MEDICAID

Chapter for Means-Tested Transfer Programs in the United States, II

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I. Introduction

In both its costs and the number of its enrollees, Medicaid is the largest means-tested transfer program in the United States and is also a fundamental part of the health care system, providing health insurance to low-income families, indigent seniors and disabled adults. In 2010, Medicaid covered 59 million individuals at a cost to state and federal governments of nearly $390 billion. Federal Medicaid expenditures, which historically have averaged between 50 and 60 percent of total program expenditures, represent about 8 percent of the federal budget and nearly 2 percent of gross domestic product (Congressional Budget Office 2014).

Because it finances different types of services for different groups of beneficiaries, it is often noted that Medicaid is essentially four public insurance programs in one (Gruber 2000). First, Medicaid is the primary source of health insurance for low-income children and parents, providing coverage for a full range of outpatient and inpatient services. Second, Medicaid provides complementary insurance for low-income seniors for whom Medicare is the primary source of insurance. Third, Medicaid covers the medical expenses of low-income disabled individuals. Fourth, Medicaid is the largest source of financing for nursing home care. In addition to differences related to the characteristics and needs of different beneficiary groups, there is considerable heterogeneity across states. Although the federal government establishes important standards, states have considerable flexibility in terms of eligibility rules, the method and level of provider payment and, to a lesser extent, program benefits. Thus, it is also often argued that Medicaid is not one program, but 51.

Expanded eligibility for Medicaid is a critical component of the Patient Protection and Affordable Care Act of 2010 (PPACA) and the Health Care and Education Reconciliation Act of 2010—together known as the Affordable Care Act (ACA). Initial projections were that roughly half of all individuals who gain insurance coverage as a result of the ACA would be enrolled in Medicaid. When the new eligibility rules went into effect in 2014, nearly 5 million people enrolled in the program (Wachino, Artiga, and Rudowitz 2014). By establishing a new federal income standard, it was expected that the ACA would significantly reduce the variation across states in eligibility rules. However, because of the 2012 Supreme Court ruling that essentially made the ACA Medicaid expansions voluntary to states, implementation of the ACA has reduced variation in eligibility rules among expansion states while accentuating differences between states that have and have not elected to expand their programs. And a number of expansion states have received waivers from the federal government allowing them to innovate on a number of dimensions. Thus, the ACA has continued not only the growth of Medicaid in terms of enrollment and expenditures but it has contributed to the increased complexity of the program.

This chapter reviews the history and structure of the Medicaid program and the large body of economic research that it has spawned in the nearly half century since it was established. Section II summarizes the program's history, goals and current rules and Section III presents program statistics, mainly related to enrollment and expenditures. Then we turn to the research on the impact of Medicaid on a broad range of outcomes. In Section IV we discuss theoretical and methodological issues important for understanding these effects. Section V reviews the empirical literature, investigating areas where studies seem to reach different conclusions and pointing to areas where we believe additional research would be fruitful. Section VI concludes.

II. Program History, Goals, and Current Rules

Founded in 1965 as Title XIX of the Social Security Amendments, Medicaid is a joint state-federal program. The federal government provides some financing and general guidelines for eligibility, services to be covered, and reimbursement rates, while states provide additional funding and administer the program. Over its nearly 50-year history, the program has undergone many changes and modifications, although there are characteristics of Medicaid that were present at its inception and remain important in the program today. One of these is the existence of both mandatory actions that states *must* take—groups of individuals that states must cover and services that states must provide—and optional actions that states *may* take. As a result, the program differs substantially across states, with different levels of generosity in eligibility, covered services, and provider reimbursement rates.

While Medicaid retains some fundamental features present throughout its nearly 50-year history, there is one key element of Medicaid that has changed in recent years. From its inception, Medicaid was available only for individuals who were actual or potential recipients of cash assistance, resulting in a means-tested program that was unavailable to large portions of the poor population. In particular, only the elderly, the disabled, or members of families with dependent children where one parent is absent, incapacitated, or unemployed (the latter only in some states) could be eligible for Medicaid. The requirement for membership in one of these groups began to be relaxed beginning with the Deficit Reduction Act of 1984, but not until the Affordable Care Act (ACA) was implemented was eligibility for Medicaid extended to low-income adults who were not elderly, disabled, or parents of a dependent child. The ACA thus represents both a continuation of the program as it has existed and a fundamental shift.

In this section, we review the history of the program, its goals, and its current rules. We organize the section chronologically, into three main periods. First is the period between 1965 and the early 1980s, when the program was characterized by strict limits on eligibility that were not solely income-based. Since many of the features of the program established at its enactment survive in some form today, in this section we also lay out the basic structure of eligibility for the program, services covered, and the structure of reimbursement. Second is the period between the early 1980s and prior to the passage of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), when definitions of eligibility began to expand although the primary route to Medicaid eligibility remained eligibility for cash assistance. In this section we focus primarily on the incremental changes that were occurring with eligibility. Finally, there is the period beginning with the passage of PRWORA and culminating with the implementation of the ACA.[1] During this time there were major changes in the program that resulted in the rules in place today.

We summarize the major legislative actions affecting Medicaid in Table 1. From these legislative actions it can be seen that Medicaid is a program of fundamental tensions: between a recognition that many poor individuals lack health insurance, resulting in a desire for expanded eligibility, and concern about substantial and growing costs of the program; between a desire to compensate providers at sufficiently high levels to ensure participation and a desire to contain

[1] Sources for this section include the Yellow Book, the chapter by Gruber in the first volume, *The Medicaid Resource Book* put out by the Kaiser Commission on Medicaid and the Uninsured (Schneider et al. 2002), CBPP (http://www.cbpp.org/cms/index.cfm?fa=view&id=2138), CBO (http://www.cbo.gov/sites/default/files/hr5661_0.pdf),
Urban Institute (http://www.urban.org/safety-net-almanac/Medicaid-CHIP/Medicaid-Legislative-History.cfm), Kaiser Family Foundation Timeline
(http://kaiserfamilyfoundation.files.wordpress.com/2008/04/5-02-13-medicaid-timeline.pdf)
Social Security Administration Annual Statistical Supplement of 2011
(http://www.ssa.gov/policy/docs/statcomps/supplement/2011/medicaid.html)
Compilation of the PPACA http://housedocs.house.gov/energycommerce/ppacacon.pdf
KCMU State Children's Health Insurance Program (CHIP): Reauthorization History
(http://kaiserfamilyfoundation.files.wordpress.com/2013/01/7743-02.pdf)
CMS Legislative Update (http://www.cms.gov/Regulations-and-Guidance/Legislation/LegislativeUpdate/index.html?redirect=/LegislativeUpdate/)
National Conference of State Legislatures
http://www.ncsl.org/portals/1/documents/health/09slapr09_CHIP.pdf

costs by capping provider compensation; and between giving states flexibility to design their own programs and ensuring uniform standards across the country. In addition to legislative action, Medicaid has been shaped in important ways by federal regulatory decisions and state choices. Below we discuss these important policy elements as well.

II.A. Implementation and Adaptation: 1965-1983

The establishment of Medicaid in 1965 grew out of earlier medical care vendor payment programs that were linked to cash assistance receipt. These earlier programs, established by the Social Security Amendments of 1950 and expanded by the Kerr-Mills Act of 1960, had the fundamental feature continued in Medicaid of providing Federal funding at state option for vendor payments for the benefit of cash assistance beneficiaries. Historical accounts of the origin of Medicaid indicate that it passed Congress with very little discussion, being viewed as largely an improvement on the existing Kerr-Mills program (Moore and Smith 2005).

The combination of building on an existing program that was tightly linked to cash assistance receipt and responding to widespread concern about impoverishment through rising health care costs led to the creation of two classes of beneficiaries. The first group was the *categorically needy*: recipients of certain cash assistance programs, including Aid to the Blind, Aid to Families with Dependent Children (AFDC), and Aid to the Permanently and Totally Disabled. These programs not only were strictly means-tested, but they also applied only to the blind, the elderly, the disabled, and members of families with a single parent. The second class of beneficiaries was the *medically needy*: individuals who would be categorically eligible except that their income and resources were above the eligibility cutoff, but who had sufficient medical expenses to bring their income after medical expenses below the cutoff (known as "spend-down"). The goals of the program at its creation were thus to provide access to medical care to those viewed as the neediest members of society and to prevent medical expense-induced indigence among single-parent families, the disabled, and the elderly (Moore and Smith 2005, Weikel and LeaMond 1976).

As with the Kerr-Mills program that preceded it, participation in Medicaid was made optional for states, although if a state elected to participate it had to include all of the public assistance categories and all recipients within those categories, and if a state chose to have a medically needy program it had to open that program to members of all eligibility categories. Although state participation was optional, Congress included in the legislation incentives for states to participate. Federal funds for earlier medical assistance programs were scheduled to end within five years, funds were offered not only to match state expenditures but also to help pay for the administration of the Medicaid program, and states participating in the Medicaid program could use its more favorable matching rate for their other categorical assistance programs (Moore and Smith 2005). The federal match rate, or federal matching assistance percentage (FMAP), is determined annually for each state based on a formula that compares a state's average per capita income level with the national average income level. The FMAP is inversely related to state per capita income and can range from 50 percent to 83 percent. Over half of the states began participating in the first year of the program (see the rows of Table 2, which show which states began participating in each year), with another 11 states beginning to participate in 1967. By 1970 all but two states (Alaska and Arizona) were participating. Generosity of the FMAP was not the only factor determining when states began participating, as some states with high match rates (including Alabama, Arkansas, and Mississippi) began participating much later than other states.[2] For comparison, the table also shows which states have decided (as of late summer 2014) to participate in the Medicaid expansion offered by the ACA; there is some correlation between deciding not to participate in the ACA at its inception and late participation in the Medicaid program. The ACA participation decision and what it entails are discussed further in the section on the most recent time period, below.

Eligibility for Families

In the initial period of Medicaid, eligibility for poor children and their families required eligibility for AFDC. To qualify for AFDC a family was required to pass stringent income and resource tests which were far below the poverty level in most states, and generally the family must have been either headed by a single parent or have an unemployed primary earner (in states with the optional AFDC-Unemployed Parent program). An exception to the family structure requirements was created shortly after the establishment of Medicaid by the Social Security Amendments of 1967, which allowed states to extend Medicaid coverage to "Ribicoff children." Named after the senator who sponsored the legislation, these were children who did not meet the family structure requirements for AFDC but who nevertheless met the income and resource requirements. The income tests required that family income less disregards for work expenses and childcare be below the state-determined *need standard*, an amount that differed depending on family size. Beginning in the early 1980s additional income tests were added, so that income less disregards less a small amount of earnings needed to be below the state's *payment standard* (also a function of family size) and gross income needed to be below a multiple of the state's need standard. Finally, the resource test required family resources to be below $1000, not including the value of the home.

[2] FMAPs from the beginning of Medicaid through the current year may be found at http://aspe.hhs.gov/health/fmap.cfm.

For illustration, calculations of the income eligibility limits as a percentage of the poverty line for a family with three members for 1987 are shown in column 1 of Table 3. The limits in column 1 illustrate two points: there was considerable variation in eligibility limits across states, and the income limits were well below the poverty line. Even the most generous states required family incomes to be below 85 percent of the poverty line, while the least generous states only covered families with incomes below one-third of the poverty line. (The other columns of Table 3, which show eligibility limits for children in later years, are discussed below.)

Eligibility for Disabled Individuals

Eligibility limits for the disabled population were also fairly stringent, although somewhat less stringent than for families. From 1966 to 1972, disabled individuals needed to qualify for the Aid to the Permanently and Totally Disabled or Aid to the Blind programs to receive Medicaid, but in the Social Security Amendments of 1972, Congress replaced the non-AFDC cash assistance programs with Supplemental Security Income for the Aged, Blind and Disabled (SSI). Under the SSI program, the federal government funds payments and sets eligibility standards. Income eligibility for SSI is determined by comparing an individual's countable income (monthly income less disregards of $20 of any income and $65 plus one half of the amount over $65 of earned income) to the Federal Benefit Rate (FBR). The FBR, which was set in 1972 and has been increased by the amount of inflation since then, is roughly 74 percent of the FPL. States have the option of including a state supplement, and a little less than half of the states do, which increases the income eligibility limits in those states.

Medicaid was intended to continue to be automatic for disabled individuals receiving assistance, but since the SSI eligibility standards were more lenient than what many states had in place in 1972, states could choose not to make Medicaid eligibility automatic with SSI eligibility. This option to use a state-specified standard, known as the "209(b)" option after the section of the 1972 Social Security Amendments enacting it, allowed a state to use eligibility criteria for Medicaid under disability no more restrictive than the ones it used in January 1972.[3] States choosing the 209(b) option must allow individuals to "spend down" to eligibility by deducting medical expenses incurred from countable income. States may also choose not to extend Medicaid eligibility to individuals who are eligible only for the state supplement.

In addition to income eligibility, eligibility for Medicaid under SSI or the 209(b) option also requires individuals to meet asset limits and disability standards. A full discussion of asset and disability provisions of SSI is beyond the scope of this chapter (see the chapter on SSI in this volume) but there are a few elements of these provisions important to note. First, asset limits, unlike income limits, are not indexed for inflation, so aside from occasional increases passed by Congress they have been declining in real terms. Second, the level of disability required to receive SSI is severe: an adult must have an "inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment(s) which can be expected to result in death or which has lasted or can be expected to last for a continuous period of not less than 12 months," while a child will be considered disabled "if he or she has a medically determinable physical or mental impairment or combination of impairments that causes marked and severe functional limitations, and that can be expected to cause death or that has lasted or can be expected to last for a continuous period of not less than 12 months."[4]

Because medical expenses for the disabled are usually quite high, the medically needy provisions of Medicaid play a more important role for the disabled (and the elderly) than for the

[3] http://www.justice.gov/sites/default/files/osg/briefs/1989/01/01/sg890212.txt There are eleven 209(b) states.
[4] http://www.ssa.gov/disability/professionals/bluebook/general-info.htm

low-income families eligibility category. The medically needy are individuals who would be categorically eligible except that their countable incomes are above the relevant cutoff (for SSI or AFDC) and who have incurred sufficient medical expenses to bring their income minus expenses below the medically need income standard. (Their resources must be below the state-set medically needy resource standard; there is no "spend down" applicable to resources.) States electing to cover the medically needy not only specify the income and resource limits that apply, but may also modify their standard benefits package for the medically needy population.[5] Roughly two-thirds of states have a medically needy program.

Eligibility for the Elderly

Eligibility for the elderly population resembles eligibility for the disabled in many ways, with a key exception being the interaction with Medicare for this population. States that participate in Medicaid are required to provide supplemental coverage through Medicaid to low-income Medicare beneficiaries for services not covered by Medicare. Elderly individuals can receive SSI if they are income-eligible for it (under the rules discussed above), and the same rules for Medicaid eligibility (including the 209(b) option and the requirement for states to allow spend-down to eligibility) apply to elderly SSI recipients as to the non-elderly disabled. Similarly, the elderly may qualify under the medically needy provisions of their state, a common route to eligibility for individuals in nursing facilities. Further expansions of eligibility among the elderly occurred during the period of expansions in the 1980s.

Services and reimbursement

Within federal guidelines, states choose their own eligibility standards and provider reimbursement rates, resulting in wide variation in such rates across states. The federal

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[5] See KCMU/Schneider et al. (2002) for a detailed discussion of the various pathways onto Medicaid for different categories of disabled individuals.

government requires certain medical services to be covered, including inpatient and outpatient hospital services, laboratory and x-ray services, physicians' services, and skilled nursing facilities. Beginning with the 1967 Social Security Amendments, states were mandated to cover "early and periodic screening, diagnosis, and treatment" (EPSDT) services for eligible children. States may also choose to cover services such as prescription drugs, eyeglasses, and dental care. Importantly, Medicaid is an entitlement program, so eligible individuals have the right to receive the services that states have chosen to cover, and states have the right to matching payments for the cost of those services.

However, the framers of Medicaid did not realize the significant potential costs of the program (Moore and Smith 2005, Weikel and LeaMond 1976), and already by 1967 there were moves to control expenditures. The 1967 amendments included legislation to cap eligibility among the medically needy to those with incomes at most 133 1/3 percent of the AFDC income eligibility level in a state. In addition, the 1972 amendments repealed the "maintenance of effort" requirement that had previously prevented states from reducing expenditures on Medicaid from one year to the next.

Passage of cost-control measures continued in the early 1980s. The Omnibus Budget Reconciliation Act of 1981 (OBRA 81) implemented several changes with major long-term implications for health care providers. First, OBRA 81 repealed the requirement that states pay Medicare hospital payment rates. Instead, states were permitted to reimburse hospitals at lower rates and to make additional payments to hospitals serving a disproportionate share of Medicaid and other poor patients. These hospitals became known as disproportionate share hospitals (DSH) and payments to them were known as "DSH payments." OBRA 81 also established new types of "Medicaid waivers" as additional potential cost-control mechanisms. A waiver is a statutorily established permission for the federal agency charged with Medicaid implementation and regulation to grant certain exceptions to the federal rules for states that apply for those exceptions.[6] The new waivers included section 1915(b) freedom-of-choice waivers, which allowed states to pursue mandatory managed care enrollment of certain Medicaid populations, and section 1915(c) home- and community-based long-term care services waivers, which allowed states to cover such services for the elderly and individuals with disabilities at risk of institutional care. In addition, the Tax Equity and Fiscal Responsibility Act of 1982 expanded state options for imposing cost-sharing requirements on beneficiaries.

II.B. Period of Incremental Expansions: 1984-1995

Following a period of legislative focus on cost containment, beginning in the mid-1980s there was a period of legislative focus on eligibility expansion. These expansions began by relaxing some of the family structure, but not income, requirements for members of low-income families. The Deficit Reduction Act of 1984 mandated coverage of three groups—children born after September 30, 1983, first-time pregnant women, and pregnant women in two-parent families with an unemployed primary earner—as long as the families were income-eligible for AFDC. Then beginning in 1986, a series of federal laws began to diminish the link between Medicaid eligibility and AFDC eligibility by extending Medicaid coverage to members of families with incomes above the AFDC limits. Under these expansions, Medicaid eligibility determination was different from AFDC eligibility determination in two fundamental ways: the eligibility limits were linked to the federal poverty line rather than to the AFDC limits, and there were no family structure requirements. In the Omnibus Budget Reconciliation Acts (OBRAs) of 1986 and 1987, Congress gave states the authority to raise the income thresholds for Medicaid

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[6] In fact, Arizona's Medicaid program has operated under a section 1115 waiver since its inception in 1982.

coverage of pregnant women, infants, and very young children above the AFDC level. In addition, OBRA 1987 required states to cover all children born after September 30, 1983 who met AFDC income standards, regardless of their family composition. The Medicare Catastrophic Coverage Act (MCCA) and Family Support Act (FSA), both of 1988, required states to extend Medicaid eligibility even further. The MCCA required coverage of pregnant women and infants and permitted coverage of children up to 8 years of age with family incomes below 75 percent of the poverty level. Coverage of eligible two-parent families where the principal earner was unemployed was mandated by the FSA. Even broader expansions took place as a result of OBRA 1989 and OBRA 1990. OBRA 1989 required coverage of pregnant women and children up to age 6 with family incomes up to 133 percent of the federal poverty level, and OBRA 1990 required states to cover children born after September 30, 1983 and under the age of 18 with family incomes below 100 percent of the federal poverty level.

The resulting eligibility limits that states established under these mandatory and optional expansions (and in some cases with the addition of state funds) as of the beginning of 1997 are shown in column (2) of Table 3. The increase in eligibility limits was strikingly large, with eligibility limits doubling, tripling, or increasing even more substantially over the AFDC income limits. Notably, there was substantial variation in eligibility limits by age within states, with limits being more generous for infants and least generous for older teens. The extent of within-state variation also varied, with some states having fairly similar eligibility limits across the board and others having larger differences. These differences in eligibility within and across states and over time have proven useful in examining the impacts of Medicaid on various outcomes, as discussed in section III, below.

This period was also a time of considerable expansion in eligibility for the elderly. Recognizing that there were substantial numbers of elderly Medicare beneficiaries with incomes above the SSI cutoff level but who needed assistance with Medicare premiums and cost-sharing requirements, OBRA 86 permitted and the MCCA required states to phase in coverage of Medicare premiums and cost-sharing for Medicare beneficiaries with incomes below 100 percent of the federal poverty level and resources at or below twice the SSI resource cutoff. States must use income- and resource-counting methodologies that are not more restrictive than those used for SSI, and may be less restrictive. These beneficiaries are known as Qualified Medicare Beneficiaries, or QMBs. OBRA 1990 established an additional category of Medicare-Medicaid dual eligibles, Specified Low-Income Medicare Beneficiaries, or SLMBs. States were required to provide Medicare premium assistance through Medicaid to Medicare beneficiaries with incomes between 100 and 120 percent of the FPL and with resources not exceeding twice the SSI resource level. Together assistance to these two groups is known as the Medicare Savings Program.

In addition to expansions in eligibility for the elderly, the MCCA included provisions to prevent "spousal impoverishment" among spouses of individuals receiving long-term care through Medicaid. These provisions have as their goal permitting the spouse still living in the community to have sufficient resources and monthly income to avoid hardship. They are triggered when one spouse enters a long-term care facility (and is likely to remain at least 30 days). The spouse remaining in the community is allowed to keep a fraction of the couple's resources and a fraction of the income received on a monthly basis. The rest is contributed to the cost of care for the institutionalized spouse. In general, due to the high cost of institutional care and the low level of income and resources required to qualify for Medicaid to pay for such care, complex rules governing transfers of assets and income were developed over this period. These rules included those attempting to discourage individuals from giving away resources to qualify for Medicaid and those intended to provide individuals in states without medically needy programs whose incomes or resources are too high to qualify for Medicaid but too low to pay for needed institutional care with ways to qualify for Medicaid. For example, such individuals may establish a Qualified Income, or Miller, trust by depositing enough income in the trust to fall below an income limit equal to 300 percent of the SSI income limit; once the individual passes away, the state receives any money remaining in the trust up to the amount Medicaid has paid on behalf of the individual (see Schneider et al. 2002 for a detailed discussion of such rules).

The period of incremental expansions was also one of substantial growth in Medicaid expenditures, as can be seen in the discussion of program statistics later in the chapter. While the increasing number of eligible individuals is one obvious source of an increase in expenditures, a key element in the increase over this time period was the increasing state use of DSH payments and related financing programs including provider-specific taxes and intergovernmental transfers (Ku and Coughlin 1995). States developed creative financing strategies in an effort to maximize federal transfers, requiring hospitals to pay provider taxes or to make donations or intergovernmental transfers, using the revenue from these sources to make DSH payments (usually back to the providers of the taxes or transfers), and then receiving the federal match on these expenditures. Concern over rapidly rising federal expenditures on Medicaid as a result of these strategies led to the Medicaid Voluntary Contribution and Provider-Specific Tax Amendments of 1991, which essentially banned provider donations, capped provider taxes and required such taxes to be broad-based and not targeted on a quid pro quo basis, and capped DSH payments (Ku and Coughlin 1995).

Another important change that occurred during this period was a move towards the use of managed care contracts for Medicaid enrollees, including both capitated plans such as Health Maintenance Organizations (HMOs) and non-capitated primary care case management (PCCM) plans. The potential benefits for states in using Medicaid managed care (MMC) include a reduction in program expenditures (through the incentive inherent in capitated plans to reduce the use of unnecessary treatments), an improvement in quality through care coordination efforts, and a reduction in the level of financial risk faced by the state (Duggan and Hayford 2013). While managed care plans in the commercial market often reduce expenditures via contracting with providers for lower reimbursement rates, the already low reimbursement rates in fee-for-service Medicaid leave little room for savings along that dimension.

II.C. Major Changes: Welfare Reform to the Affordable Care Act[7]

While the mid-1980s to mid-1990s were a period of incremental changes, the changes in Medicaid since the mid-1990s have been some of the most far-reaching in Medicaid's history, with three major pieces of legislation fundamentally changing the program. The first was the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), which eliminated the AFDC program and replaced it with the Temporary Assistance for Needy Families (TANF) program, completing the process of decoupling Medicaid for low-income families from cash assistance eligibility. Unlike AFDC, TANF eligibility does not confer automatic Medicaid eligibility. Instead, Medicaid eligibility began to be determined separately,

[7] Used for this section: http://kaiserfamilyfoundation.files.wordpress.com/2014/04/8585-a-closer-look-at-the-impact-of-state-decisions-not-to-expand-medicaid.pdf
http://kaiserfamilyfoundation.files.wordpress.com/2014/06/7235-07-medicaid-moving-forward2.pdf
http://kaiserfamilyfoundation.files.wordpress.com/2014/02/8551-the-aca-and-recent-section-1115-medicaid-demonstration-waivers1.pdf
http://kaiserfamilyfoundation.files.wordpress.com/2013/01/8318.pdf

although individuals who met the requirements for the former AFDC program were intended to continue to be entitled to Medicaid. States were required to continue using the AFDC eligibility determination processes they had in place as of July 16, 1996. Thus an individual could be eligible for Medicaid but not TANF, or vice-versa. For the most part, this change did not affect eligibility for children, since the expansion standards for children, which were more generous than AFDC eligibility standards, remained in place. However, Medicaid enrollment among children did fall immediately following the passage of PRWORA before rising again a few years later (see section III of this chapter). Also as part of PRWORA, legal immigrants were required to wait five years before they could be eligible for federally funded Medicaid, and illegal immigrants are ineligible for Medicaid except for pregnant women (who can obtain emergency care during the pregnancy). Some states did continue to provide Medicaid coverage with state funds to legal immigrants.

Another key piece of legislation was the Balanced Budget Act (BBA) of 1997. The BBA included many smaller changes to Medicaid and introduced a new public health insurance program for low-income children. Among the smaller changes enacted in the BBA, states were allowed to provide up to 12 months of continuous eligibility for children and to cover children presumptively until a formal determination of eligibility is made. The BBA also established a new level of support for Medicare beneficiaries with higher incomes, allowing partial coverage of Medicare premiums for beneficiaries with incomes between 120 and 135 percent of FPL (known as Qualified Individuals, or QIs), funded via a federal block grant. On the expenditure and reimbursement side, the BBA eliminated minimum payment standards for state-set reimbursement rates for hospitals, nursing homes, and community health centers, placed ceilings on DSH payment adjustments, and allowed states to avoid paying Medicare deductibles and coinsurance if their Medicaid payment rates for that service are lower than Medicare’s. Instead, the state pays only the Medicaid reimbursement rate, and the providers are not permitted to bill the beneficiary for the balance. This practice effectively reduces the incentive for providers to treat low-income beneficiaries (Schneider et al. 2002). The BBA also allowed states to implement mandatory managed care enrollment for most Medicaid beneficiaries without obtaining section 1915(b) waivers.

In addition, the BBA created the State Children's Health Insurance Program (called at the time SCHIP but since changed to CHIP; we use the later acronym throughout this chapter), which provided states with $40 billion over ten years in block grant funding to expand publicly provided health insurance for children. The basic structure of CHIP differs from Medicaid in several ways. First, each state is given a fixed allotment (rather than an entitlement to an unlimited federal match of spending) based on the number of uninsured children in the state and the state’s relative health care costs. Second, the match rate is higher than under Medicaid, ranging from 65 to 85 percent. Third, states are given more flexibility by the federal government in structuring CHIP coverage.

States had three options for their CHIP funds: they could expand their Medicaid programs, design a new program, or do a combination of the two. However states could not tighten their Medicaid rules, and applicants who qualified for Medicaid under the Medicaid eligibility standards in place prior to the introduction of CHIP had to be enrolled in Medicaid. If a state expands its Medicaid program, children eligible under the CHIP expansion are entitled to all Medicaid benefits, and the state must conform to all Medicaid rules. If a state creates a new program (or expands an existing state program), then the state can design new benefits packages or arrangements for services, impose limited cost sharing, and design its own eligibility rules.

However states choosing to establish their own programs were required to implement policies to prevent substitution of public coverage for private coverage, and the coverage offered under the new program had to meet federal minimum benefit standards.

There was wide variation in state implementations of the program. CHIP plans took one of three basic forms: the state enacted an initial Medicaid expansion while designing further coverage under a state program, often filling in the "gaps" in coverage across the age distribution; the state expanded Medicaid to cover additional ages and income categories, usually to as high as 200-300 percent of the poverty level; or the state implemented an entirely state-designed program. The state-designed programs sometimes included some cost-sharing (such as small premiums or copayments), were usually (though not exclusively) operated separately from Medicaid, and often incorporated a managed care component. In a few cases, the state plans included completely new features, such as premium assistance for employer-supplied insurance or coverage for parents of eligible children. In addition to increases in eligibility, state CHIP plans of all types involved new outreach efforts and efforts to minimize substitution of public insurance for private insurance (known as "crowding out"). In states with non-Medicaid-expansion CHIP plans, children who had other coverage were not eligible for the CHIP expansion (such children would be eligible for Medicaid, if their family incomes are low enough). In addition, many states incorporated a waiting period of between a month and a year, depending on the state, before a child could be enrolled in the state program after having private coverage. Other anti-crowd-out measures included premiums for higher-income families and state assistance with employer-supplied insurance premiums.

The resulting eligibility limits under CHIP as of 2001 are shown in column (3) of Table 3. Notably, CHIP permitted states to equalize eligibility across ages within a state, and while some states continued to have higher levels of eligibility for younger children, the extent of the disparity was considerably smaller. It is also clear that states were able to increase their eligibility limits overall, in most cases to 2- to 3-times the FPL.

States were permitted to spend up to 10 percent of their block grants for items other than providing insurance, and most states used some of these funds to improve participation in public health insurance. One important change in many states was the implementation of a period of continuous coverage (usually 6 months or a year). This means that once children qualify for coverage, coverage continues without interruption for the entire period, even if the child's family income increases. Other important changes that many states adopted include: elimination of a requirement that family assets be below a given level, elimination of the requirement that families come to the welfare office for a face-to-face interview (allowing applications to be mailed in), making the application simpler and/or instituting a single application for both Medicaid and CHIP programs, and outreach and publicity efforts. Outreach efforts that states report implementing took many forms, including partnerships with community organizations such as schools, health clinics, and community groups to promote enrollment, placing eligibility workers who can help fill out the forms in locations other than welfare offices, instituting a toll-free hotline to help with enrollment questions, and bilingual or multilingual applications and eligibility workers.

After its first ten years, CHIP came up for renewal in 2007. Twice Congress passed bills reauthorizing CHIP, but both were vetoed by the President. One of the main areas of disagreement was over offering coverage to higher income children, with Congress voting to offer coverage to higher income children and the administration expressing concern about negative effects of crowd-out. In late 2007 the Medicare, Medicaid and SCHIP Extension Act of

2007 was passed and signed, largely maintaining existing funding levels for the program on a short-term basis. Then in 2009 the Children's Health Insurance Program Reauthorization Act (CHIPRA) reauthorized the program and provided additional funding. It also made other changes, including removing the five-year waiting period requirement for immigrant children and pregnant women in Medicaid and CHIP, giving States the option of receiving federal funding to provide coverage to these populations without a waiting period.

The results of the coverage expansions to children beginning in the late 1980s and continuing through CHIPRA can easily be seen in Figure 1, an updated version of a figure from Card and Shore-Sheppard (2004). Health insurance coverage rates by family income as a percent of the poverty line among children exhibited a distinct U-shape prior to the expansions, as Medicaid was available only to the poorest children and private coverage rates did not equal or exceed Medicaid coverage rates except for children in families with incomes around 1.5 times the poverty line. Over the next 25 years, as the expansions took effect, insurance coverage rates smoothed out across the income distribution so that even at the lowest point coverage rates were around 85 percent, climbing above 90 percent for children with incomes above 3 times the poverty line.

In addition to the optional expansions in the laws discussed previously, over this period the federal government used its regulatory authority to add several provisions to the Medicaid rules or to encourage their use, permitting states to expand eligibility further.[8] The first, known as the 1902(r)(2) option after the section that was added to the Social Security Act by the MCCA, allows states to use more liberal methods for calculating income and resources for some

[8] The federal regulatory agency with primary authority in interpreting and implementing Medicaid legislation was known as the Health Care Financing Administration (HCFA) until June 2001, when its name was changed to the Centers for Medicare & Medicaid Services (CMS).

categories of Medicaid eligible individuals. For example, states could choose to disregard some family income or resources when determining eligibility for children or pregnant women. This raises the effective income eligibility level above the official maximum level by reducing the amount of income actually counted.[9] The second option is the Section 1115 waiver option, which permits states to apply to the federal government for a "research and demonstration" waiver. These waivers give states more flexibility in designing their Medicaid programs, including the possibility of increasing eligibility for the program. In 2001 the executive branch used its regulatory authority to implement the Health Insurance Flexibility and Accountability (HIFA) waiver initiative, which encouraged states to apply for waivers that expanded coverage without expanding funding by using changes in benefits packages and cost sharing provisions to help finance the expansions. In particular, some states obtained Section 1115 waivers in order to provide some coverage to childless, nondisabled adults, the only way in which such individuals could be covered under Medicaid. Because these waivers were required to be budget neutral for the federal government, they often entailed limits on benefits, higher cost-sharing, or enrollment caps (Rudowitz, Artiga, and Musumeci 2014).

A somewhat less well-known change that occurred to Medicaid during this period came about because of the master settlement agreement between 46 states and the District of Columbia and tobacco manufacturers. In the settlement, manufacturers agreed to make annual payments to the states intended to recompense them for the cost to state Medicaid programs of treating tobacco-induced illnesses (Schneider et al. 2002). In addition, the federal government allowed states to keep the federal share as well, and moreover states were permitted to use the tobacco

[9] http://www.nchsd.org/libraryfiles/MBI/CMS_Section1902r2Guidance.pdf

payments to fund the state portion of Medicaid, effectively raising the federal match rate above the nominal matching rate.

The Affordable Care Act

Arguably the single most far-reaching change to Medicaid is the one that was implemented most recently: the Patient Protection and Affordable Care Act of 2010 (PPACA) and the Health Care and Education Reconciliation Act of 2010—together known as the Affordable Care Act. By the time of the passage of the ACA, Medicaid eligibility had expanded substantially, but was still largely limited to individuals in the original mandated groups (families, the disabled, and the elderly). As discussed above, a few states had extended eligibility under waivers to able-bodied low-income adults who are not parents. Under the ACA, Medicaid eligibility levels for children younger than 6 were intended to remain largely unchanged, as were eligibility levels for pregnant women. For older children, if the state covered children with family incomes between 100 and 133 percent of the FPL under a separate CHIP plan, sometimes referred to as "stair-step" eligibility, the state was required to transition those children from separate CHIP to Medicaid (Kaiser Family Foundation 2013). The most significant change in the ACA, however, was the potential expansion of Medicaid eligibility to adults. According to the original legislation, Medicaid was to be expanded to all adults with family incomes below 138 percent of the FPL: 133 percent of the FPL plus a 5 percent income disregard. The legislation included a higher federal match for newly eligible adults—100 percent through 2016 then phasing down to 90 percent in 2020 and following. However, the Supreme Court decision of June 2012 ruled that states would not lose existing Medicaid funds if they did not expand Medicaid for all individuals under 138 percent of the FPL, essentially making the expansion a state option. The decisions of the states about whether to participate in the Medicaid expansion are shown in the columns of Table 2. As of late summer 2014, 24 states and the District of Columbia had chosen to expand Medicaid in the form passed in the legislation and another 5 had implemented a modified version of the ACA's Medicaid expansion under a Section 1115 waiver.

In addition to changes in eligibility for Medicaid, the ACA called for the creation of marketplaces ("exchanges") for the purchase of non-group coverage which would be federally subsidized on a sliding scale for individuals with family incomes below 400 percent of the FPL. The ACA also mandated that individuals obtain insurance coverage or pay a penalty through the tax system. Individuals who cannot obtain affordable coverage (including individuals with incomes below the FPL in states not expanding Medicaid) are exempt from the penalty.[10]

Because eligibility for premium credits through the exchanges is based on income tax rules for counting income and family size, states are required to base eligibility for Medicaid and CHIP for families and able-bodied adults on these same rules to ensure that eligibility is comparable across the different potential sources of coverage. Specifically, the tax-filing unit becomes the basis for family structure calculations, and the ACA establishes a new definition of income known as modified adjusted gross income (MAGI). MAGI is adjusted gross income (AGI) as determined under the federal income tax, plus any foreign income or tax-exempt interest that a taxpayer receives, and untaxed Social Security benefits (see UC Berkeley Labor Center 2013 for a brief summary of the components of MAGI). Assets are not considered when determining income eligibility. Any previously existing disregards (differing by state and eligibility category) that were applied to income before it is compared to the limits were eliminated and replaced with a single disregard equal to 5 percent of the FPL. Importantly, these

[10] The affordability standard for individuals is that the plan should cost less than 8 percent of their household income. For other exemptions, see https://www.healthcare.gov/fees-exemptions/exemptions-from-the-fee/

changes apply whether or not the state chooses to expand its Medicaid program. However, the blind, elderly, and disabled populations will continue to have financial eligibility determined using existing Medicaid rules (including both income and assets).

The use of MAGI and a fixed 5 percent disregard represents a major change in the way states calculate income eligibility for Medicaid. Prior to the ACA, under the freedom offered by the 1902(r)(2) option, states had some discretion about which types of income to count and how much income to disregard before comparing this net income level to the statutory net income eligibility standard. Thus not only does the ACA standardize the way income is counted across states, but it also changes how much of income is actually counted toward eligibility and which family members are included in the family unit whose income is being combined. Under the ACA, states were required to convert their net income standards to equivalent adjusted gross income standards using one of three possible strategies to determine equivalence and accounting for disregards that were used previously, with the goal being to keep the number of eligible individuals approximately the same (Center for Medicare and Medicaid Services letter to state health officials 2012). Because of these changes in how income and family group are defined, however, some individuals in eligibility groups not intended to be affected by the ACA—that is, groups that were already eligible for Medicaid and were intended to remain so—may be affected.[11]

[11] From Bitler, Orzol, and Shore-Sheppard (if possible to cite): For example, the standardized MAGI conversion methodology CMS chose in consultation with States adjusts the applicable Medicaid net income eligibility standard for each eligibility group by calculating the average size of the existing disregards for people whose net income falls within a band 25 percentage points of the FPL below the State's net income standard. It then adds this average disregard amount (as a percentage of the FPL) to the net income eligibility standard (also expressed as a percentage of the FPL). Some individuals with unusually large disregards under the old system would no longer be eligible even as some individuals with higher gross incomes and lower disregards under the old system would become eligible.

The effects of this change to income counting methodologies are reflected in the income eligibility limits made public for states. In column (4) of Table 3 we show the 2013 income eligibility limits for children, which were applied to income after state-specified disregards (that were not well publicized) were subtracted. (We show the higher of the CHIP and Medicaid eligibility limits, indicating with an asterisk states where Medicaid limits were lower than CHIP limits.) Column (5) shows the income limits in 2014 incorporating the 5 percent disregard; these income limits are applied to the family's MAGI. In most cases the apparent increase between 2013 and 2014 reflects only the change in income counting methodology and not a true increase in eligibility.[12]

In addition to the eligibility changes discussed above, there are some provisions of the ACA that specifically affect immigrants (Kenney and Huntress 2012). Undocumented immigrants are not eligible for Medicaid and are not eligible to purchase marketplace coverage. Such immigrants will still be eligible for emergency Medicaid and optionally for prenatal care under an option established for CHIP in 2002 allowing states to cover the unborn child (Heberlein et al. 2013). Legal immigrants in states that did not relax the five-year residency rule after given the option in CHIPRA are still ineligible for Medicaid until they have been in the country for five years, but they may purchase coverage through the exchanges and they are eligible for the tax credit subsidies. Individuals with incomes below 100 percent of the FPL but who are ineligible for Medicaid due to the five-year rule are eligible to receive tax credits for coverage purchased through the exchanges (Stephens and Artiga 2013). They are subject to the mandate, unless they are otherwise exempt for income reasons.

[12] Again cite Bitler, Orzol, and Shore-Sheppard if possible, because can then talk about our determination of which changes were real changes.

Overall, Medicaid today resembles in many ways the program that was established 50 years ago, although with some key differences. It remains a state-federal partnership, with the partnership being more or less contentious in different states and for different reasons including federal restrictions on state desired program flexibility, federal requirements for coverage and service provisions that states may find difficult to meet in difficult economic times, and state attempts to maximize the funding obtained from the federal government. The services provided to beneficiaries have become broader and have included some important additions, although key elements remain the same. Eligibility continues to involve a categorical eligibility determination—under which pathway to eligibility might an individual be eligible?—although the pathways have become broader and more numerous. According to the CMS there are 48 mandatory eligibility groups, 32 optional eligibility groups (including the ACA category of adults with incomes at or below 133% FPL that would subsume many of the other categories), and 9 medically needy categories.[13] The individual's eligibility pathway determines what income limit applies as well as which income counting methodology will be used. The eligibility pathway also determines whether "spending down" is permitted to qualify for coverage and whether a resource test applies and if so which one. Immigration status and date of entry to the U.S. also affect eligibility. Overall, however, it is clear that the Medicaid program has moved from being a small program that covered only some of the very poorest members of society to a central part of the health care system in the United States.

II. Program Statistics

Enrollment and Expenditures

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[13] http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-topics/Waivers/1115/Downloads/List-of-Eligibility-Groups.pdf

Figure 2 plots total Medicaid enrollments and expenditures from 1966 to 2013. Enrollment increased between 1966 and 1974 as states implemented their programs and then leveled off until the late 1980s, when enrollment increased again as a result of eligibility expansions for pregnant women and children. In the mid-1990s the combined effect of a strong national economy and Federal welfare reform legislation led to declines in enrollment. Steady growth resumed in the early 2000s and by 2010, more than 65 million people were enrolled in Medicaid.[14]

As noted in Section II, 26 states plus the District of Columbia has implemented the ACA Medicaid eligibility expansion by 2014. Among those expansion states that were providing coverage to enrollees in July 2014, Medicaid and CHIP enrollment rose by over 20 percent compared to the third quarter of 2013 (CMS 2014). In ten of those states, enrollment grew by more than 30 percent over that period. In states that did not implement the ACA Medicaid expansion, Medicaid/CHIP enrollment grew by roughly 5 percent. This enrollment growth likely reflects an increase in awareness about Medicaid as a result of the ACA rollout.

As part of the 2009 CHIPRA legislation, Congress established the Medicaid and CHIP Payment and Access Commission (MACPAC), a nonpartisan Congressional support agency charged with providing analysis and advice on Medicaid and CHIP policies related to payments, eligibility, enrollment and retention. Table 4 presents a MACPAC analysis decomposing the growth in real Medicaid expenditures from 1975 to 2010. Over that period, total real spending increased at an average annual rate of 4.3 percent. Increased enrollment, from 20.2 million to 59 million, accounted for 70.3 percent of that increase. Per capita spending grew by an average of

[14] Counts of Medicaid enrollees based on administrative data vary across sources and by measure definition—for example, the number of people enrolled at a point in time or at any point during a given year.

1.1 percent per year, accounting for the remaining 29.7 percent of the growth in real expenditures.

Ever since the program was established, non-disabled children have been the largest of all eligibility groups and they are the group with the largest absolute enrollment growth between FY 1975 and FY 2010. In percentage terms, enrollment grew at the fastest rate for adults who qualify for Medicaid on the basis of a disability. Disabled beneficiaries accounted for half of real spending growth since FY 1975, with about three-quarters of the expenditure growth for this group coming from increased enrollment. Of the four eligibility categories presented in Table 4, enrollment grew at the slowest rate for the elderly. As a result, the percentage of Medicaid enrollees over age 65 has declined over time from 16 percent in 1975 to under 7 percent in 2010.

Table 5 compares 2011 enrollment figures from administrative data to total population counts to calculate percent coverage rates for the different age groups. Out of 75.8 million people who were enrolled in Medicaid or CHIP at some point during that year, 40.2 million were children. This figure represents just over half of all children in the U.S. Measuring enrollment at a point in time yields a coverage rate of roughly 40 percent. In 2011, a similar percentage of non-elderly and elderly adults had Medicaid coverage. The point-in-time coverage rates calculated based on administrative data were 11.7 percent for 19 to 64 year olds and 13.7 percent for adults over age 65.

Medicaid enrollment tends to be underestimated in survey data (Davern et al 2009). The last two columns report coverage estimates based on the two Federal surveys that are most often used in research on health insurance: the National Health Interview Survey (NHIS) and the Current Population Survey (CPS). Although the two surveys ask about insurance coverage in different ways, they produce fairly similar estimates of coverage. For all ages, the coverage rate in the two surveys is 16.5 percent, nearly 3 percentage points lower than the point-in-time measure based on administrative data.

Table 6 presents 2011 per capita spending for the different eligibility groups broken down by service category. Although they are the largest eligibility category in terms of enrollment, because their per capita spending is so much lower than other eligibility groups, children account for only XX percent of total Medicaid expenditures. In contrast, elderly and disabled enrollees account for roughly one-quarter of total enrollment but roughly two-thirds of total spending. A large share of spending for disabled and aged enrollees is for long-term services and supports: 36 percent for the disabled and 66 percent for the elderly. Across all eligibility categories, Medicaid enrollees who use long-term services and supports represent 6% of enrollment and almost half of total spending (MACPAC 2014).

Figure 3 presents the Federal government's share of Medicaid spending from the start of the program until 2012. The Federal government paid an average of 56 percent over the 1970s and 1980s before climbing to a historical high of 63 percent in 1992. The Federal share generally declined over the next 15 years. It was 57 percent in 2007 but then spiked to 66 percent in 2009 as a result of the American Recovery and Reinvestment Act (ARRA), which included $87 billion for a temporary increase in the FMAP. Under ARRA, all states received at least a 6.2 percent increase in their FMAP; states that had experienced large increases in unemployment since 2006 received an additional reduction in their share of program spending. To qualify for this additional funding, states could not impose new restrictions on program eligibility. The temporary FMAP bump expired in 2011 and in 2012 the Federal share of total Medicaid spending was down to 56.5 percent. The state receiving the highest FMAP in FY 2012 was Mississippi at 74 percent. Twelve states received the lowest possible FMAP of 50 percent.

In FY 2012, Medicaid and CHIP accounted for 48 percent of Federal grants to states (OMB 2014).

Medicaid is the largest single program from an aggregate state budgetary perspective. In FY 2013 it accounted for a slightly larger budget share of total state spending than elementary and secondary education: 24.4 percent vs. 19.8 percent (NASBO 2013). Medicaid's share of the budget varies considerably across states, ranging in FY 2013 from a low of 7 percent in Wyoming to a high of 36 percent in Missouri. In 2012, the median state spent 22.4 percent of its budget on Medicaid. Medicaid expenditures exceeded expenditures for K-12 education in 37 states (NASBO 2013).

Provider Reimbursement

The amount that Medicaid pays providers varies considerably across states and, to a lesser extent, over time. Table 7 summarizes some of the variation in physician reimbursement rates. The figures come from several studies by Stephen Zuckerman and colleagues, who collected data on Medicaid fees for different services (Zuckerman et al., 2004; 2009; Kaiser Family Foundation 2012). To provide a sense of how Medicaid compares to other payers, the reimbursement rates are expressed as a percentage of Medicare rates, which tend to be lower than private fees. The top panel reports the national average Medicaid/Medicare ratio by broad service category. Considering all services, in 2003 Medicaid physician fees were 69 percent of Medicare fees. The national average increased to 72 percent in 2008 before falling to 66 percent in 2012. In general Medicaid fees tend to be higher relative to Medicare for obstetric services and lower for primary care.

The bottom panel of the table gives a sense of the variation across states. In each year, the large majority of states pay between 50 percent and 100 percent of Medicare. Several of the states that pay more than Medicare are sparsely populated states with small Medicaid programs: Alaska and Wyoming in all three years and Idaho, Montana, Nebraska, Nevada, New Mexico and North Dakota in 2008. At the other end of the spectrum, New Jersey and Rhode Island were the two lowest paying states in all three years, with rates that were between 35 and 42 percent of Medicare, depending on the year. New York, which has the second largest program in terms of total enrollment, has historically also had low Medicaid rates. In 2008, New York's rates were the third lowest of all states at 43 percent of Medicare rates. In 2012, New York's Medicaid fees were 55 percent of Medicare's. California, which has roughly twice as many Medicaid enrollees as New York, has also historically had low reimbursement rates. In 2012, California paid 51 percent of Medicare rates on average.

One response states have made to the substantial budgetary pressure of Medicaid has been to encourage or require recipients to enroll in managed care plans. The data summarized in Table 4 pertain to Medicaid and Medicare patients for whom physicians are paid on a fee-for-service basis. Since the early 1990s, both programs have seen a significant growth in the percentage of patients who are covered by managed care arrangements.   As shown in Figure 4, Medicaid managed care penetration grew from 9.5 percent in 1990 to 56 percent by the end of that decade. Since then, the share of Medicaid enrollees in managed care has continued to grow, though less rapidly. By 2012, roughly three-quarters of Medicaid beneficiaries were in some form of managed care.

As noted in Section II, in the context of Medicaid, the term managed care encompasses several different types of arrangements, including comprehensive risk-based plans that received a fixed payment per member per month—i.e., HMOs—as well as primary care case management programs that pay primary care providers a monthly fee to coordinate the care of enrollees. The prevalence of these arrangements varies across eligibility categories. In FY2010, 87 percent of children were covered by managed care; 62 percent of all Medicaid children were in a comprehensive risk-based plan.[15] Among non-disabled adults, 60.5 percent were in some form of managed care, including 46.8 percent in a risk-based plan. The disabled were slightly more likely to be in some form of managed care (63.1 percent) but much less likely to be enrolled in a comprehensive plan (28.7 percent). The aged were least likely to be in managed care overall: in 2010 40.6 percent were covered by a managed care arrangement and 11.9 percent were in a comprehensive plan.

IV. Review of Issues

Unsurprisingly given the magnitude of expenditures on the Medicaid program and the sizeable number of recipients, Medicaid has garnered substantial research interest covering a variety of areas. An important area of research focus is the effectiveness of the program and its design, including examinations of whether Medicaid is accomplishing its intended goals of improving access to timely and appropriate medical care and, ultimately, improving health. Research in this area has examined the impact of Medicaid eligibility and Medicaid coverage as well as the impacts of particular policy elements, such as reimbursement policy, on program effectiveness. A smaller but growing number of studies investigate the effect of Medicaid on other aspects of individual well-being, such as financial well-being. There has also been an important research focus on the unintended consequences of Medicaid and its design for beneficiaries and providers, including issues of crowding out of other sources of insurance, labor

[15] Figures on managed care enrollment by eligibility category are from Table 17 of the June 2013 MACPAC report.

supply, and provider financial impacts. In addition, the structure of the program and its relation to other means-tested programs has given rise to research on program interactions.

A. Program Take-up and Crowd-Out

As noted in the previous sections, the history of Medicaid has been marked by periods of significant expansions in program eligibility and enrollment. But, as is well known, many individuals do not take up benefits for which they are eligible. In particular, as income eligibility thresholds are increased extending eligibility to groups that previously had little experience with means-tested programs, take-up rates can fall for various reasons. Therefore, how eligibility for Medicaid translates to actual coverage is a fundamentally important question for considering the program's effectiveness. A number of studies have investigated how changes in eligibility policy affect insurance coverage. One set of papers focuses on the Medicaid expansions of the late 1980s and early 1990s (e.g. Cutler and Gruber 1996; Dubay and Kenney 1997; Card and Shore-Sheppard 2004; Ham and Shore-Sheppard 2005; Shore-Sheppard 2008; Ham, Ozbeklik, and Shore-Sheppard 2014) while other studies consider the effect of CHIP (e.g. LoSasso and Buchmueller 2004; Gruber and Simon 2008). In addition to examining the relationship between eligibility and enrollment—i.e., take-up—these studies also estimate the effect of program eligibility on private insurance coverage—i.e., "crowd-out." The potential for Medicaid to crowd out private insurance coverage has direct implications for program expenditures and the cost of increasing insurance coverage.

The most common approach used for estimating effects of expanded eligibility is an instrumental variable linear probability model (LPM), which was first used in this context in the seminal paper of Cutler and Gruber (1996). Participation in a public insurance program for child *i* in year t is determined by

$$pub_{it} = X_{it}\beta_1 + \gamma_1 elig_{it} + u_{1it}, \qquad (1)$$

where $pub_{it} = 1$ if child *i* participates in public insurance in year *t* and $pub_{it} = 0$ otherwise. Participation in private insurance is determined by

$$priv_{it} = X_{it}\beta_2 + \gamma_2 elig_{it} + u_{2it}, \qquad (2)$$

where $priv_{it} = 1$ if child *i* has private insurance coverage and $priv_{it} = 0$ otherwise. For reasons discussed below it is plausible that $elig_{it}$ is endogenous in (2) and (3) and that OLS will provide inconsistent results. However, as discussed below, it is generally agreed that there are at least two strong instruments for $elig_{it}$ that only enter (1) and (2) through the variable $elig_{it}$, i.e. satisfying the exclusion restriction is not an issue. Also it is possible to investigate this issue using data from a randomized trial in Oregon where the treatment group was made eligible for Medicaid, complementing the large literature based on nonexperimental methods.

Take-up of Medicaid is determined by γ_1, the probability that an eligible child is actually enrolled in Medicaid. Crowd-out is defined in two ways. First some researchers use γ_2, i.e. the probability that an eligible child has private insurance. Other researchers measure crowd-out by γ_1 / γ_2, i.e. the ratio of the probability that an eligible child has private insurance to the probability that an eligible child has public insurance.

The issues in this literature are as follows. Usually researchers assume unobservable heterogeneous treatment effects, so γ_1 and γ_2 are Local Average Treatment Effects, which do not allow researchers to predict the impact of nonmarginal changes in the Medicaid rules. Secondly, the imputation of $elig_{it}$ will likely result in nonclassical measurement error in this 0-1 variable, which will not be addressed by standard IV procedures. A third issue is how the model is related to a theoretical model of take-up. Fourth, should one allow the take-up and crowd-out effects to depend on observable differences between families as well as on unobservable differences? Fifth researchers often do not usually report a standard error for the crowd-out measure γ_1 / γ_2, even though this standard error is usually so large that the resulting confidence intervals are relatively uninformative. All of these issues are discussed in Section V.a below; there we conclude that take-up varies drastically across different demographic groups and that crowd-out does indeed exist but is relatively small.

The above discussion applies to providing Medicaid to children, but with the implementation of the affordable care act, there is also the issue of how childless adults will react in terms of take-up and crowd-out to being offered Medicaid. As we discuss below, there is much less evidence of the effect of providing insurance to childless adults.

B. The Effect of Public Health Insurance on Health Care Utilization and Health Status

Generally, health insurance can be expected to increase health care utilization by reducing the price of health care. However, the extent to which expanding Medicaid eligibility induces substitution of public insurance for private insurance also has implications for the impact of Medicaid on other outcomes. In particular, we would expect that the effect of Medicaid on medical care utilization and health outcomes is different for individuals who would have otherwise been uninsured as compared to individuals who drop private coverage to enroll in Medicaid. For the latter group, enrollment in Medicaid does not necessarily imply increased insurance coverage or improved access to care. Because Medicaid reimbursement rates are so much lower than rates paid by private insurers, individuals who transition from private coverage to Medicaid may experience reduced access to care in general and to certain types of costly technology in particular. Alternatively, if an individual transitions from private coverage with significant individual cost-sharing to Medicaid, then there may be no change or even an increase in access to care. Consequently the impact of Medicaid on utilization in the presence of substitution is an empirical question.

Enrollment in Medicaid is more likely to lead to increased medical care utilization for people who were previously uninsured, though even for such individuals the effects on both utilization and health may be complex. A primary effect comes from the fact that Medicaid lowers the out-of-pocket costs of all types of care, ranging from office-based primary and preventive care to specialty services and inpatient care. The relative impact on different types of care will depend on how and when individuals enroll in the program and their utilization patterns prior to enrollment. Roughly speaking, enrollees will only benefit from the full range of preventive services covered by Medicaid if they enroll when they are well. In principle, timely utilization of such care may avoid the need for more costly acute care. In the best-case scenario, improved access to primary care will improve health and produce cost offsets in the form of fewer "avoidable" hospital admissions for "ambulatory care sensitive" conditions. Early enrollment in Medicaid can also lead to more efficient utilization patterns if it shifts the site of care from costly settings, such as hospital emergency departments, to less costly ones, such as physician offices or public health clinics. These efficiency gains will not materialize if eligible individuals do not enroll until they present at a hospital. Moreover, it is quite possible for individuals to receive care that provides little clinical benefit at the margin, and more medical care is sometimes worse instead of better. Consequently a number of studies have tested for an effect of Medicaid eligibility on particular types of care, interpreting reductions in avoidable or ambulatory care sensitive admissions as improvements in health. Other studies have examined the impact of Medicaid on health directly, looking at outcomes such as blood pressure and other clinical measures of health, infant birth weight, infant or child mortality, or self-reported health status.

C. Impacts on Health Care Providers

The impact of Medicaid coverage on utilization of care and health will also depend on the willingness of different types of providers to supply services to Medicaid patients, which will depend on how Medicaid payment rates compare to what providers are paid for patients with Medicare and private insurance (Sloan, Mitchell and Cromwell 1978). As shown in Table X, Medicaid fees vary across states and over time, but in general tend to be substantially lower than those for other payers. In 2011-12, roughly 30 percent of all physicians did not accept new Medicaid patients (Decker 2013).

The effect of eligibility expansions on physicians and other providers will depend on the mix of patients they were treating prior to the expansion, the degree of crowd-out (Garthwaite 2012) and how Medicaid payment rates compare to those of other payers (Freedman, Lin and Simon forthcoming). When there is little or no crowd-out, the main effects of an eligibility expansion will be on physicians who were previously treating low-income patients, including both those with Medicaid and the uninsured. Providers specializing in treating privately insured patients will be less affected. In contrast, when eligibility expansions induce a substitution of public for private insurance, many providers, including those that were not previously treating Medicaid patients, will experience the expansion as a reduction in payment rates for patients they are already seeing.

Changes in fees, whether they arise implicitly through crowd-out or directly from a change in a state's fee schedule, will have both substitution and income effects. Some research on Medicare suggests that for that program income effects are important; physicians respond to reductions in Medicare payment rates by increasing the volume of services provided (cite). Such a response is less likely in the case of Medicaid given that Medicaid patients represent a smaller share of the patients seen by most physicians in private practice. When the substitution effect dominates, physicians will respond to a decrease in Medicaid fees by reducing their supply of services to Medicaid patients.

Medicaid eligibility and payment policies affect incentives for providers to invest in and use medical technology. When Medicaid accounts for a large share of patients for particular services, as is the case with obstetric care, hospitals will have less incentive to invest in costly technology, such as neo-natal intensive care units and physicians will have less incentive to provide more costly treatments.

In addition to financing roughly half of all births, Medicaid pays for large share of nursing home care in the US. In 2011, Medicaid was the primary payer for over 60 percent of all nursing home residents (Kaiser Family Foundation 2013). Therefore, Medicaid payment policy has important implications for the quality of nursing home care, though the relationship between payment rates and quality is complex, depending on other policies such as certificate of need (CON) regulations that limit supply. Influential theoretical work by Nyman (1985) and Gertler (1989) assumes that nursing home capacity is constrained by supply-side regulations; nursing homes compete for private patients on the basis of price and quality but face excess demand from Medicaid patients; and that quality is a common good that experienced equally by all patients in the same facility. These models predict that under these circumstances, an increase in Medicaid payment levels can lead to a reduction in quality. The reason for this counter-intuitive result is that higher payment rates will cause nursing homes to attract more Medicaid patients. Homes that were at full capacity to begin with, will therefore want fewer private pay patients, causing them to raise price and lower quality to private pay patients. At the time these papers were written, CON regulations were binding in many markets and capacity utilization rates were quite high. Over time, however, states have repealed CON laws, allowing an increase in facilities and capacity has become less tight. Thus, whether or not the negative relationship between Medicaid payment and quality held at that time, it is less likely to hold today.

D. Impacts on Labor Supply and Other Program Participation

There are two strands of the more recent literature of the effect of Medicaid. The first notes that with the decoupling of Medicaid receipt and the receipt of welfare payments (AFDC, or TANF in 1996 and later). The idea here is that this decoupling increased the rewards for a single mother to join the labor force since some or all of her children would still qualify (depending on the family's income, the state, the year and the child's age) for Medicaid coverage when she leaves welfare. Moreover, over time Medicaid eligibility has become available to more and more children. Economic theory has the unambiguous predictions i) that allowing children to keep their Medicaid should increase the labor force participation of their mothers and ii) that this effect should be increasing in the generosity of the state Medicaid program. Here the major issues are a) how to value the Medicaid benefits in dollar terms, especially for demographic groups that are unlikely to take-up Medicaid coverage for their children and b) how to model the labor supply decision. Here it seems fair to say that Medicaid has had little or no effect on the participation decisions of single mothers.

The second strand of the literature concerns the effects of Medicaid coverage of childless adults. Before the Affordable Care Act such coverage was quite rate, but with this Act the coverage will be widespread. If the coverage is available both when working and not working, the effect on participation is ambiguous since the individual's budget constraint is improved both when he or she works and when they do not work. However if it acts as an increase in unearned income and reduce hours of work and probably increase reservation wages.. Thus the effect of offering Medicaid to childless adults is an empirical question, with most of the information coming from a natural experiment in Tennessee and the above mentioned Oregon randomized trial. We would summarize these as providing different answers, and emphasize the need for more research in this area.

E. *Impacts on Family Structure*

In addition to impacts on labor supply and program participation, Medicaid may also have impacts on family structure and financial well-being. Some of these effects are tied to changes in the relationship between Medicaid eligibility and participation in other programs, particularly AFDC, while other effects arise purely from the insurance and consumption effects of publicly provided insurance. The link between AFDC eligibility and Medicaid for poor children that existed for the first twenty years of the program, and the fact that AFDC eligibility was limited to single parents (effectively, single mothers) except in states with the optional unemployed parent program, meant that marriage deprived a woman not only of an income source but also of health insurance for herself and her children. While marriage presumably replaced potential AFDC income with potential spousal earnings, the need to obtain health insurance for the entire family as well may have dissuaded some individuals from marrying. Thus by making eligibility for Medicaid for one's children not conditional on marital status, it is possible that Medicaid expansions could encourage marriage.

Medicaid could also impact family structure by affecting fertility decisions. There are several possible, sometimes offsetting, effects of Medicaid on fertility. In the framework developed by Becker (1960) and Becker and Lewis (1973), both the quantity and quality of children enter the mother's utility function. Thus covering the costs of prenatal care, delivery, and infant care lowers the price of quantity, inducing substitution in favor of quantity and causing a rise in fertility. In addition, Medicaid could also reduce miscarriages through better prenatal care. Since in this model the shadow price of children with respect to quantity is positively related to the level of quality, and vice versa, the theoretical impact of the expansions on fertility is not unambiguously positive. The expansions for medical care for children lower the price of quality, which may lead to lower birth rates.

Another possible effect of Medicaid on fertility is the effect of Medicaid on the price of ending a pregnancy or preventing conception. Following the Hyde Amendment of 1976, federal funding of abortion under the Medicaid program was restricted to cases in which the mother's life is in danger. States have the option to cover abortions in their Medicaid program but will not receive the federal match for them. Thus in some states, Medicaid funding is available to end unwanted pregnancies. In addition, Medicaid has covered the cost of family planning services since 1972, and CHIP covers family planning services for adolescents. In addition, beginning in the mid-1990s the federal government granted a number of states Section 1115 waivers to offer family planning services under Medicaid to higher income women or to women who otherwise would have lost Medicaid eligibility, typically postpartum. While it may seem clear that reducing the price of ending a pregnancy or preventing conception will reduce fertility, interactions between take-up, existing private provision of such services, and changes in sexual activity resulting from the change in the price make the fertility implications of such policies unclear (Kearney and Levine 2009).

F. Impacts on Financial Well-Being

There are a number of ways in which Medicaid may impact a family's financial circumstances. Any insurance program offers two benefits. First, insurance can be viewed as providing consumption smoothing, and this effect is likely to be especially valuable to low income families who lack access to credit markets. Secondly, insurance helps families avoid catastrophic losses in the form of medical expenses. Because Medicaid insurance is generally offered below the fair insurance price, it can be thought of as a transfer that improves the economic circumstances of the individual through the reduction in medical insurance costs and out of pocket expenses that would otherwise be incurred, which can make obtaining insurance coverage now feasible. These features of Medicaid imply that it will improve the financial circumstances of eligible families in the short run. However, Medicaid may also affect savings behavior through a variety of channels. First, Medicaid reduces uncertainty about future medical expenses, reducing the need for precautionary saving for medical expenses. Thus eligible households would be expected to save less (and therefore have lower assets) compared with ineligible households, all else being equal. However, to the extent that households do not expect to qualify for Medicaid indefinitely, the effect of this channel would be lessened. Second, the redistributive feature of Medicaid increases a household's available resources, and if the household's marginal propensity to save is greater than zero, this increase could lead to higher levels of asset holdings. The third channel by which the Medicaid program may affect savings levels is through the asset test. Otherwise-eligible households for whom the value of Medicaid is greater than the difference between current wealth and the asset limit might reduce their wealth holdings in order to qualify for insurance. Those who see Medicaid as a potential future option might also have an incentive to reduce their savings in anticipation of future eligibility. On the other hand, Medicaid protects the families from bad shocks that can drive families into debt and bankruptcy. The current research in this area has generally focused on how family medical debt, nonmedical debt and family bankruptcy is affected by Medicaid expansions; available research indicates that it improves a family's medical debt and probability of going into bankruptcy.

G. Strategies for Identifying Causal Effects

Empirical studies of all of these questions generally aim to estimate causal effects. However, given the means-tested nature of the program, there is a fundamental challenge for research in this area as in other areas of policy evaluation: endogeneity of eligibility, enrollment, and utilization. This endogeneity arises because unobservable factors affecting eligibility for the program such as earnings ability, unobserved aspects of employment, availability of insurance from other sources, and unobserved health status, are likely to be correlated with unobservable factors that affect outcomes of interest such as health insurance choices, public program participation, and labor supply. In addition, it may be difficult to control entirely for all of the factors determining both eligibility and the outcome of interest, such as varying insurance markets, changes in the economy, and changes in the supply of providers of various types.

Due to this endogeneity, merely attempting to control for as many observable differences between groups eligible and ineligible for Medicaid as possible is unlikely to produce compelling estimates of the program's effects. Researchers working on examining the impact of Medicaid on a variety of outcomes have recognized this issue and have used a number of identification strategies to try to obtain credible empirical estimates of the program's effects. These identification strategies have variously taken advantage of variation arising from aspects of the Medicaid program, including the facts that: Medicaid is a different program in every state, Medicaid is a state-federal partnership, with the federal government providing some uniform standards across states, and Medicaid is linked to a variety of other programs, each with its own unique features and variation across states. Moreover, Medicaid parameters can vary within a state either geographically (as states implement changes in one place but not in another, for example), or by some other subgroups in the population (by age, for example). The variation used can be truly random, as in the experiment extending Medicaid to a subset of low-income adults in Oregon determined by lottery discussed below, or more commonly, quasi-random, as state or federal decisions generate variation in the parameters applying to different groups.

To make the variation used by different studies as clear as possible and to provide a framework for our review of the empirical literature that follows, it is useful to provide a taxonomy of research designs within which most papers in the literature fall. Our goal here is to give a general sense of how identification is accomplished and some important benefits and drawbacks of each approach generally; we leave a more complete discussion of the details of specific papers to the following section.

1. *Randomized Experiment*

Arguably, the strongest research design for estimating causal effects is a randomized experiment, since by design there is no correlation between individual characteristics and the policy of interest. While randomized experiments are rare in Medicaid research, an important experiment, the Oregon Health Insurance Experiment, is providing insights into key Medicaid policy questions (see, e.g., Finkelstein et al. 2012, Baicker et al. 2013). In early 2008, Oregon decided to make 10,000 additional places in its Medicaid program for low-income adults newly available. Knowing that there were insufficient funds to cover everyone who would want to enroll, the state applied for permission to use a random assignment mechanism. Approximately 90,000 people signed up for the reservation list, and the state ran a randomized lottery on that group to determine which individuals would be permitted to apply for coverage. Individuals chosen in the lottery were allowed to apply, and all selected individuals who filled out and returned the application and who were found to be income eligible were enrolled.[16]

The researchers on the study matched an impressive wealth of data from hospital discharge records, credit records, prerandomization demographics from the sign-up list, and a follow-up survey of outcomes. Because of the way a lottery was used to determine eligibility, there is strong internal validity. Moreover, before looking at the data on outcomes for the treatment group, most analyses were prespecified and publicly archived in order to minimize concerns about data and specification mining. Because the population that received coverage through the experiment is basically the same as the population gaining eligibility through the ACA, there is a high degree of external validity with respect to that policy.

2. Quasi-experiments

Other studies in the literature exploit quasi-experimental variation arising from the fact that income eligibility limits, provider reimbursement rates and other important program features vary across states. Changes in state and federal policy create additional variation over time. Eligibility rules based on age create additional variation within state/year cells. Studies in the literature exploit these different "natural experiments" in various ways.

a. Difference-in-Differences

Several variants of a difference-in-differences (DD) research design have been used to estimate the effect of Medicaid policies. General methodological issues related to DD models have been discussed extensively elsewhere (see, e.g., Meyer 1995; Bertrand, Duflo and

[16] Not all of the individuals chosen in the lottery obtained Medicaid coverage; according to Finkelstein et al. (2012) "only about 60% of those selected sent back applications, and about half of those who sent back applications were deemed ineligible, primarily due to failure to meet the requirement of income in the last quarter corresponding to annual income below the poverty level."

Mullainathan 2004), so here we highlight the way different authors have used DD methods to leverage various sources of variation in the Medicaid program.

Given the latitude that states have in determining program parameters, an important source of variation is differences across states. For example, Gray (2001) uses a cross-sectional DD model to estimate the effect of Medicaid physician fees on several birth outcomes. In this model, pregnant women on Medicaid are the treatment group and other pregnant women are used as controls. Specifically, his regression models include a measure of Medicaid fees for XXX, an indicator variable for Medicaid coverage and the interaction of the two. Choi (2011) takes a similar approach to study the effect of adult dental benefits. The identifying assumption underlying this approach is that state-level differences in Medicaid fees or dental benefits should matter for Medicaid enrollees but not for other individuals in the state. An obvious limitation of this approach is that state Medicaid policy may be correlated with other important but unmeasured factors, leading to biased estimates.

Other studies have used a DD strategy to compare changes over time for groups that were subject to a change in Medicaid policy to control groups who should have been unaffected, or at least less affected. The simplest application of this approach compares outcomes in two periods—"pre" and "post"—for two groups—a "treatment" group that was the target of a policy change and a "control" group that should have been unaffected, or at least less affected. For example, to estimate the coverage effects of the Medicaid expansions of the late 1980s and early 1990s, Dubay and Kenney (1996) compare changes in coverage for low-income women and children, for whom income eligibility thresholds increased, with changes for low-income men, who were not the target of the eligibility expansions. And to study the effect of the Medicaid expansions on the use of prenatal care and birth outcomes, Dubay et al. (2001) compare pre/post differences for mothers with low and high socioeconomic status. In these models, identification is based on the assumption that in the absence of the Medicaid expansions, the outcomes studied would have trended similarly for treatments and controls.

These simple DD models do not take advantage of variation across and within states in eligibility rules or other program parameters. However, a useful feature of the Medicaid program is that there is often variation at the sub-state level. For example, the Medicaid expansions to children were phased in by age, with younger children becoming eligible sooner and at higher levels of income (see Shore-Sheppard 2008 for an illustration of the variation across states, years, and ages) so that at a particular time in a particular state, younger children faced looser eligibility standards than older ones. This helps to address the concern that there is something fundamentally different about a particular group (a state experiencing a policy change, for example) that would lead to different outcomes even in the absence of the policy. For example, Garthwaite et al. (2014) compare insurance coverage among childless adults to other adults in Tennessee and other southern states before and after a Medicaid policy change in Tennessee that affected childless adults more than parents. Alternatively, policies may be more likely to apply to certain individuals within a state. For example, Aizer (2007) studies the impacts on Medicaid enrollment of community-based outreach organizations that were placed in some areas of California but not in other areas at different times and that offered assistance to individuals speaking Spanish, Asian languages, or English, so that individuals of different races or ethnic backgrounds may have been more or less likely to benefit from the outreach. The identifying assumption in papers using this strategy is that in the absence of the policy change being studied, within a geographic area the groups would have experienced similar changes in the outcome of interest. Papers using such "triple difference" strategies often provide corroborating evidence about the identifying assumption, including evidence about trends in the two groups prior to the policy change and evidence about policy endogeneity.

b. Instrumental Variables

An alternative to the difference-in-differences approach that also utilizes variation arising from policy changes to identify causal effects is to use policy variables as instruments in an instrumental variables framework. The most widely used instrumental variables approach in the Medicaid literature is the "simulated eligibility" instrument that was pioneered by Currie and Gruber (1996 JPE, 1996 QJE) and has been used in many papers since then. The idea of this approach is to summarize the exogenous variation in Medicaid eligibility by determining the fraction of a given sample that would be eligible for Medicaid under the rules applying in a particular state at a particular time. This approach requires detailed knowledge of the rules for Medicaid eligibility so that the eligibility for any individual in a sample can be determined based on his or her observable characteristics. In order to remove the effects of any state and time-specific economic conditions that might be correlated with both eligibility and the outcome of interest, the fraction eligible is typically determined for a random sample at the national level, and often for a fixed time period as well. This simulated fraction eligible, which is essentially an index of the expansiveness of Medicaid eligibility for each subgroup in each state and time period, can then be used as an instrument for actual (imputed) eligibility at the individual level (as in the original papers by Currie and Gruber) or at an aggregated (cell) level (as in Dafny and Gruber 2005).[17]

This instrument has many benefits, as its widespread adoption makes clear: it is a useful way to summarize complicated program rules in a simple but meaningful index, it is arguably

[17] Simulated eligibility has also been used in reduced form models as an arguably exogenous index of availability of Medicaid (see, e.g., DeLeire, Lopoo, and Simon 2011).

exogenous along several dimensions, and it has a very strong first stage relationship with imputed eligibility. However, there are some issues that researchers who use this approach must consider. First, it is subject to concerns about policy endogeneity: it is possible that government policy targets groups experiencing worse economic conditions or occurs in response to other factors potentially correlated with the outcome of interest, making state expansions potentially endogenous. It is also possible that groups experiencing worse economic conditions happened to be those particularly affected by the expansions, even though the legislation was not intentionally aimed to mitigate economic conditions for these groups (Shore-Sheppard 2008). To try to account for such issues, researchers typically include state effects to account for differences across states unrelated to the expansions, time effects to control for macroeconomic shocks and economy-wide trends, and age effects to account for differences by age unrelated to the expansions. Even these fixed effects may not be enough to account for differential trends across ages or states, and if such trends are important, convincing identification may require the inclusion of two-way interactions between age, state, or time to account for them (Shore-Sheppard 2008). Even including such interactions may be insufficient if, for example, states are targeting policy at particular groups in the population in response to changes in the outcome of interest for those groups.

Second, in the linear probability model framework that is often used with this instrument, the resulting coefficients are best interpreted as local average treatment effects (LATEs)—effects for individuals whose eligibility is affected by marginal changes in the instrument, averaged across the different marginal changes present in the data (Ham, Ozbeklik, and Shore-Sheppard 2014). As Ham, Ozbeklik, and Shore-Sheppard point out, this framework has several limitations if one is interested in heterogeneity in the response to the policy or in the effects of nonmarginal changes, and they suggest an alternative framework to obtain estimates of such effects (discussed further below). However, their alternative approach relies on the same intuition of the simulated approach: since the rules determining Medicaid eligibility are observable, they can be used to determine who in the sample is affected by changes in policy.

Finally, mismeasurement (in income, for example) or the absence of information in the data about other characteristics that would result in eligibility via other paths (such as high medical expenses that would lead to medically needy eligibility or disability) may lead to misclassification of eligibility status (Hamersma and Kim 2013). While many authors using eligibility status have noted the problem, some have suggested that using simulated eligibility as an instrument would mitigate the problem. Unfortunately, as measurement error in a binary variable cannot be classical in the sense of being uncorrelated with the true value, an IV strategy will not produce consistent estimates of the parameter of interest but may instead produce an upper bound (Black, Berger, and Scott 2000).

c. Regression Discontinuity

In recent years, regression discontinuity (RD) techniques have become a standard component of the empirical economist's toolkit for estimating program effects. Such models rely on the existence of a known cutoff or threshold in a variable (known as the "assignment" variable) with different circumstances occurring for observations falling on either side of it. As long as individuals are unable to control precisely the assignment variable near the known cutoff, the RD design isolates treatment variation that is "as good as randomized" (Lee and Lemieux 2010). The examination of Medicaid, with its various eligibility cutoffs of different kinds, would seem to be a fruitful place to use an RD design, and several studies have used such an approach to estimate the impact of Medicaid eligibility on insurance coverage and utilization. For example, Card and Shore-Sheppard (2004) use various discontinuities in eligibility by age arising from the fact that eligibility under some expansions was extended only to children of certain ages. In one formulation, they use the discontinuity in eligibility between children born before October 1, 1983, who had to meet the AFDC eligibility requirements in order to be eligible and children born after that date, who could be in two-parent families and have family income as high as the poverty level. The inability to control birthdate around that cutoff (particularly since that birthdate cutoff was not established prospectively) makes it a compelling research design.

A recent study on an eligibility expansion in Wisconsin exploits the sudden imposition of an enrollment waitlist to construct a control group (Burns et al. forthcoming). The authors take an RD approach to compare individuals who signed up for coverage just before the program was closed to new enrollees to individuals who signed up just after the waitlist was established. Researchers have also applied RD methods to income cutoffs (see, e.g., De La Mata 2012, Koch 2013), although the imperfect control assumption requires more justification in the case of income. In addition, income is measured with considerably more error than birth date, and even if it is measured well income at the time of the survey may not be the same as income at the time an individual applies for coverage. Even more importantly, as discussed above prior to the ACA each state had complicated rules about disregards that changed the actual level of the income limits making the determination by the researcher of the correct income limit to apply to income observed in the data more difficult.

V. Review of Research Evidence on Impacts of Medicaid

A. Eligibility, Take-Up, and Crowd-Out

1. Children

There is now a very large literature on this issue. To keep the size of our survey within limits we group the papers into two sections. We generally discuss Group 1 papers in some detail, while summarizing the Group 2 papers more briefly.

Group 1 Papers - Children

Cutler and Gruber (1996) – Measuring Crowd-out and Take-up using the Current Population Survey 1988-1993

Cutler and Gruber (1996—CG hereafter) is the seminal paper in this literature. CG estimate an LPM using data on children from the March Current Population Survey (CPS) from 1988 to 1993. They estimate the effect of imputed Medicaid eligibility on public insurance status and on private insurance status, controlling for demographics and state and year effects. A child of age *a* in state *s* in year *t* is eligible for Medicaid if their family's income falls below the relevant Medicaid income limit. The LPM for participation in a public insurance program for child *i* in year t is given by

$$pub_{\mathrm{it}} = X_{it}\beta_1 + \gamma_1 elig_{it} + u_{1ti}, \tag{1a}$$

where $pub_{it} = 1$ if child *i* participates in a public insurance program, $pub_{it} = 0$ otherwise, X_{it} is a vector of demographic variables and u_{1it} is an error term. The LPM for private insurance coverage is given by

$$priv_{\mathrm{it}} = X_{it}\beta_2 + \gamma_2 elig_{it} + u_{2it}, \tag{1b}$$

where $priv_{it} = 1$ if child *i* has private insurance coverage, $priv_{it} = 0$ otherwise, and u_{2i} is an error term.

They use an IV version of the LPM since eligibility, $elig_{it}$, is likely to be endogenous. This potential endogeneity arises for at least two reasons. First, unobservable factors affecting eligibility are likely to be correlated with unobservable factors affecting health insurance choices. It may be the case that those with higher unobservables for determining eligibility may also have higher unobservables for determining public and private insurance coverage. In other words low income families may feel that there is less stigma of being on Medicaid than higher income families. Further, they may value Medicaid more highly, and private insurance less highly, than higher income families. In this case $elig_{it}$ would be positively correlated with u_{1it} in (1a) and negatively correlated with u_{2it} in (1b). Alternatively, low income families may have less organizational skill, making it more difficult for them to sign up for Medicaid or for private insurance. In this case $elig_{it}$ would be negatively correlated with both u_{1it} in (1) and u_{2it} in (1b). Further, parental wages, which in turn determine eligibility, are likely to be correlated with fringe benefits (including private health insurance) of the parent. Since these benefits are unobserved, they are part of the error term, and $elig_{it}$ would be negatively correlated with u_{1it} in (1) and positively correlated with u_{2it} in (2).

To address the endogeneity of the eligibility variable, CG suggest an instrument (which they call $SIMELIG_{it}$) that is the fraction of a random sample of 300 children of each age imputed to be eligible according to the rules in each state in each year. This instrument, which is essentially an index of the expansiveness (generosity) of Medicaid eligibility for each age group in each state and in each year, is correlated with individual eligibility for Medicaid but not otherwise correlated with the demand for insurance, assuming that changes in a state's Medicaid provisions are not correlated with changes in the state's availability or price of private insurance, which are unobservable to the researcher.[18]

Specifically, their LPM determining public insurance eligibility is

[18] One attractive feature of this approach is that *SIMELIG* is an extremely strong instrument.

$$elig_{it} = Z_{it}\delta + e_{it}, \qquad (1c)$$

where $Z_{it} = (X_{it}, SIMELIG_{it})$ and e_{it} is an error term. From the discussion in CG, it is clear that they interpret the coefficients γ_1 and γ_2 as LATEs, i.e. an average of treatment effects for individuals whose eligibility is affected by different marginal changes in $SIMELIG_{it}$ in the data.

An important use of these coefficients is to measure the degree of crowd-out of private insurance by public insurance. We would argue that γ_2 provides a good measure of this effect, since if 100 children become eligible, γ_2*100 will have their private insurance dropped. A popular measure of crowd-out used first by CG is γ_2 / γ_1. The idea here is that we are interested in the fraction of those going to public insurance that drop their private insurance. We see several problems with this latter approach. First, if $\gamma_2 = 0.1$ and $\gamma_2 = 0.2$, it implies less crowd-out than if $\gamma_2 = 0.01$ and $\gamma_2 = 0.01$, even though most would consider the first situation more important for crowd-out, since presumably the inefficiency is a function of the number of children who drop private insurance. . Second, some of the families who drop private coverage for their children when they become eligible may postpone signing up for Medicaid since they know their child will be covered in the event of a serious medical emergency; in this case the denominator is too small. Third, the second measure of crowd-out, γ_2 / γ_1, is likely to have much higher variance than the first measure, γ_2. For expositional purposes, suppose $V(\hat{\gamma}_k) = \sigma_k^2, k = 1,2$ and, $\mathrm{Cov}(\hat{\gamma}_1, \hat{\gamma}_2) = 0.$ Then using the delta method we find that

$$V\left(\frac{\hat{\gamma}_2}{\hat{\gamma}_1}\right) = \sigma_1^2 \left(\frac{(\gamma_2)^2}{(\gamma_1)^4}\right) + \frac{\sigma_2^2}{(\gamma_1)^2}. \qquad (2)$$

Since we expect $0<\gamma_1<1,\ k=1,2,$ each variance term in (2) is multiplied by a number greater than 1; this problem will be accentuated as we approach higher income limits, since we would expect the LATE's in this case to be getting smaller. As we show below, (2) produces a very large confidence interval for $\left(\frac{\hat{\gamma}_2}{\hat{\gamma}_1}\right)$ using the CG results.[19]

In terms of the use of $SIMELIG_{it}$ as an instrument, we would make several observations. First, it will potentially produce biased coefficients if a child used in the regressions (1) and (2) is also used in creating $SIMELIG_{it}$*;* this bias will become more serious if we assume that the error terms are correlated across children in, e.g., the same state, as researchers often do when . Second, one may be able to get a better (less noisy) instrument by using more than 300 children to create $SIMELIG_{it}$ that potentially will lead to a stronger first stage equation. The latter issue is especially important when researchers are interested in a coefficient on $SIMELIG_{it}$, since using a relatively small number of children could lead to a serious measurement error problem in $SIMELIG_{it}$ and bias in the coefficient of interest. Fourth, the income limits L_{ast} are of course equally valid IV's and can be used in place of $SIMELIG_{it}$. *Alternatively,* one could use both $SIMELIG_{it}$ and L_{ast} as IV's, since $SIMELIG_{it}$ is a complicated nonlinear function of L_{ast}. This not only would offer the possibility of a stronger first stage, but also allow for the testing the overidentifying restrictions as a specification test.

Finally, it is important to emphasize that because $elig_i$ is a zero-one variable,

[19] Most researchers, including CG, provide neither a standard error or confidence interval for $\left(\frac{\hat{\gamma}_2}{\hat{\gamma}_1}\right)$ nor $\text{Cov}(\hat{\gamma}_1,\hat{\gamma}_2)=0,$ so the confidence interval we calculate for the CG crowd-out estimate is only approximate.

measurement error in it will not be classical, and biases due to such measurement error in it will not be eliminated by the IV procedure described above. To address this issue one would need to specify a model for the measurement error; to the best of our knowledge this has not been done previously and we believe it would be a fruitful area of future research.

Using CPS data from 1988 to 1993, CG estimate γ_1 and γ_2 to be 0.23 (0.016) and 0.07 (0.013) respectively, where we have placed the standard errors in parentheses; both estimates are strongly statistically significant at conventional test levels. There results imply crowd-out of 7% using our preferred method and 32.9% using their preferred measure. The standard error for the first measure is of course 1.3% and the resulting confidence interval is [9.6%, 4.6%]. A standard error for their preferred measure is not given, but if we use the illustrative formula[20] (2) the standard error for the second measure is 24.6%, which implies a very wide confidence interval of [-16.3%, 81.8%].

Ham and Shore-Sheppard (2005a) – Measuring Crowd-out and Take-up using the 1986-1993 panels from the Survey of Income and Program Participation

Ham and Shore-Sheppard (2005a, HSa here after) first replicate CG's analysis using children from the 1986-1993 panels from the Survey of Income and Program Participation (SIPP). They argue that the SIPP offers several advantages for studying Medicaid participation and private insurance coverage over the CPS. First, data collection occurs three times per year, rather than annually, as in many data sets. Second, the survey was designed to collect income and program participation information and thus provides more detailed data on these variables. HSa estimate LATEs (standard errors) for take-up and private coverage of 0.118 (0.010) and

[20] As noted above It is an illustrative calculation since we should modify the formula for $\mathrm{Cov}(\hat{\gamma}_1, \hat{\gamma}_2)$, but an estimate of this covariance is not available.

0.006 (0.014) respectively. These estimates are directly comparable to those of CG, and their take-up coefficient is about half the size of CG's. Further, HSa find no evidence of crowd-out; formally one can reject the null hypothesis that their coefficients equal CG's. Moreover their estimate of γ_2 is a 'small zero' in the sense that its confidence interval is [0.034, -0.022].

Next, they investigate whether this difference occurs because HSa use the SIPP while CG use the CPS. They find that the difference in the estimated Medicaid take-up coefficients appears to be due to the omission of small states in the SIPP, the source of differences in private coverage results is less clear. At least some, though not all, of the difference appears to be due to the annual nature of the CPS data collection versus the tri-annual interviews of the SIPP.

HSa also extend the previous literature on Medicaid take-up and crowding out in several directions. First, they examine the impact of having Medicaid-eligible siblings on public and private coverage and find that take-up of Medicaid is increased slightly if a larger fraction of a child's siblings are eligible. Second, they allow the effects of eligibility to differ with time spent eligible, find that the longer a child has been eligible for Medicaid, the more likely he or she is to be enrolled in Medicaid. Third, they estimate simple dynamic models which allow the short-run and long-run effects of eligibility to differ. They find that the immediate impact of eligibility on take-up estimated using a lagged dependent variable model is smaller than static models indicate, while the long-run impact is larger. In addition, the dynamic model provides some of the only evidence of crowding out in the SIPP, showing a negative (though statistically insignificant) relationship between eligibility and private coverage.

Gruber and Simon (2008) – Extending and Updating the CG Model and Estimates Using the 1996-2002 SIPP data

Gruber and Simon (2008,GS hereafter) estimate an extended version of CG the 1996-2002 SIPP data. Specifically they consider the model where;

a. Participation *only* in a public insurance program for child *i* in year t is given by

$$pubonly_{\mathrm{it}} = X_{it}\beta_1 + \gamma_1 elig^*_{it} + u_{1it}, \tag{3}$$

where $pubonly_{it} = 1$ if child *i* participates in ppublic insurance in year *t* but not a private insurance plan and $pubonly_{it} = 0$ otherwise, and u_{1i} is an error term;

b. Participation in private insurance *only* is determined by

$$privonly_{\mathrm{it}} = X_{it}\beta_2 + \gamma_2 elig^*_{it} + u_{2it}, \tag{4}$$

where $privonly_{it} = 1$ if child *i* is covered by private insurance in year *t* but not by public insurance and $pubonly_{it} = 0$ otherwise, and u_{2i} is an error term.

c. Participation in private insurance and public insurance is determined by

$$privpub_{\mathrm{it}} = X_{it}\beta_3 + \gamma_3 elig^*_{it} + u_{3it}, \tag{5}$$

where $privpub_{it} = 1$ if child *i* is covered by both private and public insurance in year *t* and $privpub_{it} = 0$ otherwise, and u_{3i} is an error term.

They consider two measures of eligibility $elig^*_{it}$. One measure is that used in CG and they use $SIMELIG_{it}$ as the instrument for it (as in CG). The second measure is the fraction of children in the family eligible and for the instrument they modify $SIMELIG_{it}$ to capture the generosity of state programs toward families as opposed to a given child of age *a*. Note that the sign of γ_3 is ambiguous since we would expect $elig^*_{it}$ to increase the probability of public insurance but to decrease the probability of private insurance. CS do not give a formula for their crowd out measure, but solving back from their crowd-out estimates it appears that they are using $CO = (\gamma_3 - \gamma_2)/(\gamma_3 + \gamma_1)$ as their crowd-out measure, since a typical set of estimates[21] are γ_1= 0.072 (0.02), γ_2= -0.017 (.020) and γ_3=0.015 (0.01), and thus crowd-out equals $CO = (0.015 + 0.017)/(0.072 + 0.017) = 0.36.$ However, given the large standard errors for the parameter estimates, we expect that the estimated *CO* will have a quite large confidence interval.

Ham, Ozbeklik and Shore-Sheppard (2014b) – Using a Linear Probability Model Where Treatment Effects Depend on Observable Family Differences

One drawback of the CG approach is that it provides no information about which sub-groups have low or high responses to marginal changes in eligibility. To address this issue, Ham, Ozbeklik and Shore-Sheppard (2014b, hereafter HOSb) estimate a linear probability model where the treatment dummy variable is interacted with demographic variables to estimate LATEs for different demographic groups. Their public and private insurance equations are given by

$$pub_{\mathrm{it}} = X_{it}\beta_1 + (elig_{it}X_{it})\theta_1 + u_{1i} = \sum_{k=1}^{K} X_{itk}(\beta_{1k} + \theta_{1k}elig_{it}) + u_{1it} \qquad (6a)$$

and

$$priv_{\mathrm{it}} = X_{it}\beta_2 + (elig_{it}X_{it})\theta_2 + u_{2it} = \sum_{k=1}^{K} X_{itk}(\beta_{2k} + \theta_{2k}elig_{it}) + u_{2it}. \qquad (6b)$$

Finally HS note that, as constructed, CG's use of $SIMELIG_{it}$ will not provide consistent parameter estimates, as there will be correlation between $SIMELIG_{it}$ and the error terms in (1a-1c) for the members of the sample used to create $SIMELIG_{it}$; this problem arises $i)$ because an individual observation will be correlated with $SIMELIG_{it}$ if that individual is used to calculate it and $ii)$ an individual observation will be correlated with $SIMELIG_{it}$ if it is correlated with the

[21] These are for the case where $elig_{it}^{*}$ is measured for the child and not the family.

individuals from the same state that are used to calculate $SIMELIG_{it}$ if observations are correlated within the same state – this assumption is often used to justify clustering standard errors. They propose that researchers use a "jackknife" version of $SIMELIG_{it}$, denoted by $FRACELIG_{it}$, that will produce consistent parameter estimates. Specifically, they use all sample observations of children of a given age in a SIPP wave *except* those from the state for which the instrument is being calculated. Using standard asymptotic arguments it is clear that *ii*) will create more problems than *i*) the fact that HS' standard errors change very little when they move to $FRACELIG_{it}$ instead of $SIMELIG_{it}$ suggests that the correlation across individual error terms in the same state is not a serious issue in this context.

The natural vector of excluded instruments in (3a) and (3b) for the K by 1 vector of endogenous variables $(elig_{it}X_{it})$ is the K by 1 vector $(FRACELIG_{it} * X_{it})$. This model therefore estimates a LATE for each demographic cell in the data, and they use $\hat{\theta}_{1j}$ $(\hat{\theta}_{2j})$ to estimate group *j's* specific LATE's - the effect of eligibility on the Medicaid (private insurance) participation for a marginal person in a given group of individuals with characteristics X_{jt}.[22]

They argue that for means tested programs it is possible to make more use of LATE coefficients than is typically done since one can ascertain who are these marginal individuals within the group using a data set like SIPP. Specifically, a researcher can ascertain who becomes newly eligible in the data for a small change in the Medicaid limits that would correspond to a small change in $FRACELIG_{it}$ because family incomes are observable. For example, one could

[22] In what follows $\hat{\theta}_{1j}$ is our estimate of θ_{1j}, and we define other estimated parameters in an analogous way.

look at which children become eligible when the income limits relevant to their age and state go from 1% below their current value to 1% over their current value.

They further argue that one can use a similar approach to identify the group of children made eligible by a non-marginal expansion of Medicaid, such as a 10% increase in the income limits for each age group in each state—again we can observe which children in the data become newly eligible from this change.[23] Given this, one can do a back-of-the-envelope calculation of the predicted effect on take-up and crowd-out by applying the relevant LATE to the individuals in each group of the newly eligible. Of course, this is only an approximate solution since one is extrapolating the effects for those made marginally eligible within the group to those made eligible in the group by a 10% change. Denote the group of children who become newly eligible as *New*. (In what follows we refer to this group as the newly eligible.) Further denote the children in group *j* who become newly eligible New_j. Then a natural means of approximating take-up among all the newly eligible is

$$TNEW = \sum_{i \in New} [X_i \hat{\beta}_1 + X_i \hat{\theta}_1] / N_{New}, \qquad (7a)$$

where N_{New} is the number of newly eligible. Likewise we approximate the take-up rate among the newly eligible in group k as

$$TNEW_k = \sum_{i \in New_k} [X_i \hat{\beta}_1 + X_i \hat{\theta}_1] / N_{New,k}, \qquad (7b)$$

where $N_{New,k}$ is the number of newly eligible in group k.

The model predicts that private insurance coverage among the newly eligible becomes

[23] We abstract from the possibility that individuals above the new cutoffs may reduce their income so that their children will qualify for Medicaid.

$$PITENEW = \sum_{i \in New} [X_i \hat{\beta}_2 + X_i \hat{\theta}_2] / N_{New}. \tag{8a}$$

In the absence of the non-marginal expansion, these individuals would have had private insurance coverage given by

$$PITNENEW = \sum_{i \in New} [X_i \hat{\beta}_2] / N_{New}. \tag{8b}$$

Thus the model predicts crowd-out among all of the newly eligible as

$$CNEW = -\sum_{i \in New} [X_i \hat{\theta}_2] / N_{New}. \tag{8c}$$

Crowd-out estimates for those in group k can be estimated in similar fashion to how $TNEW_k$ is estimated and we omit them for expositional ease. We refer to this is as a back of an envelope calculation since it accounts for observable, but not unobservable, differences between the marginal individuals in each cell and those made eligible by a non-marginal expansion of Medicaid.

There is one further caveat. In many datasets, including the one we use below, there may not be enough observations to include dummy variables for each demographic cell. Instead, we have to settle for controlling for the effect of demographic variables without fully interacting them. Thus, we will only be able to control approximately for differences in observables across individuals.

HOSb use data from the 1986-1993 SIPP panels, and find a great deal of variation across demographic groups in their LATE estimates of the effect of being eligible for Medicaid take-up from the LPMI. Specifically, their LATE estimates for take-up range from 6 percent for children in the families where both parents are present to 44 percent for children in families without any earners. There are also large differences across demographic groups in terms of their back of the envelope calculations on the effect of a 10% increase in Medicaid; among the newly eligible, observably less disadvantaged children have substantially lower estimated rates of enrolling in the Medicaid.

Their estimated LATEs for the effect of becoming Medicaid eligible on private insurance coverage (i.e. crowd-out coefficients) provide little evidence of crowd-out among many demographic groups. Among the groups showing any crowd-out (that is, a negative effect statistically distinguishable from zero), the estimates range from 2 percent for children in families with one earner to 12 percent for children in families with a male head. Their crowd-out estimates are small, and while only about half are statistically significant, the standard errors indicate that the crowd-out effects have narrow confidence intervals. Although there is some evidence that crowd-out rates are higher for groups that have higher levels of private insurance coverage (children in families where the highest earner has some college or is a high school graduate exhibit higher levels of crowding out than children in families where the highest earner does not have a high school degree, for example), this explanation is clearly not the only one, as crowd-out rates are generally highest (though still small) among groups with the largest take-up responses.

Ham, Ozbeklik and Shore-Sheppard (2014a) Using a Switching Probit Model as Direct Alternative to the CG Approach

The Cutler-Gruber approach, and its extension using the LPMI, are attractive to researchers because they are easy to estimate and interpret. However, this approach does have several drawbacks. First, it allows for a non-zero probability of participating in Medicaid even if a child is ineligible for Medicaid. Second, there is no underlying theoretical model used to justify it. Third, its use for predicting the effect of nonmarginal policy changes is an approximation at best. Ham, Ozbeklik and Shore-Sheppard (2014a, hereafter HOSa) offer an alternative to the CG approach which addresses all of these problems at the cost of a substantial increase in computational difficulty. Here we start with their theoretical model. HOSa's model differs from previous theoretical work on health insurance since the goal is to obtain a guide for the empirical work rather than to obtain theoretical results *per se*. For simplicity, consider a family with one child, and when the child is eligible for Medicaid, denote the family as "eligible."[24]

Consider first an *ineligible* family with fixed income[25] I_i, whose decision focuses on whether to purchase private insurance at a cost $C_{pr,i}$. Assume that the family's utility is given by

$$U_i(D_{pr,i}) = I_i - C_{pr,i}D_{pr,i} + B_{pr,i}D_{pr,i}, \tag{9}$$

where $D_{pr,i} = 1$ if they purchase private insurance and $D_{pr,i} = 0$ otherwise; hence the direct gross utility produced from having private insurance is $B_{pr,i}$. Utility maximization implies that the family will purchase private insurance if the utility from having this insurance is greater than the utility from not having it, or

$$B_{pr,i} - C_{pr,i} > 0. \tag{10}$$

HOSa first consider an *eligible* family and assume that participating in Medicaid implies stigma and fixed costs of $C_{pub,i}$ in monetary terms. HOS first investigate the case where such a family's utility is given by

$$U_i(D_{pr,i}, D_{pub,i}) = I_i - C_{pr,i}D_{pr,i} - C_{pub,i}D_{pub,i} + B_{pr,i}D_{pr,i} + B_{pub,i}D_{pub,i}, \tag{11}$$

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[24] The one child assumption greatly simplifies the analysis without obscuring the basic message.
[25] In what follows we drop the t subscript for expositional ease.

where $I_i, D_{pr,i}, C_{pr,i}$ and $B_{pr,i}$ are defined above, $B_{pub,i}$ is the direct gross utility produced from having public insurance, $D_{pub,i} = 1$ if the family participates in Medicaid and $D_{pub,i} = 0$ otherwise.[26] However, they show that this model is not capable of producing crowd-out as eligible and ineligible families have the same decision rule for purchasing private insurance, while the whole point of the crowd-out literature is to emphasize the substitution possibilities between public and private insurance.

To incorporate crowd-out, HOSa then specify family preferences for an *eligible* family as

$$U_i(D_{pr,i}, D_{pub,i}) = I_i - C_{pr,i}D_{pr,i} - C_{pub,i}D_{pub,i} + B_{pr,i}D_{pr,i} + B_{pub,i}D_{pub,i} + INT_i\{D_{pr,i} * D_{pub,i}\}, \quad (12)$$

where INT_i represents the interaction effect on utility of having both types of insurance. If there is crowd-out, then INT_i will be negative. However, public and private insurance may also be complements (such as is the case with private insurance and Medicare) for some families, and thus INT_i can be positive. Allowing for interaction effects will not change the optimality conditions for ineligible families but will do so for eligible families.

HOSa show that the eligible family's optimization problem leads to a quite complicated econometric model, since insurance choice is determined by three conditions, which produces an econometric model where one must carry out trivariate normal integration and hence is unlikely to appeal to many applied researchers. However they also argue that the economic model can be approximated well by the following more tractable switching probit econometric model (SPM):

A child of age a in state s will qualify for Medicaid if the family income I_i is below the Medicaid income limit L_{as} or if

[26] Assume $I_i > C_{pr,i}$ for both eligible and ineligible families.

$$L_{as} - I_i > 0. \tag{13}$$

Following the existing literature, they write the rule determining if a child is eligible for Medicaid as

$$elig_i^* = L_{ast} - I_i = Z_i\delta + e_i \geq 0, \tag{14}$$

where as above $Z_i = (X_i, FRACELIG_i)$.[27]

They assume that family randomly made ineligible for Medicaid obtains private insurance coverage for its child if

$$Priv\_nelig_i^* = X_i\gamma_{ne} + u_{ne,i} > 0, \tag{15}$$

while a family randomly made eligible for Medicaid obtains private insurance coverage for its child if

$$Priv\_elig_i^* = X_i\gamma_e + u_{e,i} > 0. \tag{16}$$

Finally, they assume that a family randomly made eligible for Medicaid obtains public insurance coverage for its child if

$$Pub_i^* = X_i\mu + \varepsilon_i > 0. \tag{17}$$

They assume the error terms follow a multivariate normal distribution. The model is identified (other than by functional form) because $FRACELIG_i$ enters the eligibility index function but not the insurance coverage index functions.

HOSa then construct a likelihood function for this model. Noting that it involves bivariate integration and that no preexisting software to estimate the model is available in Stata, they offer an alternative scheme Minimum Distance which involves only linear transformations of

[27] Note that they could have used the income limits directly, but chose to follow the literature and use $FRACELIG_i$ instead. They make use of (12) and the income limits in their policy experiments

parameter estimates that are available suing Stata, and is roughly as efficient as full maximum likelihood. They also consider a version of the model where the variance-covariance matrix of the error terms is diagonal. Denote the model described above as the model with selection, and the model with the diagonal variance covariance matrix as the model without selection. There two main differences between these models and the LPMI model discussed in the previous section. First is that in the former children can only be covered by Medicaid if they are indeed eligible for it, while the LPMI the model attaches a non-zero probability of obtaining Medicaid coverage. Secondly, the model with selection can account for unobservable differences across families in counter-factual policy experiments, while the model without selection and the LPMI can only account for observable differences.

In terms of the latter, HOSa provide expressions for the models' (with and without selection) predictions for: *i*) the level of actual level of public insurance and private insurance for the entire sample and demographic groups in 1995; *ii*), crowd-out for the entire sample and demographic groups in 1995 - to the best of our knowledge, crowd-out effects have not been calculated previously for the currently eligible; and *iii*) public insurance, private insurance and crowd-out for those made eligible by a 10% increase in the 1995 Medicaid limits. In carrying out the simulations we make use of the fact that we know who is currently/who becomes eligible which, to the best of our knowledge, is again new to the program evaluation literature.

HOSa use data from the 1986-1993 SIPP panels, and the predicted take-up rates from both SPM models are highly statistically significant and have relatively narrow confidence intervals. While these predicted rates are qualitatively similar across the models, estimates accounting for selection are 2 to 5 percentage points higher; this occurs because they take into account the fact (as indicated by our parameter estimates) that those who are eligible for

Medicaid have unobservable characteristics that make them more likely to take up Medicaid. They then compare these predicted take-up rates to the *actual* take-up rates for the whole sample and the different demographic groups, again using only the 1995 data. They find that the estimates that account for selection match the data remarkably well.

The average Medicaid take-up rates range from 0.12 for children from families with more than two earners to 0.79 for children from families with no earners. The estimates show a clear pattern: eligible children from traditionally disadvantaged groups take up Medicaid at a higher rate than eligible children from typically less disadvantaged groups. For example, eligible white children have a take-up rate of 0.44 while the take-up rate for nonwhite children is fifty percent larger.[28] The estimated take-up rate for children in families in which the family head has less than a high school degree is 0.63, while it is 0.16 for children in families in which the family head has a college degree or more. Moreover, the estimated take-up rate for an eligible child from a family in which a female is a single head is 0.71, while it is only 0.30 for a child from a two-parent family. Thus traditionally welfare-ineligible populations have dramatically lower responses to Medicaid eligibility than do the traditionally welfare-eligible.

The predicted private insurance coverage rates are precisely estimated, and the model with selection predicts the actual data quite well, while the model without selection consistently overshoots the actual level of coverage; this is consistent with a model where the Medicaid eligible have unobservables that make them less likely to obtain private coverage. The private

[28] This reflects both the fact that nonwhites are more likely to take up Medicaid conditional on the other explanatory variables (see the parameter estimates in the online Appendix table), and that their values for the other explanatory variables make them more likely to participate in Medicaid.

insurance coverage rates vary widely across groups. For example, the demographic group with the lowest private insurance coverage for all the model specifications is children from families without any earner, as their private insurancte coverage rate is 0.12 when accounting for selection and 0.15 with selection ignored.

The estimated crowd-out estimates for the currently eligible are generally bigger, and more statistically significant, for the SPM model with selection and thus we focus on these estimates. Interestingly we estimate about 5% crowd-out for the entire sample, with the take-up rate for the entire sample 51%.[29] The vast majority of the crowd-out effects for the different demographic groups are statistically distinguishable from zero and negative, indicating that private and public insurance are indeed substitutes, although the degree of substitution is quite small: the estimates range from -2.6% to 8.6%. Within this range the size of crowd-out for a group appears unrelated to the private insurance coverage of the group.

In terms of the predicted effects of our estimated counterfactual increase in the Medicaid income limits by 10 percent, both SPM models produce coefficients that are statistically significant and precisely estimated. Again the estimates from the SPM model with selection are again larger than those from the model without selection. The overall levels for the newly eligible are lower (26.2%) than those for those actually eligible in 1995 (51%). This result is consistent with the economic model above since we would expect the transactions costs of applying for Medicaid are likely to be higher for the newly eligible group.

Again there are considerable differences across groups of the newly eligible in their take-up of Medicaid, although these are not as large as for the currently eligible. Further, once more the observably less disadvantaged children have substantially lower estimated rates of enrolling

[29] This suggests a crowd-out rate of about 10% using the original CG measure.

in the Medicaid program for which they are eligible, even though such children were the intended beneficiaries of the expansions. The variation across groups in response to a nonmarginal expansion is still considerable, although it is less than the variation among the currently eligible.

In terms of crowd-out, we focus on the estimates from the model with selection. For the entire sample of those made newly eligible, they find a strongly significant crowd-out effect of 8% as opposed to about 5% among the currently eligible. Among the many groups with crowd-out effects statistically distinguishable from 0, estimated crowd-out rates range from 3.0% to 11.0%. For each demographic group, the crowd-out effects are larger for the newly eligible than the currently eligible; *a prioiri* the predicted effect is ambiguous since these families are likely to face a lower cost of private insurance (through employer insurance) which can offset the likely lower valuation of Medicaid services by these families.

Group 2 Papers - Children

Dave, Decker, Kaestner, Simon: The Effect of Medicaid Expansions in the Late 1980s and Early 1990s on the Labor Supply of Pregnant Women

The authors investigate the effect of medicaid coverage for pregnant single mothers not on welfare arising from the 1996 welfare reform. The authors first present a theoretical model where they present the pregnant woman's problem. They maximize expected utility by selecting consumption and leisure, while taking into consideration that there is a probability that working can negatively affect child health. The authors argue that for women who initially had employer provided health coverage, they may be able to increase their wages by switching to Medicaid since the employer no longer needs to finance private health insurance. As noted above, a higher wage will unambiguously increase participation, but may increase or decrease hours worked depending on the strength of the substitution effect versus the income effect.

In their empirical work, they use CPS data for the years 1986-1997 and estimate the following equation

$$L_{ijt} = \alpha_j + \beta_t + \delta SIMELIG_{jt} + X_i\Gamma + Z_{jt}\lambda + u_{ijt} \tag{18}$$

for five outcomes during the year a woman gives birth: 1) employment; 2) labor force participation; 3) weeks worked; 4) usual hours worked per week and 5) wage and salary income. In outcome 3) they include those working 0 hours, while for outcomes 4) and 5) they estimate (18) with and without the zero hour individuals included; j denotes state. Note that this is a reduced-form regression, since if they had followed the literature on insurance take-up they would have estimated $\tilde{\delta}$ from

$$L_{ijt} = \tilde{\alpha}_j + \tilde{\beta}_t + \tilde{\delta} ELIG_{jt} + X_i\tilde{\Gamma} + Z_{jt}\lambda + e_{ijt}$$

$$ELIG_{kjt} = \gamma_{0j} + \gamma_{1t} + \gamma_2 SIMELIG_{kjt} + X_i\gamma_3 + Z_{jt}\gamma_{4j} + v_{ijkt}$$

On the other hand, the reduced form (18) shows the coefficient on a variable that policy makers can control, albeit indirectly, $SIMELIG_{jt}$. However, one would need to use a large number of simulations to calculate $SIMELIG_{jt}$ to eliminate simulation error which will act like measurement error and make their estimate of δ; one can also avoid this problem by using the income limits directly. They find that a 20 percent increase in $SIMELIG_{kjt}$ leads to a 6-7 percent decrease in the probability that a woman who gave birth within the past year was employed. The response was greater for uneducated women, who had a 13-14 percent decrease in their employment probability from this change in $SIMELIG_{kjt}$. The effects on the all the labor market outcomes are given below.

	Employed Last year, no state time trend	Employed Last year, state time trend	Lab Force Participation, no state time trend	Lab Force Participation, state time trend	Weeks Worked, no state time trend	Weeks Worked, state time trend
Coeff	-0.2214	-0.2054	-0.2035	-0.1796	-0.399	-0.3384
S.E.	0.0656	0.0697	0.0532	0.0586	0.2195	0.2335

Usual Weekly Hours, no state time trend	Usual Weekly Hours, state time trend	Usual Weekly Hours, no state time trend | > 0 Hours	Usual Weekly Hours, state time trend | > 0 Hours	Log Wages, no state time trend	Log Wages, state time trend	Log Wages, no state time trend | > 0 Hours	Log Wages, state time trend | > 0 Hours
-0.5225	-0.5108	-0.0801	-0.1182	-2.5799	-2.6247	-0.2499	-0.4208
0.1782	0.2062	0.0559	0.0572	0.7888	0.818	0.1867	0.2162

Hudson, Selden and Banthin: The Impact of SCHIP on Insurance Coverage of Children

The authors investigate how the eligibility expansions for SCHIP influence the take up of public and private insurance, using both IV and diff-in-diff strategies. The authors use the Medical Expenditure Panel Survey to assess the impact of eligibility expansions between 1996 and 2002. on changes in childrens' health insurance status. Their IV strategy is identical to Cutler and Gruber's model (1a)-(1c) above. . Following Cutler and Gruber, they estimate crowd out by taking the ratio of the eligibility coefficient in the private equation to the eligibility coefficient in the public equation $-\frac{\beta_E^{Private}}{\beta_E^{Public}}$.

They also propose an alternative to solve the endogeneity issue by using a quuasi-experimental difference in difference framework:

$$Y_{itk} = \beta_{0k} + \beta_{1k} treatment_{it} + \beta_{2k} post_{it} + \beta_{3k} treatment_{it} * post_{1t} + \beta_{Zk} Z_{it} + \varepsilon_{itk}, \quad \text{k=pub, priv.} \qquad (19)$$

They define the dependent variables the same way, and they define $treatment_{it} = 1$ for the individuals who are eligible in 2002, but would not have been in 1996, and zero otherwise. Further, $post_{it} = 1$ for 2002 and zero otherwise. Of course the identifying assumption is that trends for those in the treatment group are the same as those in the control group. They estimate crowd out by $\beta_{3priv} / \beta_{3pub}$. The authors conclude that SCHIP had a significant impact in decreasing uninsurance and increasing public insurance for both children targeted by SCHIP and those eligible for Medicaid. However, for private coverage, the results are less conclusive, and were dependent on the empirical specification. Estimates of SCHIP crowd-out had, as usual, wide confidence intervals and were sensitive to the estimation strategy.

Difference-in-Difference Estimates

	Treatment: Children targeted by expansions			Treatment: Children targeted by Poverty related expansions		
	beta_public	beta_private	Crowd Out	beta_public	beta_private	Crowd Out
Control: Never eligible children (300-500% FPL)	0.089 (0.02)	-0.05 (0.023)	0.557 (0.214)	0.083 (0.028)	-0.024 (0.028)	0.290 (0.379)
Control: Married Childless Women (300-500% FPL)	0.109 (0.019)	-0.051 (0.073)	0.462 (0.241)	0.111 (0.03)	-0.027 (0.029)	0.246 (0.254)

Note: standard errors in parentheses.

IV Estimates

	beta_public	beta_private	Crowd Out
1996-2002	.265* (.027)	-0.14 (0.031)	.527* (.107)
1996-1997 and 2000-2002,	.242* (.029)	-0.102 (0.033)	.421* (.126)

Note: standard errors in parentheses.

Notice the crowd-out estimates are generally significant here; to the best of our knowledge these are the only ones in the literature that are significant. Using the delta method as described above to calculate the standard error of the crowd-out estimate, we find that only the 1996-2002 IV crowd-out estimate is significant. They use a block bootstrap method for calculating the crowd-out standard errors which should produce consistent estimates of the standard errors. Thus it is something of a puzzle why the two methods produce such different standard errors for the crowd out effect.

Gresenz, Edgington, Laugesen, Escarce: Take-up of Public Insurance and Crowd out of Private Insurance under Recent CHIP Expansions to Higher Income Children

The authors analyze the effects of states expansions of Childrens' Health Insurance Program (S-CHIP) eligibility to children in higher income families on health insurance coverage outcomes. Using CPS data from 2002-2009, they ran the following empirical model:

$$Y_{itk} = \beta_{0k} + \beta_{1k} CHIPELIG_{it} + \alpha_k X_{it} + \varepsilon_{it}, \quad \text{k=pub, priv, none.} \qquad (20)$$

In (20) CHIPELIG is the eligibility for the child, which is continuous (sorry for the messup – they did not have an equation in their paper) and determined by state rules for demographic characteristics. They acknowledge that $CHIPELIG_{it}$ is endogenous, and they use the Cutler

Gruber instrument deal with this.) The authors find for the cohort of children whose families earned two to four times the federal poverty line,

Per 100 Children Who Become Eligible	
Number enroll Public4.21	4.21***
Number drop Private	0.14
Number from uninsured to insured	2.26***

Note: Statistically significant at the 1% level

In other words, four out of every 100 children who became eligible enrolled in S-CHIP. On the other hand, they find only a tiny and insignificant effect of S-CHIP on private insurance, and as a result the standard Cutler-Gruber measure of crowd-out is also tiny.

Busch and Duchovny: Family coverage expansions: Impact on insurance coverage and health care utilization of parents

The authors evaluate how medicaid eligibility can influence the take up of public insurance, private insurance, and any insurance through the implementation of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA). They estimate

$$Coverage_{itk} = X_{it}\beta_{1k} + \beta_{2k}Elig_{it} + \delta_{sk}State_s + \delta_{tk}year_t + \varepsilon_{itk}, \quad \text{k=pub, priv, none,} \qquad (20)$$

where they treat $Elig_{it}$ as endogenous, using the Cutler Gruber IV. Their estimates (standard errors) of the respective β_{2k} coefficients are

	Medicaid	Private	Uninsured
	0.148**	−0.035	−0.113**
Low income sample	(0.034)	(0.027)	(0.032)

They then look at how this influences health utilization - specifically cancer screenings. They find that there was a 29% increase in cancer screenings for previously uninsured mothers. They conclude that the expansions decreased the likelihood that a parent needed to see a doctor but did not do so because of cost.

Wolfe, Kaplan, Haveman, Chod: SCHIP expansion and parental coverage: An evaluation of Wisconsin's BadgerCare

The authors wanted to evaluate how BadgerCare (Wisconsin) influenced the probability of acquiring public health care coverage for mother only families. BadgerCare took effect during 1999, and was created to provide health care to people in Wiscoisin whose employers did not provide it but who made too much money to be covered by Medicaid. It was later expanded in 2008 so that all children have health care. The authors use administrative data (CARES, CRN). They first consider a probit model

$$\Pr(y_{it} = 1 | x_{it}\, Q_t\, Q_t^2\, BC_t) = \Phi\left(\beta x_{it} + \alpha_0 Q_t + \alpha_1 Q_t^2 + \alpha_2 BC_t\right), \tag{21}$$

where BC_t=1 if Badgercare has been implemented and 0 otherwise. The second model is a difference in difference model, where they compare the trends in public health coverage pattern (8 quarters after leaving welfare) of the people who are part of the 1997 cohort, when the BadgerCare program provides coverage relative to the 1995 cohort (for whom the program did not exist.)

The authors argue the difference in difference approach is the most appropriate, since they are better able to handle for unobserved heterogeneity the best in this model. However note that controlling for heterogeneity here affects the standard errors but not the consistency of the estimates, since BC_t is determined solely by calendar time. They conclude that the program led to a 17-25 percent increase in public health insurance.

DelaMata: The Effect Of Medicaid Eligibility On Coverage, Utilization, And Children's Health

DelaMata uses a regression discontinuity design to measure the impact of medicaid eligibility on take-up and health outcomes. The authors find that medicaid eligibility increases take up by 10-13 percent on average, with 24-29 percent increase for the lower income eligibility thresholds.

They say they find no significant effects on health outcomes in the short or medium run. They measure short and medium by contemporaneous health, one year after, and five years after. The health outcomes they analyzed are obesity, number of days missed due to illness, and self-reported "Excellent health". They find no significance at the 5% level for the tightest bandwidths for any of the polynomials.

The data used are the PSID. Their empirical specification is

$$y_{it} = \pi_0 + \pi_1 Eli_{it} + k_g\left(z_{it}\right) + k_g\left(z_{it}\right) * Eli_{it} + \pi_2 x_{it} + s_j + \gamma_t + v_{it} \tag{22}$$

The sample used consists of people just below and above the eligibility threshold. The outcomes of interest are public coverage and health outcomes. The Eli_{it} variable is a dummy that takes on a value of one if the agent is above the threshold, and 0 otherwise. The z_{it} variable represents the distance from the threshold while the $k_g\left(z_{it}\right)$ represent a polynomial of order g. The s_j are state fixed effects, γ_t are year fixed effects. x_{it} represents other covariates.

The coefficient of interest is π_1. The authors find that medicaid eligibility increases take up by 10-13 percent on average, with 24-29 percent increase for the lower income eligibility thresholds.

They next consider health outcomes and find no significant effects on health outcomes in the short or medium run. They measure short and medium by contemporaneous health, one year after, and five years after. The health outcomes they analyzed are obesity, number of days missed due to illness, and self-reported “Excellent health”.

Not covered this draft

Card & Shore-Sheppard (2004),

LoSasso & Buchmueller (2004),

Ham, Li and Shore-Sheppard (2009)

Shore-Sheppard (2008)

2. Adults

Group 1 Papers – Adults

Finkelstein et al(2012) – The Oregon Health Experiment: Evidence from the First Year

Here we focus on two studies where there was a change in Medicaid coverage for childless adults; up until now such coverage has been quite rate but will become widespread under the Affordable Care Act. Finkelstein et al (2012) uses data from a randomized trial in Oregon in 2008. In this case a randomly chosen (via a lottery) treatment group of childless adults were made eligible for Medicaid coverage. This study looks at a multitude of outcomes, most of which we discuss in other sections. In this section we simply consider treatment effect (ITT) the take-up and crowd-out of those in the treatment group. One issue is that it is not clear how the Oregon results will generalize the rest of the country simply because the Great Recession started in 2008 and Oregon’s unemployment rate rose from 6.5% in 2008 to 11.1% in 2009. Of course a randomized trial attains the gold standard of program evaluation, and at the least the experiment informs us about crowd-out and take-up during a recession.

For our purposes the estimates of interest are their first stage equations in Table III of the form

$$PUB_i = \beta_{01} + \beta_{11} LOTTERY_h + X_{ih}\beta_{21} + V_{ih}\beta_{31} + \varepsilon_{i1}, \qquad (18)$$

$$PRIV_i = \beta_{02} + \beta_{12} LOTTERY_h + X_{ih}\beta_{22} + V_{ih}\beta_{32} + \varepsilon_{i2}, \qquad (19)$$

where i denotes individual, h denotes household, $LOTTERY_h = 1$ if household h won the lottery and zero otherwise, X_{ih} are a set of explanatory variables potentially correlated with the probability of treatment and included to avoid bias in β_{1j}, j=1,2, V_{ih} are a set of explanatory variables that are included to increase efficiency but are not need to avoid bias in β_{1j}, the outcomes. Further,

$Pub_i = 1$ if the individual was covered by public insurance and zero otherwise, $\mathrm{Priv}_i = 1$ if the individual was covered by private insurance and zero otherwise Their estimates (standard errors) for take-up and crowd-out are β_{11} = 0.191 (0.006) and β_{12} = -0.0076 (.0053). Thus they find moderate take-up and no significant crowd-out effect; moreover, their crowd-out effect has a very small confidence interval of [-,0.003, 0.0183].

Garthwaite, Gross, and Notowidigdo (2014) – Using the Elimination of Medicaid in 2005 for Tennessee Childless Adults to Measure Crowd-out and Take-up.

Garthwaite, Gross, and Notowidigdo (2014, hereafter GGN) exploit a natural experiment where 170,000 childless adults in Tennessee lost their Medicaid coverage in 2005 to consider many effects which we also discuss below; here we focus on their results for crowd-out and take-up. They consider the following regressions at the state level

$$MED_{st} = \alpha_s + \delta_t + \gamma_2 I[s = TN] * \mathrm{I}[\mathrm{t} \geq 2006] + \varepsilon_{st}$$
$$= \alpha_s + \delta_t + \beta TN06_{st} + \varepsilon_{st}, \tag{20a}$$

$$PRIV_{st} = \alpha_s + \delta_t + \gamma_2 I[s = TN] * \mathrm{I}[\mathrm{t} \geq 2006] + \varepsilon_{st}$$
$$= \alpha_s + \delta_t + \beta TN06_{st} + \varepsilon_{st}. \tag{20b}$$

In (20a-20b) MED_{st} is fraction of the adult population (individuals ages 21 and 64 who are not in the armed forces and who do not have advanced college degrees) in stats *s* and year *t* with Medicaid coverage, $PRIV_{st}$ is fraction of the adult population in stats *s* and year *t* with private insurance coverage, the α_s represent state dummies and the δ_t represent state dummies. They estimate (2a) and (2b) using two estimation strategies. First they use a double difference strategy where they compare Tennessee adults to adults in other Southern states. Secondly they use a triple difference strategy where they compare Tennessee adults without children to Tennessee adults with children.

From their Table V, the difference in difference estimates (standard errors) are $\hat{\gamma}_1$ = -0.046 (0.010) and $\hat{\gamma}_2$ = 0.017 (0.012). (Note that the signs are reversed from the usual case since they are investigating the effect of a Medicaid contraction instead of a Medicaid expansion.) We would interpret these results as showing no significant crowd out with a tight 95% confidence interval of [0.041, -0.007]. However, Garthwaite et al use the CG measure, but unlike most studies, they also report a standard error for this measure. The CG crowd-out estimate is 0.36 with a standard error of 0.27 implying a 95% confidence for the CG measure of [-0.17,0.89], which we would argue is not very informative.

Their triple difference strategy produces estimates (standard errors) of $\hat{\gamma}_1$ = - 0.071 (0.017) and $\hat{\gamma}_2$ = 0.043 (0.024) We would interpret these results as showing moderately significant crowd effects out with a confidence interval of (-0.004, -0.0086). However, the CG measure is 0.36 with a standard error of 0.27 implying a 95% confidence interval of [-0.17,0.89]

Group 2 Papers – Adults

Atherly, Dowd, Coulam, Guy: The Effect of HIFA Waiver Expansions on Uninsurance Rates in Adult Populations

The authors wanted to analyze the effects of the Health Insurance Flexibility and Accountability (HIFA) demonstrations on the rate of uninsured. The authors use the CPS, and use the following empirical approach to analyze the problem:

$$Y_{ijt} = X_{ijt}\beta + \beta_T T_{ij} + \beta_P P_{ijt} + \beta_I T_{ij} P_{ijt} + u_j + u_{ijt} \qquad (26)$$

. The above was estimated via a probit model, and they present the marginal effects. The dependent variable is if individual i is insured within time t and state j. T represents treatment, X represent other control variables, P is the post implementation dummy for a diff-in-diff, and u_j are state fixed effects. β_I is the coefficient of interest. Treatment is defined as binary, and equals one for the individuals in HIFA target population in each HIFA state and zero otherwise. The control group consists of individuals lying just above the income eligibility limits of the target population in each HIFA state. The authors define Arizona, Illinois, Michigan, Maine, New Mexico, and Oregon as HIFA states, since these states implemented long-term, large-scale programs whose potential effects could be detected in their national datasets. They do not use an IV strategy, perhaps because consistent estimation of (22) in this case is much more difficult when one uses a probit equation than a linear probability model. The authors conclude HIFA increased the rate of insurance coverage by 6.4 percentage points on average in the targeted adult population.

3. The Impact of Other Policies Affecting Enrollment for Families

Along with changes in eligibility policy, states have implemented many other policies that have implications for take-up of the program. Some of these policies are intended to affect take-up, such as administrative reforms to make enrollment easier (presumptive eligibility, offering continuous coverage, or simplifying the application and renewal processes, for example) or outreach to encourage take-up. Other policies are intended to achieve other goals for the Medicaid program and have spillover effects on enrollment, such as the introduction of premiums, the implementation of eligibility for parents at higher income levels, or changes in physician fees. Still other policies are not particularly targeting Medicaid but have spillover effects anyway, such as immigration enforcement or citizenship requirements.

One concern about public health insurance expansions is that eligible individuals may be unaware that they are eligible. Consequently, some states implemented information provision or outreach campaigns. An important paper on the effectiveness of outreach is Aizer (2007). Aizer uses new data on Medicaid enrollment outreach efforts from California to address two questions: 1) how successful are various types of outreach efforts at encouraging new enrollment? and 2) what impact does this new enrollment have on ambulatory-care-sensitive hospital admissions? (The second question is discussed below in the section on utilization of care.) Outreach includes community-based application assistants (organizations trained in enrolling eligible individuals--CBOs) and a state advertising campaign. Aizer obtained data on CBO placement and administrative data on new Medicaid enrollment by ZIP code, race, and month for February 1996 to December 2000 among all children age 0 to 15. Collapsing the data to zip code-year-month-race cells, she examines the impact on enrollment of the number of CBOs in a ZIP code controlling for ZIP code and time fixed effects to account for the fact that areas with more intense outreach efforts may have higher numbers of low-income children, and to control for general trends in enrollment over this time period, respectively. She also includes other covariates that control for changes in the business cycle and in the underlying demographic composition of the state that may affect the demand for health insurance. She finds significant effects of CBOs, especially for Hispanic and Asian children. The estimates suggest that an additional Spanish-language CBO increases total new monthly Medicaid enrollment for Hispanic children by 9%, while an additional Asian-language CBO increases enrollment by 27% among Asian children. While there is some evidence of selection in where CBOs are placed, the selection effects appear negative (CBOs were placed where enrollment was falling). She finds larger effects when the CBO is also a healthcare provider. She also looks at advertising, including Spanish and English language TV ads, using a similar approach and finds that any effect of advertising is likely small. Thus information provision is important for enrollment, but targeted information provision and information provision accompanying the ability to provide services are more effective than a general information campaign.

In addition to outreach, as eligibility limits were raised the federal government began allowing states to implement a variety of policies intended to increase enrollment among the eligible. These policies included allowing applicants to apply in different places and with simpler processes. Currie and Grogger (2002) examine whether such policies were correlated with Medicaid caseloads at the state level for the period 1990-1996 and find no statistically significant relationship. However when they examine vital statistics data on births they find some evidence that shorter forms or being allowed to mail in forms instead of having to apply in person is associated with earlier initiation of prenatal care. Outstationing of eligibility workers is associated with inadequate prenatal care, however, suggesting that there may be omitted variables correlated with which states choose a particular policy.

A potential concern about increasing take-up for policymakers is that it may come at the cost of private coverage crowd-out, so under the CHIP program states were encouraged or required to implement policies to reduce crowd-out, such as mandatory waiting periods for previously insured children. Wolfe and Scrivner (2005) investigate state policy design features under CHIP using data from the 2000-2001 CPS. They find that waiting periods reduce public insurance take-up and increase the probability of being uninsured, but they find little effect for the other variables, perhaps because there is relatively little variation in state policies over such a short time period. Bansak and Raphael (2006) compare insurance outcomes in 2001 to outcomes in 1997, just before CHIP implementation. To estimate the differential effect of state policy choices, they estimate regressions in which program design variables are interacted with an indicator variable that differentiates the pre-CHIP and post-CHIP periods. They estimate the models with state fixed effects to account for unobserved state characteristics that may be correlated with both baseline levels of insurance coverage and program features. They also find that waiting periods designed to prevent crowd-out reduce the probability a child has public insurance, and their results suggest that policies allowing for continuous enrollment increase public coverage.

Another policy that was at least partly intended to dissuade crowd-out but was also a way to cover rising state spending on public health insurance was the adoption of premiums for higher income individuals. While Medicaid generally does not permit substantial amounts of cost-sharing (unless a state has obtained a waiver to do so), states have more flexibility with

CHIP, and during the early 2000s several states adopted premiums. Kenney et al. (2006) examine state administrative enrollment records from 2001 to 2004-2005 from three states (Kansas, Kentucky, and New Hampshire) and find that increases in premiums were associated with lower caseloads in all three states and with earlier disenrollment in Kentucky and New Hampshire. They find greater disenrollment with increased premiums for lower-income children in New Hampshire and for nonwhite children in Kentucky. Similarly, Marton (2007) finds that the introduction of premiums in Kentucky reduced enrollment duration in the premium-paying category but not in the non-premium-paying category, with larger effects in the first three months after the premium was introduced. Dague (2014) uses a regression discontinuity design to study the introduction of premiums in Wisconsin's Medicaid program. Premiums in Wisconsin's program increase with income, with sharp breaks in the level of the premium at various income levels. While regression discontinuity designs with income can be problematic, as discussed above, in this case the administrative data that Dague uses permits her to observe the state's exact determination of family income, which is initially self-reported by applicants but is verified either through documentation such as paycheck stubs or direct employer verification. One issue with the administrative data that she faces is that she only observes outcomes for enrollees, however she shows that in the case of studying the impact of premiums on enrollment spell length, selection would bias her against finding an effect. Interestingly, she finds large behavioral responses to the introduction of a relatively small premium, with a $10 premium requirement making enrollees 12–15 percentage points more likely to exit the program, but she finds very little evidence of responses to *changes* in premiums of a similar magnitude. This suggests that it is the premium *per se*, rather than its amount, that affects individual enrollment behavior.

There are two other policies that states may pursue that could have implications for enrollment in the program. First, the implementation of eligibility for parents at higher income levels than the AFDC level may encourage enrollment of children since the marginal benefit from completing the enrollment process would be higher if more individuals in the family could gain eligibility. The difficulty in examining the impact of parental eligibility expansions on their children is in finding variation in parental enrollment that is uncorrelated with unobserved factors determining child enrollment. Sommers (2006) uses the March CPS matched across years, focusing on loss of coverage among children who appeared eligible in both years and modeling the probability of drop-out (loss of coverage while still eligible) as a function of parental and/or sibling coverage in year 1. He uses eligibility of the parent or sibling as an instrument for parent/sibling coverage. However, elsewhere in the literature researchers have recognized that eligibility may be endogenous, since unobserved factors that are more likely to make a parent eligible may also affect coverage. Sommers tries to circumvent this issue by controlling for income, although the exogeneity of income is also questionable. He finds that if a parent is covered, the child is more likely not to drop Medicaid, but there is no statistically significant effect of sibling being covered. Second, changes in physician fees may be associated with participation if, for example, raising fees leads to greater physician participation and individuals are more likely to enroll when they believe they can obtain needed care. Indeed, Hahn (2013) estimates models of the probability of various types of coverage as a function of the ratio of Medicaid to Medicare fees and controlling for state and year fixed effects and finds that a 10 percentage point increase in the ratio is associated with a 1.24 percentage point decrease in the uninsured rate among low-income children.

Finally, it is possible that policies not particularly aimed at Medicaid may have spillover effects on Medicaid participation. Using newly obtained data on immigration enforcement activity (number of deportable aliens located per noncitizen) in the 1990s across the 33 Immigration and Naturalization Service administrative districts, Watson (2014) estimates the impact of enforcement activity on children of noncitizens. Controlling for a number of possible confounding effects with a rich set of fixed effects and demographic variables, she finds that a one log point increase in enforcement efforts (about the size of the increase in enforcement between 1994 and 2000) reduces Medicaid participation by children of noncitizens relative to children of citizens by 10.1 percentage points. Her results imply that much of the observed decline in participation in Medicaid by immigrants around the time of welfare reform can in fact be attributed to increased enforcement of immigration law. Similarly, Sommers (2010) shows that a later (2005) change requiring proof of citizenship at the time of Medicaid application was associated with a reduction in enrollment among noncitizens, although he points out that the costs of the policy (particularly the burden on citizen applicants) are significantly larger than the savings.

4. Eligibility, Take-Up, and Crowd-Out in Long-Term Care

Eligibility, take-up and crowd-out—long-term care

Brown and Finklestein (2007,2008,2009): The Small Market for Long Term Assisted Living

Brown and Finklestein (2007, 2008, 2009) provide a comprehensive view of the market for insurance for long term assisted care; they find the amount of insurance purchased, which is much lower than one would expect given the risk that people face in the absence of long term care. They obtain the first comprehensive data on prices, and use simulation methods to calculate the expected benefits of long term care to the consumer. Brown and Finklestein (2007, hereafter

BF7) analyze the supply side of the market and while Brown and Finkelstein (2008, hereafter BF8) analyze the demand side of the market. Brown and Finklestein (2009) is a very nice review of BF7 and BF8 that researchers may want to read before they look at BF7 and especially BF8. They find impediments to market efficiency on both sides of the market that can lead to the market for long term care being smaller than one would expect, but argue that the role of Medicaid on the demand side of the market is the most important.

Basically there are two problems with how the Medicaid system works. First, Medicaid is a second payer, so it only covers costs that private insurance doesn't pay. The upshot is that private insurance is a very bad deal for the majority of consumers since they pay for insurance that covers expenses that Medicaid would have covered in the absence of private insurance. They also note that Medicaid has asset limits for eligibility that remove most of the benefits of private insurance in terms of protecting the consumers' assets. Thus for those who choose to participate in Medicaid, lower asset limits discourage the purchase of private insurance. However, lower asset limits also will reduce the probability of participating in Medicaid and increase the probability of buying private insurance. *Thus the effect of the asset limits on private insurance coverage is ambiguous.*

A natural measure of the gross price of private insurance is the load factor

$$LF = 1.0 - \frac{EDPV(Benefits)}{EDPV(\text{Costs})}, \tag{1}$$

where $EDPV(\cdot)$ denotes the expected discounted private value operator, $Benefits$ denotes the payments to the consumer, and Costs denotes the premiums paid by the consumer. Ignoring administrative costs fair insurance will have a load factor of 0.0, and the smaller LF is the more actuarially unfair the insurance is to the consumer. We use the term gross price since the

Medicaid system will effectively raise the load factor to consumers and make the insurance less attractive.

BF7 note that there are four major supply side market failures that have been proposed as candidates to explain the limited size of the private long-term care insurance market: transaction costs, imperfect competition, asymmetric information, and dynamic contracting problems. Transaction costs and imperfect competition can raise prices above expected benefits. Asymmetric information can influence this when the insured population is riskier than the general population. The result is that the moral hazard effects can cause the insured people to act riskier, in addition to adverse selection. A dynamic contracting problem may raise prices is if individuals learn new information about their risk type over time.

They argue that all of these sources of market failures have at least one of two empirical implications: i) insurance will not be comprehensive in the sense that consumers will not be able to insure most of their costs as the same rates at which they can by smaller amounts of insurance, i.e. consumers will be quantity rationed; and ii) the cost of long term care insurance will less actuarially fair than other types of insurance. They show rather quickly that i) is not really a problem in the market so they focus on ii). A natural measure of the price of the insurance is the load factor defined as

To calculate the gross load factor BF7 must measure both the $EDPV(Benefits)$ and the $EDPV(\mathrm{Costs})$ to the consumer. In terms of the latter, they obtain market-wide premium data for long-term care insurance policies in 2002. Specifically, the data were collected in March 2002 by Weiss Ratings, Inc., in their annual survey of the 132 known companies in the United States that sell long-term care insurance. The 29 responding companies include, among others, all of the top five sellers of long-term care insurance policies; these sellers alone account for two-thirds of industry sales (LIMRA, 2002). They use these data to calculate $EDPV(\text{Costs})$ in (1).

To calculate $EDPV(Benefits)$, i.e. the expected expendures for the insurance company, they first use data from the 1982, 1984, 1989 and 1994 waves of the National Long-term Care Survey to compute transition probabilities across different states of health, defined by the number of limitations of daily living (ADLs), limitations to instrumental activities of daily living (IADL's), the presence or absence of cognitive impairment, and death. Next, they estimate the probability of using each type of long-term care (none, home health, assisted living, or nursing home), conditional on the underlying health status, age, and gender, using data from both the NLTCS and the National Nursing Home study. In addition to estimating probabilities of using care, the model also estimates the number of hours per week of skilled and unskilled home health care assistance required, as a function of health status, age and gender

By combining the probability of being in a given health state with the conditional probability of needing care, conditional on one's health state, one can produce gender-specific probabilities of incurring long-term care expenditures at each age, conditioning on initial health status. For this paper, they used the model to produce utilization probabilities separately for men and women, conditional on being in sufficiently good health at age 65 to be eligible to purchase a private long-term care insurance contract. They also count care utilization only it the underlying health status of the individual satisfies the health-related benefit triggers necessary for the care to be reimbursed by private insurance.

Given their estimates of $EDPV(Benefits)$ and $EDPV(\text{Costs})$, BF7 provide the first estimates of load factors in this market. They find that the LF’s in this market are higher than other insurance markets, and conclude that that one of the above models of supply side failures must hold. Moreover, they note that their estimated LF's actually understate the profitability to the firms of providing this insurance because many consumers drop their coverage early; given that premiums, but not expenditures, are front-loaded this raises the revenue, and lowers the costs, beyond that implied by (1). Moreover, they also find that load factors are between 25%-50% higher for men than women, which again would not happen in the standard competitive market. Finally, they find that men and women buy the insurance at the same rate, in spite of the fact the insurance is a much better deal for women. They take the latter as evidence that there may be serious inefficiencies on the demand side of the market.

To investigate the demand side of the market, in BF8 consider the dynamic optimization of a consumer considering the purchase of private long term care insurance, taking the supply side of the market as given, which takes into account the institutional features of Medicaid., They then calibrate the model and solve for the optimal solutions for consumers at different income levels. The model suggests that for the bottom two-thirds of the income distribution, Medicaid crowds-out private insurance. They find that the fact that Medicaid is second-payer insurance (so that instead of private insurance topping up Medicaid coverage, it actually pays for expenses that Medicaid would have covered in the absence of the private insurance) creates net load factors to the consumer of approximately 0.75-0.80, or premiums to the consumer that are five times the expected benefits. Further, the increase in the load factor is bigger for women than men, suggesting that they face similar prices once this social security effect is taken into account, thereby resolving the puzzle of why men and women buy different levels of insurance given they face different gross prices. They find that the negative role of being second payer insurance is robust to considering reasonable modifications of the model, employing alternative assumptions. They state *'even if we were to eliminate all potential market failures and make fully comprehensive policies available atactuarially fair prices, much of the population would still be unwilling to pay for these policies in the presence of Medicaid*. ….Medicaid is capable of explaining the lack of private insurance purchases for the bottom two-thirds of the wealth distribution. A related implication is that correcting whatever supply-side market failures exist in the private insurance market would not induce most individuals to purchase this insurance.' (Italics in the original.)

They continue

"To eliminate the implicit tax, it is necessary to structure the Medicaid program so that the EPDV of Medicaid payments are not reduced when the individual buys private insurance. We estimate that eliminating one but not both of the two features that produce the implicit tax—Medicaid's means testing and secondary payer status—has little effect by itself on the implicit tax, and hence on willingness to pay for private insurance. As long as Medicaid remains means tested, private insurance, by protecting assets, reduces the probability of being eligible for Medicaid. As long as Medicaid remains a secondary payer, private insurance benefits reduce Medicaid benefits one for one, even if eligible for Medicaid." (Italics in the original.)

The case for making Medicaid a first-payer insurance system seems overwhelming in their paper; of course in the current political climate the cost of such a change must also be recognized as an important factor. Without changing the asset test, making Medicaid first payer insurance probably would not drastically increase Medicaid costs given the fraction of the elderly already using Medicaid. Eliminating the asset test completely would essentially provide Medicaid coverage to everyone, and could raise Medicaid expenditures here by 50%. This could well be politically infeasible since it would both increase costs and transfers to the elderly at the cost of younger workers. We found the role of the asset test less clear in their analysis, especially since the expected impact on private insurance is ambiguous, and their their results suggest that a simple modifications of the asset test, i.e. allowing consumers to shelter 25% of their assets from the test, could result in a substantial welfare increase.

A very interesting area for future research would be to use their model to predict overall effects on the economy of different policy changes. For a given set of policies, one could calculate private and Medicaid coverage for each decile of the income distribution, and then weight the coverage for each decile by its fraction in the population. By carrying out this exercise for different policies, one could estimate the effects of various policy changes. One could also compare the model's predictions for the policy changes considered by Brown et al (2007) and Goda (2011). Finally it would also be interesting to consider the amount of insurance purchased by those who do buy insurance, to see if the model could replicate the result that the amount of insurance bought is usually smaller than one would expect.

Brown et al (2007): Medicaid Crowd-Out of Private Long-Term Care Insurance Demand: Evidence from the Health and Retirement Survey

The authors estimate the effect of decreasing the Medicaid asset limits on demand for private long-term care insurance. They estimate that a \$10,000 *decrease* in the asset limits would *increase* private long-term care coverage by 1.1 percentage points. The use the restricted access version of the Health and Retirement Survey to estimate

$$LCTS_{ist} = \beta_1 Prot_{ist} + \beta_2 Marr_{ist} + \alpha_s + X_{ist}\eta + \varepsilon_{ist}. \qquad (2)$$

where i represents individuals, t represents year, s represents state of residence and $LCTS_{ist} = 1$ if the family purchases private insurance for long term care and zero otherwise. The coefficient of interest is β_1, i.e. the coefficient on $Prot_{ist}$, which is defined as

$$
\begin{aligned}
Prot_{ist} &= Assets_{ist} && if\ Assets_{ist} < Min_{st} \\
&= Min_{st} + 0.5*\left(Assets_{ist} - Min_{st}\right) && if\ Min_{st} < Assets_{ist} < Max_{st} \\
&= Max_{st} && if\ Assets_{ist} > Max_{st}.
\end{aligned} \tag{3}
$$

In (3) Min_{st} and Max_{st} are the state minimum and maximum amount respectively of assets protected by the Medicaid program in year t; in writing (3) we have left implicit the fact that the limits depend on marital status. They acknowledge asset levels are endogenous, so they use the following first stage regression:

$$Log\left(Assets\right)_{ist} = \tilde{X}_{ist}\delta_m + v_{ist},$$

where $\tilde{X}_{ist}$ contains the same variables except that the former does not include marital status.

Based on the first stage they solve for a predicted $\hat{A}_{ist}$ and form $\tilde{P}_{ist}$ which they define as

$$
\begin{aligned}
\tilde{P}_{ist} &= \hat{A}_{ist} && if\ \hat{A}_{ist} < Min_{st} \\
&= Min_{st} + 0.5*\left(\hat{A}_{ist} - Min_{st}\right) && if\ Min_{st} < \hat{A}_{ist} < Max_{st} \\
&= Max_{st} && if\ \hat{A}_{ist} > Max_{st}.
\end{aligned} \tag{4}
$$

Their first stage equation is

$$Prot_{ist} = \mu_1\tilde{P}_{ist} + \mu_2 Marr_{ist} + \mu_{3s} + X_{ist}\mu_4 + \varepsilon_{ist}, \tag{5}$$

and their model is identified by variation in Min_{st} and Max_{st}, as well as nonlinearities. Their IV baseline estimate (standard error) for β_1 is: -0.0109 (0.0048). These estimates imply that if every state in the country moved from their current Medicaid asset eligibility requirements to the most stringent Medicaid eligibility requirements allowed by federal law - a change that would decrease average household assets protected by Medicaid by about $25,000, demand for private long-term care insurance would rise by 2.7 percentage points. While this represents a 30 percent increase in insurance coverage relative to the baseline ownership rate of 9.1 percent, it also indicates that the vast majority of households would still find it unattractive to purchase private insurance. It would be very interesting to compare this estimate to what would be produced by simulating the Brown-Finkelstein (2008) model for the economy as a whole.

Goda (2011) The impact of state tax subsidies for private long-term care insurance on coverage and Medicaid expenditures

The author uses variation in the adoption and generosity of state tax subsidies for private long-term care insurance to determine whether tax subsidies increase private coverage for long-term care. They use data from the restricted use version of the the Health and Retirement Study (HRS). Their empirical model is the following:

$$LTCI_{it} = \gamma SUBSIDY_{st} + \beta X_{it} + \omega_t + \sigma_s + \varepsilon_{it}, \tag{6}$$

where *i* represents individual, *t* represents year, *s* represents state, $SUBSIDY_{st} = 1$ if the individual lives in a state that has a subsidy at time t and zero otherwise, and $LTCI_{it} = 1$ if the individual buys insurance in year t and zero otherwise. Finally, X_{it} is a vector of individual- and state-level characteristics, including controls for education, gender, marital status, age, race, income, assets, number of children, retirement status and health status, and the state-level characteristics.

The author also estimates the equation

$$LTCI_{it} = \tilde{\gamma} TAXPRICE_{ist} + \tilde{\beta} X_{it} + \tilde{\omega}_t + \tilde{\sigma}_s + \tilde{\varepsilon}_{it}, \tag{7}$$

where $TAXPRICE_{ist}$ denotes the after-tax price of $1 of private long-term care insurance in terms of foregone consumption. They treat $TAXPRICE_{ist}$ as endogenous since it depends for example if the individual files a tax return, and if they file a return, whether they itemize. The instrument they use for TAXPRICE is the one used earlier by Currie and Gruber, which equals, for each state and year, the average after-tax price for a nationally representative sample of 5000 individuals. Because the after-tax price is calculated for the same set of individuals, the only variation in the instrument comes from changes in tax subsidies for long-term care insurance. To allow the value of the subsidy to change differentially for individuals in different socioeconomic groups, the instrument is averaged separately for low education (high school or less) and high education (some college or more) groups.

The author estimates (7) for the whole sample:

Subsidy	0.023**	0.028**	0.024**	0.027***
Std Error	0.009	0.011	0.011	0.009
State + Year Fixed Effects	No	Yes	Yes	Yes
Control Variables	No	No	Yes	Yes
Individual FE	No	No	No	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%

and then for the different income groups:

	Subsidy coefficient (std error)	
All	0.027	(0.009)
Low Wealth < 20,000	0.006	(0.013)
Medium [20000, 150000]	0.025	(0.01)
High (150000<)	0.042	(0.018)

As one might expect, the effects are largest in the high income category; again it would be interesting to compare these results to those that would be produced by a simulation of the Brown-Finkelstein model.

B. Access, Utilization, and Health

1. Children, Infants, and Pregnant Women

The discussion of take-up and crowd-out above highlighted the fact that while take-up of Medicaid is far less than full, insurance coverage under Medicaid has been rising steadily, with Medicaid anticipated to play an even larger role in health insurance in the future as it expands to cover additional populations. Consequently the literature on its impacts on health care utilization and health is important for understanding whether and how this major insurance source impacts health. Because women and children have historically accounted for the majority of Medicaid enrollment, much of the research examining effects on medical care utilization and health focuses on those populations. In addition, various features of Medicaid coverage for these populations have made obtaining plausibly causal inferences more feasible. Several important studies in this literature exploit variation arising from the eligibility expansions of the 1980s and 1990s.

Currie and Gruber (1996 QJE) estimate the effect of Medicaid eligibility on several measures of health care utilization for children, using data from the National Health Interview Survey (NHIS) from the 1984-1992 period and the simulated eligibility measure they developed as an instrumental variable calculated using data from the Current Population Survey (CPS). One outcome is the probability of not having at least one physician visit over the past 12 months. Since it is recommended that all children have an annual "well child" visit, this outcome can be seen as a general measure of access to care. Their IV estimates imply that Medicaid eligibility reduces the probability of not having a visit by nearly 10 percentage points, or roughly half of the baseline rate. They use data on the location of care to investigate whether Medicaid eligibility reduces the use of hospital emergency departments and outpatient clinics in favor of care received in physician offices, which is generally viewed as a more cost-effective site of care. They find that Medicaid eligibility has a fairly large, though imprecisely estimated, effect on the probability of receiving care in a doctor's office. The estimated effect on the probability of visiting a hospital emergency department or clinic is also positive, though again not statistically significant.

In order to explore whether the increased eligibility resulted in an improvement in health Currie and Gruber then examine child mortality in vital statistics data, which has the advantage of being calculated from the universe of US death certificates. Regressing the death rate by state-year-age-race cell on the imputed fraction eligible in that cell from the CPS and using simulated eligibility for a national sample by state, year, and age as instruments, they find a reduction of 0.13 percentage points in mortality for every 10 percentage point increase in Medicaid eligibility. While this estimate is fairly imprecisely measured, it does indicate that there was an effect of Medicaid on child health. This conclusion is reinforced by the fact that Currie and Gruber find no evidence of an effect on deaths from "external causes" (accidents, homicides, suicides, etc.) but do find an effect on deaths from "internal causes."

Currie and Gruber (1996 JPE) also use data from the vital statistics, for the period 1979-1992, to explore the impact of Medicaid eligibility changes on the fraction of births that are low birth weight (LBW) and the infant mortality rate by state and year. The analysis is essentially the same as the analysis described above for children, although in this paper they distinguish between the earliest expansions that were aimed at women well below the poverty line and that sometimes included income increases through AFDC as well as expanded access to health insurance coverage (what they call "targeted" expansions) and later expansions aimed at women with incomes as high as the poverty line or slightly higher (what they call "broad" expansions).

They find evidence both for a reduction in low birth weight incidence and a reduction in infant mortality. However, these reductions appear only to come from the earliest expansions (the "targeted" expansions that might also have involved cash assistance changes); later insurance-only expansions higher up the income distribution show no statistically significant effect.

Work by Currie and Grogger (2002) that focuses on a later time period (1990-1996) finds similar results. They use a slightly different, reduced-form, methodology, regressing individual measures of prenatal care use from the vital statistics natality data on the Medicaid-only income cutoff for pregnant women in the relevant state and year, the welfare participation rate in the state and year, and various measures of state policies intended to increase enrollment in Medicaid. One obvious concern with this specification is that the welfare participation rate may reflect unobserved factors that may affect both welfare participation and infant health outcomes, although Currie and Grogger attempt to control for such factors by including state and year effects, unemployment rates, and state-specific time trends. They find that increases in the income cutoff increase the adequacy of prenatal care for whites though not for blacks, while increases in the welfare rolls are associated with increases in the adequacy of prenatal care for both groups (and the results for state policies are mixed and generally weak). Looking at the health outcomes of low birthweight and fetal death, they find little effect of either the income cutoffs or the size of the welfare rolls on birthweight, but they find evidence of reductions in the fetal death rate with welfare participation for both whites and blacks and reductions among blacks only when income limits are higher. Overall, these results suggest the effects of expanded access to Medicaid for pregnant women on infant health appear to be weakly positive, with stronger effects for Medicaid eligibility that is accompanied by access to cash assistance (or for lower income women).

Currie, Decker and Lin (2008) estimate similar IV models for utilization and health in later childhood using data from 1986 to 2005, a period over which eligibility for public insurance increased They find that eligibility has a significantly positive effect on the probability of having at least one physician visit in a year. They also find that the relationship between family income and utilization became less pronounced over time, suggesting that the expansion of public health insurance reduced disparities in access to care. Finally, they find that children ages 9-17 who lived in states that had more generous Medicaid eligibility (including AFDC eligibility) when they were ages 2-4 had a lower probability of being in less than excellent health. This effect is small, however—a 20 percentage point increase in eligibility (roughly the increase in eligibility over the entire period of the expansions) is associated with only a 1 percentage point reduction in the likelihood of being in less than excellent health.

Card and Shore-Sheppard (2004) examine the effect of Medicaid eligibility on the probability of having at least one doctor visit in a year using a regression discontinuity design as discussed in the section on take-up and crowd-out, above, and data from the National Health Interview Survey. As with their results for take-up, they find the largest (and most statistically significant) effects for the expansion of eligibility to children below poverty, with estimates suggesting that children with newly available health insurance coverage have a 60 percent higher probability of at least one annual doctor visit, although the confidence interval on this estimate is fairly wide (the standard error is 31 percent). The estimate for children eligible only under the expansion to 133 percent of the FPL, while positive, has a substantial standard error.[30] De La Mata (2012) also uses a RD design, in income, though (as discussed earlier) the use of income as

[30] In an unpublished working paper, Meyer and Wherry (2013) use the same discontinuity as Card and Shore-Sheppard (2004) to investigate later life mortality among teens. They find a substantial reduction in mortality among black teens, but no reduction for white teens.

the assignment variable is somewhat problematic because of unobserved differences in the income counting methodologies across states that lead to actual income eligibility cutoffs differing from reported cutoffs. Using data on children ages 5-18 from the Panel Study of Income Dynamics, she finds increases in the probability of at least one doctor visit of 12-14 percentage points, but only for children eligible under lower eligibility thresholds (100-185 percent of the FPL). She finds no statistically detectable effect on health, either for contemporaneous or lagged eligibility.[31]

Currie and Gruber (1996 QJE) also examine the effect of Medicaid on inpatient utilization. As described in Section IV, the effect on this outcome is theoretically ambiguous. On one hand, there is likely to be an access effect: by providing access to costly care that low-income patients could not otherwise afford, Medicaid should have a positive effect on inpatient utilization. At the same time, by improving timely access to primary and preventive care, Medicaid may lead to health improvements that reduce the number of "avoidable" hospitalizations for conditions like asthma, gastroenteritis, dehydration and certain infections. Currie and Gruber's results suggest that the positive access effect outweighs the negative "efficiency" effect: Medicaid eligibility increases the probability of having a hospital stay by about 4 percentage points, which represents nearly a doubling of the baseline rate. The NHIS data they use does not provide details on the nature of the inpatient care received, so they are not able to obtain separate estimates of the two effects.

Dafny and Gruber (2005) explore this issue in more detail by matching data on Medicaid eligibility measured for state/year/age group cells with data from the National Hospital

[31] Other studies using different data and different research designs also find that utilization increased for children who gained eligibility for public insurance because of CHIP relative to children who did not gain eligibility (Selden and Hudson 2006; Lurie 2009; Li and Baughman 2010; Choi, Sommers and McWilliams 2011).

Discharge Survey, adapting the simulated eligibility IV approach to these aggregate data. Their results for total hospitalizations are nearly identical to Currie and Gruber's (1996 QJE): a 10-percentage point increase in Medicaid eligibility increases the pediatric hospitalization rate by 8.4 percent. They then estimate separate regressions for hospitalizations classified as avoidable or unavoidable based on the prior health services literature in this area. According to their definition, roughly one-quarter of pediatric hospitalizations during the period they study were classified as avoidable. When the dependent variable is the natural log of unavoidable hospitalizations, the coefficient on the Medicaid eligibility variable is positive and significant, with a magnitude that is similar to the estimate for all hospitalizations. For avoidable hospitalizations, the coefficient on the Medicaid eligibility rate is still positive, but smaller and not significantly different from zero.

Aizer (2007) also uses IV methods to estimate the effect of Medicaid on avoidable hospitalizations, though she estimates the effect of Medicaid *enrollment* on children who were already eligible rather than the effect of eligibility. She finds that a 10 percent increase in Medicaid enrollment leads to a 2 to 3 percent decline in avoidable hospitalizations but has no effect on hospital admissions for other conditions. These effects are large enough that the savings from reduced admissions were likely greater than the cost of the outreach program. The difference between her results and those of Dafny and Gruber can be explained by the fact that the children who gain insurance coverage because of a change in eligibility experience improved access to both outpatient and inpatient care. In contrast, since children who enrolled because of the outreach efforts already had "conditional coverage" for inpatient care in the sense that they could sign up for Medicaid if they presented at a hospital in need of acute care, the main effect of gaining coverage was improved access to primary and preventive care.

Overall, the results from the literature thus far point to expansions in eligibility for Medicaid leading to improvements in access to care and health, although the magnitudes of the effects are sometimes difficult to pinpoint and estimates often differ for different groups or at different times. Generally, expansions that occurred earlier and that affected lower income children tend to show more consistent positive effects. (Consistent with this pattern, unpublished work by Goodman-Bacon (2014) examining the impact of Medicaid's initial introduction on child mortality finds dramatic decreases in the mortality rates of nonwhite children and nonwhite neonates in high-eligibility states relative to low-eligibility states.) While the pattern of greater effects for lower income children makes sense given the greater availability of alternative health insurance sources for higher income children, the pattern is worth further exploration; in particular, it would be worthwhile to investigate the potentially important role of the tie to cash assistance that was a part of the earliest expansions. This is particularly important for those researchers interested in exploring long-term effects of the health improvements discussed here. In addition, the role of policy endogeneity in state choices is an issue that has been little explored but is worth exploring given the frequent use of state-level variation to identify models. To the extent that state choices about how far to expand their programs reflect conditions faced by individuals in the state, estimated effects of Medicaid eligibility may also reflect state responses to these conditions. Continued examination of the impact of Medicaid and CHIP expansions on short run and long run health outcomes is valuable to assess more fully the impact of these programs.

In addition to impacts of eligibility expansions on health, researchers have examined the impacts of other Medicaid policy shifts, particularly payment policy. Aizer, Lleras-Muney, and Stabile (2005) examine the infant mortality effects of an increase in Medicaid payments to hospitals in California through the DSH program. Pregnant women with Medicaid insurance may obtain care from different providers if due to low reimbursement rates providers are unwilling to treat Medicaid patients. Using infant linked birth-death certificate data, Aizer, Lleras-Muney, and Stabile find that the DSH program hospital payment increase led to a substantial move by pregnant women with Medicaid insurance to hospitals with prior low use by the Medicaid population. The desegregation of hospitals by insurance type was associated with an improvement in neonatal mortality, particularly among those with the highest levels of neonatal mortality: black infants and twins. The larger effects for black infants were particularly noteworthy since black mothers were the least likely to increase their use of private hospitals, indicating the continuing existence of some barriers (informational or otherwise) to use of higher quality care by black Medicaid recipients.

Another set of papers has examined the impact of physician fees on health outcomes, including Gray (2001), Currie, Gruber, and Fischer (1995), and Joyce (1999). These papers use variation in fees paid to physicians either across states relative to private fees (Gray), across states and time relative to private fees (Currie, Gruber, and Fischer), or in the availability of enhanced prenatal care services relative to regular prenatal care services associated with the Medicaid eligibility expansion in New York. All of these papers find that higher fees are associated with improved health outcomes.

2. Nondisabled Adults

There has been much less research on the utilization and health effects of Medicaid for adults, even though very poor single parents have had access to Medicaid coverage since its inception and parental Medicaid has expanded considerably in recent years. However, recent expansions to nonparents under various waivers have led to a rise in research on this population.[32] This research is of particular interest since the Medicaid expansion of the ACA will mainly affect adults, particularly childless adults, and thus these studies on programs in individual states provide valuable evidence on the likely effect of public insurance on the health care utilization and health of this population.

The best evidence on the effect of Medicaid on health care utilization and health for adults comes from the Oregon Health Insurance Experiment (OHIE). In three different papers (Finkelstein et al. 2012; Baicker et al. 2013; Taubman et al. 2014) the OHIE researchers estimate utilization effects using both survey and administrative data. Results from the survey data indicate sizeable effects on outpatient visits and prescription drug use. Gaining Medicaid coverage through the lottery increased the probability of having an outpatient visit by 35 percent and increased the probability of filling a prescription by 15 percent. The increased visits coincided with greater receipt of recommended preventive services. Medicaid coverage led to a 20 percent increase in the likelihood of having a cholesterol test, a 15 percent increase in blood tests for diabetes, a 60 percent increase in mammograms and a 45 percent increase in the percentage of women getting a Pap test. However, although testing clearly increased, the researchers found no significant effect of Medicaid coverage on the prevalence or diagnosis of hypertension or high cholesterol levels or on the use of medication for these conditions. For diabetes, on the other hand, having Medicaid coverage significantly increased the probability of a diagnosis and the use of diabetes medication, but there was no significant effect on measures of diabetes control (Baicker et al. 2013).

[32] Interestingly, despite the large fraction of expenditures devoted to the elderly and disabled populations, there is a dearth of research on the health and utilization effects of Medicaid for this population.

There was no significant change in inpatient utilization in the survey data, though hospital discharge data indicate that Medicaid coverage increased the probability of an admission by 2.1 percentage points, a 30 percent effect relative to the mean for the control group. This effect was driven by an increase in admissions that did not originate in the emergency room. There was also a small positive effect on the intensity of inpatient treatment as measured by a composite outcome that combines the number of inpatient days, the number of procedures and total charges.

The initial analysis of survey data indicated no significant effect of Medicaid coverage on ER utilization, with wide confidence intervals (Finkelstein et al. 2012). However, follow-up analysis using administrative data from 12 Portland area hospitals found that Medicaid coverage increased outpatient ER visits by 40 percent over an 18-month period. There was no statistically significant increase in ER visits leading to an inpatient admission. Additional analyses indicate that the effect of Medicaid on ER visits was fairly consistent across different times of day and different types of care. Medicaid led to a significant increase in visits for conditions not requiring immediate care and most types of conditions where immediate care is required.

Examining general measures of health in addition to the clinical outcomes discussed above, the treatment group reported significantly better outcomes for seven different measures of self-reported physical and mental health from a survey of lottery participants, including a significant decrease in the probability of depression (Finkelstein et al. 2012). Since Medicaid enrollees' credit reports indicated significantly lower probability of having any debt in collection and particularly any medical debt in collection and they reported significantly lower signs of financial strain in the survey, it is possible that self-reported physical and mental health may largely reflect a generally improved sense of well-being rather than physical health improvements per se (the financial results are discussed further below). Nevertheless, to the extent that health is measured by the definition of the World Health Organization ("a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity") it is clear that coverage by Medicaid improved enrollees' health.

Other studies using different research designs also find a positive correlation between Medicaid coverage and ER utilization. For example, Shen and Zuckerman (2004) find that controlling for observable characteristics, individuals with Medicaid coverage are twice as likely to have an ER visit than someone who is uninsured. Anderson, Dobkin and Gross (2012) use a regression discontinuity approach that exploits the fact that many young adults lose private health insurance, and to a lesser extent Medicaid, when they turn 19. They find that there is also a significant decrease in ER visits and inpatient admissions at that age.

In addition to the Oregon experiment, there are other recent state programs that provide insight on how the ACA Medicaid expansions will affect the health care utilization of poor adults who will gain coverage. DeLeire et al. (2013) evaluate the utilization effects of a Wisconsin program, BadgerCare Plus Core, which closely resembles Medicaid. The program enrolled poor adults in Milwaukee County who tended to have high rates of chronic illness and who had previously received care at facilities reimbursed by Medicaid Disproportionate Share funds. DeLeire and colleagues find that enrollment in the new plan led to an increase in all types of outpatient utilization, including ER visits. In another study also evaluating the utilization effect of the same program but on a rural low-income (FPL<200%) population, Burns et al. (forthcoming) found a similar effect on outpatient visits, but inconclusive results on ER use. One interesting contrast with the Oregon results is that when BadgerCare Plus Core was implemented in Milwaukee, inpatient utilization fell for individuals who transitioned to the new program. In particular, there was a large and significant decline in admissions for ambulatory care sensitive conditions. One possible explanation is that because these patients previously faced restricted access to outpatient specialty care, ER physicians may have admitted them in order to ensure they received diagnostic tests. With better access to specialists in outpatient settings, these admissions fell.

Sommers, Baicker, and Epstein (2012) compared all-cause county-level mortality (from mortality statistics), rates of insurance coverage and self-reported health status (from the CPS), and rates of delayed care because of costs from the Behavioral Risk Factor Surveillance System (BRFSS) for three states that substantially expanded Medicaid eligibility for adults since 2000 (New York, Maine, and Arizona) to neighboring states without expansions. The authors use a difference-in-differences strategy that requires the assumption that trends in the comparison states (New Hampshire, Pennsylvania, and New Mexico) accurately reflect what would have happened in the expansion states if the expansion had not occurred. They show that trends prior to the expansions were quite similar in both groups of states, lending credence to the identifying assumption. They find that Medicaid expansions increased Medicaid coverage by 2.2 percentage points and decreased rates of uninsurance by 3.2 percentage points, and were associated with a significant reduction in all-cause mortality, particularly for older adults, nonwhites, and residents of poorer counties. In addition, the authors find reduced rates of delayed care because of costs and increased rates of self-reported health status of “excellent” or “very good.”

There have been several studies of Massachusetts’ 2006 health care reform, which like the ACA increased both Medicaid and private insurance. The results from these studies paint a more optimistic picture concerning the potential for coverage expansions not only to improve access to care, but also to shift the source of care from hospitals to lower cost settings. Miller (2012) examines the change in ER visits after the Massachusetts coverage expansion using pre-reform variation in insurance coverage rates to identify causal effects. She finds that the reforms led to a reduction in ER utilization of between 5 and 8 percent. Two other results are consistent with the hypothesis that patients who gained insurance coverage shifted their source of care from the ER to physician offices. First, visits for non-urgent conditions account for nearly all the decline in ER use; Miller finds no significant effect on visits for non-preventable emergencies like heart attacks. Second, ER visits declined most during regular office hours when physician offices were likely to be open. An analysis of survey data by Long et al. (201x) also finds that ER use fell after the Massachusetts reform. And Kolstad and Kowalski (2012) find that while overall hospital admissions did not fall after the state's reforms went into effect, there was a decline in admissions coming through the emergency room and admissions for preventable conditions.

Like the Milwaukee results on inpatient admissions, Miller's finding that expanding coverage caused ER visits to fall can be understood by considering the services available to low-income uninsured patients before the reform. In Massachusetts, a state program, the Uncompensated Care Pool, paid for hospital care for residents with incomes less than 200 percent of the federal poverty level at no cost to the patient. Thus, when these individuals gained full insurance coverage through Medicaid, their access to office-based primary care improved but there was little or no change in their access to an ER and other hospital-based facilities. The cost of ER use went up for some low-income individuals who gained subsidized private insurance because of the reforms, as plans sold in the Massachusetts Connector included nontrivial co-pays for ER visits.

C. Effects on Providers

1. Impact of Medicaid Eligibility and Reimbursement Policy

In most studies on how Medicaid affects medical care utilization, the patient is the unit of analysis and the results can be interpreted mainly as demand-side effects: Medicaid reduces the pecuniary cost of receiving care, leading patients to seek more treatment. Because most of these studies identify the effect of Medicaid from either cross-sectional differences or from relatively small changes in eligibility or coverage, a partial equilibrium perspective is probably justified. However, the impact of large policy changes such as the ACA Medicaid expansions will depend on how providers respond to the resulting changes in the overall demand for care and payer mix. A small literature on how physicians and other providers respond to changes in Medicaid eligibility, coverage and reimbursement policy sheds some light on these issues.

Several studies examine the response of providers to public insurance expansions. Baker and Royalty (2000) use two years of panel data from the American Medical Association's Survey of Young Physicians to examine the impact of Medicaid eligibility expansions for pregnant women on the percentage of a physician's patients who are poor or on Medicaid. An important feature of their analysis is that they are able to distinguish between physicians in private practice and those in public health settings. They find that increased Medicaid eligibility leads public health physicians to see a greater percentage of poor patients and patients covered by Medicaid. In contrast, they find that an expansion of Medicaid eligibility has no significant impact on physicians in private practice.

Two recent studies document that on the eve of the ACA Medicaid expansions, physicians in public health clinics were substantially more likely to accept new Medicaid patients than those in private practice (Decker 2013; Rhodes et al 2014). Federal funding for community health clinics has increased significantly since the 1990s (LoSasso and Byck 2010). Much of this funding increase came as a result of a Bush Administration program, the Health

Care Center Growth Initiative, which provided grants to support over 1000 new or expanded health centers (McMorrow and Zuckerman 2013). The ACA includes $11 billion in appropriations for a further expansion of community health clinic capacity. Therefore, these clinics are likely to play an increasingly important role in meeting the increased demand for care resulting from the ACA insurance expansions.

Two more recent studies examine how pediatricians responded to the demand changes caused by the CHIP expansion (Garthwaite 2011; He and White 2013). As noted above, a large share of the children who enrolled in Medicaid or stand-alone CHIP plans was covered previously by private insurance. As a result of this crowd-out, for many physicians the main effect of the CHIP expansion was a reduction in the amount they were paid for some of their existing patients. Consistent with this, both studies find that the implementation of CHIP led pediatricians to see more publicly insured patients while at the same time reducing their weekly hours worked.

This decline in physician hours does not necessarily imply that fewer children were receiving care. Indeed, as noted above several studies suggest that the CHIP expansions led to an increase in visits for children in the income range targeted by the program. One possible way that these two results could be reconciled is if physicians were spending less time with each patient. Another possibility is that other providers were seeing more patients to meet the increase in demand. Garthwaite considers the first possibility by comparing changes in visit length for pediatricians and other types of physicians between 1993 and 2002. He finds suggestive evidence that the CHIP expansion coincided with a reduction in visit length and an increase in the percentage of visits that were shorter than 10 minutes. This response to the implicit reduction in fees associated with crowd-out is consistent with research by Decker (2007) on the effect of changes in Medicaid fees.

A recent paper by Buchmueller, Miller and Vujicic (2014) highlights the important role that auxilliary providers play in treating Medicaid patients. This study examines the response of dental practices to changes in Medicaid coverage of dental benefits for adults. Although state Medicaid programs are required to cover dental services for children, adult dental coverage is an optional benefit that most states do not provide. The study uses repeat cross-section data from the American Dental Association's annual Survey of Dental Practice to estimate the effect of Medicaid coverage policy on several supply-side outcomes: participation in the Medicaid program; the number of visits by patient insurance status and type of visit; dentists' labor supply; and the employment of dental hygienists.

The results indicate that when Medicaid covers dental care for adults, dental practices provide significantly more care to publicly insured patients. The analysis of employment practices suggest that an important way that dentists respond to increased demand from public insurance is by making greater use of dental hygienists. A 10-point increase in the percentage of a county's adults covered by Medicaid is estimated to increase the probability that a dentist employs a hygienist by XX percentage points and the number of visits with hygienists by roughly X percent. Other results suggest that the ability of dental practices to respond to Medicaid-induced demand shocks is mediated by state scope of practice regulations. The increase in visits and the use of hygienists is greater in states where hygienists are allowed greater autonomy. A state's scope of practice environment also seems to affect the extent to which increased demand from Medicaid patients leads to crowding. In states with restrictive scope practice regulations, an expansion of Medicaid dental coverage leads to modest but significant increases in the time that it takes to get an appointment and the average time spent by patients in the waiting room. Waiting times did not increase in states where hygienists are allowed more autonomy.

2. Impact of Fees

Historically, access to care has been limited by the fact that many doctors do not accept Medicaid patients. Data from the National Ambulatory Medical Care Survey indicate that in 2011-12, two-thirds of primary care physicians and 30 percent of all physicians accept new Medicaid patients (Decker 2013). Because low provider participation is attributed to Medicaid's low payment rates, the ACA includes a provision that temporarily raises Medicaid payment rates for primary care to Medicare levels (cite). A number of studies have examined the relationship between Medicaid fees and provider participation in the program. Cunningham and Nichols (2005) and Decker (2007) find that higher Medicaid fees are positively associated with the willingness of physicians to treat publicly insured patients. Baker and Royalty (2000) find such a response for private physicians in their sample. Their results suggest that higher Medicaid payments shift the site of care for low-income patients from public health settings to private physician practices. Gruber, Adams and Newhouse (1997) find a similar result when studying the effect of increased Medicaid payments in Tennessee.

Because of the way that changes in payment policy can shift the site of care, increasing payment rates may or may not increase overall utilization. Some studies using cross-sectional data find a significant relationship between Medicaid payment rates and the site of care, but find no significant relationship between payment rates and overall utilization (Long, Settle and Stuart 1986; Rosenbach 1989; Cohen and Cunningham 1995). However, other studies that analyze changes in fees suggest that access to physician services improves when Medicaid payments are increased (Gabel and Rice 1985; Shen and Zuckerman 2005; Decker 2009; White 2012).

Access problems attributed to low Medicaid fees are a significant concern in the case of dental care as dentists are even less likely than physicians to accept Medicaid (cite). Buchmueller, Orzol and Shore-Sheppard (forthcoming) find that increases in Medicaid dental fees increase the percentage of dental practices that treat publicly insured patients. Their estimates imply supply elasticities of between .12 and .23, which are slightly lower than supply elasticity estimates for physicians (Baker and Royalty 2000; Decker 2007). They and Decker (2011) also find that higher Medicaid fees are positively correlated with the dental visits for children. However, the magnitude of the effect is relatively small: a $10 increase in average Medicaid dental fees—a change slightly larger than the difference between the 75th and 25th percentiles for this variable—is predicted to lead to a 2 to 3 percentage point increase in the probability that a publicly insured child has at least one dental visit in a year. Because of this modest response, most of the expenditures associated with a fee increase go for inframarginal visits, making fee increases a costly way to increase utilization.

In addition to increasing access to care, higher provider reimbursement can influence the type of care that Medicaid patients receive. In most states, Medicaid pays obstetricians more for a cesarean section than for a normal delivery, though the differential is generally not as large as it is for private insurance. Gruber et al (1999) examine how the Medicaid fee differential affects the cesarean rate for Medicaid patients. Theoretically, the effect is ambiguous, depending on the relative magnitudes of a positive substitution effect and a negative income effect. Using 1988 to 1992 data from 11 states, they find that the substitution effect dominates: larger fee differentials lead to more cesarean deliveries.

To the extent that higher fee differentials lead physicians to over-provide cesarean sections relative to what is optimal based on clinical criteria, reducing the differential payment for performing C-sections will not only lower program expenditures, but will improve care quality. In other cases, however the additional care induced by higher levels of reimbursement may be beneficial. Currie, Gruber and Fischer (1995) use birth data aggregated to the state/year level to investigate the relationship between the ratio of Medicaid to private insurance fees and infant mortality. They find a significant negative relationship between the fee ratio and infant mortality. Gray (2001) examines the relationship between relative Medicaid fees and birth outcomes using a cross-sectional difference-in-differences approach that compares Medicaid births and non-Medicaid births. He finds that women on Medicaid are more likely to delivery infants with low birth weight but this difference is smaller in states where Medicaid fees are higher. Higher Medicaid fees also increase the receipt of early prenatal care, which may be an important mechanism for the birth weight result.

As a result of eligibility expansions for pregnant women, today Medicaid pays for over half of all births in the US. A recent paper by Freeman, Lin and Simon (forthcoming) examines how the changes in coverage brought about by those expansions affected hospital decisions to adopt neonatal intensive care units (NICUs). Theoretically, the way hospitals respond should depend on the extent of crowd-out. In markets with high rates of insurance coverage at baseline, increases in hospital revenue resulting from uninsured patients gaining Medicaid may be more than offset by a decline in revenue from patients who transition from private insurance to Medicaid. Such a decrease in reimbursement for deliveries will make investments in medical technologies like NICUs less profitable.

Freedman and colleagues find that while in the average market Medicaid expansion was not significantly related to NICU adoption, in areas where more new Medicaid enrollees were coming from private insurance Medicaid expansion led to a slowing of NICU adoption. This negative effect was most pronounced in states with the lowest Medicaid payment rates. These results are broadly consistent with earlier work by Currie and Gruber (2001) finding that increases in Medicaid eligibility increased access to costly obstetric procedures for less educated women who likely gained insurance coverage as a result of the expansion while decreasing procedure use for more highly educated women, many of whom would have had more generous private insurance in the absence of the Medicaid expansion.

3. Impact of Disproportionate Share Hospital Payments

Because of Medicaid's low payment rates and the fact that hospitals with large numbers of Medicaid patients also treat many uninsured patients, state Medicaid programs make disproportionate share hospital (DSH) payments to hospitals treating a high volume of low-income patients. Duggan (2000) studies how public, non-profit and for-profit hospitals in California responded to the introduction of DSH payments in the early 1990s. His results indicate significant differences between public and private hospitals, but little difference between private non-profit and for-profit hospitals. When DSH patients made Medicaid patients more financially attractive, there was a shift in Medicaid patients from public hospitals to private ones. At the same time, there was a reallocation of uninsured patients in the opposite direction. This pattern is consistent with private hospitals cream-skimming the more profitable low-income patients.

Duggan also examines what hospitals that received DSH payments did with that windfall. For public hospitals the increased funding from Medicaid was offset essentially one-for-one by reductions in funding from state and local governments. DSH payments led to an increase in total revenue for for-profit and non-profit facilities, both of which used the additional funds to increase their holdings of financial assets, rather than investing in new patient care facilities. Finding no significant relationship between changes in payments arising from the DSH program and infant mortality, Duggan concludes that the increased funding did not improve health outcomes for low-income patients.

Baicker and Staiger (2005) delve more deeply into what happens when states use intergovernmental transfers to divert Federal DSH payments. On average, they find that during the first decade of the DSH program, states expropriated nearly half of the DSH transfers from the Federal government. There was more diversion in larger states, states with more public hospitals and states where there is a greater difference in the tendency of public and private hospitals to treat poor patients. Like Duggan (2000) they examine the effect of DSH payments on patient health outcomes, though they use differences across state expropriation behavior and hospital ownership to distinguish between "effective" DSH payments that led to net increases in hospital funding and "ineffective" payments that did not. They find that effective DSH payments led to large reductions in mortality for infants and heart attack patients, whereas DSH payments that were expropriated by state governments had no significant effect on mortality.

One of the most significant changes in provider reimbursement was the shift toward managed care that began in the early 1990s (Figure 4). States moved Medicaid enrollees into managed care primarily in an attempt to better control health care spending. Although managed care is widely credited with reducing the growth in commercial health insurance premiums, the potential for managed care to reduce Medicaid spending is not clear. There is good evidence that mucho of the savings achieved by commercial managed care plans in the 1990s came from the ability of plans to negotiate lower prices with providers (Cutler et al 2000). Since in most states Medicaid reimbursement rates are significantly lower than private fees, price reductions are not a likely source of savings. On the other hand, Medicaid managed care organizations may be able to reduce expenditures by managing utilization more effectively, for example by reducing inpatient admissions or emergency department visits. However, even if such utilization efficiencies are achieved, the shift to managed care contracting is likely to be associated with an increase in administrative costs.

Research on this issue finds little evidence that managed care has produced cost savings. Duggan (2004) examines the impact of managed care contracting on Medicaid expenditures in California, exploiting variation arising from the way that the state implemented the policy. The state mandated 20 counties to require certain beneficiaries to enroll in managed care. These mandates were implemented on a staggered basis between 1994 and 1999. Because the timing was essentially random, Duggan uses the mandates to instrument for managed care enrollment. He finds that, contrary to the state's objective, the managed care mandates led to a large and statistically significant increase in spending. The point estimates suggest that the mandates increased spending by between 17 and 27 percent.

Given that California's Medicaid program long had lower than average provider reimbursement rates, it is perhaps not surprising that increased managed care enrollment did not produce savings. More recent work by Duggan and Hayford (2013) provides further evidence that the effect of Medicaid managed care on program expenditures varies depending on the level of state reimbursement rates. They analyze state-level data on total Medicaid spending and Medicaid managed care enrollment from 1991 to 2009. When they instrument for managed care enrollment with the share of the state's population that is subject to a managed care mandate, the estimated managed care effect is negative but statistically insignificant. However, models in which managed care enrollment is interacted with a measure of Medicaid fee generosity indicate that this null effect masks important heterogeneity among states. The coefficient on the interaction term is negative and significant, implying that in states where Medicaid fees are relatively high, the shift to managed care does reduce program spending. In states, such as California, where fees are low, managed care is associated with higher expenditures.

Several studies have examined the effect of Medicaid managed care on access to care and health outcomes. Here again, positive or negative effects are theoretically plausible. On one hand, by emphasizing coordinated primary care and making greater use of non-physician providers, managed care organization may improve access to care. Improved access combined with an emphasis on prevention may lead to improved enrollee health. On the other hand, capitated payment arrangements can create an incentive to stint on care, especially for higher risk enrollees.

Currie and Fahr (2005) use national survey data on low-income children to examine the relationship between state-level Medicaid managed care penetration and the probability of having at least one physician visit in a year. Overall, their results indicate little relationship between Medicaid managed care and this proxy for access. Kaestner, Dubay and Kenney (2005) use data from the National Natality Files to test for an effect of county-level Medicaid managed care penetration on the utilization of prenatal care. Because they do not directly observe mothers' insurance status, they stratify the analysis by education and marital status, two variables that strongly predict Medicaid enrollment. For unmarried women with less than 12 years of education, they find that living in a county with a mandatory Medicaid managed care program is negatively associated with the number of prenatal visits. However, they find generally similar results for married women with 12 to 15 years of education, who are much less likely to have Medicaid coverage. Difference-in-differences models that treat unmarried, less educated women as the treatment group and married more educated women as controls yield generally insignificant results.

In his study on California's county level mandates, Duggan uses hospital discharge data to examine the effect of managed care on in-hospital infant mortality and the percentage of premature births. He finds no statistically significant effect of managed care on either outcome. Aizer, Currie and Moretti (2007) also study birth outcomes in California over a similar period and find that managed care is associated with a lower likelihood of receiving prenatal care in the first trimester and an increased likelihood of low birthweight and neonatal mortality. They argue that the main reason for the difference between their results and Duggan's null results is that their analysis focuses more closely on women who were likely to be subject to a managed care mandate.

As noted, Medicaid beneficiaries represent a majority of nursing home patients in the US. There are a number of studies on how Medicaid reimbursement policy affects the nursing home market. Norton (2000) and Grabowski and Norton (2008) provide good reviews of this literature. One issue that has received considerable attention is the relationship between Medicaid payment levels and nursing home quality. As described in Section IV.C, the relationship can be positive or negative depending on the extent to which supply-side constraints lead to a situation of excess demand. Several early studies find evidence a negative relationship between Medicaid payment rates and input-based proxies for quality in individual states (Nyman 1985, 1988a, 1988b; 1989; Gertler 1989, 1992). However, more recent research finds a positive relationship between Medicaid payment rates and a number of different process and outcome-based measures of quality (Cohen and Spector 1996; Grabowski 2001a, 2001b, 2004; Grabowski and Angelelli 2004; Grabowski, Angelelli and Mor 2004). In one of the more recent studies, Grabowski (2001a) replicates the analysis in one of the earlier papers (Gertler 1989). Applying the methods and quality measures from the earlier study to more recent data, Grabowski finds a positive relationship between Medicaid payment and quality, which suggests that changes in market conditions are at least part of the explanation for the divergent results from the earlier and later studies. In particular, nursing home occupancy rates, an indirect indicator of excess demand, declined substantially between the mid-1970s and early 1990s.

D. Financial Impacts on Households

Finklestein et al (2012): The Effect of the Public Health coverage on Individual Finances

As noted above, a lottery was carried out in Oregon during 2008hat selected a group of uninsured low-members of the winning households to become eligible Medicaid. The authors find that after one year, the selected group was about 25 percent more likely to have insurance relative to the (nonselected) control group.

As noted above they estimate Intent to Treat Effects and Average Treatment Effects for their outcomes; here we are concerned these effects for the J financial outcomes reported in their Table VII. The ITT effects are obtained from the regression

$$y_{ihj} = \beta_{0j} + \beta_{1j} LOTTERY_h + X_{ih}\beta_{2j} + V_{ih}\beta_3 + \varepsilon_{ihj},\ \text{j=1,...,J.} \quad (1)$$

where i denotes individual, h denotes household, $LOTTERY_h = 1$ if household h won the lottery and zero otherwise, X_{ih} are a set of explanatory variables potentially correlated with the probability of treatment and included to avoid bias in β_{1j}, V_{ih} are a set of explanatory variables that are included to increase efficiency but are not need to avoid bias in β_{1j}, the outcomes. For the dependent variable in (1) they consider outcomes from three sets of financial variables: 1. Overall Financial Health - any bankruptcy, any lien, any judgement, any collection, any delinquency on their credit accounts, as well as a standardized measure that summarizes the previous variables; 2. Medical debt – any medical debt collection, the amount owed in medical collection, and a standardized measure that summarizes the previous two variables; and 3. Nonmedical debt – any nonmedical debt collection, the amount owed in nonmedical debt collection, and a standardized measure that summarizes the previous two variables. Thus for overall financial health they consider 6 outcomes, while they consider 3 outcomes each for medical debt and for nonmedical debt.

They also estimate Average Treatment Effects by estimating the following system of equations using IV

$$\text{INSURANCE}_{ih} = \delta_{0j} + \delta_{1j} LOTTERY_{ih} + X_{ih}\delta_2 + V_{ih}\delta_3 + u_{ihj},\ \text{j=1,...,J.} \tag{2}$$

$$y_{ihj} = \pi_{0j} + \pi_{1j}\text{INSURANCE}_{ih} + X_{ih}\pi_2 + V_{ih}\pi_3 + v_{ihj},\ \text{j=1,...,J.} \tag{3}$$

From Table VII their results can be summarized as follows. First, for the ITT effects and the ATE effects taken together, only one of the effects is statistically significant; probably one does not want to put too much weight on this given it is a multiple testing situation. Second, all of the IIT effects and the ATE effects are statistically significant for the medical debt variables, with the latter effects being about four times as big as the former effects. Finally, none of the IIT effects or the ATE effects is statistically significant for the nonmedical debt variables. As noted above, given these estimates are based on random assignment, one probably wants to put extra weight on them in forming an overall impression of the relevant ITT effects and ATE's.

Gross and Notowidigdo (2011): Health insurance and the consumer bankruptcy decision: Evidence from Expansions of Medicaid

Gross and Notowidigdo (2011, hereafter GN) investigate whether being eligible for Medicaid reduced consumer and firm bankruptcies. The use data from the CPS for the years 1992-2004 and exploit the variation in Medicaid eligibility provided by the Medicaid expansions over that period. They consider the regression using state level data

$$\ln(c_{st}) = \alpha_s + \alpha_t + \beta M_{st} + \varepsilon_{st}, \tag{4}$$

where s represents state, t represents year, c_{st} denotes is the number of consumer bankruptcies in state s in year t, and M_{st} denotes the fraction of population eligible for Medicaid in state s in year t. The parameter of interest is β, and they instrument M_{st} using the CG instrument discussed in the take-up and crowd-out literature. This will be a valid instrument as long as shocks to state level bankruptcies in state s do not affect Medicaid eligibility rules in the state.

Their estimate (standard error) of β is -0.8 (0.347), implying that a 10 percentage point increase in Medicaid eligibility reduces personal bankruptcies by 8%. As a specification test they run (4) when the dependent variable is business bankruptcies, since one would expect these bankruptcies to be unaffected by Medicaid eligibility. In this case the point estimate (standard error) is 0.268 (0.585). They then use their parameter estimate of β to calibrate a theoretical model, and find that the model implies that out-of-pocket medical costs are pivotal in roughly a quarter of personal bankruptcies among low-income households.

Mazumder and Miller (2014): The Effects of the Massachusetts Health Reform on Financial Distress

Mazumder and Miller (2014, MM hereafter) use detailed credit report information on a large panel of individuals[33] to examine the effect the 2006 Massachusetts health care reform on the financial outcomes for those who were uninsured before the reforms. They use a triple difference estimation strategy where they use a number of financial wellbeing measures as dependent variables

$$Y_{ijt} = \beta_c + \beta_1 Uninsured2005_j + \beta_2 MA_j * Uninsured2005_j + \beta_3 Implementation_t + \beta_4 Post_t + \beta_5 Implementation_t * MA_j + \beta_6 Post_t * MA_j + \beta_7 Implementation_t * Uninsured2005_j + \beta_8 Post_t * Uninsured2005_j + \beta_9 Implementation_t * Uninsured2005_j * MA_j + \beta_{10} Post_t * Uninsured2005_j * MA_j + \varepsilon_{ijt} . \quad (5)$$

In (5) *i* represents individual, *j* represents group, and *t* represents year, $Uninsured2005_j$ represents the uninsurance rate for county-age group j, MA_j represents a dummy if the state is Massachusetts, $\text{Implimentation}_t = 1$ for *t=2006 or 2007* and zero otherwise, and $Post_t = 1$ for t > 2007 and zero otherwise. The coefficient of interest is β_{10}, and the standard errors are clustered at the county level Post represents after 2007. The following table shows the coefficients of interest for the different choices for the dependent variable Y_{ijt}.

	Risk Score[34]	Total Debt	Amount Past Due	Fraction of Debt Past Due	Total Collections	Bankruptcy last 24 months
Coefficient	0.362	-126.4	-26.29	-0.0009	-1.676	-0.0003

33 They data used data from the Federal Reserve Bank of New York Consumer Credit Panel data set as well as the Census Small Area Health Insurance Estimates (SAHIE) data.

34 A higher risk score indicates a lower probability of future default.

STD error	0.148	87.66	8.409	0.0002	0.903	0.0001

Note that in all of these regressions, the positive impact of the reform on financial wellbeing is statistical significant at very high test levels, with the exception of the effect for total collections being significant only at the 10% level and the effect for total collections being statistically insignificant. MM finds that their qualitative results are robust to alternative choices of the comparison group and the level of geographical aggregation.

Deleire and Levy (2008): What Do People Buy When They Don't Buy Health Insurance and What Does that Say about Why They Are Uninsured?

Deleire and Levy (2008, hereafter DL) consider the regression for 18 categories of consumption Y_{itk} :

$$Y_{itk} = X_{it}\beta_k + \gamma_k uninsured_{it} + \delta_k total\,outlays_{it} + \phi_k total\,outlays_{it}^2 + \mathrm{e}_{it}, \qquad \text{k=1,...,18.} \quad (6)$$

using individual data from the 2004, 2005, and 2006 panels of the Consumer Expenditure Survey.

In ( ) X_{it} are control variables including state and year dummies, $uninsured_{it}$ is a dummy variable coded 1 if reference person of the household does not have health insurance and 0 ohterwise, and $total\,outlays_{it}$ denotes the family's total consumption outlays in year t.

The parameters of interest are the γ_k's, but because they do not instrument $uninsured_{it}$, these coefficients do not have causal interpretations.[35] They run (6) separately for "low

[35] One can view buying health insurance as one type of consumption, and that ( ) represents regressing one type of consumption on another, as is often one in the life-cycle labor supply literature (MaCurdy 1983, Altonji 1986). If one takes this view, it makes it difficult to interpret the coefficients on the uninsured variable even if one instruments it.

spenders” and “high spenders”; low spenders are those in the bottom half of the annual total expenditure distribution of their sample and high spenders are the remaining families. The following table shows the estimates of γ_k (standard errors) for the different types of consumption for the dependent variable Y_{itk}; note that the uninsured have higher levels of consumption in all categories, and many of these effects are statistically significant at conventional test levels. Dl argue first that differences in prices, preferences, and income of the uninsured help explain why some households do not buy coverage They also argue that this suggests that the uninsured lack coverage in part because they face higher prices for basic needs like housing and food.

	Low Sp.	**High Sp.**
Housing	507 (58)	1,266 (314)
Food at home	289 (28)	369 (65)
Food away	-33 (18)	-41 (86)
Transportation	57 (47)	510 (290)
Utilities	39 (21)	-102 (48)
Furniture/appliances	48* (20)	193 (149)
Clothing	13 (16)	19 (88)
Entertainment	-32 (18)	-242 (115)
Health insurance	-764 (16)	-1,710 (55)
Medical care	-80 (17)	142 (81)
Education	18 (32)	-195 (179)
Alcohol	31 (10)	60 (26)
Tobacco	139 (12)	146 (20)

Household services	8 (11)	-200 (70)
Personal care	-11 (4)	-40 (12)
Life insurance	-50 (6)	-104 (44)
Retirement pensions	-257 (28)	-789 (153)`

E. Labor Supply, Labor Market Transitions, and Other Program Participation

Group 1 Papers

Blank (1989), Winkler (1991), Moffitt and Wolfe (1992:) Studies Covering the Period when Medicaid Receipt was Coupled with AFDC Receipt

How Medicaid coverage affects the labor force participation rate and/or welfare participation of single mothers is a longstanding question in labor/public economics. Earlier research noted that welfare participation not only delivered cash benefits to a family but it also provided health insurance coverage for the family, and each of these would affect the probability of labor force (welfare) participation.

Here and in what follows we use a simplified model for a single mother where there is no difference between being out of the labor force and being on welfare. She has zero no labor income in the absence of welfare receipt, and can earn wage w if she works. Further there are no income taxes in the economy nor are there any fixed costs of participation. Further, all labor income is taxed at 100% while the family is on welfare. Finally the family values Medicaid services at what they cost. Unless otherwise noted, none of these simplifying assumptions affects the qualitative theoretical predictions of the effects of various policy changes.

We first consider the case where Medicaid receipt is tied to welfare receipt. In year t and state s, while on welfare family *i* receives welfare benefits B_{ist} and Medicaid benefits valued in dollars as M_{ist}. Their budget constraint is ACDEH in Figure 1. (Note that $AC = B_{ist}$ and $CD = M_{ist}$.) While optimization over this nondifferentiable budget constraint (and the ones that follow) is complicated, one can think of a woman first calculating her maximum utility, $U^1(w_{it})$, if she works and comparing it to her utility, $U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist})$, if she does not work.

She participates in the labor force if and only if

$$U^1(w_{it}) > U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist}).^{36} \quad (1)$$

Since $\partial U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist}) / \partial \mathrm{B}_{ist} > 0$ and $\partial U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist}) / \partial M_{ist} > 0$, an increase in B_{ist} or M_{ist} unambiguously reduces labor force participation.

Earlier researchers wanted to separately identify the effect of B_{ist} and of M_{ist} on welfare participation. Measuring B_{ist} is straight forward but they had to impute a value of M_{ist} to the family, a difficult task. To do the latter, they assumed the family valued Medicaid services at their cost of production (in an actuarial sense). Blank (1989) and Winkler (1991) followed this approach by exploiting only state and time variation (conditional on family size) in B_{ist} and M_{ist}. They find generally small and insignificant effects of the value of Medicaid on both labor force participation and welfare participation.

Moffitt and Wolfe (1992) developed a family-specific proxy for the value of Medicaid M_{ist} that took into account health conditions in the family, as described in Appendix A. The advantage of their approach is that it explicitly accounts for the fact that health insurance is worth much more to some families than others; the disadvantage is that it is based

[36] For expositional purposes we act as if these steps are sequential, but of course $U^1(w_{it})$ depends on her hours of work decision. Since we will only be looking at the participation decision this does not create a problem.

on self-reported health measures that some researchers believe will be endogenous, if only because of measurement error. They then included their imputed value of M_{ist} in cross-sectional probit equations for AFDC participation and employment that also included B_{ist} and a whole host of other conditioning variables.[37] They found that higher Medicaid benefits did not lead to significantly higher rates of AFDC participation or significantly lower rates of labor force participation for all families or for families with lower medical costs. However, they found that higher expected costs did significantly respond to higher values of M_{ist} in the expected direction. Interestingly, the literature that followed their paper did not distinguish between high health expenditure families and low health expenditure families, and this seems like a worthwhile topic for future research.

Yelowitz (1995) and Ham and Shore-Sheppard (2005b) -The Uncoupling of Welfare and Medicaid

The Medicaid expansions of the late 1980's and onwards separated the receipt of Medicaid benefits from welfare participation and changed the family's budget constraint. . Specifically, now a child of age a in state s in year t was covered if the family's income fell below an income limit L_{ast}; note that prior to this the family's income (including welfare benefits) had to fall below B_{ist}. Moreover, if the family has two children, one aged a' and one aged a'', it will face income limits $L_{a'st}$ and $L_{a''st}$ respectively, where $a' < a''$ implies $L_{a'st} > L_{a''st}$.

Thus the family's budget constraint will depend on the number of children and their ages, as well as the state of residence and the year. For simplicity, we assume that the family has one child of age *a*. Then the decoupling of AFDC and Medicaid allows the family to enjoy Medicaid benefits of $\tilde{\mathrm{M}}_{ist}$ when working; note that $\tilde{\mathrm{M}}_{ist} < \mathrm{M}_{ist}$ since the mother is not covered by Medicaid when she works.

We can draw the family's budget constraint as ACDFGH, in Figure 3. (Note that $AC = B_{ist}$, $CD = M_{ist}$ and the level of income associated with G is L_{ast}.) In this case the utility from not working $U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist})$ from the case in Figure 1 where Medicaid and welfare are coupled. However, utility while working will be a function of wages, Medicaid services, and the income limits $U^2(w_{it}, \tilde{\mathrm{M}}_{ist}, \mathrm{L}_{ist})$. Now the mother works if (and only if))

$$U^2(w_{it}, \tilde{\mathrm{M}}_{ist}, \mathrm{L}_{ist}) > U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist}). \tag{2}$$

Since $\partial U^2(w_{it}, \tilde{\mathrm{M}}_{ist}, \mathrm{L}_{ist}) / \partial \tilde{M}_{ist} > 0$ and $\partial U^2(w_{it}, \tilde{\mathrm{M}}_{ist}, \mathrm{L}_{ist}) / \partial L_{ist} > 0,$ a mother facing the budget constraint in Figure 2 is more likely to work than when she faces the budget constraint in Figure 1. In summary, for our simple model there are 4 variables that can be used to parameterize the budget constraint for the family: B_{st}, M_{st}, $\tilde{M}_{st}$ and L_{ast}.

Yelowitz (1995) was the first to exploit the delinking of Medicaid from welfare. He approximates the mother's decision rule

$$U^2(w_{it}, \tilde{\mathrm{M}}_{ist}, \mathrm{L}_{ist}) > U^0(\mathrm{B}_{ist}, \mathrm{M}_{ist}) \tag{3}$$

by

$$U^{2'}(w_{it}, \mathrm{L}_{ist}) > U^{0'}(\mathrm{B}_{ist}), \tag{4}$$

with the prediction that an increase L_{ist} (B_{ist}) will increase (decrease) labor force participation. This approach allows him to avoid the challenge of imputing the cash value of Medicaid to the family, M_{ist}; note that prior to this decoupling, $\mathrm{L}_{ist} = \mathrm{L}_{ist} = B_{ist}$. Using the income limits does come with some cost. First, it is much easier to interpret the coefficients on M_{ist} and $\tilde{M}_{ist}$, than on L_{ist}, from an economic, as opposed to a statistical, perspective. Second there is the question of how to parameterize the model for families with more than one child. Yelowitz focuses on the income limit for the youngest child, but it's not clear why this is preferable to using the income limit, e.g. for the second oldest child. Third, given that the mother only has insurance when on AFDC, it is not clear how good an approximation ( ) is.

In any case, Yelowitz uses four years of March CPS data, from 1989 to 1992 .He expresses both the Medicaid income limits for the mother's youngest child and the AFDC income limits as a percentage of the federal poverty line to obtain variables MEDICAID% and AFDC% respectively. His explanatory variable of interest is[38]

$$GAIN\%_{ist} = MEDICAID\%_{ist} - AFDC\%_{ist}, \tag{5}$$

Note that in terms of the model discussed above, if we denote the federal poverty limit (for a family the same size as I's) in year t as POV_{it}, then

$$GAIN\%_{ist} = \frac{L_{ist}}{\mathrm{POV}_{it}} - \frac{B_{ist}}{\mathrm{POV}_{it}}. \tag{6}$$

He considers index functions of the form

$$y^{*}_{kist} = \alpha_{1k} GAIN\%_{ist} + \alpha_{2k} X_{ist} + \varepsilon_{kist} \tag{7}$$

[38] This is a simpler formulation of GAIN% than used by Yelowitz but it is numerically equivalent to his specification.

where $k=1$ denotes welfare participation, $k=2$ denotes labor force participation and ε_{kist} is a standard normal random variable. Further, X_{ist} contains a large number of control variables including dummies for state, the youngest child's age, and year. Yelowitz estimates the parameters in (3) by probit analysis, and finds that $GAIN\%_{ist}$ is strongly significant with the expected sign for both labor force participation and welfare participation. Moreover, his results are robust to extending his analysis by allowing for interactions and by stratifying the sample on various demographic variables.

However, Ham and Shore-Sheppard (2005) note a peculiar feature of Yelowitz's specification: the effects of $MEDICAID\%_{ist}$ and $AFDC\%._{ist}$ are constrained to be equal in magnitude but opposite in sign. Since the constraint implies that welfare benefits had no effect on labor force or welfare participation in the period prior to the decoupling of Medicaid and AFDC it contradicts basic economic theory.. They then consider probit equations of the form

$$y^*_{kist} = \beta_{g1k} MEDICAID\%_{ist} + \beta_{g1k} AFDC\%_{ist} + \alpha_{2k} X_{ist} + \varepsilon_{kist} \tag{8}$$

and test the null hypotheses

$$H_{ok} : \beta_{g1k} = \beta_{a1k}, k = 1, 2. \tag{9}$$

They decisively reject both null hypotheses, and find that the coefficient on $AFDC\%_{ist}$ is statistically significant and has the expected signs in both the labor force participation and welfare participation equations, while the coefficient on $MEDICAID\%_{ist}$ is small and statistically in significant in both participation equations. Moreover, they replicated these results when i) they extend the CPS data to cover the period 1988-1996 and ii) when they estimate (Ham and Shore-Sheppard 2001) the model using the data from the Survey of Income and Program Participation (SIPP). They conclude that if anything, Yelowitz's approach actually indicates that the decoupling of AFDC and Medicaid did not affect labor force or welfare participation. One caveat to this result is that groups that are more likely to take-up Medicaid when eligible will be more sensitive to the income limits. Given that we know there is substantial heterogeneity in take-up across demographic groups (Ham, Ozbeklik, and Shore-Sheppard, 2014a, 2014b), it would be interesting to allow for heterogeneous treatment effects, based both on the family's demographic characteristics and the family's health status, of the income limits.

Meyer and Rosenbaum (2001) - Allowing for Multiple Program Participation

Of course in practice low income families make use of multiple programs, e.g. welfare, Medicaid, food stamps, section 8 housing the Earned Income Tax Credit, etc. To get a first look at how these programs work together, consider simply adding food stamps to the budget constraint in Figure 2. A basic food stamp program works as follows. Family *i* would obtain food stamps F_{it} if they have no labor income, and their allocation is reduced by \$0.3 for every \$1 of net earned income i.e. income after deductions. Since one of these also deductions is 20% of gross income, the effective tax rate equals $\tau=$0.24=0.3*0.8. In what follows we ignore other deductions for expositional ease, in which case the breakeven point equals $\overline{F}_{it}=F_{it}/.24$, where $\overline{F}_{it}$ can also be viewed as the food stamp income limit. In Figure 3 we show the new budget constraint in Figure 3, and a possible equilibrium at E, where the family gets food stamp benefits of $F_{it}^{*}, 0<F_{it}^{*}<F_{it}$ and the family qualifies for Medicaid, and has other consumption Y_{it}^{*}. In this case we write the participation decisions as participate if and only if

$$U^2(w_{it},\tilde{\mathrm{M}}_{ist},\mathrm{L}_{ist},\tau,\mathrm{F}_{ist})>U^0(\mathrm{B}_{ist},\mathrm{M}_{ist},\mathrm{F}_{ist}) \tag{10}$$

or in terms of the direct utility function

$$U^3(\mathrm{Y}_{it}^{*},\tilde{\mathrm{M}}_{ist},\mathrm{leis}_{ist},F_{it}^{*})>U^0(\mathrm{B}_{ist},\mathrm{M}_{ist},\mathrm{F}_{ist}), \tag{11}$$

where les_{ist} denotes leisure or time allocated to nonmarket activities.[39]

This example raises the possibility of partial participation in a program, which is a qualitatively different situation than when we simply considered AFDC and Medicaid above, and the actual optimizing behavior when working becomes important. Of course this example is too simple to describe the real world, since one needs to account for several programs, and there may be interactions between the programs.

Meyer and Rosenbaum (2001) consider the effect on labor force participation of several programs simultaneously, allowing for interactions between the programs. Their approach is based on an optimizing model where the mother compares the expected utility while working to the known utility when not working. Their crucial assumptions i) actual wages and hours for a given single woman *without* children is a draw from a common wage-hours distribution and thus each single woman *without* children uses the same wage and hours of work distribution to calculate expected utility when working ii) actual wages and hours for a given single woman *with* children is a draw from a common wage-hours distribution and thus each single woman *with* children uses the same wage and hours of work distribution to calculate expected utility when working Given this assumption, the only optimizing behavior is in the choice of whether to work or not, and one bypasses the difficult issue of optimizing subject to nonlinear and non-differentiable budget constraint. Note that even if one models wages and hours as being determined stochastically, the assumption that all women with (without) draw from the same distribution is a strong one, so they repeat their analysis separately for low, medium and highly

[39] It is not clear whether introducing food stamps reduces the likelihood of a person working since it increases both sides of (10), although it will reduce hours if she works before and after the introduction of food stamps. Because of the nonlinear budget constraint, one cannot simply compare the value of time at zero hours of work to the net wage for the first hour of work.

education women. Of course this will not correct for any age, race or cost of living differences in wage-hours packages.

They use a direct utility approach as in (11) and assume that utility is additive in income and in nonmarket time[40]

$$U(Y,\mathrm{L}) = \alpha Y + \beta leis + \delta X + e. \tag{12}$$

Let $Y_{wt}, \mathrm{les}_{wt}, Y_{nwt}$ and $leis_{nwt}$ represent respectively in year t, income when working (including the effects of all taxes and social programs), nonmarket time when working, income when not working, and nonmarket time when not working. utility when non-working is

$$U(Y_{nwt}, \mathrm{L}_{nwt}) = \alpha Y_{nwt} + \beta\,\mathrm{L}_{nwt} + \delta_{nw}\,\mathrm{X}_t + \mathrm{e}_{nw}, \tag{13}$$

which is known with certainty (e.g. full take-up of all social programs). They assume that wages and hours have a joint distribution with support points (w_j, h_k) and associated probabilities (estimated from data on working women)[41] p_{jk}, $j = 1,\ldots,\mathrm{J}$ and $k = 1,\ldots,\mathrm{K}$. Denote net income when working given the draw $(w_{j'}, h_{k'})$ by $Y_{wl'k't}$, where $Y_{wl'k't}$ reflects full take-up of all social programs for *gross* earnings $w_{j'} * h_{k'}$ in year t. Then utility when working for this draw is given by

$$U(Y_{j'k't}, \mathrm{L}_{j'k't}) = \alpha Y_{j'k't} + \beta\,\mathrm{L}_{j'k't} \tag{14}$$

and expected utility when working is

[40] For expositional ease, we ignore the fact that they also allow for fixed costs or stigma effects of collecting welfare when working, but not for fixed costs or stigma associated with welfare receipt when not working, or the receipt of Medicaid, food stamps or training if working

[41] The implicit assumption her is that non-working women would face the same distribution, i.e. there is no selection bias.

$$\sum_{j'=1}^{J}\sum_{k'=1}^{K} P_{j'k'} U(Y_{j'k't}, \mathrm{L}_{j'k't})$$

$$= \alpha \sum_{j'=1}^{J}\sum_{k'=1}^{K} P_{j'k'} Y_{j'k't} + \beta \sum_{j'=1}^{J}\sum_{k'=1}^{K} P_{j'k'} L_{j'k't} + \delta_w \mathrm{X}_t + \mathrm{e}_w \tag{15}$$

$$= \alpha E\left(Y_w\right) + \beta E(L_{wt}) + \delta_w \mathrm{X}_t + \mathrm{e}_w .$$

MR use then use the identity

$$Y_{j'k't} = LEarn_{j'k't} - Tax_{j'k't} + AF_{j'k't} + MED_{j'k't}, \tag{16}$$

where $LEarn_{j'k't}, Tax_{j'k't}$, $AF_{j'k't}, MED_{j'k't}$, denote labor earnings, net taxes, transfers from AFDC and food stamps, and the cash value of Medicaid coverage when working at wage-hours package $(w_{j'}, h_{k'})$. Taking expectations of (16) in the same fashion yields

$$E(Y_t) = E(LEarn_t) - E(Tax_t) + E(AF_t) + E(MED_t). \tag{17}$$

It is worth noting that there will be no variation across the sample in $E(LEarn_t), \mathrm{les}_{nw}$ and $E(\mathrm{les}_w)$, while the variation in $\mathrm{E}(Tax_t), E(AF_t)$ and (MED_t) comes from state of residence and the number of children in the family and their ages. MR also split up known income when not working into $Y_{nwt} = AF_{nwt} + MED_{nwt}$. They then let income from different sources have a different effect on utility, so expected utility when not working is now given by

$$EU_{nwt} = \gamma_1 AF_{nwt} + \gamma_2 MED_{nwt} . + \beta \mathrm{L}_{nwt} + \delta_{nw} \mathrm{X}_t + \mathrm{e}_{nw} \tag{18}$$

$$\begin{aligned} EU_w = {} & \alpha_1 E(LEarn_t) + \alpha_2 E(Tax_t) + \alpha_3 E(AF_t) + \alpha_4 E(MED_t) + \beta E(L_{wt}) \\ & + \delta_w \mathrm{X}_t + \mathrm{e}_w \end{aligned} \tag{19}$$

The mother participates in the labor force if $EU_w > EU_{nw}$ or

$$\begin{aligned}&\alpha_1 E(LEarn_t) + \alpha_2 E(Tax_t) + \alpha_3 E(AF_t) + \alpha_4 E(MED_t) \\ &+\beta E(L_{wt}) + \delta_w \mathrm{X}_t + \mathrm{e}_w > \gamma_1 AF_{nwt} + \gamma_2 MED_{nwt} + \beta L_{nwt} + \delta_{nw} \mathrm{X}_t + \mathrm{e}_{nw}\,.\end{aligned} \tag{20}$$

Equation (20) implies she participates if

$$\begin{aligned}&\alpha_2 E(Tax_t) + \alpha_3 E(AF_t) + \alpha_4 E(MED_t) \\ &+\beta E(L_{wt}) + (\delta_w - \delta_{nw})\mathrm{X}_t - \gamma_1 AF_{nwt} - \gamma_2 MED_{nwt} > \mathrm{e}_{nw} - \mathrm{e}_w,\end{aligned} \tag{21}$$

where in (21) we have used the fact that $E(LEarn_t), E(L_{wt})$ and L_{wt} are constant.

MR describe this as a structural approach, but it seems to us to have much more in common with the reduced-form approaches that use the income limits or use of FRACELIG as an instrument for Medicaid eligibility. The problem here is that many of these women are working so they know their wages and potential hour's constraints. Moreover, many of the non-participants will have worked in the past and have some idiosyncratic information about their opportunity set. The upshot is that if we interpret their approach as a structural one, they will have a huge measurement error problem.

A more natural structural approach in our view would follow the labor force participation literature for married women. The simplest approach would be to run, for the sample of workers, the first stage equations[42]

$$\backslash W_{kit} = \pi_{1k} E_i(Tax_t) + \pi_{2k} E_i(AF_t) + \pi_{3k} E_i(MED_t) + \pi_{4k}\mathrm{X}_{it} + v_{kit},\ \mathrm{k} = 1,2,3 \tag{22}$$

where $W_{1it} = Tax_{it}, W_{2it} = AF_{it},$ and $W_{3it} = MED_{it}$. Then use the coefficients from (22) to obtain the imputed values $ITax_{it}, IAF_{it},$ and $IMED_{it}$ for the nonparticipants. One probably also wants to use imputed values for the participants since their actual values of

[42] This also ignores selection issues. To deal with them, one would need to parameterize the wage equation and use variables that affect labor supply only through the wage to obtain exclusion restrictions for the Mills ratio.

Tax_{it}, AF_{it}, and MED_{it} are likely to be endogenous. The probit equation for participation becomes

$$\alpha_2 ITax_{it} + \alpha_3 IAF_{it} + \alpha_4 IMED_{it} + (\delta_w - \delta_{nw})\mathrm{X}_{it} - \gamma_1 AF_{inwt} - \gamma_2 MED_{inwt} > \mathrm{e}_{inw} - \mathrm{e}_{iw}. \quad (23)$$

MR estimate (21) using CPS data for 1984-1986 and find that the AFDC/Food Stamp variables are quite significant and of the expected sign, while the Medicaid variables are not; their results are robust to a number of alternative models. Thus it seems clear that the Medicaid expansions had no discernable effect on the labor force behavior of married women with children, although again it would be interesting to adjust the models for the facts that some groups have much lower take-up rates of Medicaid when eligible.

Garthwaite, Gross and Notowdigdo (2014) – Estimating the Labor Supply Effect of a Medicaid Contraction

Prior to 2005, Tennessee was one of the few states that provided Medicaid insurance to able-bodied adults without children. However in 2005 this group lost their insurance, and GGN use this natural experiment to examine the effects of this change on the subsequent employment and private insurance coverage of this group. They consider the following regression at the aggregate state level

$$\begin{aligned} L_{st} &= \alpha_s + \delta_t + \beta I[s = TN] * \mathrm{I}[\mathrm{t} \geq 2006] + \varepsilon_{st} \\ &= \alpha_s + \delta_t + \beta TN06_{st} + \varepsilon_{st}, \end{aligned} \quad (24)$$

where the α_s represent state dummies and the δ_t represent time dummies. Their estimate of β is large, positive and statistically significant. They interpret β as the effect of $TN06$ on labor supply. They acknowledge that such a reduced form regression can pick up both labor supply and demand effects. However they consider the reduced form regression for the wage

$$w_{st} = \alpha_s + \delta_t + \gamma TN06_{st} + u_{st}. \tag{25}$$

argue that since the coefficient γ is estimated to be less than zero, they can be confident that β is indeed the effect of $TN06$ on labor supply.

We believe this interpretation of their results is inconsistent with standard simultaneous equation theory and labor supply estimation. Moreover by the standard order conditions , the structural effect of $TN06$ on labor supply is not identified in their model, and that (as one would expect) the expected value of the estimate of β in (1) is a combination of labor supply and labor demand parameters. To see this write the structural labor supply equation as

$$L_{st}^{\sup} = \alpha_s^{'} + \delta_t^{'} + \pi_1 w_{st} + \pi_2 TN06_{st} + \varepsilon_{st}^{'}, \tag{26}$$

where π_2 is what labor economists would interpret as the effect of the change in Tennessee on labor supply. We consider two forms of the demand equation. In the first the demand for labor is affected by the policy change because the new workers expect employers to provide insurance

$$L_{st}^{dem} = \lambda_s + \mu_t + \varphi_1 w_{st} + \varphi_2 TN06_{st} + \varepsilon_{st}^{'}. \tag{27}$$

In the second version of the labor demand curve, which is probably closer in spirit to GGN, we set $\varphi_2 = 0,$ i.e. the policy change does not shift labor demand holding the wage constant

$$L_{st}^{dem} = \lambda_s + \mu_t + \varphi_1 w_{st} + \varepsilon_{st}^{'}. \tag{28}$$

In general we expect $\pi_1 \geq 0, \pi_2 \geq 0, \varphi_1 \leq 0,$ and $\varphi_2 \leq 0.$

By the standard order conditions, for the system described by (3) and (4), neither the labor supply or labor demand equation satisfies the order condition for identification, since there are i) no variables included in the labor supply equation but not the labor demand equation and ii) no variables included in the labor demand equation but not the labor supply equation. For the system described by (26) and (28), labor demand equation satisfies the order condition for identification but the labor supply equation does not.

To investigate what an estimate of β corresponds to, we solve for the model's reduced form equations by first setting $L_{st}^{dem} = L_{st}^{\sup} = L_{st}$ and solve (4) for the wage as a function of L_{st}

$$w_{st} = \frac{1}{\varphi_1} L_{st} - \frac{\lambda_s}{\varphi_1} - \frac{\mu_t}{\varphi_1} - \frac{\phi_2}{\varphi_1} TN06_{st} - \frac{u_{st}}{\varphi_1}. \tag{29}$$

Substituting (29) into (27) and solving for L_{st} yields

$$\begin{aligned} L_{st} = & \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\alpha_s^{'} - \frac{\pi_1\lambda_s}{\varphi_1}\right) + \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\delta_t^{'} - \frac{\pi_1\mu_t}{\varphi_1}\right) + \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\pi_2 - \frac{\pi_1\varphi_2}{\varphi_1}\right) TN06_{st} \\ & + \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\varepsilon_{st}^{'} - \frac{\pi_1 u_{st}}{\varphi_1}\right). \end{aligned} \tag{30}$$

After taking the plim of the estimated reduced form parameter $\hat{\beta}$ we have

$$\beta = \pi_2 \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\pi_2 - \frac{\pi_1\varphi_2}{\varphi_1}\right), \tag{31}$$

which is of course a combination of labor supply and labor demand structural parameters. Solving for the labor supply effect of TN06 from (31) yields

$$\pi_2 = \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)\beta + \frac{\pi_1\varphi_2}{\varphi_1}. \tag{32}$$

Since $\varphi_1 < 0$ and $\pi_1 > 0$, we have $\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)\beta > \beta$. Further, since $\varphi_1 < 0, \varphi_2 < 0, \pi_1 > 0$ and $\frac{\pi_1\varphi_2}{\varphi_1} > 0,$ we have $\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)\beta + \frac{\pi_1\varphi_2}{\varphi_1} > \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)\beta > \beta$. Note that if $TN06_{st}$ does not affect the labor demand equation, i.e. we have the system (3) and (5), we simply set $\varphi_2 = 0$ in (8) and (9) above. In this case

$$\beta = \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}(\pi_2) \quad \text{and} \qquad \pi_2 = \left(1\text{-}\frac{\pi_1}{\varphi_1}\right)\beta > \beta . \tag{33}$$

Finally if $\pi_2 = 0,$ (8) implies $\beta = 0.$ Thus β will underestimate π_2 except for the case where $\pi_2 = 0.$

GGN claim that if reduced form coefficient of TN06 in the wage equation (25), $\gamma,$ is negative one can interpret β as the effect of TENN06 on labor supply. The above discussion shows that this claim is incorrect, but still it is interesting to consider what $\gamma < 0$ in (25) implies. Below we show that if $\varphi_2 \neq 0$ and $\pi_2 \neq 0$ (i.e. TN06 affects labor supply and labor demand), or if $\varphi_2 \neq 0$ and $\pi_2 = 0$ (i.e. TN06 affects labor demand but not labor supply), the sign of γ is indeterminate. Only in the case that $\varphi_2 = 0$ and $\pi_2 \neq 0$ (i.e. TN06 affects labor supply but not labor demand) is $\gamma = 0.$ Thus $\varphi_2 = 0$ and $\pi_2 \neq 0$ is a sufficient, but not necessary condition, for TN06 to only affect labor supply.

For the system (26) and (27) the reduced form wage equation, in terms of the structural parameters is

$$\begin{aligned} w_{st} = &\left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\alpha_s^{'} - \frac{\pi_1\lambda_s}{\varphi_1}\right) - \frac{\lambda_s}{\varphi_1}\right] + \left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\delta_{ht}^{'} - \frac{\pi_1\mu_t}{\varphi_1}\right) - \frac{\mu_t}{\varphi_1}\right] \\ &+ \left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\pi_2 - \frac{\pi_1\varphi_2}{\varphi_1}\right) - \frac{\varphi_2}{\varphi_1}\right] TN06_{st} + \left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\varepsilon_{st}^{'} - \frac{\pi_1 u_{st}}{\varphi_1}\right) - \frac{u_{st}}{\varphi_1}\right]. \end{aligned} \tag{34}$$

Taking the plim of the estimated value $\hat{\gamma}$ and using (34) we have

$$\gamma = \left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}\left(\pi_2 - \frac{\pi_1\varphi_2}{\varphi_1}\right) - \frac{\varphi_2}{\varphi_1} \right]. \tag{35}$$

We note that since $\varphi_1 < 0, \varphi_2 < 0, \pi_2 > 0, \pi_1 > 0,$ we have $\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right) < 0$ and $\frac{\varphi_2}{\varphi_1} > 0.$ However the sign of $\left(\pi_2 - \frac{\pi_1\varphi_2}{\varphi_1}\right)$ is indeterminate. In other words γ can be negative if TENN)06 affects labor demand conditional on the wage, i.e. $\varphi_2 \neq 0.$ Finally, however, if $\varphi_2 = 0$ and we have the system (3) and (5), then

$$\gamma = \left[\frac{1}{\varphi_1}\left(1\text{-}\frac{\pi_1}{\varphi_1}\right)^{-1}(\pi_2) \right] < 0. \tag{36}$$

Having established that the estimate of β will underestimate the true labor supply effect of the Medicaid reduction, we consider GGN's approach to estimating β. They use two estimation strategies. First they use a double difference strategy where they compare Tennessee adults to adults in other Southern states. Secondly they use a triple difference strategy where they compare Tennessee adults without children to Tennessee adults with children. They consider the case where the dependent variable is employment rate within the adult population (individuals ages 21 and 64 who are not in the armed forces and who do not have advanced college degrees.) The difference in difference strategy indicates than TN06 increased the employment rate by 2.6 percentage points (standard error =1.1 percentage points), while the triple difference strategy in indicates than TN06 increased the employment rate by 4.6 percentage points (standard error = 2.0 percentage points). The latter is an especially large effect when one considers *i*) the estimates are lower bounds on the true labor supply effect and *ii*) that only about 4% of

Tennessee's adult population (including those in the armed forces and those with advanced degrees), i.e. the Medicaid effect is close to what one would have if everyone affected found a job.

GGN note that their results have clear implications for the effect of the introduction of the Affordable Care Act, and the differential response by states in terms of expanding Medicaid to childless adults provides an especially attractive opportunity to see if their results generalize the rest of the country. However, they also argue that one must be careful to not let this test be affected by the Great Recession; for example, in the case of 2008 Oregon Medicaid Experiment which offered households the chance to obtain Medicaid (Finkelstein et al 2012), the unemployment rate in Oregon jumped from 6.5 % in 2008 to 11.1% in 2009. We do not agree with the GGN logic, unless the jump in the unemployment rate made it harder to drop out of the labor force and receive public support. We can see how if Oregon had cut Medicaid during the 2008-2009 period the high unemployment rate would have made it difficult to replicate GGN.

Baicker et al (2013)– Using a Randomized Trial to Measure the Labor Market Effects of the Medicaid Expansion

Baicker et al consider a specification similar to Finklestein et al (2012). As noted above the consider an intent to treat equation

$$y_{ihj} = \beta_{0j} + \beta_{1j} LOTTERY_h + X_{ih}\beta_{2j} + V_{ih}\beta_3 + \varepsilon_{ij}, \qquad (37)$$

where j=1 denotes employment status, j=2 denotes earnings, j=3 is an indicator for whether earnings were above the federal poverty limit. Recall that where i denotes individual, h denotes household, $LOTTERY_h = 1$ if household h won the lottery and zero otherwise, while X_{ih} and

V_{ih} are explanatory variables. Baicker et al also estimate Average Treatment Effects by estimating

$$\text{INSURANCE}_i = \delta_{0j} + \delta_{1j} LOTTERY_h + X_{ih}\delta_2 + V_{ih}\delta_3 + u_{ihj}, \tag{38}$$

$$y_{ihj} = \pi_{0j} + \pi_{1j}\text{INSURANCE}_i + X_{ih}\pi_2 + V_{ih}\pi_3 + v_{ihj},\ \text{j=1,...,3}; \tag{39}$$

recall that INSURANCE_i =1 if the individual is covered by Medicaid and zero otherwise.

From Table 1 their results can be summarized as follows. The ITT effect and ATE (standard errors) for employment are -0.0042 (0.0037) and -0.016 (0.014) respectively; the ITT effect and ATE (standard errors) for earnings are -0.0042 (0.0037) and -0.016 (0.014) respectively; -51.74 (76.8) and -194.93 (289.0) respectively and ; finally the ITT effect and ATE (standard errors) when the dependent variable is an indicator function for whether earnings are above the federal poverty line are -0.0032 (0.0026) and 0.012 (0.0099) respectively. In other words they estimate small effects and small confidence intervals. Further, their Table 2 indicates that there are no significant ITT effects or ATEs for TANF, SSI or SSDI participation.[43]

Impact of Welfare Reform

Because AFDC participation and Medicaid participation were so tightly linked prior to welfare reform, the changes in the cash assistance system occurring due to welfare reform meant that spillovers to health insurance coverage, particularly Medicaid, were likely. While Medicaid income eligibility standards were set under PRWORA not to be more restrictive than they had been under AFDC, women leaving welfare may have been unaware that Medicaid coverage could continue and application for Medicaid became an entirely separate process. As a result, there was concern that women, in particular, lost Medicaid coverage following welfare reform

[43] Interestingly, they do see positive effects for participation in the food stamp program.

(children's eligibility standards were already higher, as has been discussed in the section above on take-up) and several groups of researchers examined the question of what the impact on health insurance coverage of welfare reform actually was. The difficulty in examining this question is in identifying the effect of welfare reform, and studies typically estimate individual models of health insurance coverage relying on state-level variation in the existence and timing of welfare reforms, or modify this approach by introducing the possibility of an untreated comparison group. Kaestner and Kaushal (2003) and Cawley, Schroeder, and Simon (2005) use married mothers as an untreated comparison group while Bitler, Gelbach, and Hoynes (2005) use married women more generally. However, DeLeire, Levine, and Levy (2006) and Ham, Li, and Shore-Sheppard (2009) argue that the assumption that married women were unaffected by welfare reform is not plausible, and Ham, Li, and Shore-Sheppard test related assumptions and conclude that women with different family structures cannot be used as untreated comparison groups. Despite the differences in approach, the papers come to broadly similar conclusions that the impact of welfare reform on insurance coverage among women was modest. Ham, Li, and Shore-Sheppard find the effect of welfare reform to be largely but not exclusively concentrated in the single mother population, estimating reductions in the probability of Medicaid coverage associated with welfare reform of about 6 percentage points (somewhat offset by an increase in private coverage) for single mothers with less than a high school education. Their evidence indicates that the effect was concentrated further among Hispanic immigrant single mothers, finding a 15 percentage point drop in Medicaid coverage for these women (and an 8 percentage point drop in the probability of any coverage).

Other Program Participation: SSI and WIC

Not available this draft

F. Effects of Medicaid on Family Structure

As discussed in Section IV, Medicaid may well have impacts on family structure both by affecting marriage probabilities and by affecting fertility. There has been very little research on the impact of Medicaid per se on marriage, though there is a long literature on the impact of AFDC and other cash welfare programs on marriage. The main results on the impact of Medicaid on marriage come from Yelowitz (1998), who looks at the probability a woman is married as a function of whether all of her children are age-eligible for Medicaid or whether any of her children are age-eligible using variation in eligibility by state, year, and age of child caused by the eligibility expansions for children of the late 1980s and early 1990s. Using only the exogenous variation in eligibility and controlling for characteristics of the mother, the number and ages of children in the family, state, year, age of youngest child, and all two-way interactions of state, year, and age of youngest child, he finds that women with all children eligible are 1.5 percentage points more likely to be married than women with at least one ineligible child, but he finds no effect for women with only some of their children eligible. Yelowitz notes that at least some of the effect that he finds may be due to selection into childbearing as a result of the expansions, but the results suggest that the marriage effect is likely to outweigh the selection effect.

However, the effect of Medicaid on childbearing is an active research area in itself. Studies in this area have focused on one or more of three possible avenues for Medicaid to affect fertility: expanded eligibility to pregnant women, infants, and children reduces the cost of having a child; funding for abortions through Medicaid is restricted to states willing to pay for abortions solely with state funds; and Medicaid covers the cost of contraception for certain groups.

To study the first avenue, expanded eligibility, researchers have focused on identifying groups more likely to be eligible for Medicaid for exogenous reasons and then examining birth rates or abortion rates for those groups. Joyce and Kaestner (1996), an early paper in this area, use a difference-in-differences estimator (eligible vs. ineligible women before and after a Medicaid eligibility expansion) and vital statistics data that include information about abortions as well as births for three states. They find evidence suggesting that the probability of abortion is lowered for unmarried non-black women with less than a high school degree, but because of the limited information about a woman's economic circumstances available in the vital statistics data, they are unable to impute eligibility for Medicaid and instead use differences in education to infer which women became eligible. Since women with higher levels of education may still be income-eligible for the expansions, this method may result in misclassification, particularly for black women. Joyce, Kaestner, and Kwan (1998), use state-quarter-race specific data from 15 states and examine the association between birth and abortion rates and Medicaid expansion using indicators for the state expanding eligibility to the poverty level and for the state expanding to 185 percent of the poverty level, controlling for state, year, quarter, and state-specific linear trends. The identification is thus from changes in eligibility over time within a state. They find an increase in the birthrate of 5 percent for white women associated with expanded eligibility but no effect for black women, and no effect on abortions. However, they do not control for other changes that might be occurring within a state over the time period so their results are suggestive rather than definitive. DeLeire, Lopoo and Simon (2011) try to take advantage of within state variation in eligibility by creating age-education-marital status demographic cells and using

Currie and Gruber's simulated eligibility index to obtain a measure of eligibility at the state-year-demographic cell level. Controlling for a variety of welfare policies and the state unemployment rate in addition to the simulated eligibility index, they find fertility is positively associated with the expansions for both whites and blacks, but once they include fixed effects for demographic cells the relationship disappears entirely. They conclude that there is no robust relationship between Medicaid eligibility and fertility. Zavodny and Bitler (2010) use a similar methodology over a somewhat longer time period. They use alternatively the Medicaid eligibility threshold applying in a demographic cell or the fraction of women in a cell who would be eligible, control for additional policy changes (including the EITC) and simultaneously examine the impact of Medicaid funding restrictions on abortion. They find some evidence of higher birth rates among whites with less than a high school education in response to expanded eligibility thresholds but no statistically significant effect when the simulated fraction eligible is used to measure eligibility. The results from these two papers suggest that any impact of Medicaid eligibility on fertility is limited and not particularly robust.

Zavodny and Bitler do find that restrictions on Medicaid funding of abortions are associated with decreases in abortion rates and increases in birth rates. This latter result generally accords with the earlier literature on Medicaid funding of abortion, (e.g. Haas-Wilson 1996; Blank, George, and London 1996; Levine, Trainor, and Zimmerman 1996; Kane and Staiger 1996), at least in finding decreases in abortion rates. The results in the literature for birth rates are somewhat more equivocal, however, with some authors finding birth rate increases (Currie, Nixon, and Cole 1996; Zavodny and Bitler 2010) and others finding birth rate decreases (Levine, Trainor, and Zimmerman 1996; Kane and Staiger 1996).

Researchers have also studied other possible effects of Medicaid abortion funding restrictions. Bitler & Zavodny (2001) find no significant effect of Medicaid funding restrictions on abortion timing, while Currie, Nixon, and Cole (1996) find no evidence of an effect on birthweight. Currie, Nixon, and Cole also find suggestive evidence of policy endogeneity in Medicaid abortion funding laws, with restrictive laws having the same effect whether or not they are enjoined by the courts and finding similar effects on high-income and low-income women. Sen (2003) finds no relationship between Medicaid funding restrictions and rates of sexually transmitted diseases among women, suggesting that Medicaid funding restrictions do not lead to increased use of safe sex behavior that prevents sexually transmitted disease, although the use of contraceptive methods such as the pill would not be detected with such an empirical strategy.

Examining contraception more directly, Kearney and Levine (2009) estimate the impact of Section 1115 waivers obtained by states to extend Medicaid family planning services to women who would otherwise not be eligible for them. They identify states and time periods with two types of waivers—expansions of family planning eligibility based solely on income and extensions of family planning eligibility to women who would otherwise lose eligibility postpartum. Using data from the Medicaid Statistical Information System and similar older data, they show that waivers, and particularly income-based waivers, were associated with larger proportions of women reported to be receiving Medicaid family planning services. Looking at birth rates by state and year and controlling for state effects, year effects, time-changing variables for states, and state-specific linear and quadratic time trends, they find that the presence of an income-based waiver reduces births by around 2 percent for non-teens and between 4.2 and 4.7 percent for teens. They also find evidence in individual data of changes in the probability of contraceptive behavior for women in states with a waiver in effect. They find that it is a relatively cost-effective approach to reducing unwanted births.

VI. Summary and Future Research Questions

Medicaid is a massive, multifaceted program touching almost every aspect of the health care and long-term care delivery systems. Covering a substantial percentage of long-term care recipients and children, and with the covered population expanding considerably under the ACA, Medicaid has moved from the margins to the mainstream. To conclude this chapter, we discuss some areas that we see as being important for future research.

Unsurprisingly, many of these areas concern the ACA. First, there is the question of the impact of states' decisions about whether and how to participate in the ACA expansion of Medicaid. What are the implications of these decisions in terms of fiscal pressures on states or the federal government? How much will fiscal pressures increase as Medicaid is used to finance coverage for growing subsets of the population? States' decisions also have implications for individuals, both in states that do and do not choose to participate. In nonparticipating states, one question is how is inequality in access to health care changing, and what are the implications of the continuing lack of insurance coverage for many low-income adults in terms of health? In participating states, the expansion of Medicaid eligibility to new groups brings new dimensions to old questions of take-up, crowd-out, labor supply, and job lock. In addition, there is the added dimension of the interaction between Medicaid and the insurance exchanges. How well integrated are the public and private dimensions of the exchanges, and how easily can individuals experiencing changes in their circumstances move from one type of coverage to another?

There are also perennial issues that are brought to the fore by the ACA, such as the relationship of the Medicaid program with providers. As we have noted, Medicaid does not compensate providers well, in general, and the question of supply of care to the insured will be an important one. In addition, there are important implications for the well-being of providers, particularly those that serve a large share of Medicaid patients, of increasing the share of Medicaid coverage in the market. Since the writers of the ACA recognized these issues and built in temporary reimbursement increases for some providers, it will be important to see how provider behavior and patient well-being are affected both by the increase and by its disappearance.

There is also the continuing and essential question of the impact of Medicaid on health. While there have been some important recent advances with the Oregon health study, health effects for adults, including for the disabled and elderly, are not well understood and thus far have been little studied. Finally, we need a better understanding of the financial impacts, again for all eligible groups, of Medicaid coverage. With expenditures of nearly $390 billion, measuring the benefits as well as the costs of this major program is crucial.

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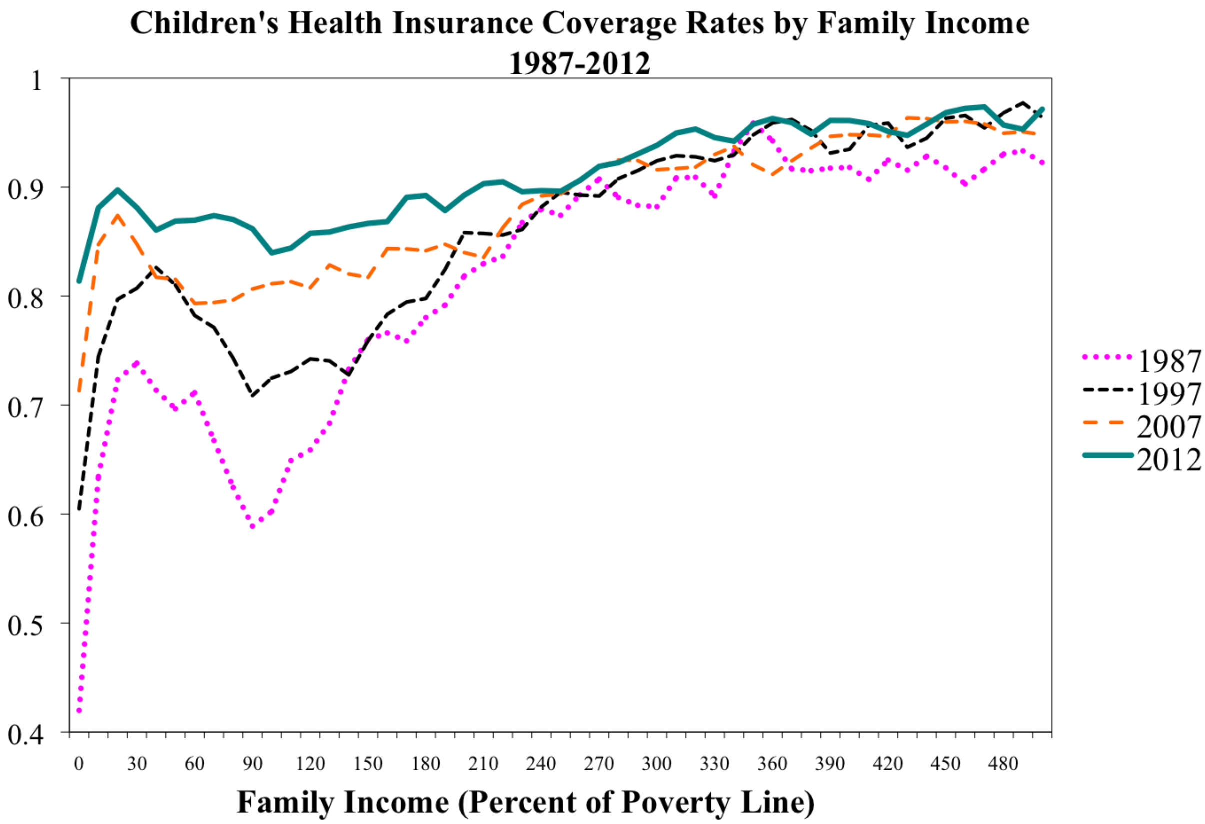
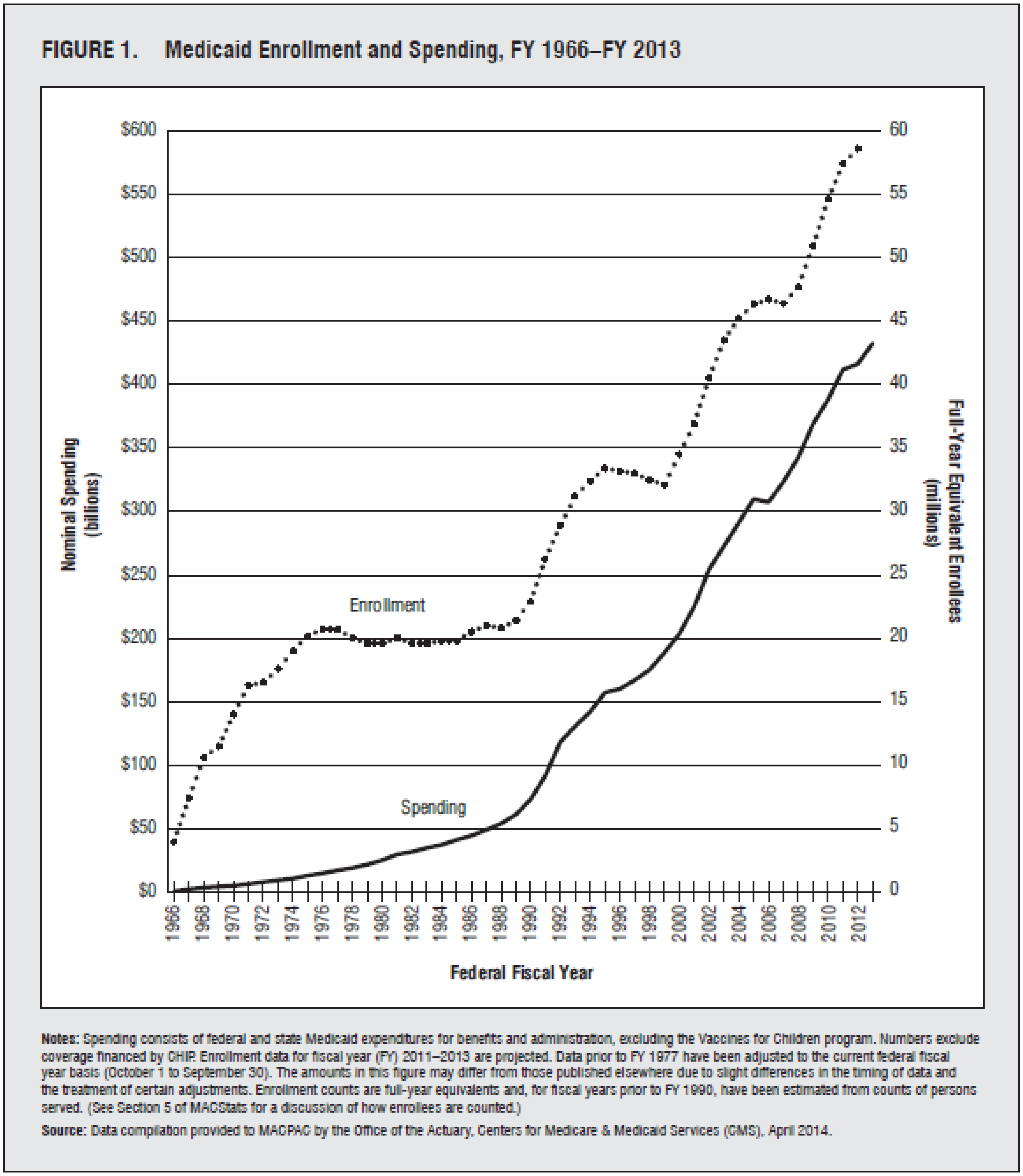
Figure 1



Notes: Updated version of Figure 1 from Card and Shore-Sheppard (2004). Data from March CPS.

Figure 2. Medicare Expenditures and Beneficiaries 1966-2012



Notes: expenditure data (nominal, in billions) covers calendar years, and are from the 2012 National Health Expenditure accounts; beneficiary data is from Table 13.4 of the 2012 Medicare and Medicaid Statistical Supplement.

Figure 3. Federal Expenditures as a Percent of Total Medicaid Expenditures

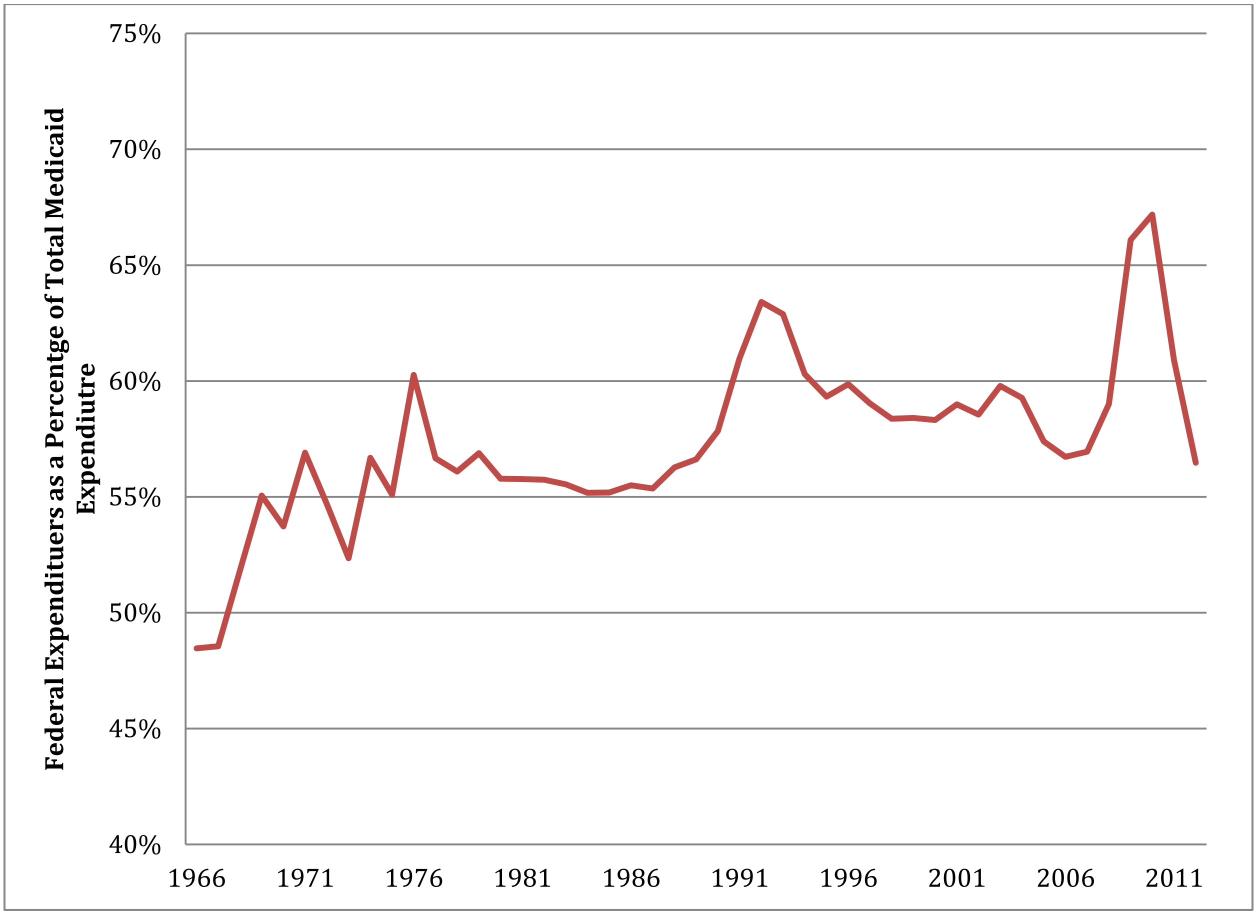


Figure 4. Percent of Medicaid Beneficiaries Enrolled in Managed Care Plans, 1991-2011.

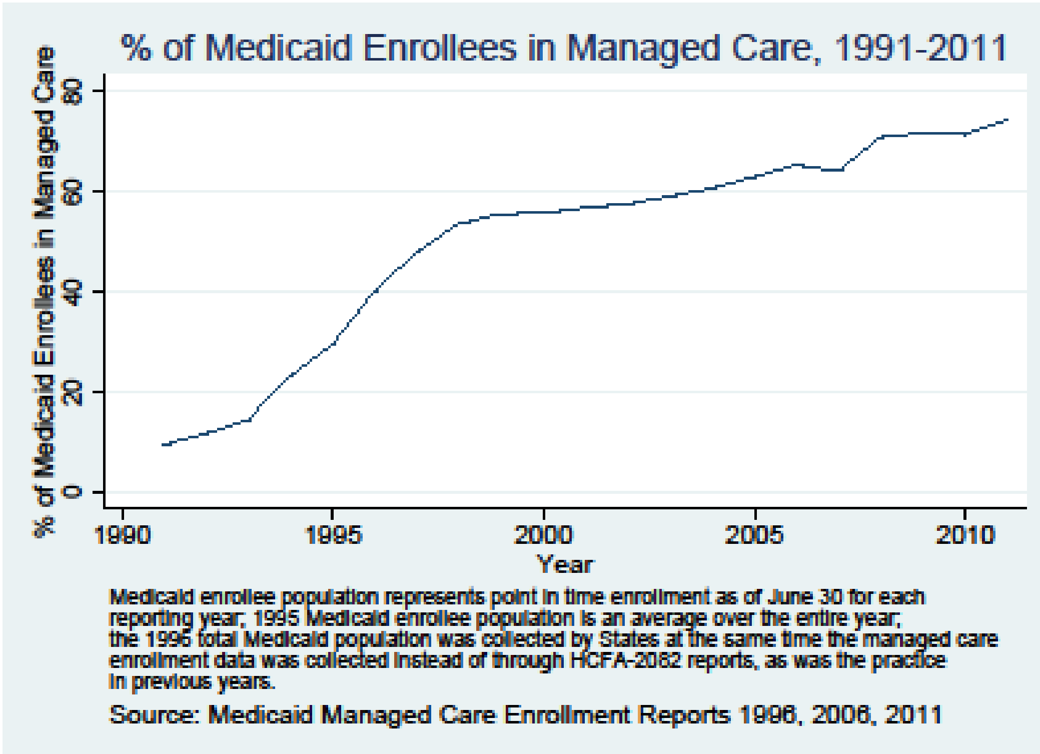


Table 1: Major Medicaid and CHIP Legislation, 1965 to 2010

Social Security Amendments of 1965	-- Established Medicaid program
Social Security Amendments of 1967	--Enacted Early and Periodic Screening, Diagnostic and Treatment (EPSDT) benefit, required for Medicaid children younger than 21 --Allowed states to extend Medicaid coverage to optional populations not receiving cash assistance, including “Ribicoff children”—individuals under 21 who would be eligible for AFDC if they met the definition of dependent child --Permitted Medicaid beneficiaries to use providers of their choice --Limited income eligibility standard for medically needy
Act of 14 December 1971	--Allowed states to cover services in intermediate care facilities for individuals with lower level care needs than skilled nursing facilities
Social Security Amendments of 1972	--Enacted Supplemental Security Income (SSI) program for elderly and disabled and required states to extend Medicaid to SSI recipients or to elderly and disabled meeting state 1972 eligibility criteria (“209(b)” option) --Repealed the Medicaid “maintenance of effort” requirement for states --Allowed states to cover care for beneficiaries under age 22 in psychiatric hospitals
Medicare-Medicaid Anti-Fraud and Abuse Amendments of 1977	--Established Medicaid Fraud Control Units
Departments of Labor and Health, Education, and Welfare Appropriations Act for FY 1977	--Enacted the Hyde Amendment, which prohibited federal Medicaid payments for medically necessary abortions except when the life of the mother would be endangered
Mental Health Systems Act, 1980	--Required most states to develop a computerized Medicaid Management Information System
Omnibus Reconciliation Act of 1980 (OBRA 80)	--Enacted the Boren amendment requiring states to pay “reasonable and adequate” rates for nursing home services instead of Medicare reimbursement rates
Omnibus Budget Reconciliation Act of 1981 (OBRA 81)	--Enacted reduction in federal matching percentages applicable from FY 1982–1984 --Extended Boren amendment payment standard to inpatient hospital services --Required states to make payment adjustments to hospitals serving a disproportionate share of Medicaid and low-income patients (DSH hospitals) --Enacted section 1915(b) freedom-of-choice waiver for mandatory managed care --Enacted section 1915(c) home and community- based waiver

	-- Eliminated special penalties for noncompliance with EPSDT requirements --Gave states with medically needy programs broader authority to limit coverage
Tax Equity and Fiscal Responsibility Act of 1982 (TEFRA)	--Allowed states to impose nominal cost-sharing on certain Medicaid beneficiaries and services
Deficit Reduction Act of 1984 (DEFRA)	--Required states to cover children born after September 30, 1983, up to age 5, in families meeting state AFDC income and resource standards --Required states to cover first-time pregnant women, and pregnant women in 2-parent unemployed families meeting state AFDC income and resource standards
Consolidated Omnibus Budget Reconciliation Act of 1985 (COBRA)	--Required states to cover pregnant women in 2-parent families (whether or not unemployed) meeting state AFDC income and resource standards
Omnibus Reconciliation Act of 1986 (OBRA 86)	--Allowed states to cover pregnant women and young children up to age 5 in families with incomes at or below 100 percent of federal poverty level --Allowed states to pay for Medicare premiums and cost-sharing for low-income Medicare beneficiaries (QMBs) with incomes at or below 100 percent of federal poverty level --Mandated coverage of emergency services for illegal immigrants who would otherwise be eligible for Medicaid
Medicare and Medicaid Patient and Program Protection Act of 1987	--Strengthened authorities to sanction and exclude providers
Omnibus Budget Reconciliation Act of 1987 (OBRA 87)	--Allowed states to cover pregnant women and infants in families with incomes at or below 185 percent of federal poverty level --Allowed states to cover children up to age 8 in families below 100 percent of poverty level --Enacted nursing home reform provisions that phased out distinction between skilled nursing facilities and intermediate care facilities, upgraded quality of care requirements, and revised monitoring and enforcement --Strengthened OBRA 1981 requirements that states provide additional payment to hospitals treating a disproportionate share of low-income patients
Medicare Catastrophic Coverage Act of 1988 (MCCA)	--Required states to phase in coverage for pregnant women and infants with incomes below 100 percent of federal poverty level --Required states to phase in coverage of Medicare premiums and cost-sharing for low- income Medicare beneficiaries (QMBs) with incomes below 100 percent of

	poverty --Established minimum income and resource rules for nursing home residents whose spouses remain in the community to prevent "spousal impoverishment"
Family Support Act of 1988 (FSA)	--Required states to extend 12 months transitional Medicaid coverage to families leaving AFDC rolls due to earnings from work --Required states to cover 2-parent unemployed families meeting state AFDC income and resource standards
Omnibus Budget Reconciliation Act of 1989 (OBRA 89)	--Required states to cover pregnant women and children under age 6 in families with incomes at or below 133 percent of federal poverty level --Expanded EPSDT benefit for children under 21 to include diagnostic and treatment services not covered under state Medicaid program for adult beneficiaries --Required states to cover services provided by federally-qualified health centers
Omnibus Budget Reconciliation Act of 1990 (OBRA 90)	--Required states to phase in coverage of children ages 6 through 18 born after September 30, 1983 in families with incomes at or below 100 percent of federal poverty level --Required states to phase in coverage of Medicare premiums for low-income Medicare beneficiaries with incomes between 100 and 120 percent of poverty (SLMBs) --Required manufacturers to give "best price" rebates to states and federal government for outpatient prescription drugs covered under Medicaid program
Medicaid Voluntary Contribution and Provider-Specific Tax Amendments of 1991	--Restricted use of provider donations and taxes as state share of Medicaid spending --Imposed ceiling on Medicaid payment adjustments to DSH hospitals (12 percent of national aggregate Medicaid spending)
Omnibus Budget Reconciliation Act of 1993 (OBRA 93)	--Established standards for state use of formularies to limit prescription drug coverage --Imposed facility-specific ceilings on the amount of payment adjustment to DSH hospitals --Tightened prohibitions against transfers of assets in order to qualify for Medicaid nursing home coverage; required recovery of nursing home payments from beneficiary estates --Established Vaccines for Children (VFC) program providing federally-purchased vaccines to states
Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA)	--Replaced AFDC with Temporary Assistance for Needy Families (TANF) and severed the automatic link between cash welfare and Medicaid. --Mandated coverage of families meeting AFDC eligibility standards as of July 16, 1996, while permitting coverage of

	higher-income families. --Prohibited Medicaid coverage for legal immigrants entering the United States after August 21, 1996, and allowed states to cover these immigrants after they have been in the country for five years. --Narrowed the eligibility criteria for disabled children.
Balanced Budget Act of 1997 (BBA 97)	--Created the State Children's Health Insurance Program (SCHIP, later referred to as CHIP), allowing states to cover uninsured children in families with incomes below 200 percent of FPL who were ineligible for Medicaid. --Allowed states to implement mandatory managed care enrollment for most Medicaid beneficiaries without obtaining section 1915(b) waivers. --Eliminated minimum payment standards for state-set reimbursement rates for hospitals, nursing homes, and community health centers, placed ceilings on DSH payment adjustments, and allowed states to shift the cost of Medicare deductibles and coinsurance requirements for low-income Medicare beneficiaries from their Medicaid programs to physicians and other providers. --Allowed partial coverage of Medicare premiums for beneficiaries with incomes between 120 and 135 percent of FPL (QIs), funded via a federal block grant. --Restored Medicaid eligibility for legal immigrants who entered the country on or before August 22, 1996 and became disabled and qualified for Supplemental Security Income (SSI) benefits thereafter. --Restored Medicaid coverage for certain disabled children who would lose their eligibility as a result of PRWORA. --Allowed states to provide up to 12 months of continuous eligibility for children. Allowed states to cover children presumptively until a formal determination of eligibility is made.
Ticket to Work and Work Incentives Improvement Act of 1999	--Allowed states to cover working disabled individuals with incomes above 250 percent of federal poverty level and impose income-related premiums on such individuals.
Emergency Supplemental Appropriations for FY 1999	--Transferred federal share of settlement funds from national tobacco litigation to states.
Breast and Cervical Cancer Treatment and Prevention Act of 2000	--Allowed states to cover uninsured women with breast or cervical cancer regardless of their income and resources.
Medicare, Medicaid, and SCHIP Benefits Improvement and Protection Act of 2000 (BIPA)	--Increased state-specific ceilings on DSH allotments --Required the Secretary of Health and Human Services to issue a final regulation restricting the amount of Medicaid payments that states may make to facilities that are operated by local governments and thus curtail the use of

	an accounting practice that allowed states to artificially inflate their reimbursable spending. --Postponed the expiration of funds appropriated for SCHIP in 1998 and 1999. --Allowed additional entities to determine presumptive eligibility.
The Jobs and Growth Tax Relief Reconciliation Act of 2003	--Raised all state Medicaid matching rates by 2.95 percentage points for the period April 2003 through June 2004 as temporary federal fiscal relief for the states due to the downturn in the economy.
Medicare Prescription Drug, Improvement, and Modernization Act of 2003	--Transferred drug coverage of individuals dually eligible for Medicare and Medicaid to Medicare starting in 2006. Medicaid still to provide some prescription drug coverage for the dually eligible population for prescription drugs not covered under the newly created Medicare Part D.
Deficit Reduction Act of 2005 (DRA)	--Provided States with increased flexibility to make significant reforms to their Medicaid programs. --Refined eligibility requirements for Medicaid beneficiaries by tightening standards for citizenship and immigration documentation and by changing the rules concerning long-term care eligibility.
Medicare, Medicaid and SCHIP Extension Act of 2007	--Reauthorized CHIP through April 2009 at then-current funding levels.
Children's Health Insurance Program Reauthorization Act of 2009 (CHIPRA)	--Reauthorized CHIP through 2013 and expanded federal funding for children's coverage by $33 billion over the next four and half years. --Established an upper income limit of 300 percent of the FPL for states to receive the more generous federal CHIP matching rate, with an exception for states that already had permission to cover higher income children. --Allowed states the option to expand coverage to legal immigrant children and pregnant women during their first five years in the country. --Required states to cover dental services, and required parity of mental health services.
Patient Protection and Affordable Care Act of 2010 (PPACA) and Health Care and Education Reconciliation Act of 2010 (HCERA)—together known as the Affordable Care Act (ACA)	--Expanded Medicaid to include all individuals under age 65 in families with income below 138 percent of the FPL starting in 2014. (Technically, the income limit is 133 percent of the FPL, but the Act also provided for a 5-percent income disregard.) The Supreme Court ruling in 2012 made this coverage expansion optional for states. --Broadened availability of long-term care services and supports, starting as early as 2010 in some instances. --Extended the authorization of the federal CHIP program for an additional two years, through September 30, 2015. Required states to maintain current income eligibility levels

	for CHIP through September 30, 2019. States prohibited from implementing eligibility standards, methodologies or procedures more restrictive than those in place as of March 23, 2010, with the exception of waiting lists for enrolling children in CHIP.

Sources: Gruber chapter, Schneider (2002) (KCMU Medicaid Resource Book: http://kaiserfamilyfoundation.files.wordpress.com/2013/05/mrbleghistory.pdf), Schneider (1997) (CBPP) (http://www.cbpp.org/cms/index.cfm?fa=view&id=2138)
CBO (http://www.cbo.gov/sites/default/files/hr5661_0.pdf),
Urban Institute (http://www.urban.org/safety-net-almanac/Medicaid-CHIP/Medicaid-Legislative-History.cfm),
Kaiser Family Foundation Timeline
(http://kaiserfamilyfoundation.files.wordpress.com/2008/04/5-02-13-medicaid-timeline.pdf)
Kaiser Family Foundation Children's Health Insurance Timeline
http://kaiserfamilyfoundation.files.wordpress.com/2007/02/5-09-13-childrens-health-insurance-timeline.pdf
Social Security Administration Annual Statistical Supplement of 2011
(http://www.ssa.gov/policy/docs/statcomps/supplement/2011/medicaid.html)
Compilation of the PPACA http://housedocs.house.gov/energycommerce/ppacacon.pdf
KCMU State Children's Health Insurance Program (CHIP): Reauthorization History
(http://kaiserfamilyfoundation.files.wordpress.com/2013/01/7743-02.pdf)
CMS Legislative Update (http://www.cms.gov/Regulations-and-Guidance/Legislation/LegislativeUpdate/index.html?redirect=/LegislativeUpdate/)
National Conference of State Legislatures
http://www.ncsl.org/portals/1/documents/health/09slapr09_CHIP.pdf

Table 2. States' Decision on ACA and Year of Original Implementation of Medicaid

	Not Implementing ACA Medicaid Expansion	Implementing ACA Medicaid Expansion	Implementing a Modified ACA Medicaid
1966	ID, LA, ME, NE, OK, UT, WI[1]	CA, CT, DE, HI, IL, KY, MD, MA, MN, NH[2], NM, ND, OH, RI, VT, WA, WV	MI[3], PA[4]
1967	GA, KS, MO, MT, SD, TX, WY	NV, NY, OR	IA[5]
1968	SC	DC	
1969	TN, VA	CO	
1970	AL, FL, MS, NC	NJ	AR[6], IN[7]
1971			
1972	AK		
1982*		AZ	

Notes: Sources- Kaiser Family Foundation http://kff.org/medicaid/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/, Arizona Medicaid website, and Gruber's Medicaid Chapter, data current as of August 2014.

[1] Wisconsin amended its Medicaid state plan and existing Section 1115 waiver to cover childless adults with incomes up to 100% FPL in Medicaid, but did not adopt the ACA Medicaid expansion.

[2] New Hampshire implemented the Medicaid expansion as of July 1, 2014, but the state plans to seek a waiver at a later date to operate a premium assistance model.

[3] Michigan is implementing the Healthy Michigan plan using a Section 1115 waiver, under which monthly premiums and required copayments will be instituted. See http://kff.org/medicaid/fact-sheet/medicaid-expansion-in-michigan/ for more details.

[4]Pennsylvania is implementing a Section 1115 waiver to expand Medicaid coverage to adults under 138% FPL through private managed care plans, with premiums for newly eligible adults 100-138% FPL. See http://files.kff.org/attachment/medicaid-expansion-in-pennsylvania-fact-sheet for more details.

[5] Iowa is using a Section 1115 waiver to charge monthly premiums for people with incomes between 101-138% FPL and another Section 1115 waiver to cover newly eligible beneficiaries with incomes at or below 100% FPL under Medicaid managed care. See http://files.kff.org/attachment/medicaid-expansion-in-iowa-fact-sheet for more details.

[6] Arkansas is implementing a premium assistance model using a waiver. See http://files.kff.org/attachment/medicaid-expansion-in-arkansas-fact-sheet for more details.

[7] Indiana has a pending waiver for an alternative Medicaid expansion plan.

Table 3: Changes in Eligibility Limits for Children[1]

State	Prior to expansions (1987)[2] (1)	Prior to CHIP (1997) inf. / <6 / 6-14 / 15-19 (2)	Under CHIP (2001) infants / older children (3)	Prior to ACA (2013) with CHIP (*=Medicaid limits lower) (4)	After ACA (2014)[3] with CHIP (*=Medicaid limits lower) (5)
Alabama	16	133 / 133 / 100 / 15	200 / 200	300*	317*
Alaska	82	133 / 133 / 100 / 76	200 / 200	175	208
Arizona	40	140 / 133 / 100 / 32	200 / 200	200*	205*
Arkansas	26	200 / 200 / 200 / 200	200 / 200	200	216
California	85	200 / 133 / 100 / 82	300 / 200	250*	266
Colorado	48	133 / 133 / 100 / 39	185 / 185	250*	265*
Connecticut	81	185 / 185 / 185 / 185	300 / 300	300*	323*
Delaware	43	185 / 133 / 100 / 100	200 / 200	200*	218*
District of Columbia	50	185 / 133 / 100 / 37	200 / 200	300	324
Florida	36	185 / 133 / 100 / 28	200 / 200	200*	215*
Georgia	35	185 / 133 / 100 / 39	235 / 235	235*	252*
Hawaii	56	185 / 133 / 100 / 100	200 / 200	300	313
Idaho	42	133 / 133 / 100 / 29	150 / 150	185*	190*
Illinois	47	133 / 133 / 100 / 46	200 / 185	300*	318*
Indiana	35	150 / 133 / 100 / 100	200 / 200	250*	255*
Iowa	52	185 / 133 / 100 / 39	200 / 200	300*	317*
Kansas	55	150 / 133 / 100 / 100	200 / 200	232*	250*
Kentucky	27	185 / 133 / 100 / 33	200 / 200	200*	218*
Louisiana	26	133 / 133 / 100 / 100	150 / 150	250*	255*
Maine	56	185 / 133 / 125 / 125	200 / 200	200*	213*
Maryland	47	185 / 185 / 185 / 34	200 / 200[4]	300	322
Massachusetts	67	185 / 133 / 133 / 133	200 / 200	300*	305*

Michigan	65	185 / 150 / 150 / 150	200 / 200	200*	217*
Minnesota	73	275 / 275 / 275 / 275	280 / 275	280 (inf) / 275	288 (inf.) / 280
Mississippi	16	185 / 133 / 100 / 34	200 / 200	200*	214*
Missouri	38	185 / 133 / 100 / 100	300 / 300	300*	305*
Montana	49	133 / 133 / 100 / 41	150 / 150	250*	266*
Nebraska	48	150 / 133 / 100 / 34	185 / 185	200	218
Nevada	39	133 / 133 / 100 / 45	200 / 200	200*	205*
New Hampshire	55	185 / 185 / 185 / 185	300 / 300	300	323
New Jersey	55	185 / 133 / 100 / 41	350 / 350	350*	355*
New Mexico	35	185 / 185 / 185 / 185	235 / 235	235	305
New York	68	185 / 133 / 100 / 87	185 / 185	400*	405*
North Carolina	36	185 / 133 / 100 / 100	200 / 200	200*	216*
North Dakota	51	133 / 133 / 100 / 100	140 / 140	160*	175*
Ohio	41	133 / 133 / 100 / 32	200 / 200	200	211
Oklahoma	43	150 / 133 / 100 / 48	185 / 185	185	210
Oregon	55	133 / 133 / 100 / 100	170 / 170	300*	305*
Pennsylvania	52	185 / 133 / 100 / 100	235 / 235	300*	319*
Rhode Island	69	250 / 250 / 250 / 250	300 / 300	250	266
South Carolina	27	185 / 133 / 100 / 18	150 / 150	200	213
South Dakota	50	133 / 133 / 100 / 100	200 / 200	200*	209*
Tennessee	21	400 / 400 / 400 / 400	400 / 400 / 100[5]	250*	255*
Texas	25	185 / 133 / 100 / 17	200 / 200	200*	206*
Utah	52	133 / 133 / 100 / 100	200 / 200	200*	205*
Vermont	79	225 / 225 / 225 / 225	300 / 300	300	318
Virginia	49	133 / 133 / 100 / 100	200 / 200	200*	205*
Washington	68	200 / 200 / 200 / 200	250 / 250	300*	305*

West Virginia	34	150 / 133 / 100 / 100	200 / 200	300*	305*
Wisconsin	75	185 / 185 / 100 / 100	185 / 185 (200 after enrlmt.)	300*	306*
Wyoming	49	133 / 133 / 100 / 55	133 / 133	200*	205*

Sources: Shore-Sheppard (2003) Table 1,
Heberlein, M., T. Brooks, and J Alker. “Getting into Gear for 2014: Annual Findings of A 50-State Survey of Eligibility Rules, Enrollment and Renewal Procedures, and Cost Sharing Practices in Medicaid and CHIP, 2012–2013.” Washington, DC: Kaiser Commission on Medicaid and the Uninsured, 2013.
Kaiser Family Foundation. “Medicaid and CHIP Income Eligibility Limits for Children at Application, Effective January 1, 2014.” Available at http://kff.org/health-reform/state-indicator/medicaid-and-chip-income-eligibility-limits-for-children-at-application-effective-january-1-2014/. Accessed Nov 11, 2013.
Kaiser Family Foundation. “Medicaid and CHIP Income Eligibility Limits for Pregnant Women at Application, Effective January 1, 2014.” Available at http://kff.org/medicaid/state-indicator/medicaid-and-chip-income-eligibility-limits-for-pregnant-women-at-application-effective-january-1-2014/. Accessed Nov 11, 2013.

[1] Eligibility limits are as a percent of the federal poverty threshold for that year. Note that until the ACA eligibility limits that are apparently equal may actually differ through differences in the two states’ choices of what income and resources are counted.

[2] Eligibility is through eligibility for AFDC; limits are for a family of 3.

[3] Difference from prior column may solely be a result of different methods of counting income. See text.

[4] Maryland also had premium assistance eligibility to 300% of the poverty threshold

[5] Tennessee had a 1115 waiver to operate TennCare. Its CHIP expansion covered children <19 born before October 1, 1983, who could not have enrolled in Medicaid before.

Table 4. Components of Growth in Real Medicaid Benefit Spending, FY1975 – FY2010

	FY 1975 (in FY 2010 dollars)	**FY 2010**	**Annual Growth Rate**	**Relative Contribution to Real Spending Growth, FY 1975 to FY 2010**
All Eligibility Groups				
Spending per Beneficiary	$4,463	$6,588	1.1%	29.7%
# Beneficiaries (millions)	20.2	59.0	3.1	70.3
Total Benefit Spending (millions)	$90,181	$388,611	4.3	100.0
Children				
Spending per Beneficiary	$1,748	$2,481	1.0	3.2
# Beneficiaries (millions)	9.6	30.0	3.3	16.1
Total Benefit Spending (millions)	$16,776	$74,398	4.3	19.3
Adults				
Spending per Beneficiary	$3,494	$3,726	0.2	0.4
# Beneficiaries (millions)	4.5	15.4	3.6	13.5
Total Benefit Spending (millions)	$15,825	$57,256	3.7	13.9
Disabled				
Spending per Beneficiary	$9,795	$18,857	1.9	12.7
# Beneficiaries (millions)	2.5	9.3	3.9	38.3
Total Benefit Spending (millions)	24,136	$176,143	5.8	50.9
Aged				
Spending per Beneficiary	$9,252	$18,841	2.1	13.4
# Beneficiaries (millions)	3.6	4.3	0.5	2.4
Total Benefit Spending (millions)	$33,445	$80,815	2.6	15.9

Source: Table 2 from June 2013 MACPAC report. MACPAC report data are drawn from CMS 2012 Medicare and Medicaid Supplement tabled 13.4 and 13.10; Medicaid Statistical Information System (MSIS) annual person summary (APS) and CMS-64 net financial managements report data as of May 2013.
Notes: Number of beneficiaries excludes those individuals for whom basis of eligibility is unknown. Dollar amounts are deflated using the GDP price deflator for health care. FY 2010 data unavailable for Idaho and Missouri; FY 2009 values used instead.

Table 5: Medicaid and CHIP Enrollment by Age, Data Source and Enrollment Period, 2011

	Ever Enrolled	Point in Time	NHIS	CPS
All Ages				
Total Medicaid/CHIP Enrollment	75.8	60.4	50.5	50.8
Population	312.3	311	305.9	308.8
Enrollment as a Percentage of Population	24.3%	19.3%	16.5%	16.5%
Children Under Age 19[1]				
Total Medicaid/CHIP Enrollment	40.3	32.4	29.5	26.3[2]
Population	78.5	78.4	78.7	74.1
Enrollment as a Percentage of Population	51.3%	41.3%	37.5%	35.6%
Adults 19-64				
Total Medicaid/CHIP Enrollment	29.0	22.4	17.8	20.6
Population	192.1	191.4	187.4	193.2
Enrollment as a Percentage of Population	15.1%	11.7%	9.5%	10.7%
Adults 65 and Older				
Total Medicaid/CHIP Enrollment	6.5	5.6	3.1	3.9
Population	41.7	41.1	39.7	41.5
Enrollment as a Percentage of Population	15.5%	13.7%	7.9%	9.4%

Notes: Columns 1-3 are drawn from tables 16-19 from the June 2014 MACPAC report. MACPAC report data is drawn from Medicaid Statistical Information System (MSIS) as of February 2014; CHIP Statistical Enrollment Data System data as of May 2014; the National Health Interview survey (NHIS); and U.S. Census Bureau vintage 2012 data on the monthly postcensal resident population by single year of age, sex, race, and Hispanic origin. Column 4 is based on “Income, Poverty, and Health Insurance Coverage in the United States: 2011” (DeNavas-Walt et al), table C-3.

1. The CPS data is for Children under 18 years of age
2. This number (DOES/DOES NOT) include enrollees in CHIP

Table 6. Medicaid Benefit Spending by Eligibility Group and Service Category, FY 2011

	Total	Children	Adult	Disabled	Aged
Total Expenditures ($ billions)	$386.4	$73.4	$59.1	$165.1	$88.8
Per Capita Expenditures ($)					
Total	$7,236	$2,854	$4,368	$19,031	$16,236
By Service Category					
Hospital	$1,470	$617	$1,365	$4,412	$1,072
Non-hospital acute	$1,139	$737	$692	$2,866	$1,393
Drugs	$266	$113	$213	$907	$105
Managed Care	$1,830	$1,302	$2,049	$3,198	$1,606
LTSS—non-institutional	$1,012	*	*	$4,271	$2,884
LTSS—institutional	$1,264	*	*	$2,757	$7,700
Medicare premiums	$256	N/A	N/A	$620	$1,476

Source: Figures 3 and 4 from the June 2014 MACPAC report. MACPAC report data is drawn from Medical Statistical Information System (MSIS) annual person summary (APS) data and CMS-64 Financial Management Report net expenditure data from CMS as of February 2014. Notes: * indicates value of less than $100. Due to changes in methods and data, FY 2011 data is not directly comparable to data from previous years (for example, in Table 2): spending totals in FY 2011 exclude disproportionate share hospital payments, which were previously included. Maine and Tennessee were excluded due to MSIS spending data anomalies.

Table 7. Ratio of Medicaid Physician Fees to Medicare Fees, Composite Fee Index for Selected Years

	2003	**2008**	**2012**
National Average			
All Services	0.69	0.72	0.66
Primary Care	0.62	0.66	0.59
Obstetric Care	0.84	0.93	0.78
Other Services	0.73	0.72	0.70
Distribution of Ratio for All Services by State			
Minimum	0.35	0.37	0.37
Median	0.80	0.88	0.77
Maximum	1.37	1.43	1.34
States with Medicaid/Medicare Ratios:			
Less than 0.50[1]	3	3	2
0.50 to .75	18	14	19
0.75 to 1.0	26	23	27
Greater than 1.0	4	11	3

Source: Zuckerman et al (2004); Zuckerman et al (2009); Zuckerman et al (2012).
Notes: Data represent the national average of Medicaid-Medicare fee indexes within given categories. Underlying source data is from the Urban Institute Medicaid Physician Fee surveys.
1: Categories are inclusive of lower boundary.