.077** (0.030)	-0.171*** (0.052)	0.008 (0.015)	-0.002 (0.079)
(2) Fraction Eligible	0.018** (0.009)	0.001 (0.004)	0.029* (0.015)	-0.002 (0.003)	-0.025* (0.014)
R-squared	0.569	0.400	0.412	0.287	0.401
Observations	16,969	16,968	16,134	16,134	16,134

Notes: OLS 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. See notes to Table 10.