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The Effect of the Children's Health Insurance Program on Pediatricians' Work Hours

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Objective: Our study examines changes in physicians' work hours in response to a coverage expansion.
Methods: We use as a natural experiment the Children's Health Insurance Program (CHIP), which was established in 1997 and significantly expanded children's eligibility for public health insurance coverage. The magnitude of the CHIP expansion varied across states and over time, allowing its effects to be identified using a state-year fixed effects model. We focus on pediatricians, and we measure their self-reported work hours using multiple waves (pre- and post-CHIP) of the physician survey component of the Community Tracking Study. To address endogeneity concerns, we instrument for CHIP enrollment using key program features (income eligibility cutoffs and waiting times).
Results: We find a large negative relationship between the magnitude of a state's CHIP expansion and trends in pediatricians' work hours. This relationship could be due to key supply-side features of CHIP, including relatively low provider reimbursements and heavy use of managed care tools.

Keywords: Children's Health Insurance Program, health insurance, pediatrician, labor supply, Community Tracking Study

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Introduction

The Congressional Budget Office (CBO) has estimated that providing insurance coverage for all of those who are currently uninsured would increase the demand for health care services by 2 to 5 percent (Congressional Budget Office, 2008). But, for the quantity of services to actually increase, providers have to supply the additional care, and it is not clear whether, or how, they will do so. Based on a purely demand-driven model of physician labor supply, the CBO and other researchers have hypothesized that a large coverage expansion could lead, in the short run, to physicians working longer hours to accommodate such an influx of patient demand. On the other hand, a supply-driven model hypothesizes that physicians could choose to work fewer hours with a large coverage expansion, due to constraints on the supply side. To test between the two hypotheses, we analyze the impact of the Children's Health Insurance Program (CHIP), a public health insurance program for children in low- and middle-income families.

Established in 1997, CHIP has several features that make it well suited to our purposes. First, the CHIP expansion was large, resulting in almost one in five children becoming newly eligible for public coverage—that expansion in eligibility is roughly similar in magnitude to the expansion for adults that will occur under the Affordable Care Act (ACA). Second, states play a central role in designing and financing their CHIP programs, and have some latitude to determine eligibility criteria. As a result, eligibility criteria and other key program features vary widely from state to state, which we exploit in our analysis. Third, CHIP was established relatively recently. This allows access to fairly rich and recent data sources, and also makes it more plausible that any findings would be relevant to upcoming reforms.

We use a state-year level panel data analysis, with observations spanning the period before and after the establishment of CHIP. Our regressions include state- and year-fixed effects, to account for time-invariant state characteristics and national trends over time. We use as our key outcome the logged state-year mean of pediatricians' self-reported annual work hours. We measure the magnitude and timing of each state's CHIP expansion in two ways. First, we use state-level administrative data on actual CHIP enrollment to measure the share of children enrolled in CHIP in each year. Second, we instrument for actual CHIP enrollment using two strong predictors of actual CHIP enrollment. The first instrument, following Currie and Gruber (1996), is the simulated percentage of children eligible for public coverage in a given state and year using each state's CHIP rules applied to a fixed national sample of children. The second instrument is the share of children in each state and year who are subject to a CHIP waiting period of 6 months or more. (In some states children must have been uninsured for a minimum period of time in order to be eligible for CHIP.) The instruments abstract away from unobserved variables, such as local economic conditions, that might affect both actual enrollment in public coverage and pediatrician work hours.

We find that pediatricians in states with larger CHIP expansions substantially *reduced* their annual work hours relative to pediatricians in states with smaller expansions. In our preferred specification, a 5 percentage point increase in the share of children enrolled in CHIP is associated with a decrease of 14 percent in pediatrician work hours (p-value <= 0.001). Alternative specifications produce similar results and, in a falsification exercise, we find that CHIP does not have the same type of association with changes in work hours among internal medicine physicians.

These findings are clearly inconsistent with the hypothesis that physicians will work longer hours to accommodate an influx of demand following a coverage expansion. What is less clear is whether the association we find is causal and, if so, why pediatricians would actually work fewer hours in response to a coverage expansion. We propose two competing hypotheses to be addressed in future work. The first is that the CHIP expansions reduced average reimbursement rates for pediatricians, and that the reduction in reimbursement rates prompted pediatricians to reduce their hours. The second is that CHIP plans rely heavily on managed care tools, such as gatekeepers, and that those managed care tools led pediatricians to reduce their work hours.

Background on the Children's Health Insurance Program (CHIP)

In recent decades, there have been two waves of expansion of public health insurance coverage for children. The first began in the late 1980s when Medicaid eligibility was expanded to children in families with incomes too high to qualify for cash welfare assistance. That expansion and its effects on children's utilization of health care services are described in some detail by Currie and Gruber (1996).

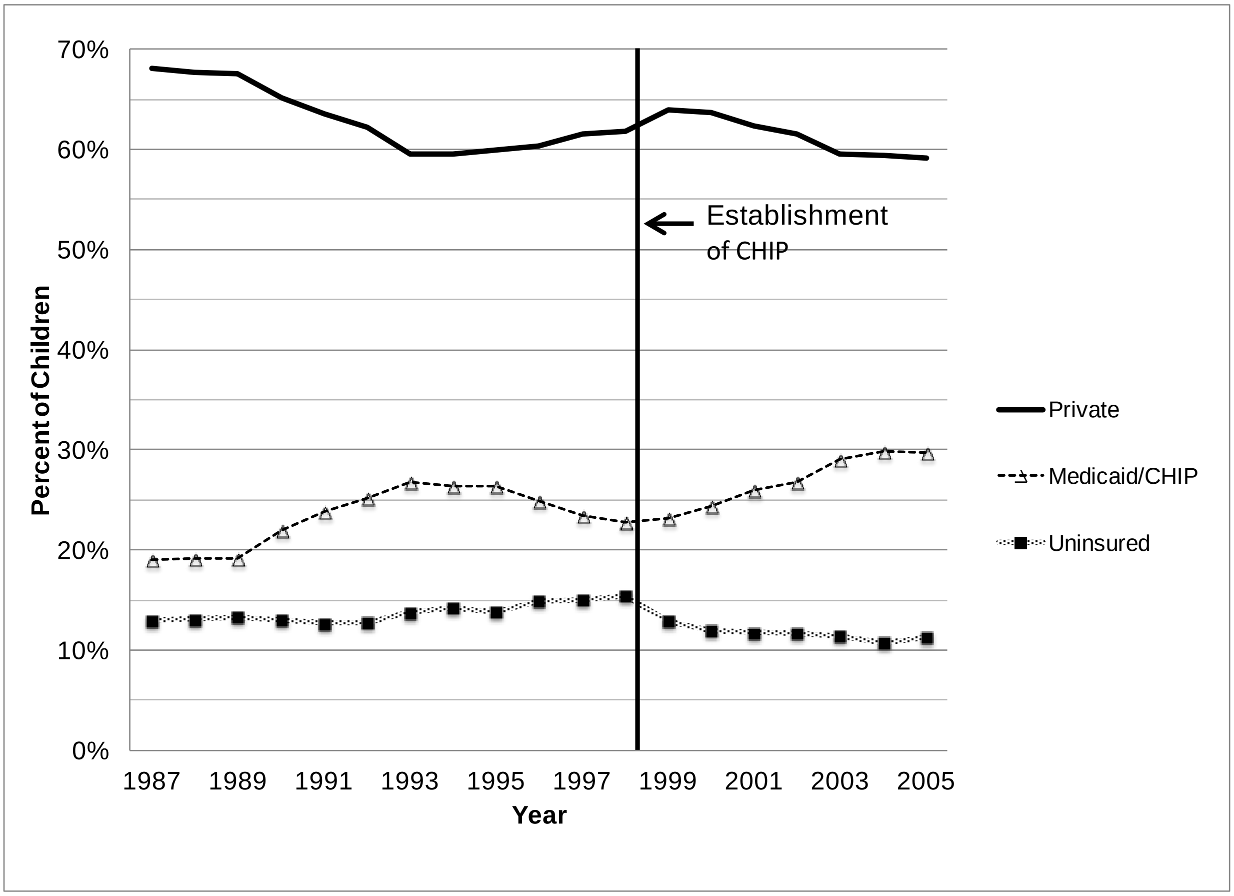
The second wave of coverage expansions, which is the focus of our study, began with the Balanced Budget Act of 1997 (BBA). The BBA established CHIP through the creation of Title XXI under the Social Security Act. CHIP's main goal is to lower the number of uninsured children by expanding public coverage to children in households with income too low to afford private health insurance, but not low enough to qualify for Medicaid. CHIP and Medicaid are layered programs, in the sense that CHIP eligibility begins where Medicaid eligibility ends and extends to higher income levels.

In CHIP programs, income eligibility cutoffs vary by state. Children up to age 19 may be eligible for the CHIP program, and CHIP income cutoffs are typically between 200 percent and 300 percent of the federal poverty level. In Medicaid, cutoffs vary both by state and with the age of the child. Federal statute requires states to extend Medicaid eligibility up to 133 percent of the poverty level for children up to age 5, and up to 100 percent of the poverty level for children ages 6 through 18. Many states have extended Medicaid eligibility further, though, often up to 185 percent of the federal poverty level for younger children.

The implementation of CHIP has had a significant effect on insurance coverage among children (Davidoff, Kenney, & Dubay, 2005; Wang, Norton, & Rozier, 2007; Kenney, 2007; Currie, Decker, & Lin, 2008; and Anderson, Dobkin, & Gross, 2010). According to the Congressional Research Service (2009), about 7.4 million children were enrolled in CHIP at some point during 2008, representing almost 10 percent of the population under age 19. CHIP has also had a significant impact on the share of children uninsured.

Exhibit 1 shows trends from the U.S. Census Bureau's Current Population Survey Annual Social and Economic Supplement (CPS-ASEC); in the share of children with public, private, or no health insurance coverage. The vertical line marks the start of the CHIP program. This figure shows a decline, beginning in 1998, in the share of children without any insurance coverage and, at the same time, an increase in the share of children with public coverage. The adult population, which was not directly affected by CHIP, did not experience a similar decline in uninsurance.[1]

Exhibit 1. CHIP Increased the Share of Children with Public Coverage and Decreased the Share Uninsured



SOURCE: U.S. Census Bureau's Current Population Survey Annual Social and Economic Supplement (CPS-ASEC; 2006).

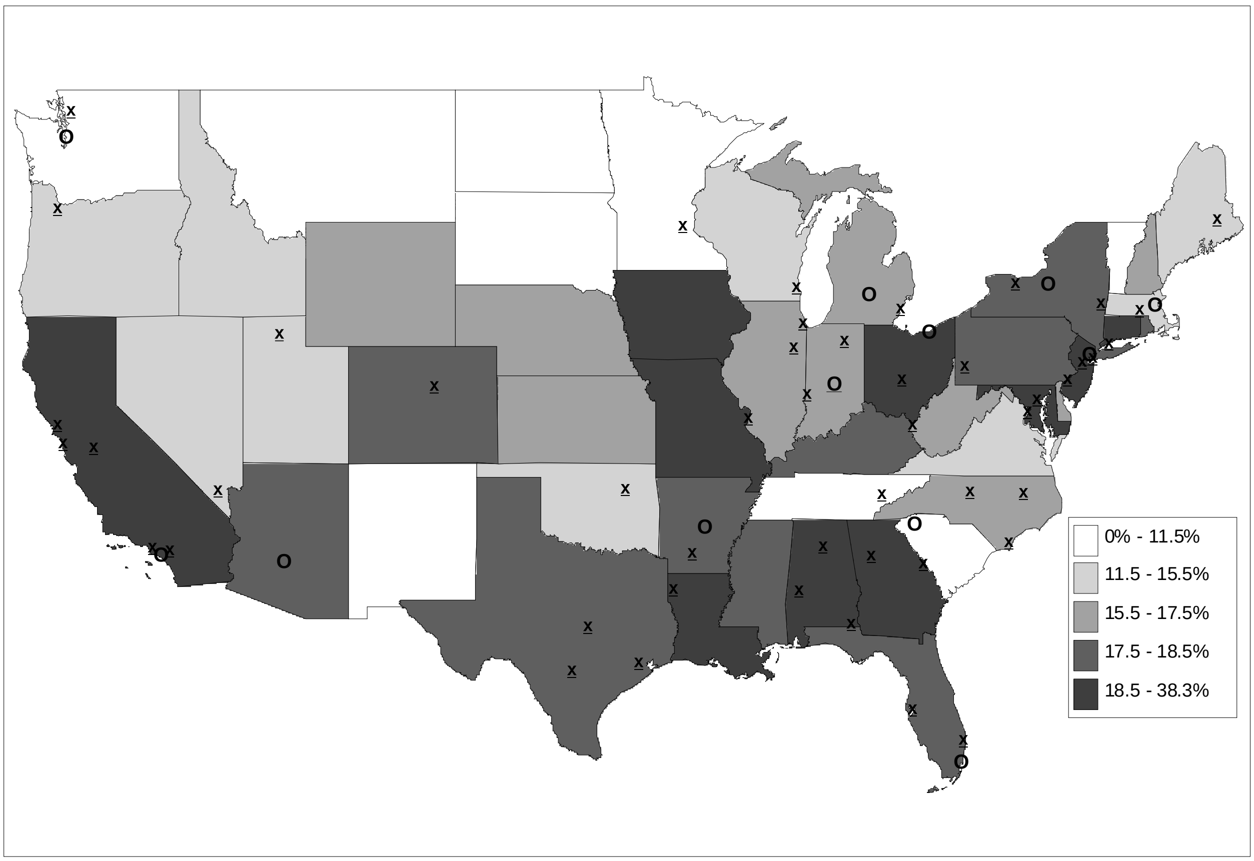
States Determine Many Key Features of Their CHIP Programs

CHIP law gives the states the power to implement their own programs, and there are variations in CHIP eligibility rules across states. Although there is a myriad of program details that

[1]A limited number of states have received waivers to make some adults eligible for CHIP, and about 300,000 adults are enrolled in CHIP.

distinguish programs across states,[2] one of the most important features is the range of income over which children may be eligible. For example, the CHIP upper income eligibility threshold in 2005 ranged from 140 percent of the federal poverty level (FPL) in North Dakota to 350 percent in New Jersey. Also, even though all states implemented CHIP within a few years of program inception, the timing of those expansions varied across states. For example, some states expanded eligibility aggressively in the beginning of the program while others expanded gradually. The variation across states in the magnitude of the CHIP expansion, based on our simulated eligibility measure, is illustrated in Exhibit 2. In that figure, the states shaded darkest are those with the largest expansions. In the state with the largest expansion—New Jersey—almost 40 percent of children became newly eligible for public coverage due to the establishment of CHIP.

Exhibit 2. Size of CHIP Eligibility Expansion (difference, in percentage points, between simulated eligibility in 1997 and 2005; Community Tracking Study [CTS] sites indicated by O's and x's)



NOTE. x indicates a normal CTS study site, and O indicates a "high-intensity" (larger sample) site. Alaska and Hawaii (not shown) are in the 2nd and 3rd categories, respectively.

[2]For example, the eligibility threshold may differ across age of the child within the same state, and many states cover infants in families with higher income than older children. Many states also allow so-called income "disregards," discussed below. These factors are not discussed in detail, but they are incorporated in the data analysis whenever possible.

In addition to income eligibility criteria, states determine a number of other important features of their CHIP programs within the boundaries set by federal statute. For example, some states have chosen to set up their CHIP programs as extensions of their state Medicaid programs with higher income cutoffs, but otherwise the same benefits and cost sharing. Other states have chosen to set up standalone CHIP health plans distinct from Medicaid, and still others have used a combination of the two approaches. Among those states that have standalone CHIP programs, some impose premiums, and the amount of those premiums varies widely from state to state. (Requiring premiums for Medicaid-based CHIP programs is, in general, prohibited.)

States have adopted a variety of mechanisms to attempt to minimize the crowding out of private coverage. One common mechanism is the use of so-called "waiting periods." If a state uses a waiting period, children in that state are only deemed eligible for CHIP if they have been uninsured for a minimum period prior to applying. Among states that use them, the length of the waiting period ranges from one month to one year.

The Effects of CHIP on the Market for Physician Services

When a child enrolls in the CHIP program, it affects several aspects of the market for pediatrician services, both on the supply and demand side. Those effects differ depending on where CHIP-covered children "come from," meaning whether and how they would be insured in the absence of CHIP (the counterfactual). Based on recent research by Gruber and Simon (2008), about three out of five children covered under CHIP come from private coverage, and two out of five come from uninsured. That fairly even split means that it is important to consider both cases.

We will first focus on children who come to CHIP from private coverage. Those children face a decrease in out-of-pocket prices for medical services, due to CHIP's relatively high actuarial value (Watson Wyatt Worldwide, 2009). From a demand-side perspective, this would obviously spur increased utilization of services. But, moving from private coverage to CHIP also affects the supply side of the market. The payment rate that a physician receives for treating a child covered by public insurance is substantially lower than the rate for treating a privately insured child. A 2009 actuarial model built by Ingenix Consulting (2009a, 2009b) incorporates the assumption that the national average reimbursement rate for a physician office visit was $81 for a privately insured child versus $47 (over 40 percent lower) for a child enrolled in Medicaid or CHIP. (The Ingenix model, unfortunately, does not separately specify payment rates for Medicaid versus CHIP.)[3] A child who moves from private coverage to CHIP is also likely to

[3]Unfortunately, to our knowledge no one has systematically measured physician payment rates specifically in the CHIP program and compared those payment rates to Medicaid payment rates and private payment rates. Based on personal communications with analysts at the Urban Institute, the Congressional Budget Office, and the Medicaid and CHIP Payment and Access Commission, our understanding is that fees in CHIP plans tend to be similar to Medicaid fees, and are low relative to private payment rates. Ingenix's estimate of the combined Medicaid/CHIP payment rates is probably a good proxy, therefore. In Medicaid-based CHIP programs, which currently account for about one-quarter of CHIP enrollees (Medicaid and CHIP Payment and Access Commission, 2011, p. 81), the payment rates will be the same. In standalone CHIP programs, there are reasons to think payment rates might be higher in CHIP than in Medicaid (e.g., a higher federal match rate), and there are reasons to think payment rates might be lower (e.g., CHIP does not have the same payment floor restrictions as Medicaid).

encounter increased use of managed care tools, such as gatekeepers and assigned doctors.[4] The price elasticity of demand refers to the sensitivity of demand to a physician calling for higher payment rates. CHIP plans, compared to private plans, are presumably more highly price elastic due to their more intensive use of managed care tools.

For a child who comes to CHIP from being uninsured, the most obvious effect is a drop in the out-of-pocket price. Less obvious is the fact that moving a child from uninsured to CHIP also likely reduces the payment rate that the physician receives. One piece of evidence on the difference in physician payments for the uninsured versus publicly insured comes from Gruber and Rodriguez (2007). They used detailed visit-level data on physician billing and payments to compare physician revenues for services provided to uninsured patients (including zeros for uncollected amounts) with revenues for otherwise identical services provided to insured patients. They report that for three quarters of physicians the fees they receive for serving Medicaid patients are lower than the fees paid out-of-pocket by the uninsured. And for almost 60 percent of physicians the Medicaid fees are less than two-thirds the fees paid by the uninsured.

In terms of care management, an uninsured patient is not subject to any of the limitations that an insurer would impose on their choice of provider or their choice of treatment plan. Therefore, moving a child from uninsured to CHIP increases the use of managed care tools. In terms of the price elasticity of demand, McGuire (2000) observes that "... when patients make choices of medical suppliers, demand for suppliers is likely to be inelastic. When organized buyers (insurers, HMOs) make choices, however, demand can be more elastic, driving prices downward" (p. 473). The fact that CHIP plans use gatekeepers and limit the choice of physicians likely means that the sellers' demand elasticity is increased when a child moves from being uninsured to CHIP.

In general, then, moving children into CHIP—whether from private coverage or from uninsured—increases demand (through reduced out-of-pocket payments), and also tends to constrain supply through multiple mechanisms (lower payment rates, expanded use of managed care tools, and increased buyer leverage). The effect of CHIP on pediatricians' labor supply will depend on the relative influence of those competing demand- versus supply-side effects. There are many possible margins along which pediatricians might adjust, including employment vs. self-employment, location of practice, and so on. We focus on work hours per year, partly because it is a good summary measure of labor supply and partly because it is available in our data.

[4]Based on the authors' calculations using the 2009 National Health Interview Survey (NHIS), the share of children whose parents report a gatekeeper arrangement was 47 percent among privately insured children, and 78 percent among children enrolled in CHIP. (Gatekeeping was identified by those responding yes to the following NHIS item: "If [you need/he needs/she needs] to go to a different doctor or place for special care, [do you/does he/does she] need approval or a referral? Do not include emergency care.") The share of children whose parents report that they are free to see any doctor who accepts the plan was 48 percent among privately insured children versus 25 percent among children enrolled in CHIP.

Theory and Evidence on Physician Labor Supply

This study provides evidence to test predictions from the theoretical literature, but also builds on two strands of empirical literature. As McGuire (2000, p. 464) points out, there is no single widely accepted formal theory of physician behavior, but rather a hodgepodge of models, each emphasizing different features of the market. Two of those models are relevant to the current study, because they make predictions that are clearly testable against our results:

Demand-driven model (perfect agency, or "take all comers"). Under certain assumptions, physicians will supply whatever volume of services is demanded by patients. To obtain this result, we either have to assume that physicians' objective function is perfectly aligned with patients' interests—both medical and financial—(i.e., perfect agency), or we have to assume that physicians have no ability to influence the volume of services (i.e., take all comers). In either of these cases, an expansion of insurance coverage will lead to a drop in the out-of-pocket price and an increase in the patient's desired quantity, which will inexorably result in an increase in the quantity supplied. These assumptions rest on very shaky ground, because they are clearly inconsistent with the rationale for the invention of managed care (i.e., to ration care using tools other than patients' out-of-pocket liability) and also a vast body of research indicating that financial incentives do affect physicians' behavior (for a particularly salient example, see Hickson, Altmeier, & Perrin, 1987). Nevertheless, "take all comers" is implicitly built into the official health reform estimates from the Centers for Medicare & Medicaid Services (Office of the Actuary, 2010).

Supply-driven model (fixed costs with heterogeneous patient panels). Glied and Zivin (2002) describe a model of physician behavior in which they treat a mixture of patients with various insurance arrangements. Their model is predicated on the notion that physicians control the volume and type of services they provide (they do not take all comers), and that they respond to the financial incentives created by their patients' insurance plans. In their model, a "fixed cost" refers to "durable equipment or office capacity (intellectual or physical) that cannot vary for [different] types of patients." A physician's choice of how many weeks to work, when to open and close the office, when to have call-in times available, and how long a typical appointment lasts can all be considered "fixed-cost" type decisions. In Glied and Zivin's formulation, if one type of patient becomes more common (e.g., an increase in the Medicaid share due to an eligibility expansion), physicians will tend to realign their fixed-cost decisions to fit better with the expanded patient type. If we apply Glied and Zivin's model in the context of this paper, we would predict that pediatricians would choose to work fewer hours as CHIP enrollment expands. As discussed earlier, enrolling more children in CHIP generally means a lower average payment rate for pediatricians. If the pediatrician labor supply curve is upward sloping, the lower payment rates will lead pediatricians to choose to work less.

We build on literature consisting of empirical studies on the determinants of physician labor supply and output that test between the two models of physician behavior presented above.[5] Several studies have examined the relationship between physician fees and volume in the Medicare context. The central controversy in this literature is the direction of the volume response, i.e., when reimbursement rates are decreased, does the volume of services increase or decrease? Some of the earlier papers, such as Nguyen and Derrick (1997), find a significant volume offset, meaning that a decrease in fees leads to an increase in volume. More recently, however, Hadley et al. (2009) report that the volume of physician services is positively related to fees, which they point out, is "consistent with the general economic proposition that supply curves for medical services are positively sloped." Staiger, Auerbach, and Buerhaus (2010), in a longitudinal analysis of physician work hours, also provide evidence to support a positively sloped supply curve, reporting the following: (1) mean hours worked among physicians has declined steadily since the early 1990s, (2) the decline in work hours parallels a decline over time in inflation-adjusted physician fees, and (3) at the geographic level, physician work hours are positively associated with physician fees.

Finally, we build on empirical literature examining the effects of health insurance on individuals' utilization of physician services. The best-known study in that long line of literature is the RAND Health Insurance Experiment (HIE), which randomly assigned individuals to health insurance plans with different cost sharing features. The HIE showed that individuals in a "free care" plan (i.e., no cost sharing) used almost 70 percent more outpatient services than individuals enrolled in what was essentially a high-deductible (95 percent coinsurance) plan (Newhouse & the Insurance Experiment Group, 1993). More directly relevant to this study is Currie and Gruber (1996), which examines the effects of Medicaid eligibility expansions between 1984 and 1992 on children's medical care utilization and health outcomes. They report that making a child eligible for Medicaid reduces the probability of going for an entire year without a doctor's visit by approximately half.

There is only one published study we are aware of—Enterline, McDonald, and McDonald (1973)—that directly examines the effects of a major coverage expansion on physician work patterns. That study measured physician work hours and practice patterns immediately before and after the introduction of universal coverage for physician services in Quebec in 1970. The authors of that study were surprised and puzzled to find that, as a result of universal coverage, average physician work hours fell by about 15 percent.[6] The Quebec

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[5]Much of the analysis of physician supply is normative, and addresses the question of how many physicians "need" to be trained and licensed to satisfy some projected level of demand for services. Cooper (2004) summarizes some of the approaches used to make such projections.

[6]Unfortunately, the authors do not report the effect, if any, of the Quebec coverage expansion on physician fees—it is not clear, therefore, the extent to which the drop in work hours was fee-driven.

experience, though far in the past and not U.S.-based, strongly suggests the inadequacy of an analysis based solely on demand-side effects.

Methodology

Our main analysis is a set of panel data regressions, with observations at the state-year level, and with state- and year-fixed effects. The outcome of interest is self-reported hours worked per year among pediatricians, and the key predictor is share of children enrolled in CHIP. In addition to state-fixed effects, we include the following: Census division-year fixed effects, two controls for pediatricians' demographics (percent male, and percent over age 55), two controls for state economic conditions (the logged gross state product per capita, and the unemployment rate), and a measure of the Medicaid physician fee schedule relative to the national average.[7] Our data include one wave pre-CHIP (1996–7), and three waves post-CHIP (1998–9, 2000–1, and 2004–5). We use a semi-log specification, with the natural logarithm of mean hours regressed on the share enrolled, and we weight each observation by the number of pediatricians reporting hours in each state-year. Our analysis is limited to the 34 states included in the sample frame for the survey on physician hours.

For the purposes of a descriptive analysis, we divide states into CHIP expansion terciles based on the predicted share of children enrolled in CHIP in 2004–5. We use those terciles to compare state demographics and economic characteristics, and also to summarize trends in pediatricians' work hours.

As a benchmark against which to test our regression results, we measure the hypothetical increase in demand for physician services from the CHIP expansion. This summarizes CHIP's predicted effects on utilization of pediatrician services, based on a purely demand-driven model. This demand-driven model is similar in spirit to the one used by the Centers for Medicare & Medicaid Services' Office of the Actuary (OACT) to estimate the effects of health reform on national health spending.

Fixed Effects Estimates

Our key estimating equation is:

$$\log Y_{s,t} = \alpha_s + \beta_{r,t} + \gamma Enr_{s,t} + \delta X_{s,t} + \varepsilon_{s,t} \qquad (1)$$

Where $Y_{s,t}$ is the state-year mean annual hours worked, α is a set of state-fixed effects, $\beta_{r,t}$ is a set of division-year fixed effects, $Enr_{s,t}$ is the share of the under-19 population enrolled in CHIP, $X_{s,t}$ are state-year level controls, and ε is an error term. The coefficient of interest is γ. The two controls for pediatrician demographics were chosen on the basis of their predictive values in a

[7]The Medicaid physician fee index is taken from a series of papers by researchers at the Urban Institute (S. Norton, 1999; S. A. Norton, 1995; Zuckerman, McFeeters, Cunningham, & Nichols, 2004; Zuckerman, Williams, & Stockley, 2009). Those Medicaid fee indices are only available for selected years (1993, 1998, 2003, and 2008). We used linear interpolation for the years in between.

pediatrician-level analysis of hours worked. Nonetheless, the estimates are robust to including different sets of controls. The state fixed effect controls for time-invariant characteristics that may be correlated with both simulated percentage eligible and labor supply outcomes, and the division-year fixed effects allow separate year effects for each of the nine Census divisions. In all regressions, we calculate robust standard errors clustered at the state level and we weight each observation by the number of physicians responding in that state-year.

OLS Estimates

Our OLS estimates use as our enrollment measure the actual CHIP monthly enrollment in each state-year as a share of the under-19 population, $Enr_{s,t}^{actual}$.

Reduced Form and IV Estimates

There are two possible sources of bias in the OLS estimates that are cause for concern. The first is reverse causality. Suppose that, for some reason unrelated to CHIP, pediatricians' work hours and the overall supply of pediatricians are expanding within a state. That expansion in pediatrician supply could make it easier for the state to establish its CHIP health plans and find participating providers, which could lead to increased enrollment in CHIP. Reverse causality would tend to bias the OLS results upwards. The second possible source of bias is the volatility from year to year in actual CHIP enrollment within a state. Presumably, pediatricians' labor supply decisions (especially the choice of part-time versus full-time work) reflect a fairly long-term decision-making process that would not react instantly to changes in CHIP enrollment. That volatility, which would tend to bias the OLS results toward zero, can be smoothed out by instrumenting for CHIP enrollment.

The physician survey data are limited in the following two important ways: First, the main study sites are only located in 34 states; second, each survey wave spans two years and they have occurred at irregular intervals (e.g., there was no survey during 2002–3). While those limitations are unavoidable in the analysis of physician work hours, they can be avoided in the creation of an instrument for CHIP enrollment.

To create our instrument for CHIP enrollment, we first run a standalone model based on a complete dataset—all 51 states, with data for each year from 1997 through 2005—that is weighted by the under-19 population. The standalone CHIP enrollment model is:

$$Enr_{s,t}^{actual} = \phi_s + \varphi_{r,t} + \eta_t Elig_{s,t}^{sim} \cdot Year_t + \kappa Wait_{s,t} \cdot Year_t + \lambda X_{s,t} + \upsilon_{s,t} \qquad (2)$$

where $Elig_{s,t}^{sim} \cdot Year_t$ and $Wait_{s,t}$ are our key predictors of CHIP enrollment.

Then, to match the multi-year waves of our physician survey data (1998–9, etc.) we take the means of the predicted values from the appropriate year-pairs. (We also take the year-pair means of the eligibility and waiting period variables, and use those to conduct a Sargan test.) The resulting predicted value, $Enr_{s,t}^{hat}$, is then used in two ways. In the reduced form estimates,

$Enr^{hat}_{s,t}$ is entered directly. In the IV estimates, $Enr^{hat}_{s,t}$ is used as an excluded instrument for $Enr^{actual}_{s,t}$

Simulating Eligibility for CHIP

To predict changes in enrollment in public coverage, we use a simulated percentage eligible, similar to Currie and Gruber (1996).[8] This measure is preferred to the actual percentage eligible for CHIP, because the simulated measure isolates the change in program generosity rather than incorporating other factors that may be endogenous to physician labor supply. In particular, looking at changes in actual percentage eligible for CHIP across time and states includes changes in demographic and economic conditions. Because demographic and economic changes can be driven by underlying unobservable factors that also influence physician labor supply, the estimate of the effect of actual percentage eligible on physician labor supply could be biased. For example, if there is faster technological growth in the healthcare industry in some states in particular years, which may induce faster economic growth that in turn may reduce the actual percentage eligible for CHIP and also higher physician labor supply, the estimate of the effect of actual percentage eligible will be biased downward. To eliminate this bias, using a fixed national sample abstracts away from these other factors and focuses purely on program eligibility rules.

For example, to measure eligibility for New Jersey in 2005, we applied the New Jersey CHIP eligibility threshold for that year (350 percent of the FPL) to a representative sample of children from all states, which yields 63.3 percent of the sample eligible. In contrast, for Alaska, the eligibility threshold in 2005 was 168 percent of the FPL; applying that different threshold to the same sample of children yields 44.5 percent eligible. Because the eligibility thresholds change over time and across states, the simulated percentage eligible also varies over time and across states.

For our simulated measure, a child is considered eligible if the child's family income is less than a given multiple (e.g., 350 percent in New Jersey in 2005) of the federal poverty level for that child's family size. In calculating family income we follow the practice in Medicaid and CHIP of applying so-called "disregards." Disregards allow limited amounts of certain types of income (typically up to about \$100 per month) or expenses (e.g., child care up to \$200 per month) to be excluded for purposes of determining eligibility. Those disregards vary from state to state and differ between the Medicaid and CHIP programs. To determine simulated eligibility, we apply the state-specific disregards for Medicaid (for simulated eligibility in 1996–7) or CHIP (for simulated eligibility in later years).

More specifically, our simulated eligibility for each combination of child (i), state (s), and year (t) is:

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[8]One difference between this study and Currie and Gruber's is that their measure of simulated eligibility is calculated separately for children of different ages—that approach is appropriate for their analysis, because they are matching simulated eligibility to surveys of individual children and their health care utilization patterns. We, instead, calculate a single eligibility measure for each state for children of all ages.

$$Elig_{i,s,t}^{sim} = 1\left[\frac{\left(Family\ Income_{i,2005} - Disregards_{s,t}\right)}{FPL\left(Family\ size_i, State_i\right)} < Income\ eligibility\ cutoff_{s,t}\right] \quad (3)$$

where 1[ ] is the indicator function, *FPL*() is the federal poverty level in 2005 for child i,[9] and *Income eligibility cutoff*$_{s,t}$ is the eligibility cutoff as a percent of the FPL for a given state and year.[10] Our measure of eligibility at the state-year level is:

$$Elig_{s,t}^{sim} = \frac{\sum_i Elig_{i,s,t}^{sim}}{N} \quad (4)$$

where N is the number of children in the entire sample.

CHIP Waiting Periods

Waiting periods have been shown in previous research to significantly reduce CHIP enrollment (Bansak & Raphael, 2007). For each state-year we measure the share of children who were eligible for CHIP coverage—using the simulated eligibility measure—and who were subject to a waiting period of 6 months or greater. In general, only standalone CHIP programs imposed waiting periods. Therefore, we divide children who were eligible for CHIP into the following 2 groups: (1) eligible for a Medicaid-based CHIP program, and (2) eligible for a standalone CHIP program (some states have combination programs with both types of children). The waiting period variable, $Wait_{s,t}$, equals the share of children who, based on a state's CHIP program design, were subject to a waiting period of 6 months or longer. We experimented with also including a measure of the share of children subject to a waiting period of less than 6 months and found that it was not a strong predictor of CHIP enrollment.

Demand-based Benchmark

We calculate a demand-based benchmark against which we compare our regression results. We use 2005 for this exercise, because it is the last year for which the physician survey data are available. The notion behind the benchmark is to measure the increase in physician work hours that would satisfy the hypothetical change in demand due to the CHIP expansion as predicted by a purely demand-driven model (assuming no change in visit length or in the number of pediatricians per child).

To calculate the benchmark, we divide children into several subpopulations. The first two subpopulations represent children who are not directly affected by the CHIP expansion—this includes children who were not eligible for public coverage under either the 1997 rules or

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[9]The child's state of residence is included in the *FPL*() function to reflect the fact that the FPL is somewhat higher for residents of Hawaii and Alaska.

[10]This approach implicitly assumes that income has grown at the same rate at the FPL. The FPL is indexed by the consumer price index (CPI). According to the U.S. Census Bureau (2006), between 1997 and 2005, income among lower-income households (i.e., at the 10th and 20th percentiles) grew only very slightly faster than the CPI (0.1 percent and 0.3 percent annually, respectively).

the 2005 rules (the never eligibles), and children who were eligible under both the 1997 rules and the 2005 rules (the always eligibles). The last three subpopulations represent children who became eligible for public coverage due to the CHIP expansion. These children are further divided into (1) those who were not enrolled in CHIP in 2005 and whose cost sharing and demand were, presumably, unaffected, (2) those who were enrolled in CHIP and who would otherwise have been uninsured, and (3) those who were enrolled in CHIP and who would otherwise have been enrolled in private coverage. For each of those subpopulations we calculate the size of the population in 2005, the change attributable to CHIP in their out-of-pocket spending and, using standard RAND-based elasticities, the demand-driven change in the volume of physician services. We then calculate a child population-wide hypothetical change in demand using the sizes of the different subpopulations.

Data

Physician labor supply

The Community Tracking Study includes a physician survey component (the CTS-PS). It is a nationally representative panel survey of U.S. physicians who provided direct patient care for at least 20 hours per week. The funding source is the Robert Wood Johnson Foundation and its principal investigator is the Center for Studying Health System Change. The data are collected through computer-assisted telephone interviews from a random sample of the American Medical Association Masterfile and the American Osteopathic Association.

The CTS-PS was conducted in four rounds: 1996–97, 1998–99, 2000–01, and 2004–05.[11] The first three rounds have similar sample sizes of 12,528, 12,304, and 12,406; due to financial constraints, the fourth round has a significantly smaller sample size of 6,628. The number of pediatricians surveyed in each round was 1627, 1727, 1802, and 793. Physicians were identified as pediatricians if, in the CTS survey, they identified pediatrics (or a pediatric subspecialty) as their primary specialty.

Each CTS sample is distributed across 51 metropolitan and nine non-metropolitan areas summing to 60 core CTS sites. Of these 60 core CTS sites, there are 12 high-intensity sites where a larger number of physicians were sampled. The rest are low-intensity sites. To augment the 60 core CTS sites, an independent supplemental national sample of physicians was also surveyed. The independent supplemental national sample was not conducted in the fourth round, however, restricting that round to the 60 core CTS sites. The 60 CTS sites are located in 34 states, and only those 34 states were included in our work hours analysis, even though there were some pediatricians reporting hours who were practicing in non-CTS states.

[11]The Center for Studying Health System Change also conducted a more-recent physician survey in 2008. The survey design and sampling methodology are significantly different from the previous physician surveys, however, and the sample size is much smaller. Those differences are large enough that we chose not include the 2008 data in our analysis.

The CTS collected a comprehensive set of information from the physicians surveyed. However, a subset of this information is used for the following analysis. This includes the outcome variable, hours of direct patient care per year, which is the product of two CTS variables: hours of direct patient care per week and weeks worked per year. Also, physician age and sex are used as control variables. The CTS also includes a set of sampling weights that are used to calculate state-year means.

Simulated Percentage Eligible

The calculation of simulated percentage of children eligible for CHIP consists of two components. The first is a fixed national sample of children (and their families), and the second is the state CHIP eligibility rules. The fixed national sample is extracted from the Survey of Income and Program Participation (SIPP) and the CHIP eligibility rules are collected from a variety of sources detailed below.

2004 SIPP

All children up to age 19 from the 2004 panel of the SIPP are used as the fixed national sample (n = 25,563). We use income reported in the SIPP in May, 2005. Individuals in the SIPP are grouped into health insurance units, which are collections of individuals who are (or could be) covered under the principal individual's health insurance plan. To simulate eligibility for Medicaid and CHIP we use annual income of the health insurance unit, disregarding certain types of expenses such as child support and child care. Finally, SIPP sampling weights are used to calculate means.

Eligibility for Medicaid and CHIP

Data on state Medicaid and CHIP income eligibility criteria were collected for each year from 1997 through 2005 from a number of sources including the Congressional Research Service (2000), Mathematica Policy Research, Inc. (2007), and the National Governors Association (2001, 2003, 2005). Because a number of data sources were used, inconsistencies sometimes arose. Wherever possible, these were resolved with state fact sheets and state annual reports filed by the state CHIP administrators to CMS.

CHIP Waiting Periods

Data on states' CHIP waiting periods were collected from a series of reports by the National Academy for State Health Policy (Kaye, Pernice, & Cullen, 2006; Pernice, Riley, Pelletier, & Kaye, 1999; Pernice, Wysen, Riley, & Kaye, 2001). These data were checked against a separate source (Lutzky & Hill, 2001), and any inconsistencies were resolved.

Results

CHIP resulted in a major expansion in eligibility for public coverage among children. In 2005, the CHIP expansion population, meaning those children who were eligible for public coverage under the 2005 rules, but not under the 1997 rules, totaled about 14 million children, or 17.9 percent among that age group.

As shown in Exhibit 3, our hypothetical measure of demand for pediatrician services increases by 2.4 percent as a result of CHIP—this benchmark increase in demand is large enough that it is reasonable to test for associated changes in pediatricians' hours. For the 4 million children who were in the CHIP expansion group and who were actually enrolled in CHIP at a point in time in 2005, their out-of-pocket payments for medical care declined substantially, and their hypothetical demand for care increased correspondingly.

Exhibit 3. What Impact Did CHIP Have on Children's Hypothetical Demand for Pediatricians' Services in 2005?

Population	Number[a] (millions)	Share (percent)	Change in out-of-pocket share (percentage points)	Hypothetical change in demand (percent)
Not eligible for public coverage in 2008	42.9	55.4%	0%	0%
Eligible for public coverage under Medicaid (1997 rules)[b]	22.3	28.7%	0%	0%
Expansion population (eligible for public coverage under 2008 rules, not eligible under 1997 rules)[b]				
Not enrolled in public coverage	8.3	10.7%	0%	0%
Enrolled in public coverage				
Otherwise uninsured [c]	*1.6*	*2.1%*	-100% (100%→0%)	+68%[e]
Otherwise privately insured	*2.4*	*3.1%*	-25% [d] (25%→0%)	+31% [e]
CHANGE IN HYPOTHETICAL DEMAND				+2.4%[f]

[a]The total population under age 19 is calculated from U.S. Census Bureau (2008).
[b]Calculation of eligibility for Medicaid and CHIP is described in the Methodology section.
[c]Assumes a crowd-out rate of 60%, based on Gruber and Simon (2008).
[d]The out-of-pocket share among privately insured children is calculated from the 2004 MEPS.
[e]Based on results from the RAND Health Insurance Experiment, as reported by Newhouse and the Insurance Experiment Group (1993), p. 41. The hypothetical change in demand is based on outpatient expenditures under free care, 25 percent coinsurance, and 95 percent coinsurance.
[f]For a more detailed explanation on the assumptions and steps used to produce this calculation, see the discussion in the appendix.

For our estimating strategy to work well there needs to be variation across states in the size of their CHIP expansions. As shown in Exhibit 4, this is, in fact, the case. In the group of states with "small" expansions (i.e., in the lowest tercile) about 12 percent of children became newly eligible for public coverage and just over 3 percent were enrolled in CHIP in 2005. In the group of states with "large" expansions, about 21 percent of children became newly eligible and almost 7 percent were enrolled. We calculated the hypothetical change in demand separately for the different groups of states, and found that it is over 2 percentage points higher in the large expansion states compared to the small expansion states (+3.5 percent versus +1.2 percent).

There are some differences worth noting between the states with large versus small CHIP expansions. As shown in Exhibit 4, states with large CHIP expansions tend to be more urban, have higher income per capita, and have larger Hispanic populations. These differences underscore the importance of including state-fixed effects in our regression analyses, and the importance of allowing for division-specific year effects.

Exhibit 4. State CHIP program, demographic, and economic characteristics by size of their CHIP expansions.

	States, Grouped by Size of CHIP Expansion Population		
	Small	Medium	Large
Number of states	23	19	9
Population under age 19 (m)	25.3	26.5	26.0
Share of children eligible			
(% of population under age 19)			
Medicaid (1997 rules)	29.8%	25.4%	26.4%
CHIP expansion (2001 rules)	11.8%	17.5%	20.3%
Share enrolled in CHIP in 2005			
(% of population under age 19)	2.6%	4.9%	7.8%
Hypothetical change in demand	1.2%	2.3%	3.5%
Urban (% of population)	78.6%	73.4%	85.8%
Income per capita ($000s)	29.8	27.8	30.5
Poverty (% of population)	9.7%	11.7%	12.8%
Race/ethnicity			
Hispanic (% of population)	9.0%	11.2%	19.0%
Black (% of population)	9.1%	12.2%	15.4%

NOTE. States are grouped into terciles based on the share of their under-19 population enrolled in CHIP in 2004–5. These state characteristics are calculated from the 2000 Census and, therefore, represent the true population-level means. We do not, therefore, report tests of whether differences between the states are statistically significant.
SOURCE: Authors' calculations.

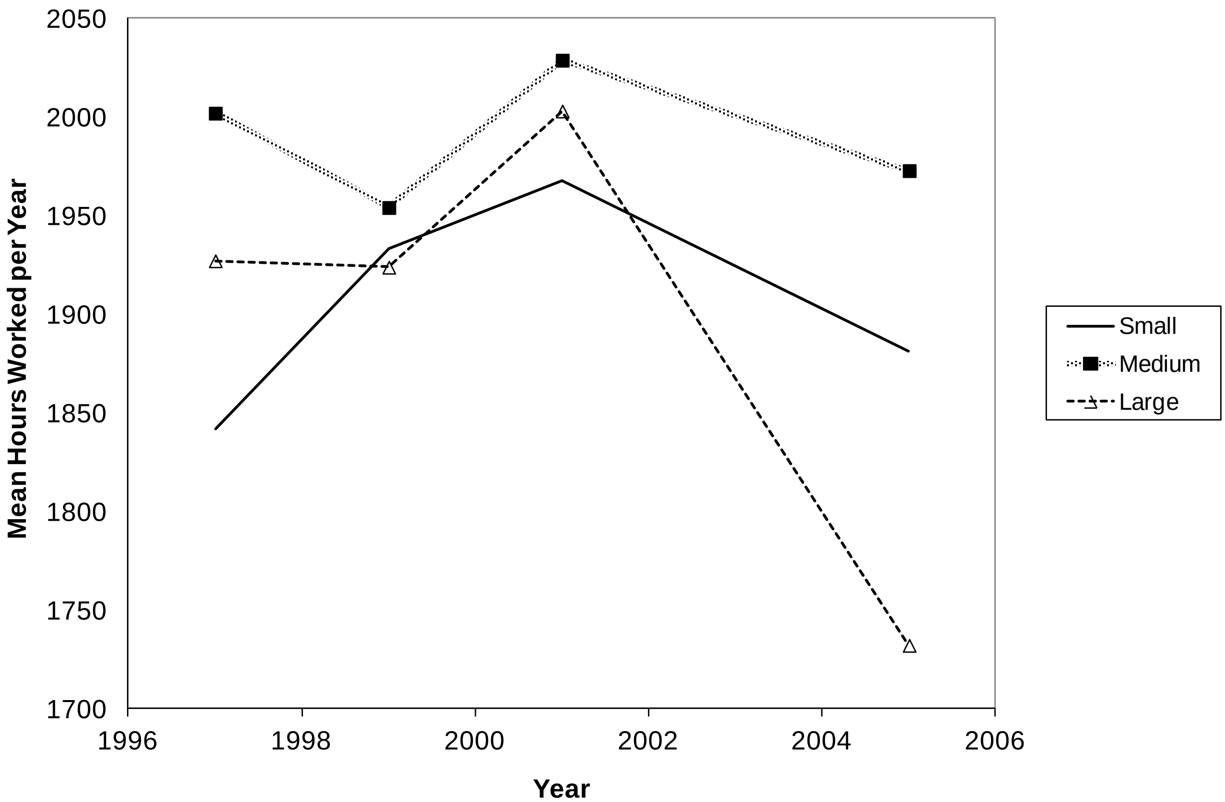
Exhibit 5 provides a graphical summary of the trends in pediatricians' annual work hours, with pediatricians grouped into terciles based on the size of the CHIP expansion in their state. Overall, pediatricians' work hours increased from 1996–7 to 2000–1, and then declined fairly sharply. The decline in work hours between 2000–1 and 2004–5 is consistent with the broader decline in work hours among all physicians reported by Staiger, Auerbach, and Buerhaus (2010).

The scatterplots in Exhibit 6 provide a graphical analysis of the relationship between CHIP expansions and changes in pediatricians' work hours. In all three plots, the baseline is 1996–7, the period before CHIP implementation. Each graph then contains a comparison between that baseline and a different end period. The first graph's end period is 1998–9, the second is 2000–1, and the last is 2004–5. In the individual graphs, each bubble represents a state and the size of the bubble is proportional to the number of pediatricians reporting hours in the CTS data (averaged over the two waves). The solid black line is the observed relationship between the change in pediatrician hours and the simulated CHIP enrollment,[12] based on a regression analysis only including the selected years. The gray line represents the hypothetical relationship, determined by the demand-based benchmark (Exhibit 3). What is striking about these graphs is the contrast between the hypothetical relationship, which is positively sloped, and the actual relationship,

[12]Instead of the actual CHIP enrollment, we use the simulated CHIP enrollment to be consistent with the reduced form regressions presented below. However, the graph yields the same conclusion if actual CHIP enrollment is used.

which is negatively sloped. That negative slope persists across the three successive graphs and becomes more pronounced in the later waves.

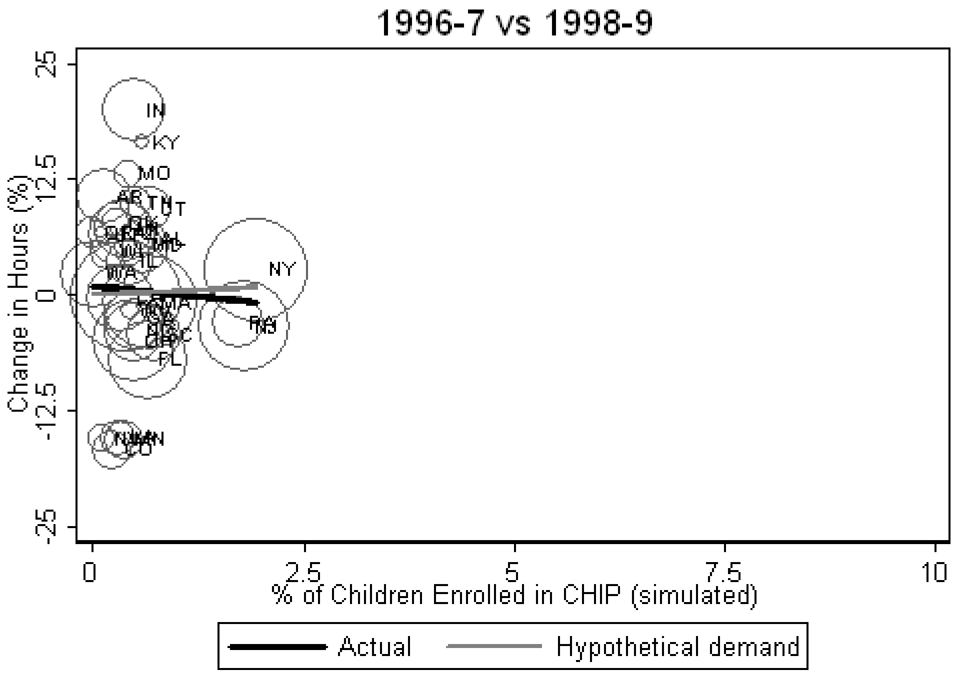
Exhibit 5. Trends in Pediatricians' Work Hours, by Size of State CHIP Expansion



NOTE. States are grouped into terciles based on the share of their under-19 population enrolled in CHIP in 2005.
Based on a purely demand-side analysis, we would expect that pediatricians' hours would increase in states with large expansions relative to pediatricians in states with small expansions.

Based on the trends shown in Exhibit 5, however, the opposite appears to be true. Between 1996–7 and 2004–5, pediatrician hours increased in states with the smallest CHIP expansions, and declined in states with the medium-sized and large CHIP expansions.

Exhibit 6. State-level Scatterplots: Predicted Size of CHIP Expansion (x-axis) Versus Change in Pediatrician Work Hours (y-axis)



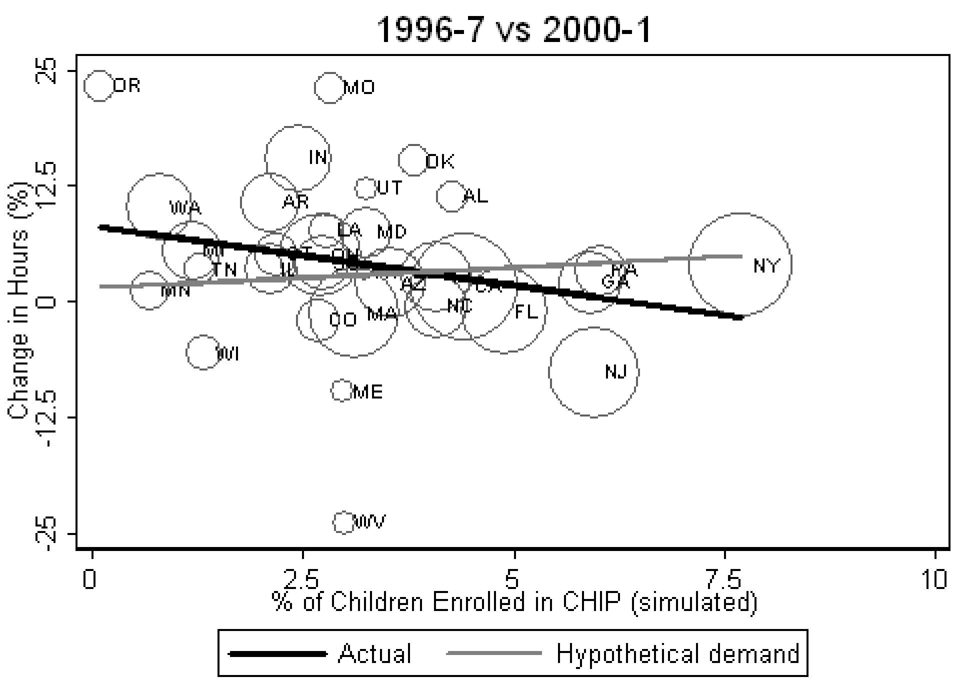
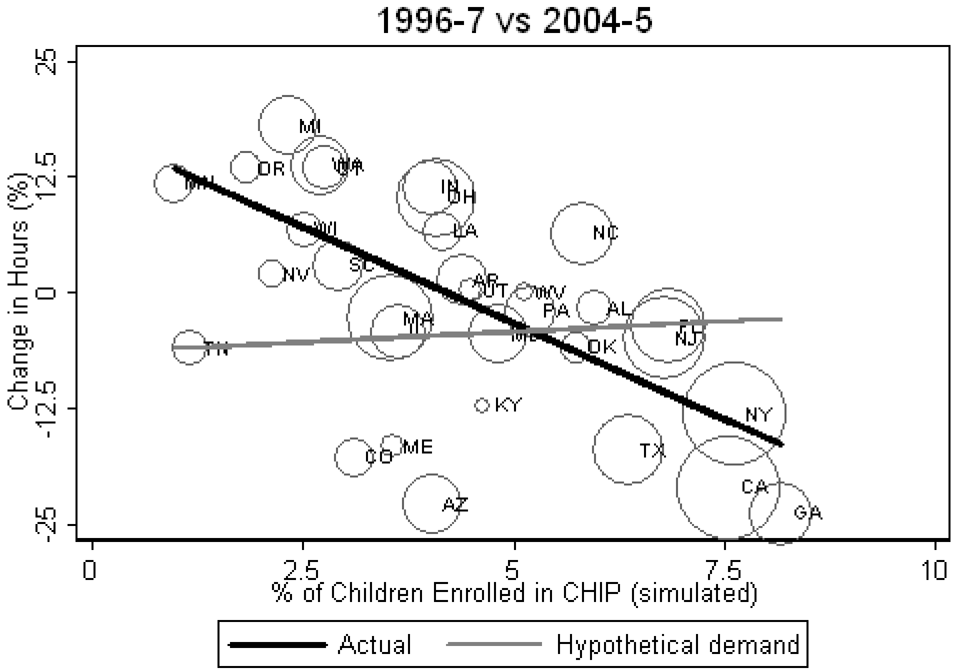


Exhibit 6 (cont.)



NOTES. The size of each bubble indicates the number of pediatrician self-reports in that state, averaged over the two waves shown. The "Actual" line indicates the slope of a regression that only includes the selected waves. The "Hypothetical demand" line indicates the relationship predicted by the hypothetical demand calculation illustrated in Exhibit 3. The predicted size of the CHIP expansion is the difference in the predicted enrollment between the two waves shown, from the first-stage model (model 1, coefficients shown in Exhibit 7).

Exhibit 7 presents the results of the standalone model used to predict CHIP enrollment. Both the simulated eligibility measure and the waiting period measure are strongly associated with CHIP enrollment. To help interpret the coefficients, suppose that in a given state 10 percent of the child population were made newly eligible for public coverage in 2005 due to CHIP. The enrollment model implies that in that state 2.92 percent of children (10 percent * 0.292) would be predicted actually to enroll in CHIP (assuming no waiting period). If in that state there were a waiting period of 6 months or longer for all CHIP-eligible children, then 1.67 percent [10 percent * (0.292 – 0.125)] of children would enroll.

The relationship between the share eligible and actual CHIP enrollment strengthens over time, as shown by the increase in the magnitude of the eligibility coefficient estimates in the interactions with later years. That phase-in reflects the fact that it took states many years to fully operationalize their CHIP programs and draw children into them.

Exhibit 7. First-stage Model of CHIP Enrollment, 1997–2005

Model Number	1 (Create instrument)	
Dependent variable	Monthly CHIP Enrollment (% of population <19)	
Level of observation	State-year	
Coefficient estimates (standard errors)		
Year fixed effects		
1997	-0.024	(0.015)
1998	-0.022*	(0.013)
1999	-0.025**	(0.012)
2000	-0.026**	(0.010)
2001	0.000	(0.009)
2002	0.012	(0.008)
2003	0.014*	(0.008)
2004	0.003	(0.007)
2005	excluded	
Year * CHIP expansion (% of under-19 population)		
1997	excluded	
1998	0.013	(0.027)
1999	0.066**	(0.028)
2000	0.160***	(0.032)
2001	0.229***	(0.034)
2002	0.289***	(0.033)
2003	0.303***	(0.034)
2004	0.286***	(0.034)
2005	0.292***	(0.033)
Year * Waiting period 6 months or greater (% of under-19 population eligible for CHIP expansion and subject to waiting period)		
1997	excluded	
1998	-0.010	(0.037)
1999	-0.069***	(0.025)
2000	-0.115***	(0.025)
2001	-0.142***	(0.026)
2002	-0.175***	(0.026)
2003	-0.166***	(0.026)
2004	-0.148***	(0.026)
2005	-0.125***	(0.026)
Ln(GSP per capita)	-0.013	(0.038)
Unemployment rate	-0.003**	(0.001)
Medicaid physician fee index (national average=1.00)	-0.011	(0.007)
State-fixed effects	Yes	

Exhibit 7 (cont.)

Division-year fixed effects	Yes
Weighted	Yes (population <19)
R-squared	0.9383
Number of observations	459 (51 states * 9 years)

NOTES. * signifies statistical significance at the 10% level, ** signifies statistical significance at the 5% level, and *** signifies statistical significance at the 1% level. Standard errors are clustered at the state level.
SOURCE: Authors' calculations.

Exhibit 8 summarizes the main results of our regression analyses of pediatrician work hours. In the OLS model, the coefficient on CHIP enrollment is negative, but is imprecisely estimated and not statistically significant. In the reduced form and IV models, in contrast, CHIP enrollment is strongly negative and statistically significant. The coefficient from the IV model implies that a

Exhibit 8. Estimating the Impact of CHIP Expansions on Pediatrician Work Hours

Model Number	2 (OLS)		3 (Reduced form)		4 (IV)	
Dependent variable	Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year	
Type of physician	Pediatrician		Pediatrician		Pediatrician	
Level of observation	State-year		State-year		State-year	
Coefficient estimates (standard errors)						
Actual CHIP enrollment	-0.05	(1.10)				
Predicted CHIP enrollment			-2.79*	(1.38)	-2.74**	(1.09)
Male (% of pediatricians)	0.28**	(0.11)	0.26**	(0.10)	0.24***	(0.08)
Over age 55 (% of pediatricians)	-0.20	(0.15)	-0.15	(0.15)	-0.16	(0.14)
Ln(GSP per capita)	-0.88	(0.85)	-1.18	(0.81)	-1.41*	(0.82)
Unemployment rate	0.01	(0.02)	-0.02	(0.02)	-0.03	(0.02)
Medicaid physician fee index (national average=1.00)	-0.06	(0.14)	-0.07	(0.11)	-0.04	(0.09)
State-fixed effects	Yes		Yes		Yes	
Year-fixed effects	Yes		Yes		Yes	
Division-year fixed effects	Yes		Yes		Yes	
Weighted	Yes		Yes		Yes	
First-stage diagnostics on excluded instrument						
Coefficient estimate	n/a		n/a		1.02***	(0.18)
Partial r-squared	n/a		n/a		0.3495	
F-statistic (1, 33)	n/a		n/a		30.49	
R-squared	0.7471		0.7685		0.4294	
Number of observations	136		136		136	

NOTES. * signifies statistical significance at the 10% level, ** signifies statistical significance at the 5% level, and *** signifies statistical significance at the 1% level. Standard errors are clustered at the state level. Models are weighted by the number of physicians self-reporting hours in each state and year. The r-squared values for the IV models are calculated after first partialing out state effects.
SOURCE: Authors' calculations.

five percentage point increase in the share of children enrolled in CHIP (which is roughly the difference between states with large versus small expansions) is associated with an almost 14 percent decline in work hours.

The first stage of the IV analysis is strong enough to satisfy conventional rules of thumb, as indicated by the partial r-squared and the f-statistic on the excluded instrument (16.94).

Additional Analyses

Exhibit 9 presents additional results, including a falsification test in which we regress work hours among internal medicine physicians on our CHIP expansion variables. Children comprise only a small share of internal medicine physicians' patient population. We do not, therefore, expect that they would be directly affected by the CHIP expansions, at least not nearly to the same extent as pediatricians. The regression results are reassuring, in that they do not indicate a statistically significant negative relationship between CHIP expansions and the work hours of

Exhibit 9. Additional Regression Analyses

Model Number	5 (internal medicine, OLS)		6 (internal medicine, IV)		7 (exclude 2004–5, IV)		8 (region–year, IV)	
Dependent variable	Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year	
Type of physician	Internal medicine		Internal medicine		Pediatrician		Pediatrician	
Observation Level	State-year		State-year		State-year		State-year	
Coefficient estimates (standard errors)								
Actual CHIP enrollment	1.61	(1.13)						
Predicted CHIP enrollment			0.34	(1.31)	-0.97	(1.08)	-2.00**	(0.97)
Male (% of physicians)	-0.04	(0.10)	0.00	(0.08)	0.25**	(0.10)	0.19**	(0.08)
Over age 55 (% of physicians)	-0.16	(0.16)	-0.11	(0.11)	-0.02	(0.16)	-0.17	(0.13)
Ln(GSP per capita)	0.64	(0.94)	0.38	(0.62)	-2.02***	(0.63)	-0.81	(0.61)
Unemployment rate	0.01	(0.02)	-0.01	(0.02)	-0.02	(0.03)	-0.01	(0.02)

Exhibit 9 (cont.)

Model Number	5 (internal medicine, OLS)		6 (internal medicine, IV)		7 (exclude 2004–5, IV)		8 (region–year, IV)	
Dependent variable	Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year		Log of Mean Patient Care Hours per Year	
Type of physician	Internal medicine		Internal medicine		Pediatrician		Pediatrician	
Observation Level	State-year		State-year		State-year		State-year	
	Coefficient estimates (standard errors)							
Medicaid physician fee index (national average=1.00)	0.01	(0.15)	-0.03	(0.10)	-0.21	(0.14)	-0.03	(0.10)
State-fixed effects	Yes		Yes		Yes		Yes	
Year-fixed effects	Yes		Yes		Yes		Yes	
Division-year fixed effects	Yes		Yes		Yes		No	
Region-year fixed effects	No		No		No		Yes	
Weighted	Yes		Yes		Yes		Yes	
First-stage diagnostics on excluded instrument								
Coeff. estimate (std error)	n/a		0.98***	(0.22)	1.07***	(0.36)	1.04***	(0.20)
Partial r-squared	n/a		0.3737		0.3536		0.4544	
F-statistic (1, 33)	n/a		20.32		8.68		28.03	
R-squared	0.7480		0.4860		0.5433		0.3601	
Observation Count	136		136		102		136	

NOTES. * signifies statistical significance at the 10% level, ** signifies statistical significance at the 5% level, and *** signifies statistical significance at the 1% level. Standard errors are clustered at the state level. Models are weighted by the number of physicians reporting hours in each state and year. The r-squared values for the IV models are calculated after first partialling out state effects.
SOURCE: Authors' calculations.

internal medicine physicians. The IV model (6) yields a coefficient near zero and is not statistically significant. It is worth noting that, among internal medicine physicians, the OLS coefficient is well above zero, albeit not statistically significant, and much larger than the IV estimate (1.61 versus 0.34). That discrepancy between the internal medicine OLS and IV results is consistent with the possibility of upward bias in the OLS pediatrician estimates.

We report two additional specification tests. The first (model 7) excludes 2004–5 in order to test the sensitivity of the results to the length of the panel. The second (model 8) includes census region-year interactions rather than division-year. The model excluding 2004–5 does not yield statistically significant results, and its first stage is weak—this supports the inclusion of the observations from 2004–5. The results from the region-year model are very similar to the main model, which is reassuring.

Conclusion

The ACA will, beginning in 2014, significantly expand enrollment in public insurance coverage and reduce the number of the uninsured.[13] The effects of that type of large-scale coverage expansion—on access to care, and on system-wide health spending—are complex and depend on the responses of physicians, hospitals, and other medical providers. We have only a limited understanding of what happens when an influx of new demand for physician services encounters a supply of physicians that is relatively fixed, at least in the short run.

In our analysis, we first demonstrate that the implementation of CHIP has led to the enrollment of millions of children in public coverage, and a decrease in both the number and share of children who are either uninsured or have private insurance coverage. By shifting millions of children into public coverage, CHIP substantially reduced out-of-pocket payments for medical services. However, our results indicate a *negative* relationship between the size of a state's CHIP expansion and the trends in work hours among pediatricians in that state.

We find that these results provide a convincing case that public insurance expansions are not producing the responses from pediatricians expected by many observers and predicted by a purely demand-driven model. Two possible explanations for this finding are the lower fees that pediatricians receive from CHIP, and the fact that health plans in CHIP are heavily managed. As modeled in a supply-driven theory by Glied and Zivin (2002), the CHIP expansion changed pediatricians' patient mix and lowered payment rates for pediatrician services thereby reducing the incentive for pediatricians to work longer hours, and changing their fixed cost decisions. One possible mechanism for such a reduction in work hours is an increase in part-time work arrangements. Since the 1990s, Cull et al. (2002) document a rise in the share of pediatricians working part-time. They attribute this shift toward part-time work to the influx of women into the profession, but the CHIP expansions could also have played a role.

Currie and Gruber (1996) and other researchers have linked expansions of children's eligibility for public coverage with increased utilization of medical services. One obvious question is how to reconcile those findings with the findings in this paper. It is important to note that they can both be true—i.e., the number of pediatrician office visits increases in response to coverage expansions, but pediatricians' work hours decline. This would occur if the CHIP expansions resulted in significantly shorter average visit times. Unfortunately, the CTS does not report the number of patient visits provided, so this hypothesis cannot be tested directly with the data on hand. It is also possible that the CHIP expansions were associated with increases in

[13]The provisions and estimated effects of the Senate and House bills have been described by the Congressional Budget Office (2009, 2010).

utilization among the targeted population, but that those increases were offset (and perhaps more than offset) by decreases in utilization among other populations. This could occur if, for example, CHIP led to longer waiting times for appointments for all children and lower utilization of pediatrician services among children outside the CHIP expansion population. That type of spillover—in which expanding coverage to one population reduces utilization among another—has been demonstrated in Britain and Canada.[14] A direct test of this spillover hypothesis in the context of CHIP is a valuable avenue for future research.

The ACA differs from CHIP in several key ways, and we should expect, therefore, that the ACA's effects on physician labor supply will differ from those reported here. First, the Medicaid expansion in the ACA targets childless adults with very low incomes (below 138 percent of poverty)—in that income range there will be relatively little crowdout from private to public coverage, and so the ACA's effect on average fees will probably be smaller. Second, along with expanding Medicaid, the ACA expands private insurance by establishing the new health insurance exchanges and by imposing a penalty on those who remain uninsured. Third, the ACA couples a coverage expansion with a temporary increase in Medicaid fees for office visits provided by primary care physicians (including pediatricians). We expect that the fee increase will tend to expand physician supply.

In considering future public insurance expansions, it is important to not rely on a purely demand-driven model of physician behavior, but also to assess their effects on reimbursement rates and on physicians' work incentives. Especially in cases where expansions will bring a large number of patients into public insurance coverage, physicians may end up working less than they would otherwise. Because of these supply-side responses, the implications of large coverage expansions for system wide health spending is not as obvious as it would at first appear.

Disclaimer

This research was conducted while the authors were at the Congressional Budget Office (CBO). The views expressed in this paper are those of the authors, and do not represent the views of the CBO, the U.S. Government Accountability Office, or the Center for Studying Health System Change.

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[14]See, for example, Stewart and Enterline's (1961) analysis of the effects of the establishment of the National Health Services in England and Wales. Also see Enterline's (1973) discussion of the Quebec experience.

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Appendix

Children's Medical Costs

Exhibit A1 tabulates mean costs for health care services among children with private coverage only and public coverage only from the 2004 Medical Expenditure Panel Survey (MEPS). These co-payment rates are extracted from the 2004 Medical Expenditure Panel Survey Household Component (MEPS). MEPS is a large-scale survey of individuals containing information about the use and cost of health services and health insurance status. It is administered by the U.S. Department of Health and Human Services and consists of 33,403 individuals. For this study, age of the individual, health insurance status, total health expenditures by cost category, and out-of-pocket expenditures by cost category are used to calculate the co-payment rates for privately versus publicly insured children.

Out-of-pocket costs for children with private coverage equal about 25 percent of the total costs, whereas for children with public coverage out-of-pocket costs total about 4 percent of total costs. This suggests that public coverage is nearly free and is much more generous than private coverage. Consequently, children who switch from private coverage to public coverage in response to the CHIP expansion should increase their demand for physician services since these services become cheaper.

Methodology for Calculations in Exhibit 3

Calculating these hypothetical demand increases rely on the following key assumptions:

1. Expansions in CHIP have led to more children eligible for public insurance.
2. More children eligible for public insurance has led to more children enrolled in public insurance.
3. Public insurance is generally more generous than lack of insurance and private insurance.
4. More generous insurance leads to higher utilization of medical services, which includes physician services.

In particular, the hypothetical demand increase is calculated using the following methodology:

1. The number enrolled into CHIP is calculated using the 2004 SIPP.
2. The number of these enrolled are disaggregated into those who switched from uninsurance and those who switched from private insurance. This breakdown is based off a "crowd-out" rate of 60% as estimated by Gruber and Simon (2008).
3. Taking average co-payment rates of private and public insurance from the 2004 MEPS, we assume that switching from private insurance reduces co-payment rates from 25% to 0%. For those who switch from no insurance to public insurance, we assume that these children go from full payment to 0%.

4. Finally, to translate these reductions in out-of-pocket costs of medical services into increases in demand for these medical services, we use the demand elasticity from the RAND Health Insurance Experiment, as reported by Newhouse and the Insurance Experiment Group (1993), p.41. The hypothetical change in demand is based on outpatient expenditures under free care, 25% coinsurance, and 95% coinsurance.

Admittedly, these calculations of hypothetical demand increases resulting from the CHIP expansions are rough estimates. However, they provide a useful benchmark to compare the actual relationship between CHIP expansions and physician labor supply outcomes.

Exhibit A1. Mean annual out-of-pocket costs and total costs among children, by type of coverage

	Out-of-Pocket Costs ($)	
Category	Private Coverage Only	Public Coverage Only
Total	333.67	36.718
	(16.034)	(5.453)
Office visits	78.642	5.506
	(5.782)	(1.039)
Outpatient	16.101	0.886
	(2.682)	(0.586)
Emergency room	9.548	1.646
	(1.109)	(0.603)
Inpatient	4.167	0.667
	(1.528)	(0.318)
Dental	168.049	18.216
	(13.395)	(5.084)
Prescription	57.163	9.797
	(3.468)	(1.164)
	Total Costs ($)	
Category	Private Coverage Only	Public Coverage Only
Total	1327.341	890.898
	(58.031)	(96.905)
Office visits	369.101	227.703
	(17.736)	(12.936)
Outpatient	229.633	93.72
	(30.878)	(12.944)
Emergency room	80.719	60.857
	(7.259)	(7.035)
Inpatient	126.208	240.021
	(27.110)	(91.696)
Dental	376.278	97.354
	(22.565)	(8.887)
Prescription	145.401	171.243
	(8.277)	(13.261)

SOURCE: 2004 Medical Expenditure Panel Survey (MEPS), standard error in parentheses.

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