

# Subsidizing Health Insurance for Low-Income Adults: Evidence from Massachusetts

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June 2018

## Abstract

How much are low-income individuals willing to pay for health insurance, and what are the implications for insurance markets? Using administrative data from Massachusetts' subsidized insurance exchange, we exploit discontinuities in the subsidy schedule to estimate willingness to pay and costs of insurance among low-income adults. As subsidies decline, insurance take-up falls rapidly, dropping about 25% for each \$40 increase in monthly enrollee premiums. Marginal enrollees tend to be lower-cost, indicating adverse selection into insurance. But across the entire distribution we can observe – approximately the bottom 70% of the willingness to pay distribution – enrollees' willingness to pay is always less than half of their *own* expected costs that they impose on the insurer. As a result, we estimate that take-up will be highly incomplete even with generous subsidies: if enrollee premiums were 25% of insurers' average costs, at most half of potential enrollees would buy insurance; even premiums subsidized to 10% of average costs would still leave at least 20% uninsured. We briefly consider potential explanations for these findings and their normative implications.

JEL codes: H51; I13.

Keywords: Health insurance; subsidies; low-income.

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# 1 Introduction

Governments spend an enormous amount of money on health insurance for low-income individuals. For instance, the U.S. Medicaid program (at \$550 billion in 2015) dwarfs the size of the next largest means-tested programs – food stamps and the EITC (\$70 billion each).<sup>1</sup> Perhaps because of these high and rising costs, public programs increasingly offer *partial* subsidies for health insurance, requiring enrollees to pay premiums to help cover costs. Partial subsidies are a key feature of market-based programs such as Medicare Part D and the Affordable Care Act (ACA) exchanges, and even traditional low-income programs like Medicaid and the Children’s Health Insurance Program (CHIP) increasingly require premiums for some enrollees (Smith et al. (2015), Brooks et al. (2017)). Partial subsidies are also a textbook policy response to adverse selection if a full coverage mandate may not be efficient (Einav and Finkelstein, 2011). In such settings, measuring willingness to pay and costs is important for analyzing the impact and desirability of alternative subsidies.

In this paper, we estimate low-income individuals’ willingness to pay (WTP) for health insurance, assess how it compares to the cost they impose on the insurer, and discuss the positive and normative implications for subsidized health insurance programs. We do so in the context of Massachusetts’ pioneer health insurance exchange for low-income individuals, known as “Commonwealth Care” or “CommCare.” Established in the state’s 2006 health care reform, CommCare offered heavily-subsidized private plans to non-elderly adults below 300% of poverty who did not have access to insurance through an employer or another public program. Public subsidies were substantial: on average for our study population, enrollee premiums are only about \$70 per month – or less than one-fifth of insurer-paid medical claims (\$359 per month) or insurer prices (\$422 per month). There was also a health insurance mandate backed by financial penalties.

We use a regression discontinuity design, together with administrative data on enrollment and medical claims, to estimate demand and cost for CommCare plans. Our main analysis focuses on fiscal year 2011, when the insurance options had a convenient vertical structure. We also present some complementary results for the full 2009-2013 period over which we have data.

The analysis leverages discrete changes in subsidies at several income thresholds. Subsidies were designed to make enrollee premiums for the cheapest insurer’s plan “affordable”; in practice, the subsidy amount changes discretely at 150%, 200% and 250% of the federal poverty line (FPL). These discontinuities in program rules provide identifying variation in enrollee premiums. The cheapest plan’s (post-subsidy) monthly enrollee premium increases by about \$40 at each of the discontinuities, and more generous plans experience a \$40 to \$50 increase in (post-subsidy) monthly enrollee premiums.

We first document two main descriptive patterns. First, enrollee demand is highly sensitive to premiums. With each discrete increase in enrollee premiums, enrollment in CommCare falls by about 25%, or a 20-24 percentage point fall in the take-up rate. Second, we find that despite the presence of a coverage mandate, the market is characterized by adverse selection: as enrollee premiums rise, lower-cost enrollees disproportionately drop out, raising the average cost of the remaining insured population. We estimate that average medical claims rise by \$10-\$50 per month (or 3-14%) with each

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<sup>1</sup>See U.S. Department of Health and Human Services (2015), U.S. Department of Agriculture (2016), and U.S. Internal Revenue Service (2015).

premium increase.

We use a simple model to analyze the implications of these descriptive patterns. The nature of the individual choice problem lends itself naturally to a vertical model of demand in which individuals choose among a “high-coverage” ( $H$ ) option, a “low-coverage” ( $L$ ) option, and a third option of uninsurance (“ $U$ ”); the vast majority of enrollees who buy insurance choose the high-coverage option,  $H$ . We use the model – which is a slight extension of Einav, Finkelstein, and Cullen (2010) – along with the premium variation to map out curves for willingness to pay, average costs of insurance, and costs of marginal enrollees.

The model allows us to translate the descriptive patterns into two main results. First, even large insurance subsidies are insufficient to generate near-complete take-up of insurance by low-income adults. For example, at the median of the willingness to pay distribution, willingness to pay for  $H$  is about \$100 per month – less than one quarter of average costs of \$420 per month if all those with above-median willingness to pay enrolled in  $H$ . Even with a subsidy that makes enrollee premiums for the  $H$  plan equal to 25% of insurers’ average costs, at most half the population would purchase insurance if offered  $H$ . Subsidies making enrollee premiums 10% of insurers’ average costs still leave at least 20% uninsured.

These findings suggest that even modest enrollee premiums can be a major deterrent to universal coverage among low-income people. This deterrent is likely to be even larger in the ACA exchanges, in which income-specific premiums are significantly higher than in CommCare – 2-10% of income for the benchmark plan in the ACA versus 0-5% of income in CommCare.<sup>2</sup> Our results may thus help explain coverage outcomes in the ACA exchanges, where early evidence suggests highly incomplete take-up (Tebaldi (2017); Kaiser Family Foundation (2016)). The price responsiveness we document is also useful for generating predictions of coverage rates under alternate reform proposals or subsidies.

Second, although adverse selection exists, it is not the primary driver of low take-up. The cost of marginal consumers who enroll when premiums decline is less than the average costs of those already enrolled, indicating that plans are adversely selected (Einav, Finkelstein, and Cullen, 2010). But across the entire in-sample distribution – which spans the 6th to the 70th percentile of the willingness to pay distribution – the willingness to pay of marginal enrollees still lies far below their own expected costs imposed on insurers for either the  $H$  or  $L$  plans. For example, for the median willingness to pay individual, the gap between the costs of the marginal enrollee and average costs of enrollees explains only one-third of the \$300 gap between willingness to pay and average costs. In other words, most individuals would not enroll even if prices were subsidized to reflect marginal enrollees’ own expected insurer costs.

This finding contrasts with textbook models of insurance markets in which demand is assumed to exceed own cost, and adverse selection is widely viewed as the major barrier to insurance coverage. In our setting, enrollment is low not simply because of adverse selection, but because people are not willing to pay their own cost imposed on the insurer.

In the final section of the paper, we briefly explore potential explanations for our findings and ana-

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<sup>2</sup>These are based on authors’ calculations using ACA and CommCare policy parameters. The ACA premiums are for the second-cheapest silver plan; the CommCare premiums are for the cheapest plan.

lyze their normative implications. One explanation is that the costs individuals impose on the insurer differs from the costs they would pay if they were uninsured because of uncompensated care. Back-of-the-envelope calculations using other estimates of the prevalence of uncompensated care suggest this could explain the low WTP. Additionally, a range of behavioral explanations, such as optimistic beliefs that under-estimate expected costs, could explain low WTP, and also have important normative implications. We briefly discuss potential normative rationales for subsidies based on behavioral biases, as an offset to the externalities resulting from uncompensated care (i.e., the Samaritan’s dilemma (Buchanan, 1975; Coate, 1995)), or as a means of redistribution to low-income households.

**Related Literature** While a substantial literature estimates demand and costs for health insurance, there is relatively little work providing such estimates for low-income adults on whom much public policy attention is focused.<sup>3</sup> This is likely because, until recently, most of the low-income uninsured either were not offered health insurance or faced prices that were difficult to measure. This precluded standard demand and welfare analysis based on choices, as has been widely used in the study of private (often employer-provided) health insurance markets (see Einav, Finkelstein, and Levin (2010) for an overview). One effort to surmount this obstacle is Krueger and Kuziemko (2013), who conducted a survey experiment designed to elicit willingness to pay for hypothetical plan offerings among a broad sample of the uninsured from the full spectrum of the income distribution. In another attempt to circumvent the lack of direct estimates of willingness to pay, Finkelstein et al. (2015) assume a normative utility function over estimates of the reduced form impact of Medicaid in order to infer willingness to pay for Medicaid by a low-income population.

The 2010 passage of the ACA has given researchers an opportunity to directly study how low-income insurance demand responds to subsidies (e.g. Tebaldi (2017); Frean et al. (2017)), although the ACA’s subsidy schedule lacks the sharp discontinuities present in Massachusetts, which we exploit for our research design.<sup>4</sup> Nonetheless, our estimates of insurance demand in the low-income adult population in Massachusetts are roughly similar Tebaldi’s (2017) estimates for a largely low-income population in the California ACA exchange.<sup>5</sup> Such findings are also consistent with substantially incomplete take-up of subsidized insurance under the ACA (e.g. Kaiser Family Foundation (2016)).

Our finding that low-income enrollees in Massachusetts value formal health insurance products at substantially below their average cost is consistent with other estimates for other low-income populations (e.g. Finkelstein et al. (2015), Tebaldi (2017)) but contrasts with findings for higher-income populations. In particular, Hackmann, Kolstad, and Kowalski (2015) study the *unsubsidized* Mas-

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<sup>3</sup>There is more work on demand for employer-sponsored insurance, although this literature does not typically go so far as to estimate a demand curve. However, our results are qualitatively consistent with incomplete take-up of employer coverage, despite the large subsidies of employee premiums (Cooper and Schone, 1997; Farber and Levy, 2000).

<sup>4</sup>In other related papers, Dague (2014) examines how enrollment duration in Wisconsin Medicaid responds to increases in monthly premiums, and Chan and Gruber (2010) study the intensive margin of low income individuals’ price sensitivity in their choice among health plans in Massachusetts. Ericson and Starc (2015) estimate demand in the high-income (>300% of poverty) Massachusetts exchange using age discontinuities in insurer prices, but their estimates are for demand among plans *conditional* on buying insurance. None of these studies estimate willingness to pay for insurance.

<sup>5</sup>Tebaldi (2017) estimates a 2-4% decline in enrollment for an across-the-board \$100 annual premium increase for subsidized enrollees without children. Proportionally scaling down our central estimate (25% decline for a \$39/month = \$468/year) would imply a decline of 5.3% for a \$100/year premium increase.

Massachusetts health insurance exchange for individuals *above* 300% of poverty. They also find evidence of adverse selection but estimate that willingness to pay *exceeds* own costs over the entire population of potential consumers, in contrast to our estimates for a low-income population. One natural explanation for these divergent findings is that low-income individuals likely have much greater access to uncompensated care. Indeed, a growing empirical literature documents the large role of uncompensated care for the (predominantly low-income) uninsured and the impact of insurance in decreasing unpaid bills (see e.g. Garthwaite, Gross, and Notowidigdo (2015); Finkelstein et al. (2012); Mahoney (2015); Dobkin et al. (2016); Hu et al. (2016)).<sup>6</sup> Another potential explanation is differential behavioral biases among lower and higher income individuals (e.g. Mullainathan and Shafir (2014)).

Finally, our results have implications for the broader literature on adverse selection in health insurance markets. The empirical literature has extensively documented the presence of adverse selection in health insurance markets but concluded that the welfare cost of the resultant mis-pricing of contracts is relatively small. This literature however has “looked under the lamppost” – primarily focusing on selection across contracts that vary in limited ways, rather than selection that causes a market to unravel, leaving open the possibility of larger welfare costs on this margin (Einav, Finkelstein, and Levin, 2010). Our work, however, finds evidence of significant adverse selection on the extensive margin of purchasing insurance versus remaining uninsured – a finding consistent with past work on the Massachusetts reform (Chandra, Gruber, and McKnight, 2011; Hackmann, Kolstad, and Kowalski, 2015; Jaffe and Shepard, 2017). But it also finds that adverse selection is not the primary driver of limited demand for formal insurance among low-income adults.

The rest of the paper proceeds as follows. Section 2 presents the setting and data. Section 3 presents the basic descriptive empirical evidence, documenting the level and responsiveness to price of both insurance demand and average insurer costs. Section 4 uses a simple model of insurance demand to translate the empirical results from Section 3 into estimates of willingness to pay and costs for insurance. Section 5 briefly considers potential explanations for low willingness to pay and normative implications. The final section concludes.

## 2 Setting and Data

### 2.1 Setting: Massachusetts Subsidized Health Insurance Exchange

#### CommCare

We study Commonwealth Care (“CommCare”), a subsidized insurance exchange created under Massachusetts’ 2006 “Romneycare” health insurance reform that laid the foundation for many of the health insurance exchanges created in other states under the Affordable Care Act (ACA). CommCare operated from 2006-2013 before shifting form in 2014 to comply with the ACA. We focus on the market in fiscal year 2011 (July 2010 to June 2011) but also present descriptive results for fiscal years 2009-2013,

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<sup>6</sup>Differences in the availability of uncompensated care may also reconcile our findings with results from a calibrated life cycle model suggesting that the low-income elderly’s willingness to pay for Medicaid is above their costs (De Nardi et al., 2016); unlike low-income adults, low-income elderly do not have access to substantial uncompensated nursing home care (the primary healthcare covered by Medicaid), either in the De Nardi et al. (2016) model or in practice.

the full period over which we have data. The market rules described below apply to 2011; the rules for other years are similar except in some details.

CommCare covered low-income adults with family income below 300% of the federal poverty level (FPL) and without access to insurance from another source, including an employer or another public program (i.e., Medicare or Medicaid). This population is similar to those eligible for subsidies on the ACA exchanges. Given Medicaid eligibility rules in Massachusetts,<sup>7</sup> the CommCare-eligible population consisted of adults aged 19-64 without access to employer coverage and who were either (1) childless and below 300% of FPL, (2) non-pregnant parents between 133% and 300% of FPL, or (3) pregnant women between 200% and 300% of FPL.

CommCare specified a detailed benefit structure (i.e., covered services and a schedule of cost sharing rules) and then solicited competing private insurers to provide these benefits. Each insurer offered a single plan that had the standardized set of benefits but could differ in its network of hospitals and doctors. Between 4 and 5 insurers participated in the market each year. Benefit design and participating insurers were very similar to the Massachusetts Medicaid program. In particular, CommCare enrollees faced very modest co-pays.<sup>8</sup>

Eligible individuals could enroll during the annual open enrollment period at the start of the fiscal year, or at any time if they experienced a qualifying event (e.g., job loss or income change). To enroll, individuals filled out an application form with information on age, income over the last 12 months, family size, and access to other health insurance. The state used this form to determine whether an applicant was eligible for Medicaid, CommCare, or neither. The form was also used to calculate income as a share of FPL for determining an enrollee's premiums. However, as discussed below, the translation from income and other information on the form into FPL units was not readily transparent to applicants on the form.

If approved for CommCare, individuals were notified (by mail and/or email) and provided information on the premiums for CommCare plans. They then had to complete a second form (or contact CommCare by phone/online) to choose a plan and pay the first month's premium. Individuals who did not make a plan choice and the associated payment did not receive coverage. Coverage commenced at the start of the month following receipt of payment. Once enrolled, individuals stayed enrolled as long as they remained eligible and continued paying premiums. Income and eligibility status changes were supposed to be self-reported and were also verified through an annual "redetermination" process that included comparisons to tax data and lists of people enrolled in employer insurance.

Figure 1 shows a snapshot of the key section of the plan choice form displaying an enrollee's plan options and premiums. Appendix A shows the entire plan choice form and snapshots of the initial application form. We take-away two conclusions from these documents. First, enrolling in subsidized insurance may involve non-trivial hassles; our willingness to pay measure will implicitly incorporate

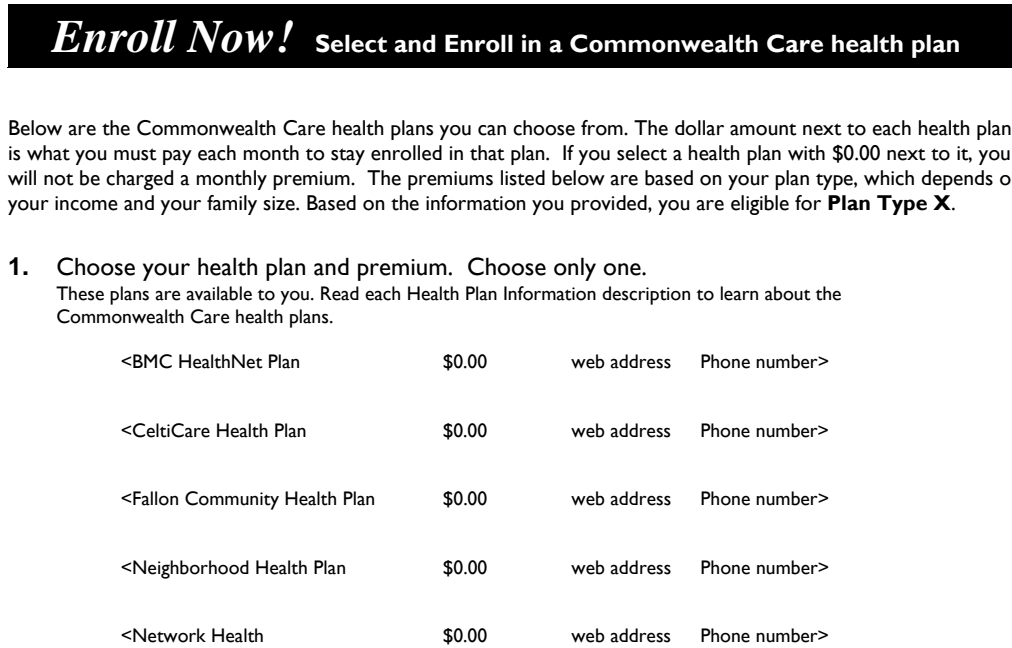
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<sup>7</sup>During our study period, Medicaid covered all relevant children (up to 300% FPL) and disabled adults, as well as parents up to 133% FPL and pregnant women up to 200% FPL. Medicaid also covered long-term unemployed individuals earning up to 100% FPL and HIV-positive individuals up to 200% FPL – both relatively small groups.

<sup>8</sup>Enrollees below 100% of FPL received benefits equivalent to Medicaid. Enrollees between 100-200% FPL received a plan that we estimate (based on claims data) has a 97% actuarial value, while those between 200-300% FPL received a 95% actuarial value plan. The slight change in generosity at 200% FPL is a potential threat to the RD analysis of demand and costs at 200% FPL; we show below that our main results are not sensitive to excluding this discontinuity.

these hassle costs (see Section 4.1). Second, the plan choice form displays enrollee premiums prominently, while referring enrollees online for information about provider networks; employee premium information thus appears to be quite salient, which may help explain our findings that potential enrollee demand responds strongly to premiums.

Figure 1: Snapshot of CommCare Plan Choice Form



NOTE: The figure shows a snapshot of the key section of the plan choice form sent to accepted CommCare applicants. As noted in the text, enrolling in CommCare involves two steps: (1) an application form, which collects information on income, family size, and access to other insurance, which lets the state determine eligibility, and (2) a plan choice form, which applicants must return to choose a plan. More extensive snapshots of these forms are included in Appendix A.

## Subsidy Structure

Insurers in CommCare set a base plan price that applied to all individuals, regardless of income (or age, region, or other factors). The actual payment the insurer received from CommCare equaled their base price times a risk score intended to capture predictable differences in health status.

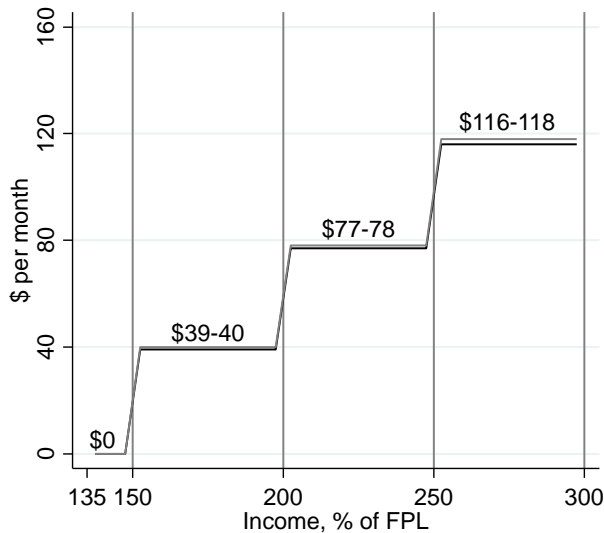
Enrollees paid premiums equal to their insurer’s base price minus an income-varying subsidy paid by the state.<sup>9</sup> Subsidies were set so that enrollee premiums for the lowest-price plan equaled a target “affordable amount.” This target amount was set separately for several bins of income, with discrete changes at 150%, 200%, and 250% of FPL. Figure 2, Panel A shows the result: enrollee premiums for the cheapest plan vary discretely at these thresholds. For the years 2009-2012 (shown in black), the cheapest plan is free for individuals below 150% of FPL and increases to \$39 per month above 150% FPL, \$77 per month above 200% FPL, and \$116 per month above 250% of FPL. In 2013 (shown in

<sup>9</sup>We will use “price” to refer to the pre-subsidy price set by insurers and “premium” to refer to the post-subsidy amount owed by enrollees.

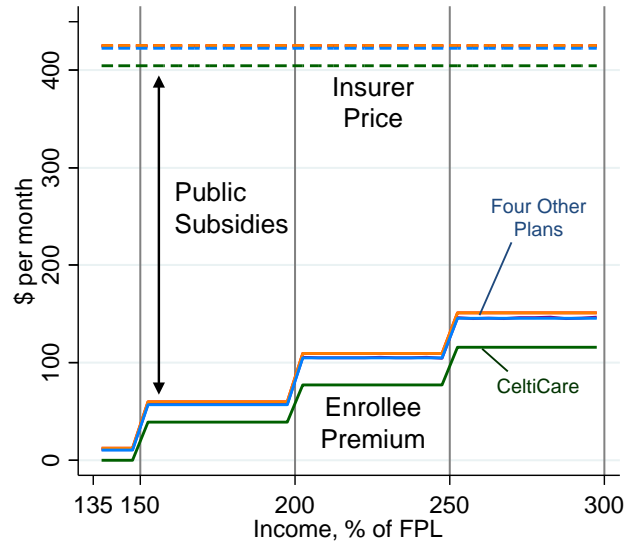
gray), these amounts increase slightly to \$0 / \$40 / \$78 / \$118. Consistent with the goal of affordability, these premiums were a small share of income. For instance, for a single individual in 2011 (whose FPL equaled \$908 per month), these premiums ranged from 0-5% of income (specifically, 2.9% of income just above 150% FPL, 4.2% just above 200% FPL, and 5.1% just above 250% FPL).

Figure 2: Insurer Prices and Enrollee Premiums in CommCare Market

Panel A: Premiums for Cheapest Plan (2009-2013)



Panel B: Prices, Subsidies, and Premiums in 2011



NOTE: Panel A plots enrollee premiums for the cheapest plan by income as a percent of FPL, noting the thresholds (150%, 200%, and 250% of FPL) where the amount increases discretely. The black lines show the values that applied in 2009-2012; the gray lines show the (slightly higher) values for 2013. Panel B shows insurer prices (dotted lines) and enrollee premiums (solid lines) for the five plans in 2011. In this year, four insurers set prices within \$3 of a \$426/month price cap, while CeltiCare set a lower price (\$405) and therefore had lower enrollee premiums.

## 2011 Plan Options

We analyze the market in 2009-2013 but focus especially on fiscal year 2011 when the market had a useful vertical structure with plans falling into two groups. In 2011 CommCare imposed a binding cap on insurer prices of \$426 per month. Four insurers – BMC HealthNet, Fallon, Neighborhood Health Plan, and Network Health – all set prices within \$3 of this cap. The exception was CeltiCare, which set a price of \$405 per month. Figure 2, Panel B shows these insurer prices and the resulting post-subsidy enrollee premiums by income. The prices and premiums of the four high-price plans are nearly indistinguishable, while CeltiCare’s premium is noticeably lower.

Along with its lower price, CeltiCare also had had a more limited network than other plans. We estimate that CeltiCare covered 42% of Massachusetts hospitals (weighted by bed size), compared to 79% or higher for the other three plans offered statewide.<sup>10</sup> Both because of this limited network and

<sup>10</sup>One plan (Fallon Community Health Plan) was only active in central Massachusetts, so its network is difficult to compare to the other insurers.



because of its lack of long-term reputation with consumers (it had entered the state insurance market only in 2010), CultiCare was perceived by enrollees as less desirable, aside from its lower price.<sup>11</sup>

As a result, in much of our analysis that follows we pool the 2011 plans into two groups: CultiCare as a low coverage (“ $L$ ”) option and the other four plans with extremely similar prices pooled together as a high coverage (“ $H$ ”) option. We interpret  $H$  as a composite contract that gives enrollees a choice among the four component insurers, with its utility equal to the max over these four insurers. When we specify and estimate a model of insurance demand in Section 4, we will further assume that  $H$  is perceived as higher quality than  $L$ . We also show in an extension in Section 4.4 below that we can generate fairly tight bounds on willingness to pay in a more general model that does not assume this vertical structure.

Figure 3 zooms in on enrollee premiums for the  $H$  plan and the  $L$  plan in 2011 by income. We define the enrollee premium for  $H$  as the share-weighted average of the component plans; Appendix Table 5 reports these separately for each component plan. As previously discussed, enrollee premiums for the cheapest plan  $L$  ( $p_L$ ) – subsidized to equal a target affordable amount – jump at 150%, 200%, and 250% of FPL. The premium of the  $H$  plan ( $p_H$ ) also jumps at these thresholds. Notably,  $p_H$  jumps by *more than*  $p_L$  at each of these thresholds. This occurs because CommCare chose to apply non-constant subsidies across plans with the goal of narrowing premium differences across plans for lower-income groups. Importantly for our demand estimation, this subsidy structure creates variation in both premium levels and differences between  $H$  and  $L$ . Specifically, the difference  $p_H - p_L$  grows from \$11 below 150% FPL, to \$19 from 150-200% FPL, to \$29 from 200-250% FPL, and to \$31 above 250% FPL.

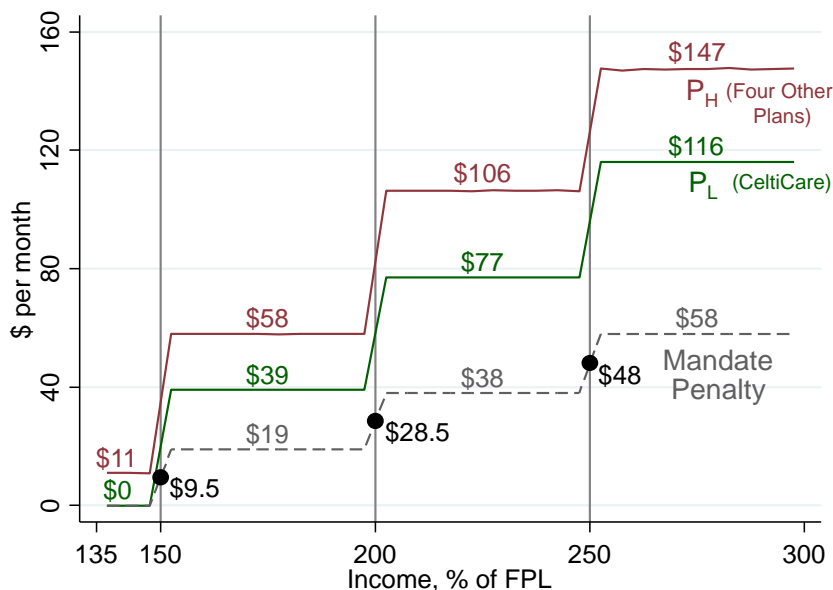
The final relevant option for people eligible for CommCare was to remain uninsured and pay a penalty for being uninsured - the so-called “mandate penalty” which increased the cost of remaining uninsured. The dotted gray line in Figure 3 shows the statutory mandate penalty at each income, which the state set to be half of the lowest CommCare premium ( $p_L$ ). In practice, however, the actual penalty an individual would owe likely diverges from the gray line for two reasons. First, the mandate is assessed based on total annual income (reported in end-of-year tax filings), whereas the measure used to determine enrollee premiums is self-reported on the program application and measures income over the last 12 months (e.g., the prior July to June for someone enrolling during open enrollment). Thus, the actual *expected* mandate penalty is unlikely to change discontinuously at the income thresholds, since someone just above a threshold is equally likely to have total annual income (relevant for the mandate) above or below the threshold. Figure 3 shows in black dots the expected mandate penalty for individuals near each threshold, which we assume is simply the average of the statutory penalty above and below the threshold. A second reason the actual mandate penalty may differ is that individuals may be able to avoid paying even if they are uninsured. For instance, the law does not impose a penalty if an individual is uninsured for three or fewer consecutive months during the year or if an individual qualified for a religious or hardship exemption.<sup>12</sup>

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<sup>11</sup>Consistent with this perception, when all plans were available for free – which was the case for enrollees below 100% of FPL – 96% of enrollees chose a plan other than CultiCare.

<sup>12</sup>The three-month exception is empirically important: based on a state report, almost 40% of the 183,000 uninsured people above 150% FPL in 2011 were uninsured for three or fewer months (Connector and of Revenue, 2011).

Figure 3: Premium and Mandate Penalty Variation, 2011



NOTE: The figure shows how 2011 enrollee premiums and the mandate penalty vary across incomes (as a percent of the federal poverty level, FPL).  $P_L$  denotes the enrollee premium for the  $L$  plan (CeltiCare), while  $P_H$  is the share-weighted average of the enrollee premiums in the four  $H$  (non-CeltiCare) plans. “Mandate Penalty” (dashed gray line) is the statutory mandate penalty at each income level. The black dots show the expected mandate penalty for a person near the income discontinuities, which is the average of the two mandate penalties on either side of the discontinuity.

It is unclear how to use the mandate penalty when calculating revealed willingness to pay. For the reasons discussed above, an individual’s actual mandate penalty is difficult to determine. Moreover, individuals may discount the mandate penalty because it is incurred in the following year’s taxes, or even be unaware of it. In our baseline demand estimates, we will use the sticker premiums for insurance, effectively ignoring the saved penalty when an individual buys insurance. This will make our estimates a conservative upper bound on individuals’ willingness to pay for insurance. In robustness analysis in Section 4.4 below, we also report the lower willingness to pay estimates that we find when we normalize premiums by the expected mandate penalty values (shown in black dots).

## 2.2 Data

### Administrative Data: Enrollee Plan Choices, Claims, and Demographics

Our primary data are enrollee-level and claim-level administrative data from the CommCare program for fiscal years 2009-2013. We observe enrollee demographics and monthly plan enrollment linked to data on their claims and risk scores. All data is at the individual level because CommCare only offers individual (not family) coverage.<sup>13</sup>

We observe each enrollee’s chosen plan at a monthly level. We define total enrollment as the

<sup>13</sup>These de-identified data were obtained via a data use agreement with the exchange regulator, the Massachusetts Health Connector. Our study protocol was approved by the IRBs of the Connector and our affiliated institutions (Harvard, MIT, and NBER).

annualized number of enrollee months in CommCare or a specific plan. In practice, most enrollees are in the same plan for the whole year. We also observe enrollees' choice sets, including the prices, subsidies, and enrollee premiums of each option (summarized in Figures 2 and 3). Enrollee-linked insurance claims data allow us to measure each person's monthly costs (both insurer-paid and out-of-pocket).

The most important demographic we observe is the individual's family income as a percent of FPL (rounded to the 0.1% level), which is the running variable for our RD analysis. This variable is calculated by the regulator from information on family income and composition that enrollees report in their initial CommCare application, and is used to determine premiums and subsidies. This variable is updated based on any subsequent known changes – which in principle, enrollees are required to self-report when they occur – and based on information from annual audits. We also observe information from CommCare's records on enrollee age, gender, zip code of residence, and risk score, a measure of predicted spending calculated by CommCare.

Throughout our analysis, we limit attention to individuals above 135% of FPL because of the significant eligibility change at 133% FPL – above this threshold, parents cease to be eligible for Medicaid and become eligible for CommCare. Table 1 reports some summary statistics from the administrative data for CommCare enrollees in fiscal year 2011 between 135 and 300 percent FPL. Ninety percent of CommCare enrollees are in the *H* plan, despite higher enrollee premiums (see Figure 3). About 20 percent of enrollees are between 135 and 150 percent of the federal poverty line. CommCare's subsidies are quite large. Average enrollee premiums (\$70 per month) cover less than 20% of insurer-paid medical costs (\$359/month) or prices (\$422).

### **Survey Data: Eligible Population for CommCare**

We supplement the administrative data on CommCare enrollment with estimates of the size of the CommCare-eligible population from the 2010 and 2011 American Community Survey (ACS), an annual 1% random sample of U.S. households. We use these data to estimate the number of people eligible for CommCare in each 1% FPL bin between 135% of FPL and 300% FPL. To be coded as eligible, an individual must live in Massachusetts and be: a U.S. citizen, age 19-64, not enrolled in another form of health insurance (specifically, employer insurance, Medicare or Tricare), and not eligible for Medicaid (based on income and demographics).<sup>14</sup> Because the ACS is a 1% sample (and because of clustering in reported income at round numbers), our raw estimates of the size of the eligible population by 1% FPL bin are relatively noisy. We therefore smooth the estimates using a regression of raw counts by 1% FPL bin on a polynomial in income. Appendix B reports additional details on sample construction and shows the raw counts of eligibles by FPL, as well as the smoothing regression fit.

Rather than use the ACS estimates directly to estimate the size of the eligible population, we use it to estimate two statistics: the shape of the eligible income distribution and the average take-up rate for our study population. We do this because comparing the raw implied counts of the eligible population in the ACS to the number enrolled in CommCare from our administrative data would

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<sup>14</sup>The ACS does not distinguish Medicaid from CommCare coverage (both are coded as “Medicaid/other public insurance”), so we cannot directly exclude Medicaid enrollees.

Table 1: CommCare Summary Statistics in 2011: Premiums, Enrollment and Costs

	<b>Any Plan</b> (1)	<b>H plan</b> (2)	<b>L Plan</b> (3)
<b>Enrollment</b>			
N (# of unique individuals)	107,158	96,391	14,828
Average monthly enrollment	62,096	55,599	6,497
Share of Enrollees	100%	90%	10%
Average income (% of FPL)	193%	193%	189%
Share below 150% FPL	20%	18%	29%
Average Age	44.4	44.9	40.2
Share Male	41%	40%	47%
<b>Medical Claims (Monthly)</b>			
Insurer-Paid	\$358.5	\$377.3	\$197.9
Total	\$377.3	\$396.4	\$213.4
<b>Prices, Subsidies and Premiums (Monthly)</b>			
Insurer Price	\$422.2	\$424.2	\$404.9
Enrollee Premium	\$70.0	\$72.8	\$46.0
Public Subsidy	\$352.2	\$351.4	\$358.9

NOTE: Table show summary statistics from CommCare administrative data for fiscal year 2011 for enrollees between 135 and 300 percent of FPL.

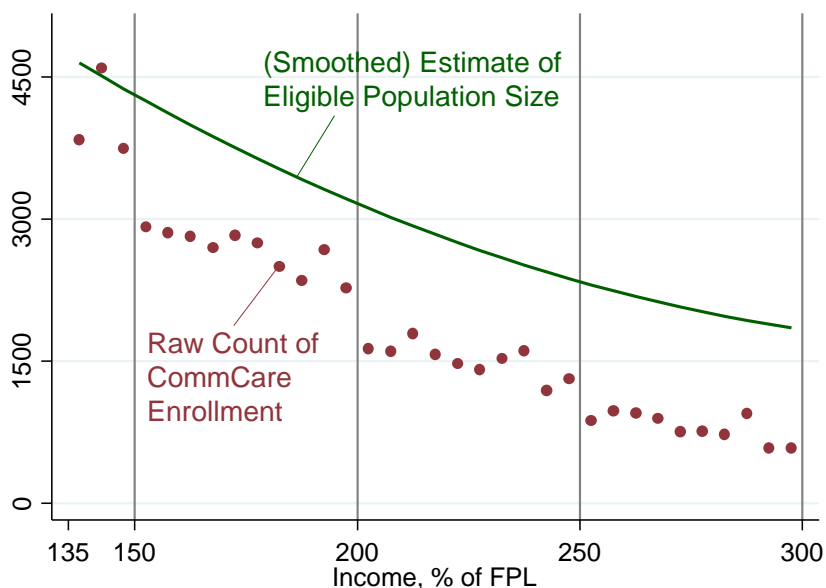
imply that only 37% of eligible individuals enroll in CommCare. This number seems low compared to the take-up estimate in the ACS data itself, where we find that 63% of eligible individuals report having insurance (see Appendix B for details). We suspect the ACS take-up estimate is closer to the truth since it closely matches estimates from a MA health insurance survey in the fall of 2010 (Long, Stockley, and Dahlen, 2012) and estimates from tax filing data.<sup>15</sup> We conservatively use the higher take-up estimate internal to the ACS and show in sensitivity analysis that if we instead use the ACS estimates of the eligible population directly, this produces a substantially lower take-up rate and in turn yields even lower estimates of the share insured under a given subsidy scheme.

Specifically, we take our estimates of the number of eligible individuals in the ACS by FPL bin (see Panel A of Appendix Figure 14) and scale the whole distribution down by a constant multiple (of 0.59) so that dividing the administrative count of enrollees by our adjusted eligible population size yields an average take-up rate of 63% (the rate calculated in the ACS).

Measuring the eligible population is difficult, and our approximation is, of course, imperfect. Fortunately, as we discuss in more detail below, the exact size of this population is not critical to estimate

<sup>15</sup>Specifically, Long et al. (2012) find a 90% insurance coverage rate for non-elderly adults below 300% of FPL, nearly identical to the 89% rate we estimate using the ACS. Further, using statistics from state tax filings (used to determine who owes the mandate penalty), we estimate that about 107,000 tax filers earning more than 150% of the FPL were uninsured at a typical point in time during 2011 (Connector and of Revenue, 2011). This number is calculated from state-reported statistics on the number of full-year and part-year uninsured (separately for  $\leq 3$  months and  $> 3$  months) and a midpoint assumption about the part-year groups' duration of uninsurance. From the ACS data, we estimate that there were 108,342 uninsured tax filers earning  $>150\%$  of FPL (treating each "health insurance unit" as a single tax-filer). These two estimates are remarkably close, suggesting that the ACS's uninsured estimates are accurate.

Figure 4: Eligible and Enrolled Population, 2011



NOTE: Figure shows our (smoothed) estimate of the CommCare-eligible population in 2011 (based on ACS data), and raw enrollment counts in CommCare in 2011 by bins of 5% of the FPL.

*changes* in enrollment and costs at the income discontinuities. Using this information (from administrative data alone), we can generate our key result: that willingness to pay is far below costs for marginal enrollees who drop coverage at each discontinuity. However, the ACS estimates are important for understanding *what share* of the eligible population these marginal enrollees comprise and *where* in the population distribution they lie. This is also necessary for translating our results into estimates of take-up shares under various subsidy policies. As discussed, in this sense, our baseline approach is a conservative one.

Figure 4 shows our (smoothed) estimate of the size of the eligible population by FPL bin. Note that the decline in the estimated number of eligible people by income does not reflect the shape of the overall income distribution in that range, but rather the shape of the *eligible population* income distribution. Eligibility requires, among other things, that the individual not have access to employer-sponsored insurance, which tends to increase with income (Janicki, 2013). For comparison Figure 4 also shows the raw counts of the number enrolled in any CommCare plan by FPL bin; we use the difference between the eligible population estimate and the number of CommCare enrollees as the number of people choosing uninsurance.

### 3 Descriptive Analysis

#### 3.1 Regression Discontinuity Design

We use the discrete change in enrollee premiums at 150%, 200% and 250% of FPL to estimate how demand and costs change with enrollee premiums. We estimate a simple linear RD in which we allow

both the slope and the intercept to vary on each side of each threshold. Specifically, we run the following regression across income bins ( $b$ ) collapsed at the 1% of FPL level:

$$Y_b = \alpha_{s(b)} + \beta_{s(b)} Inc_b + \epsilon_b \quad (1)$$

where  $Y_b$  is an outcome measure in that income bin  $b$ ,  $Inc_b$  is income (as a % of FPL) at the midpoint of the bin, and  $s(b)$  is the income segment on which bin  $b$  lies (either 135-150%, 150-200%, 200-250%, or 250-300% FPL). Notice that the unit of observation is the income bin, while the slope and intercept coefficients vary flexibly at the segment level. Our outcomes are either measures of plan enrollment shares, or enrollee costs or characteristics. We run all regressions using bin-level data and report robust standard errors.

The key assumption is that the eligible population size is smooth through the income thresholds at which subsidies change (150%, 200%, and 250% FPL). This would be violated if people strategically adjust (or misreport)<sup>16</sup> their income to get just below the thresholds and qualify for a larger subsidy.<sup>17</sup> While in principle such manipulation would be possible, in our setting the process by which individuals' reported incomes were translated into the % of FPL formula for determining subsidies were largely shrouded from the individuals during the application process. Perhaps as a result, we find minimal evidence of any such manipulation (See Section 4.4 below). Moreover, because of the relatively linear patterns we find away from the discontinuity, alternative methods (such as constructing a donut-hole around the discontinuity) would lead to very similar estimates.

### 3.2 Evidence from Pooled Years (2009-2013)

#### Insurance Demand

Figure 2 showed that premiums increase discontinuously at 150, 200, and 250% of FPL. Figure 5, Panel A shows that enrollment drops significantly at each of these income thresholds. Specifically, the figure plots average monthly enrollment in the CommCare market over the 2009-2013 period by income bin. It also superimposes estimates from the linear RD model in equation (1), using average monthly enrollment as the dependent variable. At each of the three discontinuities, enrollment falls by 30% to 40%. All three changes are statistically distinguishable from zero ( $p < 0.01$ ).

#### Cost of Insurance and Adverse Selection

Figure 5, Panel B plots average insurer costs by income bin, again superimposing estimates from the linear RD model in equation (1). Average insurer costs are defined as the average claims paid by the insurer for the set of people who are enrolled in that month.

<sup>16</sup>Enrollees were required to show proof of income (e.g., via recent pay stubs) when applying but in theory could adjust hours or misreport self-employment income to get below subsidy thresholds.

<sup>17</sup>In addition, there are minor changes in eligibility just above 200% FPL – pregnant women and HIV-positive people lose Medicaid eligibility and become eligible for CommCare – that also technically violate the smoothness assumption. This will bias our RD estimate of demand responsiveness to price slightly towards zero, since the eligible population grows just above 200% FPL. In sensitivity analysis, we show that our main results are robust to excluding this discontinuity.

The figure shows that average costs of the insured rise as the enrollee premium increases. For example, we estimate a discontinuous increase in costs of \$47.3 (s.e. \$7.7) per enrollee per month at 150% FPL and of \$32.4 (s.e. \$8.7) at 200% of FPL. We find a smaller but noisier increase of \$6.2 (s.e. \$11.9) at 250% FPL; this imprecision may reflect the smaller size of the eligible and enrolled populations at 250% of FPL (see Figure 4).

These patterns indicate the presence of adverse selection: increases in average costs indicate that the marginal enrollees (who exit in response to the premium increase) are less costly than the average enrollee who remains. An alternative way to test for adverse selection would be to examine whether characteristics of the enrollees that are associated with higher costs and not priced by insurers increase when premiums rise (Finkelstein and Poterba, 2014). In Appendix Figure 23 we also show that, consistent with adverse selection, the average age and risk score (i.e. predicted medical spending) of enrollees increase at these income thresholds. In other words, in response to higher premiums, younger and lower-risk enrollees are more likely to leave the market. These results are, not surprisingly, more precisely estimates than the analysis of realized insurer claims in Figure 5, Panel B. The claims measure, however, captures all potential dimensions of selection (both observable factors that go into the risk score factors that do not).

*A priori*, it was unclear whether this market would suffer from adverse selection. On the one hand, insurers were not allowed to vary prices based on individuals' health characteristics (such as age, gender, or pre-existing conditions); this would tend to generate adverse selection. On the other hand, in an effort to combat adverse selection, Massachusetts imposed a mandate on individuals to buy coverage, backed up by financial penalties. Our results suggest the coverage mandate and associated penalty were not sufficient to prevent adverse selection.

### 3.3 Evidence from 2011

In most of the rest of the paper, we study data from fiscal year 2011, which has the convenient vertical differentiation of plans discussed above. Here we present reduced form evidence on demand and costs for 2011 alone, focusing on overall enrollment and enrollment in the *H* plan.

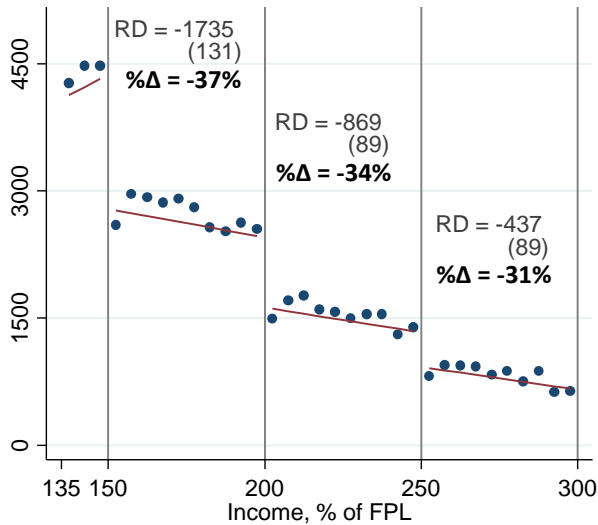
#### Insurance Demand

Figure 6 shows statistically significant (at the 1% level) declines in overall CommCare and *H* plan enrollment at each enrollee premium threshold (see Figure 3). The drops in enrollment do not occur only when premiums rise from zero to a positive amount (150% FPL threshold): enrollment falls by 20-30% at all three thresholds.

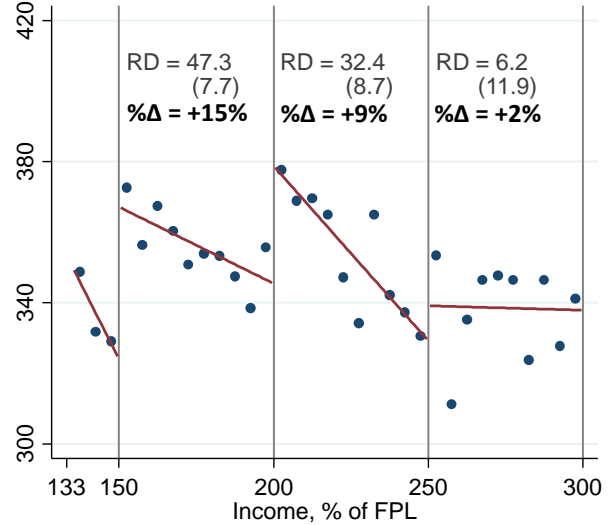
Figure 7 transforms these raw enrollment counts into market shares, using our estimate of the eligible population (see Figure 4) as the denominator. Panel A shows that the share enrolled in any CommCare plan falls by a statistically significant 24-27% at each discontinuity at which enrollee premiums rise by \$38-39 per month. The size of these *percent* drops are identified directly from the fall in enrollment in the administrative data. But, we can also use our estimate of the size of the eligible population from the ACS to make inferences about the levels of take-up rates as a function of the

Figure 5: CommCare Enrollment and Average Insurer Costs, 2009-2013

Panel A: Average Monthly Enrollment by Income



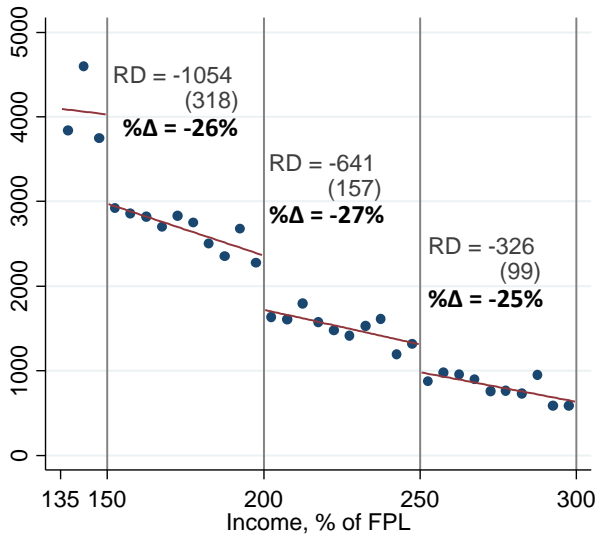
Panel B: Average Monthly Insurer Costs



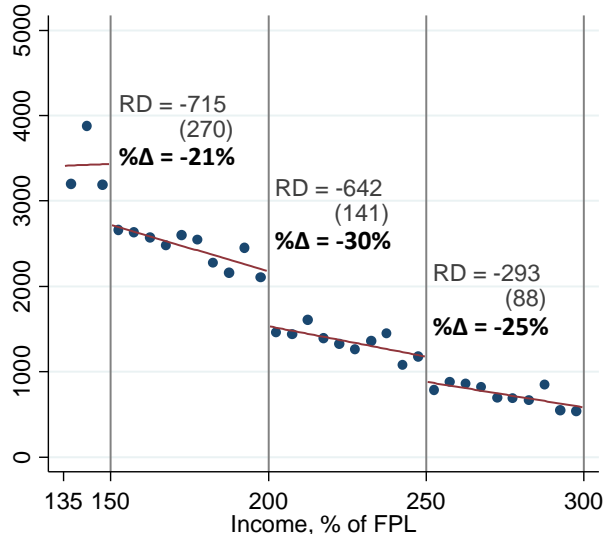
NOTE: The figure shows discontinuities in enrollment and average insurer costs at the income thresholds (150%, 200%, and 250% of FPL) at which enrollee premiums increase (see Figure 2). Panel A shows average enrollment in CommCare (total member-months, divided by number of months) by income over the 2009-2013 period our data spans. Panel B shows average insurer medical costs per month across all CommCare plans over the same period. In each figure, the dots represent raw values for a 5% of FPL bin, and the lines are predicted lines from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled just to the right of each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “%Δ =”.

Figure 6: CommCare Enrollment, 2011

Panel A: Any Plan



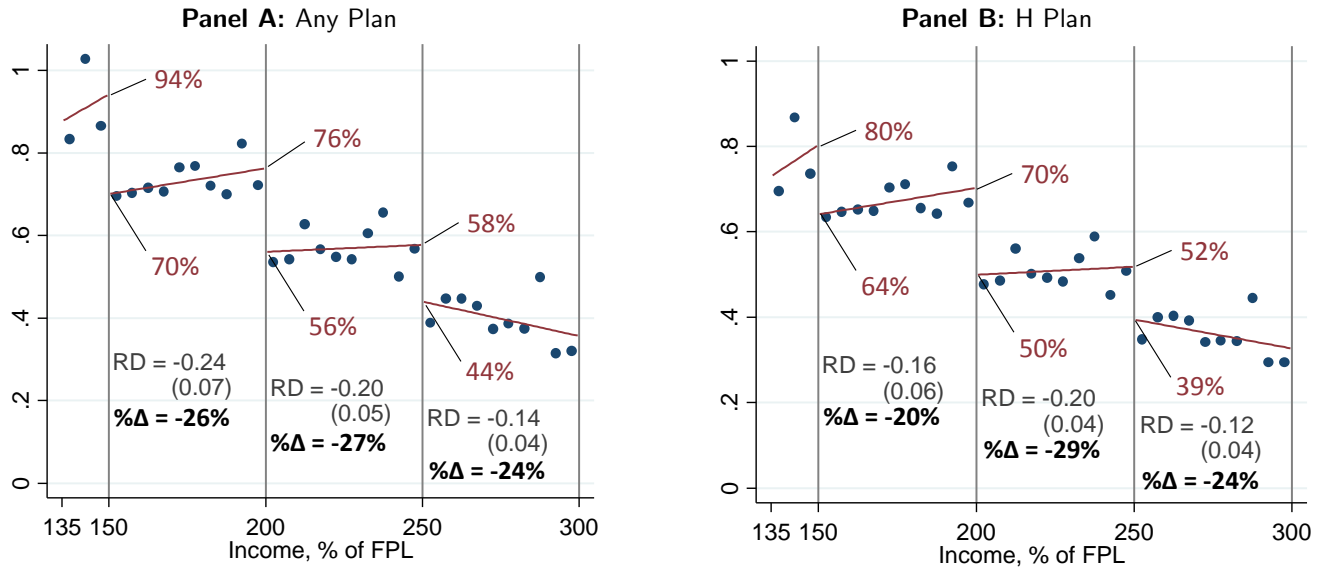
Panel B: H Plan



NOTE: Figure shows average enrollment (defined as total member-months, divided by number of months) by income in 2011. Panel A shows enrollment in any CommCare plan, Panel B shows enrollment in the *H* plan. In each figure, the dots represent raw averages for a 5% of FPL bin, and the lines (and labels) are predicted lines from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled just to the right of each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “%Δ =”.



Figure 7: Share of Eligible Population Enrolled, 2011



NOTE: NOTE: Figure shows share of eligible population enrolled (in bins of 5% of the federal poverty level) in any CommCare plan (Panel A), and in the *H* plan (Panel B). In each figure, the dots represent raw averages for a 5% of FPL bin, and the lines (and labels) are predicted lines from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled below each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “%Δ =”.

enrollee premium. Take-up rates fall from 94% when insurance is free (below 150% FPL) to 70% where the cheapest premium increases to \$39 per month (above 150% FPL). Take-up rates continue to fall with premiums, declining to below 50% as the cheapest premium rises to \$116 per month (above 250% FPL).<sup>18</sup>

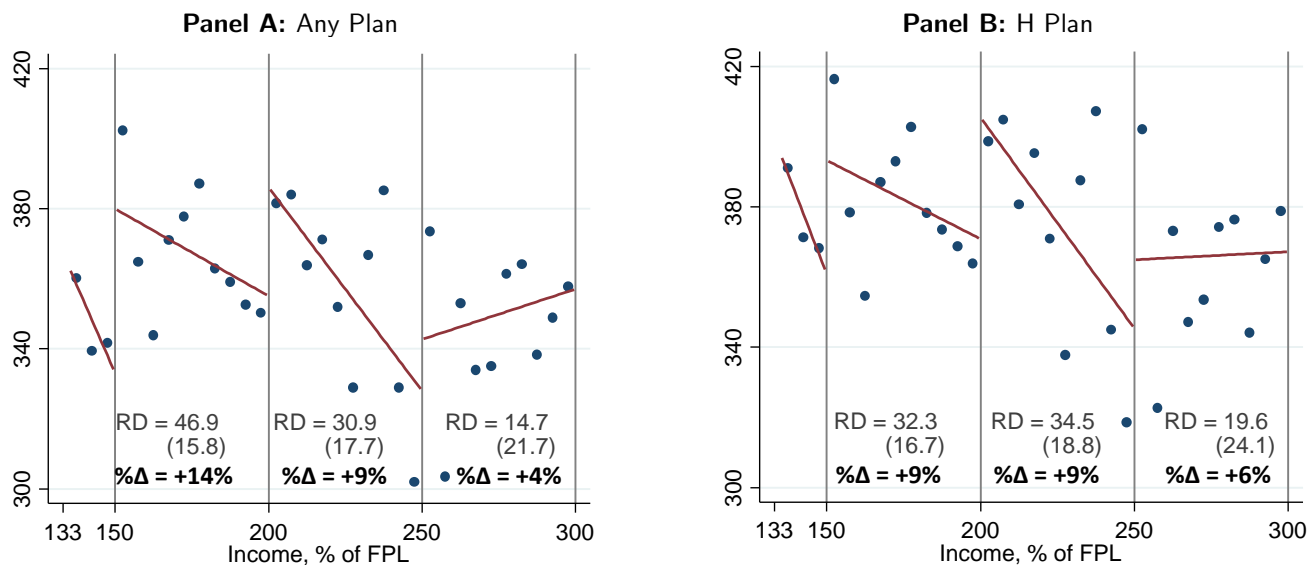
### Cost of Insurance

Figure 8 shows that average monthly insurer costs rise as enrollee premiums increase at each income threshold. Panel A indicates that at 150% of FPL, average costs for CommCare enrollees increase by \$47 (about 14%); this is statistically distinguishable from zero at the 1% level. We also see increases in average costs at the 200% and 250% thresholds, but the increases are somewhat smaller (\$31 and \$15, or 9% and 4%) and less precisely estimated. These magnitudes are similar to the more precise estimates for the pooled 2009-2013 years shown above.

Panel B shows analogous estimates for the 2011 enrollees in the *H* plan. Again we see increases in average costs at all three discontinuities; however, these are less precisely estimated.

<sup>18</sup>The pattern of enrollment by income within a constant premium range should not be interpreted with caution; demand is estimated conditional on eligibility and - as can be seen in Figure 4 - eligibility declines with income. Therefore the sample is differentially selected by income, since the set of higher income people without access to employer-provided health insurance (an eligibility criteria) naturally is differentially selected than the set of lower income individuals without access.

Figure 8: Discontinuities in Average Insurer Costs, 2011



NOTE: Figure shows average monthly insurer medical costs for enrollees (in bins of 5% of the federal poverty level) for any CommCare plan (Panel A) and the  $H$  plan (Panel B). In each figure, the dots represent raw averages for a 5% of FPL bin, and the lines are predicted from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled below each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “% $\Delta$  =”.

## 4 Willingness to Pay and Cost Curves

We use a model of insurance demand and cost to map the 2011 descriptive results into estimates of willingness to pay and cost curves that we use for counterfactual analysis. The model follows Einav, Finkelstein, and Cullen (2010), but incorporates three plan options: the  $H$  plan, the  $L$  plan, and uninsured ( $U$ ), as opposed to a binary model considered in Einav, Finkelstein, and Cullen (2010). Motivated by our institutional setting, we assume a vertical model of insurance demand. The vertical structure is helpful for tractability. We show in the sensitivity analysis of Section 4.4 that we can derive fairly tight bounds on willingness to pay that are similar to our point estimates below but do not rely on the vertical model assumptions.

### 4.1 Setup and Assumptions

Consider an insurance market where contracts  $j$  are defined by a generosity metric  $\alpha$ . We assume there are two formal insurance contracts  $j = H$  and  $L$ , with  $\alpha_H > \alpha_L$ . In addition, there is an outside option of being uninsured,  $U$ , which is weakly less generous than  $L$  ( $\alpha_U \leq \alpha_L$ ). Let  $w(\alpha; i)$  be the (dollar) willingness to pay (WTP) of consumer  $i$  for an  $\alpha$ -generosity contract. Let  $p_{ij}$  be the enrollee premium of contract  $j$ , and normalize  $p_{iU} = 0$  so that premiums are defined relative to  $U$ . Finally, there is an (additively separable) “hassle cost” of the enrollment process for contract  $j$ ,  $h_j$ . We normalize  $h_U = 0$  and assume the formal insurance contracts  $H$  and  $L$  involve the same hassle cost  $h_H = h_L \equiv h$ . This hassle cost,  $h$ , will be positive if enrolling in formal insurance involves a greater

hassle relative to remaining uninsured (e.g., due to the hassle of applying for insurance and making an active plan choice) and negative if staying uninsured involves greater hassle (or stigma).

With these assumptions, we write the utility of consumer  $i$  for plan  $j$  as:

$$\begin{aligned} u_{ij} &= w(\alpha_j; i) - h - p_{ij} & \text{for } j \in \{L, H\} \\ u_{iU} &= w(\alpha_U; i). \end{aligned}$$

We denote the willingness to pay  $W_j$  for plan  $j$  relative to  $U$  as:

$$W_j(i) = (w(\alpha_j; i) - w(\alpha_U; i)) - h, \quad \text{for } j \in \{L, H\}$$

which is the maximum price at which the consumer would choose plan  $j$  over  $U$ . We denote the willingness to pay  $\Delta W_{HL}(i)$  for plan  $H$  relative to plan  $L$  as:

$$\Delta W_{HL}(i) \equiv W_H(i) - W_L(i) = w(\alpha_H; i) - w(\alpha_L; i). \quad (2)$$

We impose a vertical demand model (see Tirole, 1988) using the following two assumptions about preferences:

**Assumption 1. Vertical preferences for generosity:** *Everyone prefers more generous contracts:  $w(\alpha; i)$  is increasing in  $\alpha$ .*

**Assumption 2. Single dimension of heterogeneity in value for generosity (increasing differences):**  *$w(\alpha; i) = w(\alpha; s)$ , where  $1 - s \in [0, 1]$  indexes increasing value for generosity, with  $dw(\alpha; s)/d(1 - s) > 0$  and  $d^2w(\alpha; s)/d\alpha d(1 - s) > 0$ .*

Note that we use  $1 - s$  as the index of WTP for generosity – i.e.,  $s = 0$  is the highest WTP type and  $s = 1$  is the lowest. This ensures that  $s$  is the x-axis value on a standard demand curve (where highest-WTP types are on the left) and simplifies notation for our graphical analysis below.

Assumption 1 implies that  $W_H(i) > W_L(i)$  for all  $i$ . It thus rules out cases in which people disagree about the quality of plans  $H$  and  $L$  (i.e. different people would prefer  $H$  or  $L$  at the same price). As noted in Section 2 the data are consistent with this vertical assumption: when the price of  $H$  and  $L$  are the same – specifically CommCare enrollees below 100% of FPL for which all plans are free – 96% of enrollees choose  $H$ .

Assumption 2 imposes increasing differences in WTP for generosity. This means that both the value for  $H$  relative to  $L$  and value for  $L$  relative to  $U$  are increasing in a single index of preferences,  $1 - s$ .<sup>19</sup> This rules out cases in which the people who value  $L$  relative to  $U$  by more than average also care less than average about  $H$  relative to  $L$ , and vice versa.

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<sup>19</sup>Note that Assumption 2 ensures that a single crossing property holds and generalizes the standard assumption in a vertical model of demand (Tirole, 1988). The standard vertical model assumes that  $v(\alpha_j; s) = \beta(1 - s) \cdot \alpha_j$  so that choice-specific utility equals  $\beta(1 - s) \cdot \alpha_j - p_j$ , where  $\beta(1 - s)$  is the value of generosity for type  $s$  (with  $\beta'(1 - s) > 0$ ). This model satisfies our Assumption 2.

## Demand Curves

We define the demand for product  $j \in \{U, L, H\}$ ,  $D_j(p_L, p_H)$ , as the fraction of the population purchasing  $j$  at prices  $\{p_L, p_H\}$ . Assuming that prices are such that there is positive demand for all contracts, Assumptions 1 and 2 imply that those with the lowest  $s$  choose  $H$ , those with the highest  $s$  choose to remain uninsured,  $U$ , and those with interim values of  $s$  choose  $L$ . Moreover, with positive demand for all plans, the model has the tractable feature that demand depends only on *price differences* between adjacently ranked options. Specifically,  $D_H$  depends only on  $p_H - p_L$ ,  $D_U$  depends only on  $p_L$ <sup>20</sup> and  $D_L$  depends on both  $p_H - p_L$  and  $p_L$ .

Figure 9 illustrates how the willingness to pay curves translate into the fraction enrolling in each plan. The figure plots  $W_L$  and  $W_H$  against a horizontal axis of  $s$  so that these curves are downward sloping. The vertical preference assumption (1) implies that  $W_H > W_L$  at all points. The increasing differences assumption (2) implies that the the gap  $W_H - W_L$  widens as  $W_L$  increases (as one moves left).

We denote the point  $s_{HL}^*$  to be the point of indifference between  $L$  and  $H$ , which occurs where the vertical distance between  $W_H - W_L$  equals  $p_H - p_L$ . All types to the left of this enroll in  $H$ , and the demand for  $H$  equals  $s_{HL}^*$ . Likewise, the point  $s_{LU}^*$  at which  $p_L$  intersects the  $W_L(s)$  curve determines the person who is indifferent between  $L$  and  $U$ . All types to the right of  $s_{LU}^*$  remain uninsured, and those just to the left enroll in the  $L$  plan. Mathematically, these points  $s_{HL}^*$  and  $s_{LU}^*$  are defined by the equations:

$$\begin{aligned} \Delta W_{HL}(s_{HL}^*) &\equiv W_H(s_{HL}^*) - W_L(s_{HL}^*) = p_H - p_L \\ W_L(s_{LU}^*) &= p_L \end{aligned} \quad (3)$$

Given these definitions, a necessary and sufficient condition for demand for all contracts to be positive is for:

$$\text{Positive Demand Condition:} \quad 0 < s_{HL}^* < s_{LU}^* < 1.$$

Without loss of generality (since it is an arbitrary index), we assume a uniform distribution over  $s$  types. Because  $\Delta W_{HL}(s)$  and  $W_L(s)$  are monotonically decreasing functions (by Assumption 2), the equations in (3) implicitly define  $s_{LU}^* = W_L^{-1}(p_L)$  and  $s_{HL}^* = \Delta W_{HL}^{-1}(p_H - p_L)$ . Define the demand for product  $j \in \{U, L, H\}$  as the fraction of the population purchasing  $j$  at prices  $\{p_L, p_H\}$ . Assuming the positive demand condition holds,<sup>21</sup> these are given by:

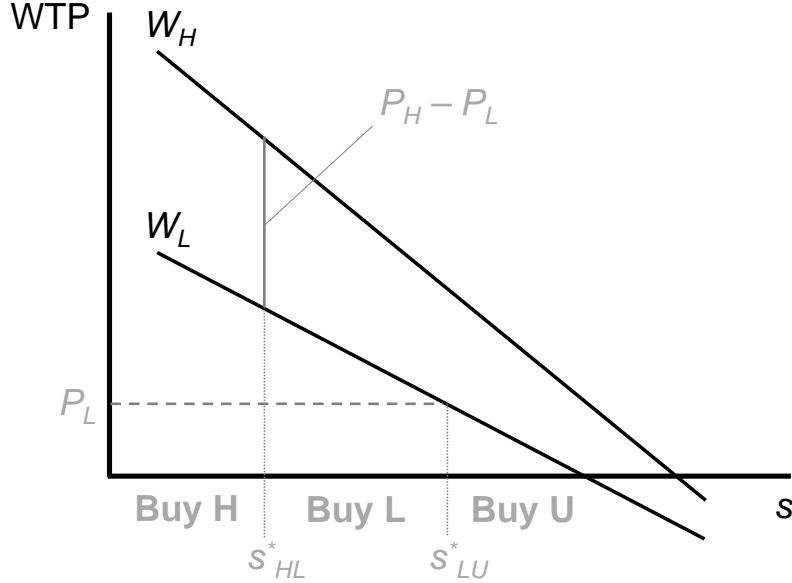
$$\begin{aligned} D_H(p_H - p_L) &= s_{HL}^* &= \Delta W_{HL}^{-1}(p_H - p_L) \\ D_L(p_L, p_H - p_L) &= s_{LU}^* - s_{HL}^* &= W_L^{-1}(p_L) - \Delta W_{HL}^{-1}(p_H - p_L) \\ D_U(p_L) &= 1 - s_{LU}^* &= 1 - W_L^{-1}(p_L) \end{aligned} \quad (4)$$

where the demand for  $H$  only depends on the price difference  $p_H - p_L$ , and the demand for  $L$  depends

<sup>20</sup>In general, demand for  $U$  would depend on  $p_L - p_U$ , but  $p_U$  is normalized to zero.

<sup>21</sup> Practically speaking, in our empirical setting, we observe positive demand for all products, so will assume the positive demand condition holds (though it would be conceptually simple to generalize these curves to the more general case).

Figure 9: Willingness to Pay Curves: Model



NOTE: Figure shows the theoretical implications of our vertical model for the willingness to pay ( $W_j$ ) curves for the  $H$  and  $L$  plans. The model assumptions imply that both  $W_H$  and  $W_L$  are downward sloping (i.e., decreasing with  $s$ ) and that the gap between  $W_H - W_L$  is also narrowing as  $s$  increases. Under the positive demand condition for prices (which this graph assumes), the lowest- $s$  types (furthest left on the x-axis) buy  $H$ , middle- $s$  types (between  $s_{HL}^*$  and  $s_{LU}^*$ ) buy  $L$ , and the highest- $s$  types choose  $U$ .

on both  $p_L$  and  $p_H - p_L$ . We will often analyze “demand for formal insurance” (i.e. pooled demand for  $H$  or  $L$ ) which is calculated from the above equations as  $1 - D_U$ , which depends only on  $p_L$ , not  $p_H$ .

### Insurer Costs

We denote by  $C_j(s)$  the expected costs to the insurer of enrolling type  $s$  in plan  $j$ .<sup>22</sup> As is standard in the literature, we define insurer costs as medical claims paid and abstract from administrative costs. We also adopt the standard assumption that  $C_j(s)$  is independent of the premium charged for the insurance plan. We define average costs  $AC_j(s)$  as the average costs of all individuals with type  $\tilde{s} \leq s$ :

$$AC_j(s) = \frac{1}{s} \int_0^s C_j(\tilde{s}) d\tilde{s}. \quad (5)$$

where recall that we have assumed  $s \sim U[0, 1]$ . If premiums are such that all types  $\tilde{s} \leq s$  choose the  $j$  plan, then the cost imposed on the insurer would be given by  $AC_j(s)$ .

<sup>22</sup>In a setting with a binary contract choice (as in Einav et al. (2010a)), the variation in  $C_j(s)$  with respect to  $s$  is referred to as the marginal cost curve for contract  $j$ ; with three contracts as we have here, there can be two different margins of selection into a contract and so the “marginal cost curve” language is less useful.

## 4.2 Constructing Willingness to Pay and Cost Curves

### 4.2.1 Willingness to Pay ( $W_j$ )

We combine the modeling assumptions above with the empirical patterns documented in Figure 7 to construct the empirical analogues of the  $W_H(\cdot)$  and  $W_L(\cdot)$  curves in Figure 9. Figures 10-11 walk through this exercise.

Panels A and B of Figure 10 plot the willingness to pay curves for the  $L$  contract ( $W_L(\cdot)$ ) and for the  $H$  contract relative to  $L$  ( $\Delta W_{HL}(\cdot)$ ), respectively. Each line segment represents points derived from our three income RDs at 150% FPL (in blue), 200% FPL (red), and 250% FPL (green). Equation (4) shows that  $W_L^{-1}(p_L)$  equals  $1 - D_U(p_L)$ , the share of people who purchase formal insurance at enrollee premium  $p_L$ . Therefore, we obtain the  $W_L$  curve by plotting observations of  $(1 - D_U, p_L)$  derived from market shares and premiums around each income discontinuity from our RD estimates (see Figures 3 and 7). Similarly, Equation (4) shows that  $\Delta W_{HL}^{-1}(p_H - p_L)$  equals  $D_H(p_H - p_L)$ , the share of people who purchase the  $H$  plan at premium difference  $p_H - p_L$ . We therefore obtain the  $\Delta W_{HL}$  curve by plotting observations of  $(D_H, p_H - p_L)$  from the same RD estimates.

In principle, we could identify part of a willingness to pay curve using only one premium discontinuity. In practice, we combine the data from all three discontinuities because it lets us observe demand over a wider range of premiums. As a result, at two of the enrollee premiums, we observe (and plot) two different market shares. This is because each pricing discontinuity identifies a demand curve for individuals at a given income level, and these demand curves need not be the same. For example, the premiums that apply between 150-200% FPL identify one point on the demand curve for 150% FPL (“from the right”) and one point on the demand curve for 200% FPL (“from the left”).

In practice, we observe that demand in fact varies little with income. In other words, market shares are relatively flat within an income range that has constant premiums, as was evident in Figure 7.<sup>23</sup> As a result, the demand line segments for the three income groups (shown in different colors in Figure 10) nearly intersect.

To adjust for remaining differences in demand across incomes, we extend our theoretical framework above to allow willingness to pay for insurance to vary with income,  $y$ . We define our index  $s$  conditional on a fixed income level,  $y$ , and we denote  $w(\alpha; s, y)$  to be the willingness to pay of a type  $s$  for a single income group,  $y$ . To allow us to combine demand information across income groups, we assume that income functions as a horizontal shifter of the willingness to pay curves:

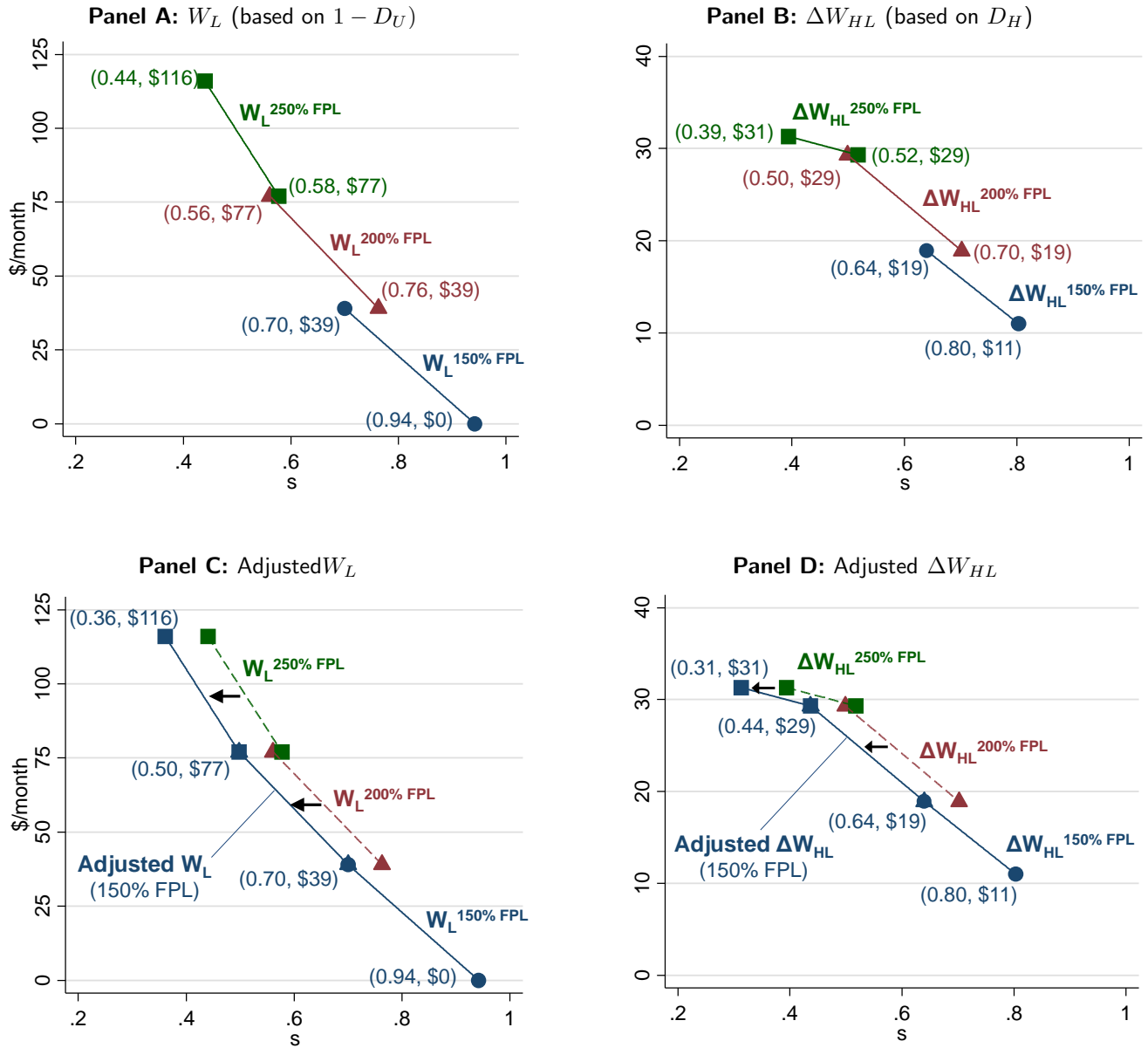
$$w(\alpha; s, y) = w(\alpha; s + \lambda_y).$$

This assumption implies, for example, that  $W_L^{150\%}(s) = W_L^{200\%}(s + \lambda_{200\%} - \lambda_{150\%})$ .

Panels C and D of Figure 10 illustrate the implications of this assumption graphically. Specifically, we horizontally shift the Panel A and B willingness to pay curves estimated at the discontinuities at 200% FPL and 250% FPL so that willingness to pay (i.e. demand) lines up with the curve estimated

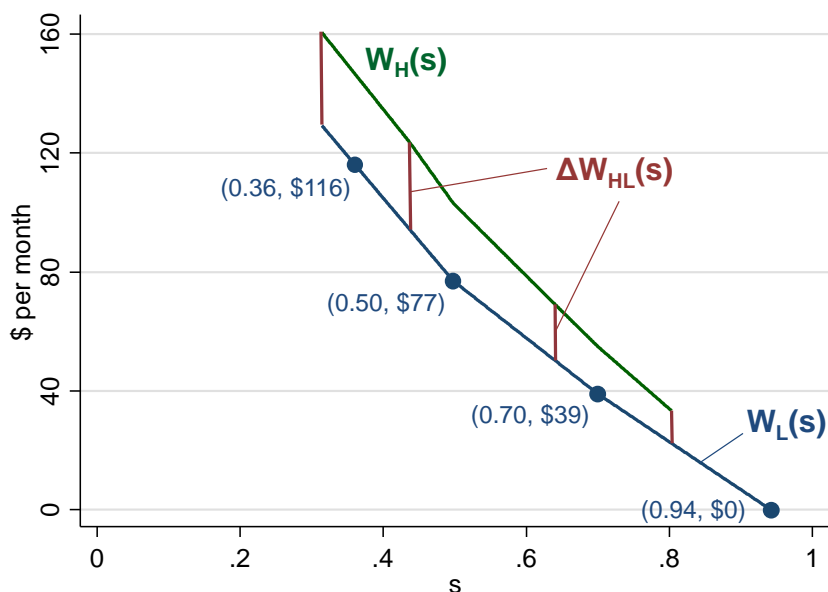
<sup>23</sup>This does not necessarily imply that income effects of insurance demand are small; recall that the eligible population consists of people who, among other things, do not have access to employer-provided health insurance. The nature of the eligible population may therefore be changing with income as well.

Figure 10: Willingness to Pay Curves: Empirical



NOTE: Figures show our construction of the willingness to pay curves ( $W_L$  and  $\Delta W_{HL}$ ) based on the demand points in our RD estimates in Figure 7 and the premium variation at each discontinuity from Figure 3. Panel A shows the  $W_L$  points, each of which represents an observation of  $(1 - D_U, p_L)$  drawn from either side of our income discontinuities at 150%, 200%, and 250% FPL. Panel B shows the  $\Delta W_{HL}$  points, each of which is an observation of  $(D_H, p_H - p_L)$  from either side of the discontinuities. Panel C and Panel D show how we adjust the  $W_L$  and  $\Delta W_{HL}$  curves horizontally to line up with the 150% FPL line segment.

Figure 11: Final Willingness to Pay Curves



NOTE: Figure shows our final estimated WTP curves. The blue curve is the adjusted  $W_L$  curve shown in Panel C of Figure 10, with the large dots representing observed points. The  $W_H$  curve (in green) is constructed by vertically summing the  $W_L$  and  $\Delta W_{HL}$  curve (as shown in Panel D of Figure 10) at each x-axis value (of  $1 - s$ ). The red vertical bars in the figure represent the observed points of the adjusted  $\Delta W_{HL}$  curve. We extrapolate the  $W_L$  curve slightly out of sample (from  $1 - s = 0.36$  down to  $1 - s = 0.31$ ) to be able to add on the final point of the  $\Delta W_{HL}$  curve.

at 150% FPL. We chose to line up the curves at 150% of FPL since that is the threshold with the greatest share of the eligible population (see Figure 4); results would be qualitatively similar if we instead created a demand curve at the 200% or 250% FPL threshold. In practice, since demand is relatively flat with respect to income, the shift is not very large: the 200% FPL curve is shifted leftward by 6% points in  $s$  space, and the 250% FPL curve is shifted leftward by an additional 2% points. The resultant willingness to pay curves consist of three piece-wise linear segments.

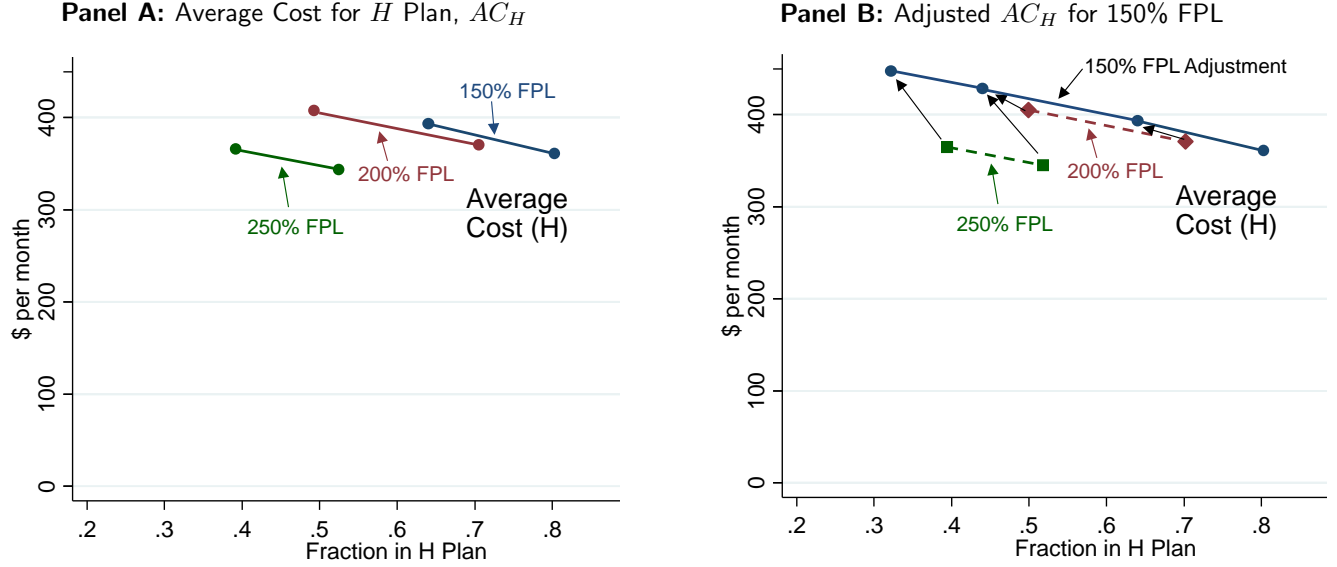
Our horizontal shift approach assumes that we can infer the slope of the WTP curve for people at 150% of FPL at higher prices than we observe in the data from the slope of the WTP curve slope at these higher prices for people at 200% and 250% of FPL. While we cannot test this assumption, our sense is that it is likely to be conservative (in the sense of slightly overstating WTP at 150% of FPL); because the 150% FPL enrollees are poorer, we might expect them to drop out of the market more quickly at higher prices than do the 200% and 250% FPL enrollees.<sup>24</sup>

Finally, in Figure 11 we use our estimates of  $W_L(\cdot)$  and  $\Delta W_{HL}(\cdot)$  from Panels C and D of Figure 10 to construct  $W_H(s)$  as  $W_L(s) + \Delta W_{HL}(s)$  using equation (2). The resulting  $W_L$  and  $W_H$  curves allow us to infer willingness to pay for  $L$  and  $H$  for people earning 150% of FPL. Willingness to pay for  $H$  is non-trivially higher than for  $L$ . The additional value ( $\Delta W_{HL}$ ) ranges from \$11 to \$31/month, or

<sup>24</sup>Consistent with this, if we had simply linearly extrapolated the line segment for 150% FPL leftward, we would generate a slightly lower  $W_L$  curve. However, the difference would not be large –  $W_L(0.50)$  would be \$71 (vs. \$77 in our estimates) and  $W_L(0.36)$  would be \$94 (vs. \$116 in our estimates). The linearly extrapolated  $\Delta W_{HL}$  curve would be even closer, never differing by more than \$3 from our version. The similarity of these estimates gives us additional confidence that our assumption is a reasonable approximation.



Figure 12: Construction of Average Cost Curves ( $H$ )



NOTE: Panel A shows the raw average cost points for the  $H$  plan, drawn from the RD estimates around each of our three income discontinuities (see Figure 8 Panel B; for convenience, Appendix Table 6 summarizes those estimates). Panel B shows how we generate our adjusted  $AC_H$  for 150% FPL by translating the 200% and 250% FPL line segments to line up with the 150% FPL segment.

11-30% of the median type's WTP for  $L$ . The median type has total WTP for  $H$  ( $W_H$ ) of \$103/month. Using our in-sample variation, we can infer  $W_L$  over the range  $s \in [0.36, 0.94]$  – i.e., all but the highest 36% and lowest 6% of the WTP distribution. Similarly, our variation lets us infer  $W_H$  over the range  $s \in [0.31, 0.80]$  – i.e., all but the highest 31% and lowest 20% of the distribution.

#### 4.2.2 Cost Curves

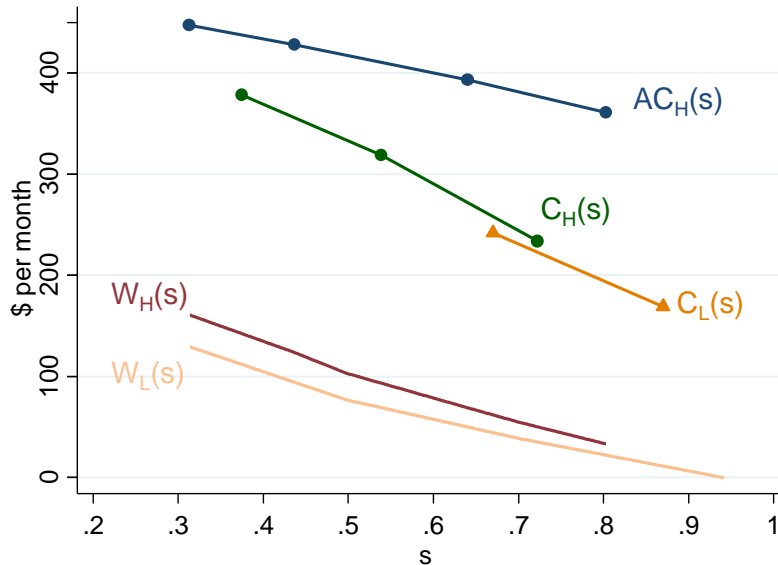
In Figure 12 we construct the average cost curve for the  $H$  plan,  $AC_H$ . In Panel A we plot estimated average costs for enrollees in the  $H$  plan on each side of the premium discontinuities (from Panel B of Figure 8) against the shares in the  $H$  plan at each discontinuity (from Panel B of Figure 7). For instance, just below the 150% FPL discontinuity, 80% are in the  $H$  plan, and the average cost is \$361. Just above the discontinuity, 64% of people are in the  $H$  plan and average cost is \$393. Therefore, the average cost curve for 150% FPL flows through the points (64%, \$393) and (80%, \$361).

In Panel B, we once again adjust the average cost curves to obtain a single curve applicable to individuals at 150% of FPL. To do so, we assume that the slopes of the average cost curves are stable with income so that one can vertically shift the average cost curves for the 200% FPL and 250% FPL thresholds to align with the 150% FPL average cost curve.<sup>25</sup> To be consistent with how we adjusted the  $W_j$  curves, we also shift the shares along the horizontal axis to align with the 150% FPL curve.

The cost of the marginal enrollee ( $C_H$ ) can be straightforwardly derived from average costs ( $AC_H$ )

<sup>25</sup>Specifically, this assumes that the *slopes* of the average cost curves with respect to type,  $s$ , are stable with income even though the *levels* of costs are declining in income (see Figure 8 Panel B).

Figure 13: Willingness to Pay and Cost



NOTE: Figure reproduces  $AC_H$ ,  $W_H$ , and  $W_L$  from Figures 11 and 12b. The  $C_H$  curve is constructed using the formula in equation (6) for each pair of  $AC_H$  points, with the x-value set as the midpoint between the two points x-values. The  $C_L$  curve is constructive using the approach described in the text.

and demand ( $D_H$ ) shown in Panel B of Figures 8 and 7, respectively. The logic is identical to the two-plan case considered in past work (Einav, Finkelstein, and Cullen, 2010); Appendix C provides more detail on the mechanics of constructing  $C_H$ .

Because we do not have variation in  $p_L$  and  $p_H$  that is orthogonal to  $p_H - p_L$ , we cannot use the same method to estimate  $AC_L$  and  $C_L$ . However, because the market share of  $L$  is relatively small (for example just above 150% FPL, Appendix Figure 24 shows that just 6% of the population enrolls in the  $L$  plan), the average  $L$  enrollee is similar to the marginal enrollee. We therefore use the average cost of the  $L$  plan for individuals just below and just above the 150% FPL threshold to approximate  $C_L(s)$  for the range of  $s$  that these two sets of individuals span. Again, Appendix C provides more detail.

### 4.3 Results and Implications for Take-up

Figure 13 displays our key findings for individuals at 150% of FPL; Appendix Table 7 summarizes the numbers in the Figure at key points in the willingness to pay ( $s$ ) distribution. Throughout the entire range of  $s$  spanning our data,<sup>26</sup> the  $W_H(s)$  curve is substantially below both  $AC_H(s)$  and  $C_H(s)$ . The gap between  $C_H$  and  $AC_H$  is sizable, indicating significant adverse selection, especially for lower-WTP types. For instance, if the highest-WTP half of the market ( $s \leq 0.5$ ) enrolls in the  $H$  plan, the marginal enrollee (i.e.,  $s = 0.5$ ) costs  $C_H(0.5) = \$333$  per month, about 20% less than the average enrollees' cost of  $AC_H(0.5) = \$417$ .

<sup>26</sup>Our price variation spans roughly the 70th to the 6th percentile of the WTP distribution (essentially all but the top 30 percent of the WTP distribution).

The fact that throughout the range of our data we find  $C_H(s) > W_H(s)$  is particularly striking, since  $W_H(s)$  and  $C_H(s)$  represent enrollee WTP and insurer costs *for the same people*.<sup>27</sup> Throughout the observed distribution,  $W_H(s)$  is less than half of  $C_H(s)$ . At the median of the WTP distribution,  $W_H(0.5)$  is only \$103 per month, less than one-third of  $C_H(0.5) = \$333$ . Even at the highest in-sample point of the WTP distribution (the 69th percentile, or  $s = 0.31$ ),  $W_H(0.31)$  of \$162 per month is still substantially below average costs of insuring the top 31 percent of the WTP distribution ( $AC_H(0.31) = \$448$ ), as well as costs for the 69th percentile WTP individuals ( $C_H(0.31) = \$399$ ). Even if one could eliminate adverse selection and set premiums for marginal enrollees equal to their expected costs imposed on the insurer (i.e.,  $p_H(s) = C_H(s)$ ), at least 70 percent of individuals would not buy  $H$ .

WTP for  $L$  is also far below its costs,  $C_L$ . Indeed, the gap between  $W_L$  and  $C_L$  is larger than between  $W_H$  and  $C_H$  over the entire range that we can observe both sets of curves. Specifically, to the right of  $s = 0.64$ ,  $C_L$  ranges from \$177 to \$241 per month whereas  $W_L$  is less than about \$50 per month. Indeed, the observed  $C_L$  points lie above our *maximum* in-sample  $W_L$  estimate of \$129 per month. Assuming adverse selection leads to a  $C_L$  curve that rises with  $W_L$ ,  $C_L$  will also be above  $W_L$  for the 70% of the population for which we can measure demand for  $H$  or  $L$ .

The implied  $C_L$  curve is quite similar to the  $C_H$  curve over the regions of the  $s$  distribution where both are observed. This suggests that obtaining the more generous  $H$  contract instead of the  $L$  contract does not significantly increase costs. Therefore the much lower observed average cost in the  $L$  plan (see Table 1) is driven largely by favorable selection rather than by the causal impact of the plan on costs for the same type,  $s$  (i.e. moral hazard).

**Take-up under Counterfactual Subsidies** These results imply low take-up of even heavily subsidized insurance for low-income adults. For example, at 150% of poverty, individuals in MA face a \$39 enrollee premium for the  $L$  plan, which is a 90% subsidy relative to the insurer price (see Figure 2, Panel B). Our estimates of  $W_L$  and  $W_H$  indicate that, with a 90% price subsidy, only 69% of the market would enroll if offered  $L$ , and only 76% would enroll if offered  $H$  (with the corresponding enrollee monthly premium of \$42.40). These estimates have implications for understanding enrollment in the ACA subsidized exchanges, where enrollee premiums are significantly higher than in Massachusetts at a given income level. For instance, for an individual at 175% FPL in 2011, the ACA would make the second-cheapest silver plan cost 5.2% of income (or \$83 per month),<sup>28</sup> even though the ACA silver plan has an actuarial value below the plans we study in Massachusetts.<sup>29</sup> Our estimates suggest that at an enrollee premium of \$83, only about half of the market would buy  $L$  and only about 60% would buy  $H$ .

<sup>27</sup>Our willingness to pay and cost curves were adjusted to reflect those of the 150% FPL income group. If we had instead adjusted  $W_H$  and  $AC_H$  to line up with the estimates at 200% FPL or 250% FPL, we would still find  $C_H$  substantially above  $W_H$ .

<sup>28</sup>This calculation applies the ACA's subsidy rules (see [https://www.irs.gov/irb/2014-50\\_IRB/ar11.html](https://www.irs.gov/irb/2014-50_IRB/ar11.html)) – which specify the premium of the second-cheapest silver plan as a percent of income – to the FPL for a single individual in 2011.

<sup>29</sup>We estimate that CommCare plans have an actuarial value of about 97% for enrollees between 100-200% of poverty. In the ACA, the baseline silver plan has an actuarial value of 87% for enrollees between 150-200% FPL.

Table 2: Implications of Alternative Subsidies for  $H$  Plan

Subsidy		Enrollee Premium	Share Insured	Marginal Enrollee		Average Cost
% of AC	\$/month			WTP	Cost	
50%	\$246	\$246	3%	\$246	\$488	\$492
---	(\$25)	(\$25)	(9%)	(\$25)	(\$41)	(\$50)
75%	\$314	\$105	49%	\$105	\$335	\$418
---	(\$18)	(\$6)	(3%)	(\$6)	(\$34)	(\$25)
90%	\$328	\$36	79%	\$37	\$208	\$364
---	(\$16)	(\$2)	(1%)	(\$2)	(\$113)	(\$18)
100%	\$329	\$0	96%	\$0	\$139	\$329
---	(\$34)	(\$0)	(1%)	(\$0)	(\$131)	(\$34)

NOTE: Table summarizes the implications of our estimates for enrollment and costs for  $H$  under alternative subsidies (shown in the rows), with bootstrapped standard errors shown in parentheses. We consider subsidies that correspond to 50%, 75%, 90%, and 100% of equilibrium average costs (column 1). These lead to enrollee premiums for  $H$  of \$246, \$105, \$36, and \$0 per month (column 3). The second column shows the corresponding dollar amount of the subsidy. The fourth column shows the share of the eligible population purchasing insurance (i.e. the offered  $H$  plan). The next two columns show WTP and costs of the marginal enrollee – the marginal WTP by definition equals the enrollee premium. The final column shows average costs of the insured population. Standard errors are calculated by a nonparametric bootstrap method that repeatedly resamples our original enrollee-level dataset, performs the RD regressions, and calculates the WTP and cost curves that generate these statistics. Note that while our analysis of 75% and 90% subsidies uses “in-sample” demand and cost curves, analysis of 100% and 50% subsidies requires extrapolating demand and costs outside of our in-sample range, which spans all but the top 31% and bottom 6% of the willingness to pay distribution. Appendix D shows the simple linear extrapolation we use to approximate willingness to pay and costs out of sample for these two estimates.

The results also suggest that without subsidies that lower enrollee premiums substantially below average insurer cost of enrollees, relatively few low-income people would take up insurance. To illustrate this, Table 2 summarizes predicted take-up under potential subsidies for plan  $H$ . With enrollee premiums that are 75% below average costs (i.e., a subsidy in excess of \$300 per month) only 50% of the population would enroll. Premiums would need to be 90% below average costs in order to induce 80% enrollment. Interestingly, the per-enrollee subsidy cost increases by only \$2 as subsidies move from 90% to 100% of average cost, reflecting the fact that average enrollee costs are declining steeply as healthier individuals are brought into the market.

#### 4.4 Sensitivity

Our key findings of low take-up and willingness to pay well below insurer costs are robust to a number of alternative implementation choices. Table 3 summarizes some of these results. Each row represents a single deviation from the baseline specification, as indicated. In all the alternative specifications we consider below, our main results continue to hold:  $W_H$  is substantially below  $AC_H$  and  $C_H$ , which implies limited take-up even with substantial subsidies. Indeed, the sensitivity analysis highlights the

Table 3: Sensitivity Analysis: WTP and Cost Estimates for  $H$  Plan

Robustness Specification	In-Sample Range of $s$	Median WTP ( $s = 0.5$ )			Share Insured with Subsidy (as % of $AC_H$ )	
		$WTP_H$	$C_H$	$AC_H$	75% Subsidy	90% Subsidy
<b>Baseline Estimates</b>	[0.31, 0.94]	\$103	\$333	\$417	49%	79%
<b>(1) Alternate RD Specifications</b>						
Smaller Bandwidth (25% FPL)	[0.29, 0.94]	\$100	\$318	\$418	48%	78%
Quadratic Functional Form	[0.28, 0.84]	\$98	\$351	\$403	49%	73%
Omit 200% FPL Estimates	[0.30, 0.94]	\$97	\$343	\$412	46%	79%
<b>(2) Alternate Take-up Estimates</b>						
Unscaled ACS Eligible Pop.	[0.19, 0.56]	\$24	\$186	\$354	29%	46%
<b>(3) Accounting for Mandate Penalty</b>						
Use Normalized Premiums	[0.31, 0.94]	\$93	\$333	\$417	32%	68%

NOTE: Top line (“Baseline Estimates”) reproduces results from Figure 13 and Table 2. The remainder of the table shows analogous estimates with (1) alternate RD specifications, (2) alternate take-up estimates, and (3) premiums normalized by the expected mandate penalty. For each specification, we report the in-sample range of  $s$  values; estimates of  $W_H$ ,  $AC_H$ , and  $C_H$  at the median of the WTP distribution ( $s = 0.5$ ); and the share who purchase  $H$  under various subsidies as a percent of  $AC_H$ .

conservative nature of our baseline assumptions; under plausible alternative specifications, the share who enroll in  $H$  at a given subsidy level is always (weakly) lower, sometimes substantially so.

**RD Specification** Our baseline specification allowed a (linear) slope and intercept to vary on each side of the 150%, 200%, and 250% thresholds (see equation 1). In practice, this meant a bandwidth of 50% of FPL everywhere but to the left of the 150% FPL threshold. The first two rows of Table 3 show results using a narrower (25% of FPL) bandwidth, and results with the baseline bandwidth but a quadratic (rather than linear) functional form for the running variable. The third row shows results from our baseline specification excluding one of our three thresholds: the 200% of FPL threshold.<sup>30</sup> As we discussed in Section 2, this threshold is potentially problematic because of two other small changes at 200% FPL that could affect enrollment or costs independently of the change in enrollee premium: eligibility expands slightly at 200% FPL (to cover pregnant women and HIV-positive individuals for whom Medicaid eligibility ceases) and copays increase slightly at 200% FPL, resulting in a decline in plan actuarial value from 97% to 95%.

**Examining manipulation of the running variable** A key threat to the validity of our empirical design is if individuals manipulate the running variable (the CommCare-specific income measure as a share of FPL) in order to qualify for higher subsidies. A standard way to look for such manipulation

<sup>30</sup>We fill in the (now missing) space between the 150% and 250% FPL line segments by extrapolating the 150% FPL segment linearly.

is to examine how the density of the population varies around the RD thresholds. Appendix Figure 14 shows the density of the eligible population in the ACS data for 2011, as well as for a similar ACS sample of CommCare-eligible individuals pooled over 2009-2013. The figure shows no evidence of bunching in the ACS income distribution at the thresholds. However, the data are somewhat noisy for 2011 alone, and more importantly, the income measure reported in the ACS may not be the same as what is reported to CommCare for purposes of determining subsidy eligibility. It is the CommCare-specific income measure for which we are concerned about potential manipulation, not what is reported to the ACS. Since our administrative data only include those who actually enroll in CommCare, we cannot look for bunching per se in the CommCare income measure as we cannot separately identify income manipulation from the take-up response to higher premiums.<sup>31</sup>

Turning to the administrative data on plan enrollment, we can look for other patterns consistent with strategic manipulation, including whether there is an upward spike in the number of enrollees just below the subsidy threshold or a decline just above the threshold (see Kleven (2016)). Panel A of Figure 5 shows some slight evidence of lower enrollment (relative to the linear slope in income that we fit) to the right of the thresholds in the 2009-2013 pooled data. Appendix Figure 25 examines this further by showing enrollment by FPL separately for each year. The slightly lower-than-projected enrollment to the right of the subsidy threshold in the pooled 2009-2013 data appears to be entirely driven by the 2012 and (especially) 2013 data. There is no evidence of manipulation in the earlier years; as we explain in Appendix J, there is an administrative rather than strategic explanation for the limited bunching that we see in 2012 and 2013. The lack of manipulation in 2011 – our base year – suggests that any attempt to adjust for it using standard techniques (e.g. donut RDs as in Diamond and Persson (2016)) would not substantively affect our baseline estimates.

**Alternative Estimates of Take-up** As we discussed in Section 2, the administrative data alone are sufficient to estimate willingness to pay, average cost, and own costs for the enrolled population and thus produce our key result that willingness to pay is substantially below average cost and own costs. However, an estimate of the eligible population size is essential for pinning down where in the distribution of willingness to pay for insurance our observed demand changes occur.

Our baseline estimates scaled the shape of the eligible population income distribution in the ACS to match the ACS estimate that on average, 63% of the eligible population enrolls in CommCare. As discussed, the ACS’s coverage estimates match other survey estimates, as well as estimates based on tax filing data. However, if we instead divide the administrative counts of enrollment in CommCare by the raw ACS estimates of the size of the eligible population, we estimate only a 37% take-up rate. As shown in Table 3, this implies an even lower fraction of the population that will be insured at a given subsidy. For example, with this alternative take-up rate, we estimate that with a 75% subsidy of average costs, only 29% of eligible individuals would enroll in  $H$ , compared to 49% in our baseline

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<sup>31</sup>Recent work by Heim et al. (2016) and Kucko et al. (2018) find evidence of modest income bunching in response to notches in the ACA subsidy schedule at, respectively, 400% of FPL (above which subsidies end) and 100% of FPL in non-Medicaid expansion states (below which people fall into a “coverage gap”). These notches are far larger than our \$40 per month amounts – e.g., the Kucko et al. (2018) notch is about \$250 per month – and the responses are modest; for example, using the universe of IRS tax data, the Kucko et al. (2018) paper suggests an excess mass of only about 20,000 tax filers and that is limited to the self-employed (i.e. no detectable response for wage earners).

analysis. Right below 150% FPL, using the the raw ACS estimates for the denominator suggests 56% take-up, compared to our baseline estimate of 94%. The lower take-up estimates based on the ACS denominator may reflect the fact that income in the ACS is a noisy measure of the administratively recorded income in the CommCare data.

**Accounting for the Mandate Penalty** Our baseline analysis assumes that individuals do not take account of the expected mandate penalty for remaining uninsured when deciding whether or not to buy insurance. While we argue in Section 2 that this is a reasonable assumption in our institutional environment, the last row of Table 3 shows that accounting for the mandate penalty – which lowers the effective premiums – implies even lower willingness to pay than our baseline estimates.<sup>32</sup> For example, our estimates now imply that with a 75% subsidy of average costs, only about 32% would enroll in  $H$ .

**Inertia in Plan Demand and Robustness to New Enrollees** Our estimates thus far have abstracted from inertia or switching costs, which have shown to be relevant for health insurance plan choices (Handel, 2013; Ericson, 2014; Polyakova, 2016). If individuals do not make “active choices” each year once they are enrolled in CommCare this raises potential concerns with our estimates.

One concern is that enrollees’ income might change, leading them to move across the RD income threshold, but they might be unaware of the change or not re-optimize their choices.<sup>33</sup> This would suggest that our estimates understate the impact of higher premiums on insurance demand.

A second concern is that enrollees may not respond to changes in relative premiums for  $L$  compared to  $H$ , affecting our estimates of  $W_L$  relative to  $W_H$ . This seems potentially relevant, since the  $L$  plan (CeltiCare) was new to the market in 2010, so enrollees who entered the exchange prior to 2010 did not have it as an option when they first joined. However, our main findings are driven by a shift in demand from any formal insurance ( $H$  or  $L$ ) to uninsurance at the RD income thresholds. Thus, switching between  $H$  and  $L$  is less likely to be empirically important for our main results. Further, because  $L$  was unavailable prior to 2010, lack of awareness of  $L$  would likely push upward our estimates of demand for  $H$  relative to  $L$ .

A third, and related, concern is that in years prior to 2011, the premiums for the different plans that make up the  $H$  composite plan varied.<sup>34</sup> This motivated our focus on 2011 when the premiums were quite similar, so these plans can be pooled into a single “ $H$ ” option (defined as the preferred choice among the four component plans) with price  $p_H$ . However, if individuals made their choices in other years, this could be problematic.

To investigate the potential importance of such concerns for our estimates, we re-estimated demand on the sub-sample of new enrollees. We define new enrollees as those who enroll for the first time in 2011 (since the market opened in 2006); by definition, therefore, they must make an active choice in

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<sup>32</sup>Specifically, we normalize premiums by subtracting the expected mandate penalty values (shown by the black dots in Figure 3) from the “sticker premiums” shown in that same figure; note that effective premiums are everywhere lower, but the premium change at the FPL thresholds remains the same. Appendix Table 6 reports the normalized premiums by FPL.

<sup>33</sup> Institutionally, lack of awareness seems less likely to be relevant, since the administrative income variable (used for calculating subsidies) changes only if an individual is audited (a salient event) or self-reports a change.

<sup>34</sup>For instance, in 2010 for individuals in the 150-200% FPL group, enrollee premiums for the four  $H$  plans varied from \$39 to \$64 per month.

2011. The results for new enrollees in 2011 are shown in Appendix Figures 26 and 27 for enrollment in any plan and enrollment in the  $H$  plan respectively. In each case, Panel A shows results for all enrollees (for comparison) while Panel B shows results for new enrollees. New enrollees comprise about one-sixth of all enrollee-months. The percent reductions in enrollment at the income discontinuities are similar for new enrollees and all enrollees; for example, enrollment in any plan declines by 22 to 28 percent for new enrollees, compare to 25 to 27 percent for all enrollees. This suggests that inertia is unlikely to be biasing downward our estimates of how much demand falls as premiums rise.

**Relaxing Assumptions of Vertical Model** Our analysis thus far has assumed a vertical model of demand with two CommCare options,  $H$  and  $L$ . In Appendix E, we show that we can eliminate the vertical assumptions and still obtain *bounds* on WTP for CommCare (“ $W^{Ins}$ ”) – defined as an individual’s WTP for her most preferred plan. Assuming only that consumers are optimizing when making their plan choices, we can use the enrollee premium for the cheapest plan ( $p^{min}$ ) as a lower bound on  $W^{Ins}$  at a given point in its distribution, and the premium of the most expensive plan ( $p^{max}$ ) as an upper bound. Our RD subsidy discontinuities then serve as exogenous variation in  $p^{min}$  and  $p^{max}$  that let us map out these lower and upper bounds on  $W^{Ins}$  across a range of the population distribution. We find that the resultant lower and upper bounds of  $W^{Ins}$  are, in fact, quite similar to the  $W_L$  and  $W_H$  estimates from the baseline vertical model. The lower bound on  $W^{Ins}$  is identical to  $W_L$  by construction – both are generated by plotting the share purchasing any insurance against the premium of the cheapest plan ( $L$ ). The upper bound on  $W^{Ins}$  is also only slightly above  $W_H$ .

## 5 Discussion and Normative Implications

Our finding that individuals are not willing to pay the costs they impose on the insurer suggests there are significant barriers to setting up private markets for low-income adults. Insurers cannot recoup their costs if individuals aren’t willing to pay for them.

This raises a potential puzzle, since in the standard model of insurance, individuals are willing to pay their own expected costs *plus* a value of risk protection. One parsimonious explanation is that the relevant costs that drive an individual’s demand for insurance is not the costs they impose on the insurer – which is what our cost curve estimates reflect – but rather the costs they would pay if they were uninsured. It is now well documented that uninsured (predominantly low-income) individuals do not pay their full medical costs when they receive medical care (see e.g. Garthwaite, Gross, and Notowidigdo (2015); Finkelstein et al. (2012); Mahoney (2015); Dobkin et al. (2016); Hu et al. (2016); Brevoort et al. (2017)). While there is considerable uncertainty in the exact prevalence of uncompensated care, national estimates suggest that the uninsured pay only about 20% to 35% of their cost of care (Coughlin et al. 2014; Hadley et al. 2008; Finkelstein, Hendren, and Luttmer, 2015). This is remarkably similar to our estimated ratio of WTP to own costs imposed on the insurer for the  $H$  plan. Thus when we compare individual willingness to pay not to the cost of the insurer, but rather to the estimates of what they would pay if they were uninsured, we find that willingness to pay is quite similar to the the costs they would incur if they were uninsured; in Appendix F, we walk



through this calibration exercise in more detail.

Of course, we do not directly observe the amount paid out of pocket by the uninsured in our sample – thus there is considerable uncertainty around whether our calibration of the individuals’ own expected costs if uninsured is above or below WTP. Nor are we able to directly estimate the impact of access to uncompensated care on willingness to pay for insurance in our setting. This caveat is particularly important given the large literature suggesting that health insurance choices may be rife with behavioral biases.<sup>35</sup> This raises the possibility that consumers might not respond “rationally” to changes in uncompensated care; indeed, as suggested by Fadlon and Laibson (2017), the current uncompensated care system could be a response by a rational planner to anticipated behavioral biases that would lead individuals to not purchase insurance even in the absence of uncompensated care. For example, there is substantial evidence of individuals underestimating the probability of negative events (see e.g. Moore and Healy (2008) for a review); Spinnewijn (2015) estimates that unemployed individuals under-estimate the expected duration of unemployment by over 70%. In our context, such under-estimation of expected costs could easily close the approximately 200% gap between willingness to pay and insurer costs, and would still depress demand even in the absence of uncompensated care.

Both behavioral biases and access to uncompensated care may play a larger role for lower income populations. Behavioral biases may be particularly acute among low-income populations who are may be making purchase decisions under greater constraints or stress (Mani et al. (2013); Mullainathan and Shafir (2014); Bhargava et al. (2017)). Lower-income individuals also have greater access to uncompensated care than higher income individuals (Mahoney (2015); Dranove et al. (2015)); in Appendix G we show that greater access to uncompensated care (as measured by proximity to safety net providers) is associated with a greater gap between willingness to pay and insurer costs. We also show in Appendix G that within our own sample, the gap between willingness to pay and insurer costs narrows as we move from the 150% FPL threshold to the 200% threshold to the 250% threshold. Out of sample, our finding of willingness to pay below insurer costs for the low-income population in Massachusetts contrasts with Hackmann, Kolstad, and Kowalski (2015)’s estimate that higher-income individuals in Massachusetts (above 300% of FPL) are willing to pay the cost they impose on the insurer.

We are unable to quantify the relative roles of behavioral biases and uncompensated care in reducing willingness to pay so far below insurer costs in our setting. However, we believe we can rule out several other potential explanations for our finding. One is moral hazard – some of the cost incurred may not be fully valued by the individuals because they only consume the care if they don’t have to pay for it. But to close the gap in our setting, insurance would have to increase costs by a factor of at least 200%, which is an order of magnitude larger than most plausible estimates of the impact of moral hazard

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<sup>35</sup>Ericson and Sydnor (2017) provide a recent overview. A partial list of examples of behavioral biases that have been documented for health insurance choices includes inertia Handel (2013), confusion about contract dimensions (e.g. Bhargava et al. (2017); Handel and Kolstad (2015)), over-weighting certain financial plan features relative to others (e.g. Abaluck and Gruber (2011)), and making sub-optimal choices (e.g. Abaluck and Gruber (2011); Kling et al. (2012); Handel (2013)). Our previous finding of similar (or if anything lower) demand responsiveness by new enrollees suggests that inertia or inattention are not primary drivers of low willingness to pay, but naturally we cannot rule out behavioral biases more broadly.

on utilization.<sup>36</sup> Another possibility, recently emphasized by Hendren (2017) is that observed demand may understate the ex-ante value of insurance measured before the individual has learned something about her health type; WTP might be higher if the individual considered a purchase decision prior to learning their health type. In practice, however, as we show in Appendix I, our estimates suggest that even though an *ex-ante* willingness to pay measure may be significantly higher than our baseline willingness to pay estimates, it would still be below own cost.

Yet another potential factor creating a wedge between willingness to pay and costs that we suspect is not quantitatively important in our setting are liquidity constraints, i.e., the inability to borrow against future income at market rates of interest. As Casaburi and Willis (2016) observe, most insurance products require individuals to pay the premium up front, thus transferring income across time as well as states. We suspect, however, that liquidity constraints are unlikely the primary driver of low willingness to pay in our context. One reason is that the majority of marginal enrollees choose to pay for the *H* instead of the *L* plan, suggesting that although they might be liquidity constrained, they are not up against the corner of their budget constraint. In addition, the premiums we study represent only about 0-5 percent of family income. Of course, the fact that individuals are low income – and therefore high marginal utility of consumption – may reduce their willingness to pay, but that is a separate point from liquidity constraints and one we return to below when we consider normative implications.

**Normative Implications** Thus far we have focused on positive analysis of demand for insurance among a low-income population, and its implications for how insurance take-up would vary under alternative subsidies. Normative analysis faces (at least) two additional hurdles. First, we must be willing to accept our estimates of willingness to pay as the welfare-relevant metric. The presence of behavioral biases – which, as noted, have been extensively described in health insurance choices – raises concerns with this assumption. So too does Hendren’s (2017) point that observed demand may understate the ex-ante value of insurance measured before the individual has learned something about her health type.

Second, even were we to accept estimated willingness to pay as the welfare-relevant metric, normative analysis needs to consider the fact that the subsidy recipients are a low-income population (perhaps with a high marginal utility of consumption), which presumably reduces their willingness to pay for any good, including health insurance. One approach would be to apply a social welfare function that takes this into account by using a parameterization of social marginal utilities of income that translate individual willingness to pay into social willingness to pay (Saez and Stantcheva, 2016). In other words, even if recipient willingness to pay does not exceed costs, social willingness to pay may exceed cost. Another approach would be to follow Hendren (2016) and compute the marginal value of public funds (MVPF) – i.e. the ratio of marginal benefit to marginal cost – for an incremental

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<sup>36</sup>For example, in Appendix H we translate the estimates from Chandra et al. (2014) on the impact on health care spending of more vs. less generous plans in our MA CommCare population; this suggests that relative to being uninsured, insurance coverage would increase spending by roughly 15-25 percent. This is broadly consistent with the results from the Oregon Health Insurance Experiment, which found that Medicaid for low-income adults – a close analog to CommCare – increases health care spending by about 25% relative to being uninsured (Finkelstein et al., 2012).

government subsidy for health insurance. This could then be compared to the MVPF of alternative redistributive programs to a low-income population, such as cash transfers through the Earned Income Tax Credit (EITC). For this normative approach, liquidity constraints are not relevant; if demand for health insurance is low in part because individuals have a high marginal value of current cash due to liquidity constraints, that will (and should) increase the MVPF of cash transfers relative to in-kind subsidies.

If the existence of substantial uncompensated care for the low-income uninsured is a primary driver of low willingness to pay for formal insurance, a crucial question concerns the ultimate economic incidence of the uncompensated care that is provided in the absence of formal insurance; is this, for example, on the government, the low-income uninsured themselves, or more affluent third parties? A large role for uncompensated care in explaining why willingness to pay is substantially below (gross) insurance costs also suggests a potential efficiency – rather than purely redistributive – rationale for subsidies, as an offset to the implicit tax that uncompensated care imposes on formal insurance (Coate, 1995). There are also other possible distortions created by the current system of charity care provision, such as potential distortions in providers' decisions of whether to locate or expand certain services in low income areas (e.g. Dranove et al. (2015)).

## 6 Conclusion

This paper estimates willingness to pay and costs for health insurance among low-income adults using data from Massachusetts' pioneer subsidized insurance exchange. For at least 70% of the low-income eligible population, we find that willingness to pay for insurance is far below insurers' average costs. From a positive economics perspective, our results point to substantial challenges in getting to universal coverage via partially subsidized insurance programs like the ACA's exchanges. For example, we estimate that even subsidizing premiums down to 10% of insurer costs would generate only 80% coverage. This reality may underlie the incomplete take-up of insurance under the ACA, despite a coverage mandate and generous subsidies.

We find evidence of adverse selection, but show that, by itself, adverse selection cannot explain limited demand; we estimate that at least 70% of the eligible population would not enroll even if prices were subsidized to reflect own expected costs. The magnitude of the gap between willingness to pay and own costs is also substantially larger than what could plausibly be explained by moral hazard effects of insurance. Of course, expected costs reflect costs to the insurer, not necessarily costs the individual would pay if uninsured. Adjusting our cost estimates for existing estimates of the magnitude of available uncompensated care for the uninsured, we find that WTP is roughly close to these costs. Other analyses using a calibrated utility model (rather than revealed preference) for welfare analysis of health insurance for low-income adults similarly finds willingness to pay that is substantially below gross costs imposed on the insurer and quite close to the net costs of insurance that account for the uncompensated care that would be provided if the individual remained uninsured. (Finkelstein et al., 2015).

The large literature on behavioral biases in health insurance purchase decisions suggests that such

biases could also play a large role in reducing estimated of willingness to pay. Crucially, they also suggest caution in normative analysis of health insurance subsidies based on our demand estimates. While it is typical to use revealed preference in welfare analysis of demand for employer-provided health insurance (see e.g. Einav et al. (2010) for a review), there may be reluctance to do so in our context.

Normative analysis should also consider that the subsidy recipient population is poor, which provides a natural potential redistributive rationale for policy. This does not, however, speak directly to the relative merits of providing in-kind subsidies for health insurance as opposed to cash transfers, such as through an expansion of the Earned Income Tax Credit. Given the existence of substantial uncompensated care provision to the low-income uninsured, any redistributive analysis of subsidies to low-income individuals for health insurance must tackle the important, but challenging, question of the economic incidence of this uncompensated care provision. This is an important direction for future work.

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# Online Appendix

## Subsidizing Health Insurance for Low-Income Adults:



### Evidence from Massachusetts

Amy Finkelstein, Nathaniel Hendren, Mark Shepard

## Appendix A: CommCare Application and Enrollment Forms

### Application Form for CommCare

The following shows the application form that must be submitted to apply for CommCare. This form collects information on income, family status, and other sources of health insurance. The state uses this form to determine whether a person was eligible for CommCare, Medicaid (MassHealth) or neither. In addition to the main six pages below, there is a signature page and five pages of “supplements” that certain groups of applicants need to fill out.

 <b>MassHealth</b> Commonwealth of Massachusetts DHHS www.mass.gov/masshealth	<b>Medical Benefit Request</b>		For office use only Date received:
This is an application for <b>MassHealth</b> , the <b>Children's Medical Security Plan (CMSP)</b> , <b>Healthy Start</b> , <b>Commonwealth Care</b> , and the <b>Health Safety Net</b> . You do not have to be a U.S. citizen/national to get these benefits. <b>Please print clearly.</b> Please answer <b>all</b> questions and fill out all sections and any supplements that apply to you and your family. If you need more space to finish any section on this form, please use a separate sheet of paper (include your name and social security number), and attach it to this form.			
<b>Head of Household</b>			
1. Last name	First name	MI	Street address City State Zip
Mailing address (if different from street address or if living in a shelter) <input type="checkbox"/> homeless City State Zip			
Is this person applying? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, is this person a U.S. citizen/national? <input type="checkbox"/> yes <input type="checkbox"/> no Social security number* <input type="checkbox"/> C <input type="checkbox"/> I			
Date of birth / / Gender <input type="checkbox"/> M <input type="checkbox"/> F Spoken language choice Written language choice			
Telephone numbers: Home: ( ) Call: ( ) Work: ( )			
Race (optional) Ethnicity (optional) E-mail			
<b>Other Family Members</b>			
List all other members of your family group. Do not repeat head of household information in this section. See instruction page for description of a family group.			
2. Last name	First name	MI	
Is this person applying? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, is this person a U.S. citizen/national? <input type="checkbox"/> yes <input type="checkbox"/> no Social security number* <input type="checkbox"/> C <input type="checkbox"/> I			
Date of birth / / Gender <input type="checkbox"/> M <input type="checkbox"/> F Spoken language choice Written language choice			
Race (optional) Ethnicity (optional) Relationship to head of household			
3. Last name	First name	MI	
Is this person applying? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, is this person a U.S. citizen/national? <input type="checkbox"/> yes <input type="checkbox"/> no Social security number* <input type="checkbox"/> C <input type="checkbox"/> I			
Date of birth / / Gender <input type="checkbox"/> M <input type="checkbox"/> F Spoken language choice Written language choice			
Race (optional) Ethnicity (optional) Relationship to head of household			
4. Last name	First name	MI	
Is this person applying? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, is this person a U.S. citizen/national? <input type="checkbox"/> yes <input type="checkbox"/> no Social security number* <input type="checkbox"/> C <input type="checkbox"/> I			
Date of birth / / Gender <input type="checkbox"/> M <input type="checkbox"/> F Spoken language choice Written language choice			
Race (optional) Ethnicity (optional) Relationship to head of household			
*Applicants must provide a social security number if one has been issued. Applicants for MassHealth Limited are not required to provide a social security number or proof of application for a social security number.			
<b>Pregnancy</b>			
Are you or any family member pregnant? <input type="checkbox"/> yes <input type="checkbox"/> no Name:			
Are you or this person pregnant with: <input type="checkbox"/> 1 baby? <input type="checkbox"/> twins? <input type="checkbox"/> triplets? If more, how many? Due date / /			

<b>Residency (You must fill out this section.)</b>
Are you and all members of your household who are applying for benefits living in Massachusetts with the intention to stay? <input type="checkbox"/> yes <input type="checkbox"/> no If no, list the names of the members of your household (including yourself)* who are applying and who are not residents of Massachusetts and who intend to leave.
*Do not include infants born in Massachusetts who have not left the state.
<b>General instructions for filling out the Working Income, Nonworking Income, AND College Student sections</b> Each family member who has income and/or is aged 19 or older must fill out all sections on this page through page 4.
<b>Working Income (You must fill out this section.)</b>
1. Name
Is this person currently working or seasonally employed? (You must answer this question.) <input type="checkbox"/> yes <input type="checkbox"/> no If yes, fill out the <b>Employer Information</b> section below. If no, answer the next two questions below. You do not have to fill out the "Employer Information" section below.
Has this person worked in the last 12 months before the date of application? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, how much did this person earn in the last 12 months before taxes and deductions? Note: If you answered "yes" to this question, you MUST enter a dollar amount on this line. \$ If no, go to the next section (Nonworking Income).
<b>Employer Information</b> Employer name
Employer address, and telephone number
Type of work (Check all that apply) <input type="checkbox"/> full-time <input type="checkbox"/> day labor <input type="checkbox"/> part-time <input type="checkbox"/> seasonal yearly wage: \$ <input type="checkbox"/> self-employed <input type="checkbox"/> sheltered workshop yearly wage: \$
Number of hours per week Weekly pay before deductions \$ Date began getting this amount of pay / /
Is health insurance offered that would cover doctors' visits and hospitalizations? <input type="checkbox"/> yes <input type="checkbox"/> no (Answer yes even if you cannot get it now, chose not to sign up for it, or dropped insurance that was available.) If you answered no to the above question, was health insurance offered in the last six months? <input type="checkbox"/> yes <input type="checkbox"/> no Send proof of income, like a copy of one recent pay stub. If self-employed, see the MassHealth Member Booklet for information about the needed proof.
2. Name
Is this person currently working or seasonally employed? (You must answer this question.) <input type="checkbox"/> yes <input type="checkbox"/> no If yes, fill out the <b>Employer Information</b> section below. If no, answer the next two questions below. You do not have to fill out the "Employer Information" section below.
Has this person worked in the last 12 months before the date of application? <input type="checkbox"/> yes <input type="checkbox"/> no If yes, how much did this person earn in the last 12 months before taxes and deductions? Note: If you answered "yes" to this question, you MUST enter a dollar amount on this line. \$ If no, go to the next section (Nonworking Income).
<b>Employer Information</b> Employer name
Employer address, and telephone number
Type of work (Check all that apply) <input type="checkbox"/> full-time <input type="checkbox"/> day labor <input type="checkbox"/> part-time <input type="checkbox"/> seasonal yearly wage: \$ <input type="checkbox"/> self-employed <input type="checkbox"/> sheltered workshop yearly wage: \$
Number of hours per week Weekly pay before deductions \$ Date began getting this amount of pay / /
Is health insurance offered that would cover doctors' visits and hospitalizations? <input type="checkbox"/> yes <input type="checkbox"/> no (Answer yes even if you cannot get it now, chose not to sign up for it, or dropped insurance that was available.) If you answered no to the above question, was health insurance offered in the last six months? <input type="checkbox"/> yes <input type="checkbox"/> no Send proof of income, like a copy of one recent pay stub. If self-employed, see the MassHealth Member Booklet for information about the needed proof.

**Nonworking Income (You must fill out this section.)**

**Rental Income** Do you or any family member get rental income? (You must answer this question.)  yes  no **HW**  
If yes, enter the monthly amount of rental income (before taxes and deductions) on this line. \$ \_\_\_\_\_

Name of person getting rental income \_\_\_\_\_  
If no, go to the next section (Unemployment Benefits).  
Send proof of rental income.

**Unemployment Benefits** Are you or any family member getting an unemployment check? (You must answer this question.)  yes  no **HW**  
If yes, fill out this section and answer all questions. Send proof of unemployment benefits.  
If no, go to the next section (Other Nonworking Income).

Name of person getting unemployment benefits \_\_\_\_\_  
Is this check from the Commonwealth of Massachusetts?  yes  no  
If yes, in the 12 months before this person became unemployed, did this person work for an employer in Massachusetts?  yes  no  
(Do not include federal employers, like the U.S. Postal Service.)  
Enter the monthly amount of unemployment benefits (before taxes and deductions). \$ \_\_\_\_\_

Name of person getting unemployment benefits \_\_\_\_\_  
Is this check from the Commonwealth of Massachusetts?  yes  no  
If yes, in the 12 months before this person became unemployed, did this person work for an employer in Massachusetts?  yes  no  
(Do not include federal employers, like the U.S. Postal Service.)  
Enter the monthly amount of unemployment benefits (before taxes and deductions). \$ \_\_\_\_\_

**Other Nonworking Income** Do you or any family member have any other income? (You must answer this question.)  yes  no **HW**  
If yes, fill out this section.  
If no, go to the next section (College Student).  
Please describe the source of the income (where it comes from) for each family member. If anyone has more than one source, list on separate lines.  
Send proof. Some types of other income are: (You do not have to send proof of social security or SSI income.)  
• alimony • dividends or interest • social security • veterans' benefits (federal, state, or city)  
• annuities • pensions • SSI • workers' compensation  
• child support • retirement • trusts • other (Please describe below.)

Name	Type of income (all that apply from list above)
Source (where the income comes from)	Monthly amount before taxes \$
Name	Type of income (all that apply from list above)
Source (where the income comes from)	Monthly amount before taxes \$
Name	Type of income (all that apply from list above)
Source (where the income comes from)	Monthly amount before taxes \$

2. Policyholder name \_\_\_\_\_ Date of birth / / \_\_\_\_\_  
Social security number\* \_\_\_\_\_ Insurance company name \_\_\_\_\_  
Policy type (Check one.)  individual  couple (two adults)  dual (one adult, one child)  family Policy start date \_\_\_ / \_\_\_ / \_\_\_\_  
Policy number \_\_\_\_\_ Group number (if known) \_\_\_\_\_  
Employer or union name \_\_\_\_\_  
Policyholder contribution to premium costs (Complete one.) \$ \_\_\_\_\_ per week \$ \_\_\_\_\_ per quarter \$ \_\_\_\_\_ per month  
Insurance type (Check one.)  Employer or union subsidized (employer or union pays some or all of the insurance cost)  TRICARE  
 other federal or state subsidized (government pays some or all of the insurance cost)  student health insurance through school  
 nonsubsidized, like self-employment or COBRA (policyholder pays total insurance cost)  Medical Security Program

Names of covered family members \_\_\_\_\_  
Insurance coverage (Check all that apply.)  doctors' visits and hospitalizations  catastrophic only  vision only  pharmacy only  dental only  
If you have long-term-care insurance, send a copy of the policy.  
\* Required, if obtainable and one has been issued, whether or not this person is applying.

**Part B: Subsidized Health Insurance You May Be Eligible For**

Are you or any member of your family in one of the uniformed services?  yes  no  
If yes, fill out the section below. (The uniformed services are the Army, Navy, Air Force, Marine Corps, Coast Guard, Public Health Services, National Oceanic and Atmospheric Administration, and the National Guard or Reserves.)

1. Name: \_\_\_\_\_  
Active Duty?  yes  no Retiree?  yes  no Reserves?  yes  no Medal of Honor?  yes  no

2. Name: \_\_\_\_\_  
Active Duty?  yes  no Retiree?  yes  no Reserves?  yes  no Medal of Honor?  yes  no

Have you or any member of your family served in the U.S. military or can you be considered a dependent of someone who has served in the U.S. military?  
Yes, I have served. Name: \_\_\_\_\_  
 Yes, I am a dependent of someone who has served. Name: \_\_\_\_\_  
 No, I am neither a veteran nor a dependent.

**American Indian/Alaska Native**

Certain American Indians and Alaska Natives may not have to pay MassHealth premiums and copays.  
Are you or any member of your family who is applying a federally recognized American Indian or Alaska Native who is eligible to receive or has received services from an Indian health-care provider or from a non-Indian health-care provider through referral from an Indian health-care provider?  yes  no  
If yes, name of person(s): \_\_\_\_\_

**College Student (You must fill out this section.)**

Are you or any family member a college student? (You must answer this question.)  yes  no  
If yes, fill out this section and answer all questions.  
If no, go to the next section (Health Insurance You Have Now and Subsidized Health Insurance You May Be Eligible For).

1. Name of college student \_\_\_\_\_  
Is this person eligible for health insurance from college?  yes  no  
Is this person a college student in Massachusetts with at least 75% of a full-time schedule?  yes  no  
(Note: If you are not sure that this person has 75% of a full-time schedule, contact the school to find out if the number of credits the student is taking would require the student to get the health insurance the school offers to students.)  
If yes, is this student planning to get health insurance coverage from the school, but is waiting for coverage to start?  yes  no  
If yes, what is the date that the school health insurance coverage starts? \_\_\_ / \_\_\_ / \_\_\_\_

2. Name of college student \_\_\_\_\_  
Is this person eligible for health insurance from college?  yes  no  
Is this person a college student in Massachusetts with at least 75% of a full-time schedule?  yes  no  
(Note: If you are not sure that this person has 75% of a full-time schedule, contact the school to find out if the number of credits the student is taking would require the student to get the health insurance the school offers to students.)  
If yes, is this student planning to get health insurance coverage from the school, but is waiting for coverage to start?  yes  no  
If yes, what is the date that the school health insurance coverage starts? \_\_\_ / \_\_\_ / \_\_\_\_

**Health Insurance You Have Now and Subsidized Health Insurance You May Be Eligible For**

Even if you or any family member have other health insurance, MassHealth may be able to help you pay your premiums. Health insurance can be from an employer, an absent parent, a union, a school, Medicare, or Medicare supplemental insurance, like Medigap. All applicants must fill out the health insurance section. Do not include MassHealth or any health plan you enrolled in through Commonwealth Care when answering the questions below.

Do you or any family member get Medicare benefits?  yes  no  
If yes, name(s): \_\_\_\_\_  
Claim number(s): \_\_\_\_\_  
Do you or any family member have health insurance other than Medicare?  yes  no  
If yes, fill out both Part A below and Part B on the next page.  
If no, fill out Part B on the next page.

**Part A: Health Insurance You Have Now**

1. Policyholder name _____	Date of birth / / _____
Social security number* _____	Insurance company name _____
Policy type (Check one.) <input type="checkbox"/> individual <input type="checkbox"/> couple (two adults) <input type="checkbox"/> dual (one adult, one child) <input type="checkbox"/> family	Policy start date ___ / ___ / ____
Policy number _____	Group number (if known) _____
Employer or union name _____	
Policyholder contribution to premium costs (Complete one.) \$ _____ per week \$ _____ per quarter \$ _____ per month	
Insurance type (Check one.) <input type="checkbox"/> Employer or union subsidized (employer or union pays some or all of the insurance cost) <input type="checkbox"/> TRICARE	
<input type="checkbox"/> other federal or state subsidized (government pays some or all of the insurance cost) <input type="checkbox"/> student health insurance through school	
<input type="checkbox"/> nonsubsidized, like self-employment or COBRA (policyholder pays total insurance cost) <input type="checkbox"/> Medical Security Program	

Names of covered family members \_\_\_\_\_  
Insurance coverage (Check all that apply.)  doctors' visits and hospitalizations  catastrophic only  vision only  pharmacy only  dental only  
If you have long-term-care insurance, send a copy of the policy.

\* Required, if obtainable and one has been issued, whether or not this person is applying.

**General instructions for filling out the Injury, Illness, Disability, or Accommodation, Absent Parent, and U.S. Citizenship/National Status and Immigration Status sections below**

The HIV section is optional. You must answer all questions in each of the three sections after the HIV section.

**HIV Information (optional)**

MassHealth may give benefits to people who are HIV positive who might not otherwise be eligible.  
Do you or any family member who is HIV positive want to apply for these benefits?  yes  no  
If yes, fill out this section.  
Send proof of income, U.S. citizenship/national status, and identity, or qualified alien status to see if you can get benefits for up to 60 days while we wait for you to send us proof of your HIV-positive status. For more information, see the MassHealth Member Booklet.  
Name(s): \_\_\_\_\_

**Injury, Illness, Disability, or Accommodation**

Do you or any family member have an injury, illness, or disability (including a disabling mental health condition) that has lasted or is expected to last for at least 12 months? (If legally blind, answer yes.)  yes  no  
Do you or any family member need health care because of an accident or injury?  yes  no  
Do you or any family member applying for MassHealth require a reasonable accommodation because of a disability or injury?  yes  no  
If you answered yes to any of these three questions, you must fill out Supplement A (the blue sheet).

**Absent Parent**

Has any child in the household been adopted by a single parent or has a parent who is deceased or unknown?  yes  no  
Does any child in the family have a parent who does not live with you who is not included in the previous question?  yes  no  
If you answered yes to either of these questions, you must fill out Supplement B (the yellow sheet).

**U.S. Citizenship/National Status and Immigration Status**

The U.S. citizenship/national status of parents does not affect the eligibility of their children.

**U.S. Citizens**

For applicants born in Massachusetts who want help getting proof of their U.S. citizenship, please fill out Supplement D (the red sheet).  
For applicants born outside Massachusetts who want help getting proof of their U.S. citizenship, MassHealth may be able to help you. Please call MassHealth Customer Service at 1-800-841-2900 (TTY: 1-800-497-4648 for people who are deaf, hard of hearing, or speech disabled).

**Persons who are not U.S. citizens/nationals**

If you or any other family member applying for MassHealth or Commonwealth Care fits any of the immigration status codes on Supplement C (the orange sheet), numbered 1 through 17, you must fill out Supplement C.  
If you or any other family member applying for benefits does not fit any of the immigration status codes on Supplement C (the orange sheet), numbered 1 through 17, you or that family member may get only one or more of the following: MassHealth Limited, Healthy Start, CMSP, or the Health Safety Net. You do not have to fill out Supplement C.

Note: A social security number is not required for approval for MassHealth Limited. We will not match the names of applicants for MassHealth Limited with any other agency including the Department of Homeland Security (DHS). You do not need to send proof of immigration status. MassHealth Limited pays for emergency services only. See the MassHealth Member Booklet for more information.

List below the names of family members who want to get only one or more of the following: MassHealth Limited, Healthy Start, CMSP, or the Health Safety Net.

Name(s): \_\_\_\_\_  
Name(s): \_\_\_\_\_



## Appendix B: Estimating the CommCare Eligible Population in the ACS

We estimate the size of the eligible CommCare population in Fiscal Year 2011 using data from the 2010-2011 American Community Survey (ACS). This appendix describes how we estimate the size of the population eligible for CommCare using the American Community Survey (ACS). Our estimation has two main steps: first, we apply CommCare’s eligibility criteria to the ACS data to limit to the sample of individuals likely eligible for CommCare. Second, we estimate the eligible population by income bin, using a regression to smooth the raw counts in each bin. Below, we describe each step in detail.

### Applying CommCare Eligibility to ACS Data

We begin with ACS data from 2010-2011, using both years because our CommCare year of interest, fiscal year 2011, spans July 2010-June 2011.<sup>37</sup> To take an average of the population across years, we multiply sample weights by 1/2.

We begin by defining family income as a share of the poverty line, analogous to the measure used by CommCare. Specifically, we sum total personal income across all members of an individual’s “health insurance unit” (HIU), a variable defined by the University of Minnesota’s SHADAC to approximate family unit definitions used by public insurance programs. We divide this total income by the FPL defined by the year and the HIU size.

We then define people as CommCare eligible if they are U.S. Citizens in the relevant age range (19-64) and income range (less than 300% FPL) who are not enrolled in another form of health insurance (specifically, employer insurance, Medicare, or Tricare) and are not eligible for Medicaid (based on income and demographics). We discuss each of these restrictions in turn. The top panel of table 4 shows the ACS sample size, the (unweighted) number of individuals dropped at each of stages, and the estimated population size (scaled up using 1/2 of the ACS person weights).

Restricting to the relevant age range (row 1) and income range (row 2) is straightforward. In row 3 we restrict to U.S. citizens. Nearly all non-citizens are ineligible for CommCare, with the exception of long-term green card holders (longer than 5 years). Because we cannot separately measure this latter group in the ACS, we exclude all non-citizens. In row 4, we exclude any individual who reports having employer-sponsored insurance (ESI), Medicare, Tricare, or privately purchased insurance. The remaining individuals have incomes/demographics that make them eligible for Medicaid or CommCare, and they are either enrolled in these programs or uninsured.<sup>38</sup>

The last two rows of the table show how we exclude individuals eligible for Medicaid (MassHealth) instead of CommCare. We cannot directly measure Medicaid eligibility in the ACS.<sup>39</sup> Instead, we approximate it by excluding the two largest groups we know are Medicaid eligible: parents with

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<sup>37</sup>We obtained ACS data from the IPUMS-USA website (Ruggles et al., 2015).

<sup>38</sup>There are a very small number of individuals in this sample who have VA coverage but nothing else. These individuals are eligible for CommCare or MassHealth but have not taken it up, so we count them as “uninsured” for our purpose.

<sup>39</sup>We cannot even directly measure Medicaid enrollment; the ACS does not distinguish between Medicaid and CommCare (both are coded as “Medicaid/other public insurance”).

income below 133% of FPL, and the disabled (proxied by under 65 and SSI receipt). Parents with dependents under 18 are eligible for Medicaid below 133% FPL and eligible for CommCare above this cut-off. We focus on income groups above the cutoff so that results are not affected by this large compositional change in eligibility, and use the 135% FPL cutoff to avoid ambiguity right at the 133% FPL cutoff and to maintain equal-size 5% FPL bins for later analysis. This approach misses a few groups who are Medicaid eligible but whom we cannot easily measure in the ACS – specifically, pregnant women below 200% FPL and HIV-positive people below 200% FPL. Based on the number of women below 200% FPL with a child under one year old, we estimate that pregnant women may constitute 0.4% of our eligible sample. The HIV-positive group is likely to be even smaller.<sup>40</sup>

The final sample in the ACS includes 2,856 observations. Scaling this up to a population size using the ACS’s person weights, we estimate a CommCare-eligible population size of 168,041 Massachusetts residents earning 135-300% of FPL for FY 2011. These individuals do not have ESI, Medicare, Tricare, or nongroup coverage and based on their income and demographics are ineligible for Medicaid. Of these 105,241 (or 63%) report having health insurance (all via “Medicaid/other public insurance” ). In theory, all of these people should have CommCare (since they are Medicaid-ineligible), so 63% is our estimated CommCare take-up rate in the ACS. Of course, income measurement error in the ACS may lead us to overstate or understate the eligible population.

## Estimating Smoothed Eligible Population

We next use this restricted sample to estimate the CommCare-eligible population by income bin.

Figure 14 shows the raw estimates, with each point representing the estimated eligible population size for a 5% of FPL bin. These estimates are quite noisy, both because the ACS is a 1% sample and because of clustering in reported income at round numbers (which is emphasized in the very high outlier points). To prevent this noise from introducing error into our estimates of market shares from the administrative data, we construct a smoothed estimate of the eligible population by income bin. Specifically, we regress the raw population counts by 1% of FPL bin on a quadratic polynomial in income as a percentage of FPL. The predicted values from this regression (multiplied by 5 to match the 5% FPL bins we use in our analysis) are shown in the red curve in Figure 14.

We use the value of this curve at the midpoint of each income bin for our smoothed estimate of the CommCare-eligible population size.

## Appendix C: Construction of Cost Curves

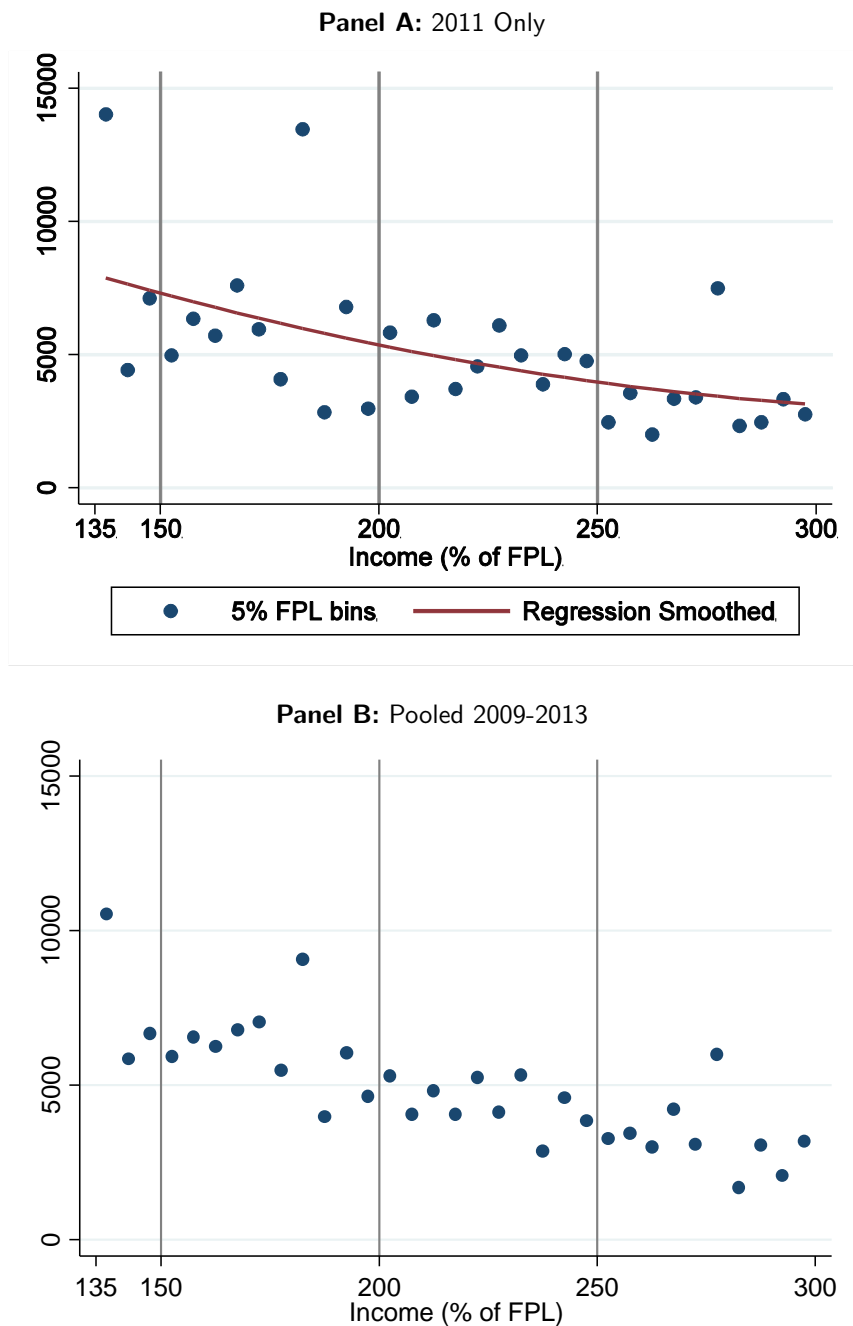
**Constructing  $C_H$**  In addition to the average cost curves, we construct the cost to the insurer of marginal enrollees,  $C_H$ . To do so, note that the *total costs* to the insurer under the  $H$  contract at prices  $p = \{p_L, p_H\}$  equals:

$$TC_H(p) \equiv \int_0^{s_{HL}^*(p)} C_H(s) ds = s_{HL}^*(p) \cdot AC(s_{HL}^*)$$

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<sup>40</sup>Details of Medicaid eligibility rules are based on MMPI (2012).

Figure 14: Estimate of CommCare Eligible Population from ACS Data



NOTE: Panel A shows our smoothed estimates of the CommCare-eligible population from the 2010-2011 ACS data. The dots are raw estimates of the annual eligible population size (weighting by the ACS “person weight” to generate a population estimate) by 5% of FPL bin. Because these data are relatively noisy – especially at high outlier points that reflect round income numbers like \$20,000 – we use a quadratic regression to generate a smoothed estimate of the eligible population size. The resulting estimates are shown in the curve. Panel B shows the raw estimates of the annual eligible population size from the pooled 2009-2013 ACS data.

Table 4: ACS Sample Construction

Sample / Exclusion	ACS Sample Size			Est. Population
	# Dropped	% Dropped	# Remaining	# Remaining
<b>Full ACS Mass. Sample (2010-11)</b>			<b>135,009</b>	<b>6,572,395</b>
Drop Age <19 or ≥ 65	52,362	39%	82,647	4,147,512
Drop Income > 300% FPL	47,790	35%	34,857	1,863,450
Drop Non-Citizens	3,994	3%	30,863	1,602,621
Drop People with Medicare, ESI, Tricare	19,961	15%	10,902	601,145
<b>Sample Eligible for CommCare or Medicaid</b>	--	--	<b>10,902</b>	<b>601,145</b>
Limit to 135-300% FPL	7,862	72%	3,040	178,772
Drop Disabled (under 65 and receiving SSI)	184	2%	2,856	168,041
<b>Final Sample</b>	--	--	<b>2,856</b>	<b>168,041</b>

NOTE: The table shows how we construct our ACS sample of the population eligible for CommCare, as described in the text of Appendix B. It starts from the full ACS 2010 and 2011 (pooled) samples of Massachusetts residents and shows the number of observations dropped and remaining at each step. The final column refers to the estimated population size, applying the appropriate ACS “person weights” (and dividing in half to compute an annual estimate from the two years of pooled data).

where  $AC(s)$  was defined in equation (5). This formula integrates over all the individuals who choose the  $H$  contract at these prices. Under the vertical model structure, this corresponds to types for which  $s \leq s_{HL}^*(p_H - p_L)$ .

Now, consider the variation induced by the discontinuities, where both  $p_L$  and  $p_H$  may vary. To capture this, we introduce some additional notation. Let  $\theta$  parameterize the price changes at the discontinuity so that  $p_L$  changes by  $\frac{dp_L}{d\theta}$  and  $p_H$  changes by  $\frac{dp_H}{d\theta}$ . The policy induces a change in  $p_H - p_L$  of  $\frac{d(p_H - p_L)}{d\theta} = \frac{dp_H}{d\theta} - \frac{dp_L}{d\theta}$ . Despite the fact that both  $p_H$  and  $p_L$  vary at the discontinuities, one can still use variation induced by the policy to estimate  $C_H(s)$ . To see this note that:

$$\underbrace{\frac{dT C_H}{d\theta}}_{\text{Change in total costs in } H} = \underbrace{\frac{ds_{HL}^*}{d\theta}}_{\text{Change in } D_H} \times \underbrace{C_H(s_{HL}^*)}_{\text{Cost of marginal consumers}}$$

where  $\frac{dT C_H}{d\theta} = \frac{dT C_H}{d(p_H - p_L)} \frac{d(p_H - p_L)}{d\theta}$  is the impact of the policy change (i.e. the discontinuity) on total costs of the  $H$  insurers and  $\frac{ds_{HL}^*}{d\theta} = \frac{ds_{HL}^*}{d(p_H - p_L)} \frac{d(p_H - p_L)}{d\theta}$  is the net impact of the policy on demand for  $H$  (since  $D_H = s_{HL}^*$ ). Given estimates of the policy change on total costs of  $H$ ,  $\frac{dT C_H}{d\theta}$  and on demand for  $H$ ,  $\frac{dD_H}{d\theta} = \frac{ds_{HL}^*}{d\theta}$ , we can solve for the cost of the marginal type in the  $H$  contract,  $s_{HL}^*(p)$ ,

$$C_H(s_{HL}^*) = \frac{\frac{dT C_H}{d\theta}}{\frac{dD_H}{d\theta}}. \quad (6)$$

Because the pricing change does not affect the costs of infra-marginal types, we can infer the costs of the marginal group by measuring the change in total costs and demand for  $H$ . This logic is identical to the two-plan case considered in past work (Einav, Finkelstein, and Cullen, 2010). The key requirement for equation (6) to be valid is that  $p_H$  and  $p_L$  do not change by the same amount at the discontinuities

(so that  $d(p_H - p_L) \neq 0$ .)<sup>41</sup>

Panel B of Figures 7 and 8 showed how shares ( $D_H$ ) and average costs (or  $AC_H$ ) changed at the pricing discontinuities. We map these – using the  $AC_H$  curve adjusted to 150% of FPL from Panel B of Figure 12 – into  $C_H$  in (6) using the identity that total costs equal average costs times demand:  $TC_H = AC_H \cdot D_H$ . The resulting  $C_H(s)$  curve is shown in Figure 13, along with the previously estimated curves  $W_H$ ,  $AC_H$  and  $W_L$ . We place the  $C_H$  values along the horizontal axis points that correspond to the midpoint of the relevant average cost segment. The downward slope of each average cost curve in turn implies that the cost curve  $C_H(s)$  lies below the average cost curve,  $AC_H(s)$ .

**Constructing  $C_L$**  Because we do not have variation in  $p_L$  and  $p_H$  that is orthogonal to  $p_H - p_L$ , we cannot use the same method to estimate  $AC_L$  and  $C_L$ . Absent such independent variation in prices, it is difficult to separate the costs of those who enter/exit the  $L$  plan into the  $H$  plan, and those who enter/exit the  $L$  plan into uninsurance,  $U$ . Appendix Figure 24 shows the regression discontinuity results for enrollment in the  $L$  plan, the  $L$  plan’s market share, and average monthly insurer costs among  $L$  enrollees. We see statistically significant decreases in enrollment and increases in costs at the 150% threshold. There is little evidence of changes at other thresholds.

However, we can draw some inferences about  $C_L$  by exploiting the fact that the market share of  $L$  is relatively small. This implies that the average  $L$  enrollee is similar to the marginal enrollee. For instance, just above 150% FPL, Appendix Figure 24 shows that just 6% of the population enrolls in the  $L$  plan, and we estimate (see Figure 10, Panel A) that the marginal individual who enrolls at that premium is at  $s = 0.70$  in the WTP distribution. Thus, the 6% who buy at that premium span  $s \in [0.64, 0.70]$ , and the average cost of the  $L$  plan just above 150% FPL provides an approximation to  $C_L(s)$  for individuals in this narrow range of WTP.

We use this strategy to estimate the  $C_L(s)$  for individuals at 150% of FPL. A similar strategy could be used at other income thresholds but we focus on 150% for simplicity. In practice, this means that we use our estimates (see Appendix Table 6) of the average  $C_L$  of \$169 per month for those enrolled just below 150% FPL (where the relevant  $s$  range is  $s \in [0.80, 0.94]$ ) and \$242 per month just above 150% FPL (where the relevant  $s$  range is  $s \in [0.64, 0.70]$ ).<sup>42</sup>

We include these two  $C_L(s)$  points (locating them at the midpoint of each  $s$  range) in Figure 13. The implied  $C_L$  curve is quite similar to the  $C_H$  curve over the regions of the  $s$  distribution where both are observed. This suggests that obtaining the more generous  $H$  contract instead of the  $L$  contract does not significantly increase costs. Therefore the much lower observed average cost in the  $L$  plan (see Table 1) is driven largely by favorable selection rather than by the causal impact of the plan on costs for the same type,  $s$  (i.e. moral hazard).

<sup>41</sup>Note that although the impact on demand is driven both by changes in  $p_H$  and  $p_L$ , we only need to observe the *net* impact on demand and costs. Under the vertical model, there is only one type of marginal consumer for the  $H$  plan – i.e., those with  $s = s_{HL}^*$ .

<sup>42</sup>Note that the empirical distribution of average claims for those in  $L$  shown in Appendix Figure 24, Panel C is not the analog of the “average cost” concept defined in equation (5) since the figure shows average claims for all those enrolled in  $L$ ; some individuals with higher WTP will in fact enroll in  $H$ .



## Appendix D: Extrapolating out of sample

Appendix Figure 15 shows the simple extrapolation we used to approximate willingness to pay and cost out of sample; we use this out-of-sample extrapolation only for the 100% and 50% subsidy counterfactuals in Table 2.

We extrapolate by extending the left-most segments of  $W_H$  and  $AC_H$  linearly to the left (and recalculating  $c_H$  using equation (6)).<sup>43</sup> Likewise, we extend the right-most segments of  $W_H$  and  $AC_H$  out to its value above the right-most value of  $W_L$  that we observe ( $s = 94\%$ ) using a linear extrapolation of the right-most segment of the  $\Delta W_{HL}$  and  $AC_H$  curves.<sup>44</sup>

This extrapolation leads to estimates of willingness to pay that are still everywhere far below average and own costs. Because demand lies everywhere below average costs (falling short by more than \$225;  $W_H$  never exceeds 52% of average costs), our extrapolation suggests the market would fully unravel in the absence of large government subsidies. Because individuals' WTP lies everywhere below their own expected cost they impose on the insurer (by at least \$140;  $W_H$  never exceeds 53% of  $C_H$ ), this suggests that even if insurers were able to price discriminate on WTP type (i.e., based on  $s$ ), the market would unravel. In this sense, adverse selection cannot explain the low take up of  $H$  by low-income individuals. Even if the quantile of WTP,  $s$ , were known to insurers and they were allowed to price on this information, they would still not be able to profitably sell insurance.

Naturally, a concern with this linear extrapolation is that it assumes away the possibility that there is a subset of the population with much higher demand than other types, so that demand increases non-linearly. While we cannot of course rule this out, the most natural source for willingness to pay increasing non-linearly would be if the variance of costs (i.e. risk) were higher for higher willingness to pay individuals, and this does not appear to be the case. To test for this, Appendix Figure 16 explores how the standard deviation of costs changes around our pricing discontinuities. While the results are fairly noisy, there is no evidence that the standard deviation of costs is increasing at the price discontinuities where willingness to pay of those enrolled is also increasing. While this does not guarantee that the linear extrapolation is appropriate, it does suggest that it is not entirely inconsistent with the underlying cost variation in the data.

## Appendix E: WTP Estimates without a Vertical Model

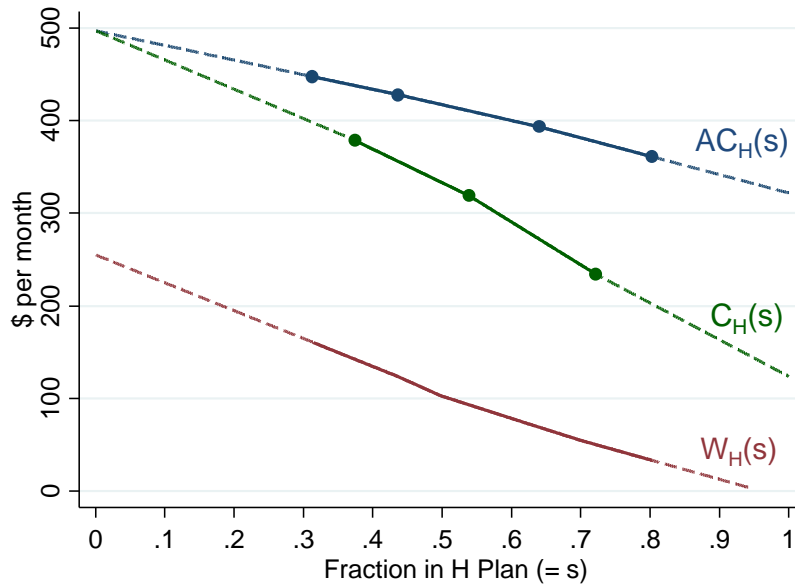
Our vertical model involves non-trivial assumptions about the nature of the market and preferences of consumers. These assumptions – while reasonable for CommCare in 2011 – will not be reasonable in all settings, including for CommCare in other years. In this section, we develop a model with fewer assumptions that gives us bounds on the WTP for access to a given set of insurance plans.

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<sup>43</sup>It would also be possible to extrapolate  $c_H$  linearly and recalculate  $AC_H$  accordingly. In practice, this produces even higher estimates of both cost curves, meaning that our conclusion that WTP is entirely below costs is unchanged.

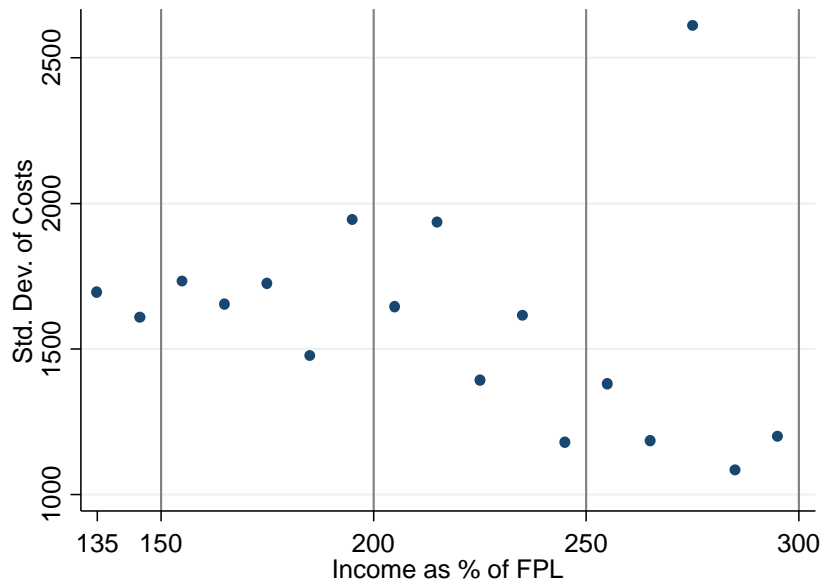
<sup>44</sup>Interestingly,  $W_H$  is quite close to zero at this point (about \$4). This does not occur by construction but is consistent with the idea that these people have virtually no willingness to pay for health insurance, whether  $H$  or  $L$ . The model implies that  $W_L$  is zero or negative for the rest of the  $s$  distribution, and based on the estimates, the same is also true of  $W_H$ ; in the context of the model, this can be explained by transaction costs in enrolling (even at a zero “sticker” price), which reduces the net willingness to pay for a formal contract below the uninsured option. Of course, it is also possible that these 6% who do not enroll at zero price are uninformed about their eligibility (e.g. Bhargava and Manoli (2015)).

Figure 15: Value and Cost of  $H$  – Extrapolation



NOTE: The figure shows out-of-sample extrapolations for  $W_H$ ,  $AC_H$  and  $C_H$ . The solid lines are our in-sample estimates, identical to those shown in Figure 13. The dashed lines are the extrapolations. Both  $W_H$  and  $AC_H$  are extrapolated linearly using the slope of the left-most and right-most line segment.  $C_H$  is extrapolated by calculating  $C_H$  based on the implied values from  $AC_H$ , applying the formula for  $C_H$  in equation (6).

Figure 16: Standard Deviation of Insurer Costs across Enrollees, by %FPL ( $H$  Plan)



NOTE: The graph shows the standard deviation of insurer costs, by 10% of FPL bin. The standard deviation is calculated across individuals in the data for 2011, using each individuals average insurer-paid cost per month enrolled. As we discuss in the text, there is little evidence that the standard deviation jumps discretely at the income thresholds where subsidies and take-up changes.

**Setup and WTP for Insurance** The setup is very general. Consider an insurance market with plan options  $j = 1, \dots, J$  and an outside option of uninsurance,  $j = U$ . Let  $W_{ij}$  be the willingness to pay of consumer  $i$  for plan  $j$ , where we normalize WTP relative to  $W_{iU} = 0$ . Let  $p_{ij}$  be the premium of each plan (which can vary across consumers), where we also normalize  $p_{iU} = 0$ . Consumers choose among available options to maximize their utility, which equals:

$$u_{ij} = W_{ij} - p_{ij}.$$

Note that by our normalizations,  $u_{iU} = 0$ .

We would like to estimate the willingness to pay for (any) CommCare insurance ( $W_i^{Ins}$ ), defined as the willingness to pay for each consumer's most preferred plan:

$$W_i^{Ins} = \max_{j \neq U} \{W_{ij}\}$$

A challenge in measuring the WTP for insurance is that while we want the maximum value of  $W_{ij}$  across  $j$  options, in CommCare consumers choose plans to maximize  $W_{ij} - p_{ij}$ . However, we can use choices in CommCare to get bounds on  $W_i^{Ins}$ . To do so, note that if someone chooses  $U$  in the CommCare setting, it implies that  $W_{ij} \leq p_{ij}$  for all  $j \neq U$ . This in turn implies that

$$\text{Choose } U : \quad W_i^{Ins} \leq \max_{j \neq U} \{p_{ij}\} \equiv p_i^{max} \quad (7)$$

Thus,  $p_i^{max}$  is an upper bound on the value of access to CommCare for people who choose not to buy into it. Similarly, if an individual chooses to take up CommCare, we know that  $W_{ij} \geq p_{ij}$  for at least one plan. Therefore, we can bound their  $W_i^{Ins}$  from below by the cheapest plan's price:

$$\text{Choose } j \neq U : \quad W_i^{Ins} \geq \min_{j \neq U} \{p_{ij}\} \equiv p_i^{min} \quad (8)$$

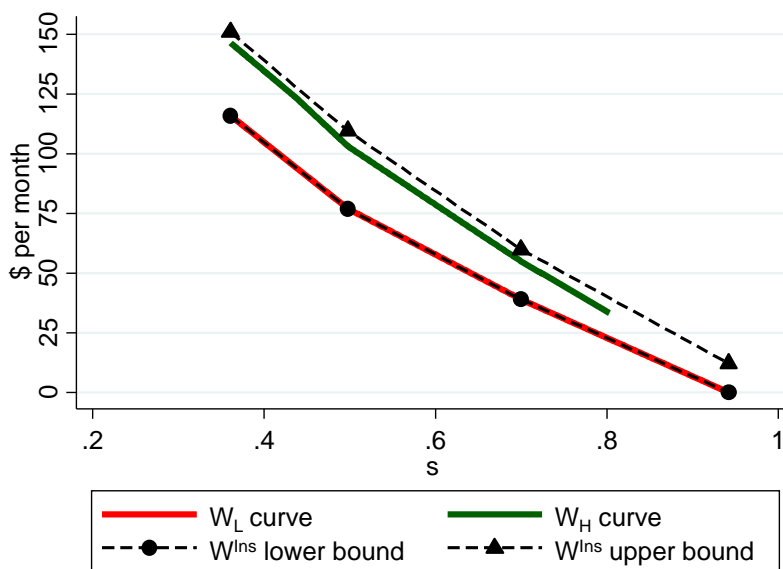
We can now map these bounds into bounds on a  $W^{Ins}$  curve. Let  $s$  be an index that orders people according to decreasing  $W_i^{Ins}$ . Without loss of generality, let the distribution of  $s$  be uniform on  $[0, 1]$ . Let  $W^{Ins}(s)$  denote the WTP for insurance for someone with index  $s$  (i.e., the  $(1 - s)$ th quantile of WTP). Suppose that at a given vector of premiums we observe that  $1 - s^*$  share of people choose  $U$ , while  $s^*$  choose formal insurance. For the marginal type  $s^*$ , both conditions (8) and (7) hold, so we can say that:

$$p^{min} \leq W^{Ins}(s^*) \leq p^{max}$$

We use this result, along with our variation in premiums, to estimate bounds on the  $W^{Ins}(s)$  curve. Specifically, we use the same income discontinuities in premiums discussed above. At each side of the discontinuity, we measure  $p^{min}$  and  $p^{max}$  and estimate  $1 - D_U$ . We then plot  $1 - D_U$  (as x-values) against the bounds  $\{p^{min}, p^{max}\}$  (as y-values) using the points on either side of the discontinuity. As with our estimates of  $W_L$  and  $W_H$ , we implement this exercise at each income level separately and then shift the curves horizontally to line up with the curve for 150% of FPL.

Appendix Figure 17 shows the resulting bounds for  $W^{Ins}$ , with our baseline estimates of  $W_L$

Figure 17: Bounds on Willingness to Pay for CommCare Insurance, 2011



NOTE: Figure shows our estimated bounds for WTP for CommCare ( $W^{Ins}$ ), whose construction is described in the text of Appendix E. The lower and upper bounds for  $W^{Ins}$  are shown in black dashed lines (with the point estimates shown in circles and triangles, respectively). For comparison, the graph shows our baseline estimates of  $W_L$  (solid red line) and  $W_H$  (solid green line) that were derived using the vertical model.

and  $W_H$  from the vertical model shown for comparison. The estimated bounds are relatively tight and quite close to the  $W_L$  and  $W_H$  curves. Indeed, the lower bound on  $W^{Ins}$  is identical to  $W_L$  by construction; both are generated by plotting the share purchasing formal insurance versus the premium of the cheapest plan ( $L$ ). The upper bound on  $W^{Ins}$  is above  $W_H$ , but only slightly higher – a result that does not occur by construction but reflects the fact that the premiums of the  $H$  plans are quite similar and that few people choose  $L$ . From this exercise, we conclude that our basic estimates of (low) willingness to pay for CommCare insurance are robust to relaxing the vertical model assumptions.

Relaxing the vertical model assumptions for estimating costs is more challenging. Intuitively, our vertical model assumes we can pool the four non-CeltiCare plans into a single composite  $H$  option for which a type- $s$  individual has a single expected cost  $C_H(s)$ . As premiums for  $H$  increase slightly, individuals of a single  $s$  type ( $s_{HL}^*$ ) leave the plan, and we can estimate  $c_H(s_{HL}^*)$  using average costs before and after the change. However, it is also possible that some individuals may switch *among* the plans within  $H$  as premiums change. If we weaken the composite plan assumption, this switching could have an independent effect on  $AC_H$  and  $TC_H$ . In practice, however, we expect any bias to our cost estimates from any switching among  $H$  plans to be small. First, there is little reason to expect significant switching, since the premiums of the  $H$  plans are nearly identical to each other on both sides of the income thresholds (see Appendix Table 5). Second, given the similarity of  $C_H(s)$  and  $C_L(s)$  (see Figure 13), it seems unlikely that cost differences among the (much more similar)  $H$  plans for a given  $s$  type would be large.

## Appendix F: Calibration of Individual’s Costs if Uninsured

Figure 18 compares individual’s willingness to pay ( $W_H$ ) not only to the cost to the insurer ( $C_H$ ) but also to estimates of the cost the individual would pay if they were uninsured, which we denote by  $C_U^{OOP}$ .

To construct  $C_U^{OOP}$ , we proceed in two steps. First, we construct a cost curve that is adjusted for moral hazard,  $C_H^{NoMH}(s) \equiv \frac{C_H(s)}{1+\phi}$ , where  $\phi = 25\%$  assumes that having health insurance increases costs by 25%.<sup>45</sup> This is denoted in Figure 18 by  $C_H^{NoMH}(s)$ . Second, we multiply by the percentage of medical costs,  $p$ , that uninsured individuals pay for medical care. The resulting cost curves  $C_U^{OOP}(s) = p \cdot \frac{C_H(s)}{1+\phi}$ , reflects the expected cost that a type  $s$  would pay out-of-pocket if uninsured – which is lower than the expected cost  $C_H(s)$  imposed on the insurer. Figure 18 shows the resulting cost curve for  $p = 20\%$ , motivated by estimates from existing literature (Coughlin et al. 2014; Hadley et al. 2008; Finkelstein, Hendren, and Luttmer, 2015).

The expected out-of-pocket costs of the uninsured ( $C_U^{OOP}$ ) is much more comparable to willingness to pay and consistent with WTP reflecting out-of-pocket costs if uninsured plus a risk premium, as would be implied by a neoclassical model of insurance. However, strong conclusions from this calculation should be taken with caution, as it requires two parameters ( $p$  and  $\phi$ ) that are uncertain and are not directly estimated in our setting.

## Appendix G: Heterogeneity Analysis

We explore several dimensions of possible heterogeneity in willingness to pay and the gap between willingness to pay and insurer costs. First, we show that willingness to pay is lower – and the gap between willingness to pay and insurer costs is larger – for individuals who live closer to safety net providers. This is consistent with a role for access to uncompensated care in reducing willingness to pay, although naturally there may be other differences across areas that could explain the findings.

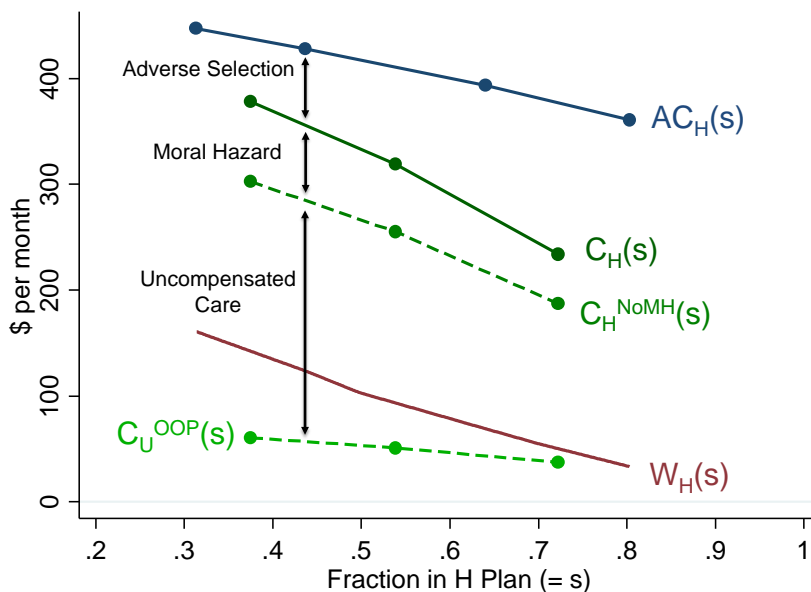
Second, we show that willingness to pay is lower – and the gap between willingness to pay and insurer costs is larger – for lower income individuals. This is consistent with behavioral biases that are larger for lower income individuals and/or greater access to uncompensated care by lower income individuals. Again, of course, an important caveat is that individuals who vary in income may vary in other ways that could separately explain these findings.

**Variation by Proximity to Safety Net Providers** We analyze how willingness to pay and costs vary with physical proximity to safety net providers. Certain providers have a reputation for generosity towards poor uninsured patients – notably, Community Health Centers (CHCs) and certain “safety net” hospitals, the largest of which in Massachusetts is Boston Medical Center (BMC). We therefore analyze WTP and costs for subgroups of enrollees based on their location of residence relative to these providers.

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<sup>45</sup>In Section 5 we discuss two independent back of the envelope calculations that suggest that this is a reasonable approximation for the moral hazard effects of CommCare coverage for previously uninsured individuals. One is based on estimates of impacts of copays in CommCare on health care spending from Chandra et al. (2014), and one is based on impacts of Medicaid on healthcare spending in the Oregon Health Insurance Experiment from Finkelstein et al. (2012)).

Figure 18: Calibration: Cost Curve Adjusted for Moral Hazard and Uncompensated Care



NOTE: Figure reproduces  $W_H(s)$ ,  $AC_H(s)$  and  $C_H(s)$  curves from figure 13. In addition, it shows results of a back-of-the-envelope calibration showing the role of moral hazard and uncompensated care. Adverse selection reflects the gap between the average cost ( $AC_H$ ) and cost of marginal enrollees ( $C_H$ ). Moral hazard reflects the effect of insurance to increase utilization (which we assume to be about 25%); the cost curve without moral hazard is denoted  $C_H^{NoMH}(s)$ . Uncompensated care reflects the share of health care costs incurred by the uninsured covered by third parties, assumed to be 80%; the resulting expected out-of-pocket costs of the uninsured is denoted  $C_U^{OOP}(s)$ .

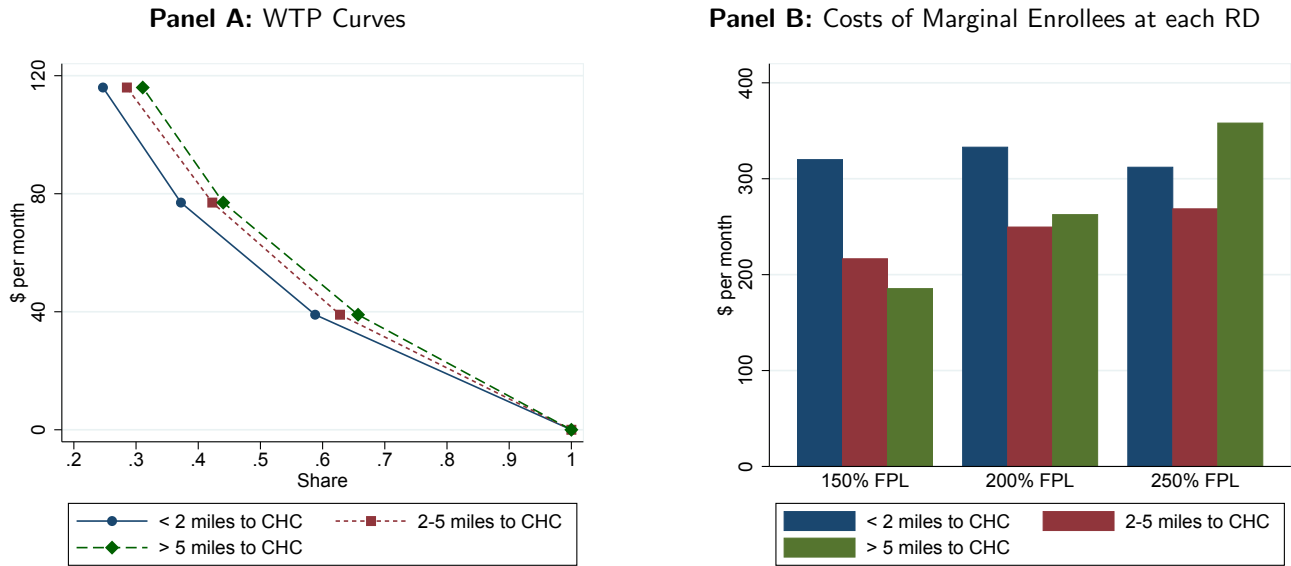
We identify CHCs in Massachusetts using a provider network list posted by the CommCare exchange for 2013.<sup>46</sup> We code enrollee distance to the nearest CHC using Google Maps driving distance from the centroid of their zip code of residence to the CHC’s zip code. About 33% of our sample lives within 2 miles of a CHC, and another 27% live within 2-5 miles. We also analyze the data for Boston-area residents based on proximity to Boston Medical Center (BMC) or one of its affiliated CHCs. Specifically, we define 13 zip codes containing these BMC providers (and one adjacent zip code) as “nearby BMC” and analyze these versus other zip codes in the Boston area, defined as within 10 miles of the city center.<sup>47</sup>

Because power is a concern (especially for costs), we implement our RD analysis on the pooled 2009-13 dataset. We report two sets of analyses. First, we run enrollment count RD regressions (analogous to Figure 5) and calculate the percent decrease in enrollment at each of the income thresholds. A larger fall in enrollment indicates a more elastic (flatter) WTP curve. To visualize the resulting WTP curves, we normalize share enrolled to be 1.0 when insurance is free (just below 150% of FPL) and compute subsequent shares by sequentially scaling down by the percent change in enrollment at each

<sup>46</sup>We are happy to share this list on request. A slightly more recent (but nearly identical) list for 2015 is available at the Connector’s website: <https://betterhealthconnector.com/wp-content/uploads/ConnectorCare-2015-Hospital-CHC-List.pdf>

<sup>47</sup>Specifically, the zip codes defined as “nearby BMC” are 02118, 02119, 02120, 02121, 02122, 02124, 02125, 02126, 02127, 02128, 02130, 02131, 02210. These zip codes approximately extend from East Boston and South Boston down to Roxbury, Dorchester, and Mattapan.

Figure 19: Variation by Proximity to a Community Health Center



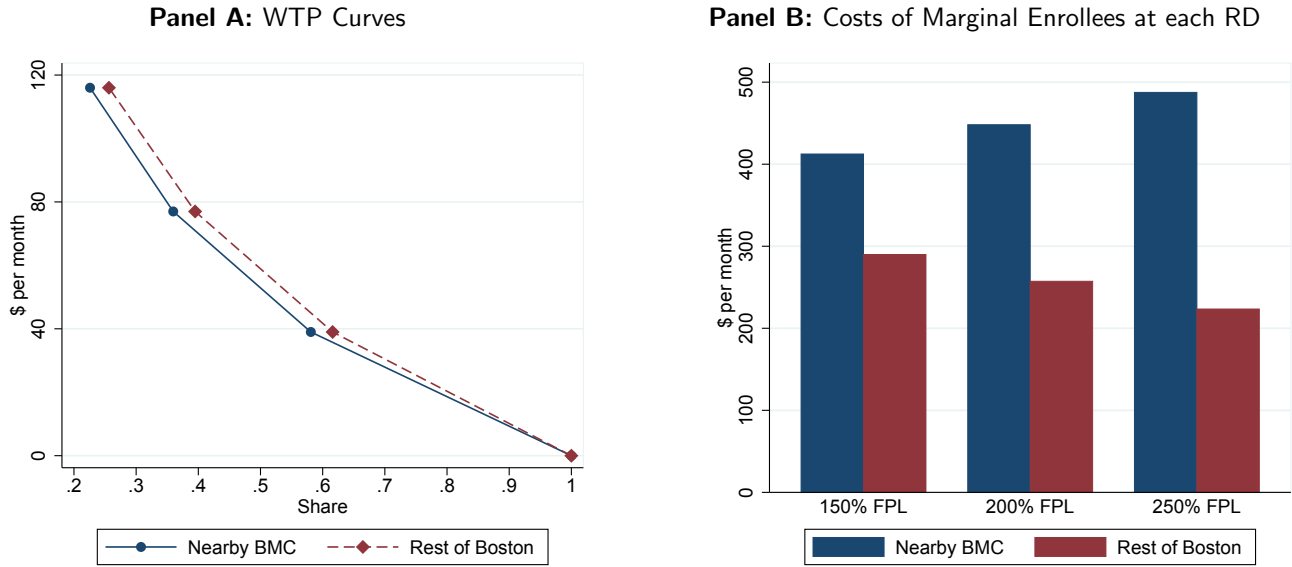
NOTE: The figure shows WTP curves (panel A) and marginal enrollees' costs (panel B) for different subgroups of enrollees based on their proximity of their residence to a Community Health Center in Massachusetts. All analyses are based on pooled 2009-2013 data. As discussed in text, the WTP curve is constructed using RD estimates of the percent change in enrollment at each income threshold where premiums increase. The cost estimates are calculated using RD estimates of average costs and the enrollment change.

RD. We plot these shares against the premiums they correspond to. The results are shown in panel A of Figures 19 and 20. In both cases, the WTP curves are modestly more elastic – i.e., enrollment falls more at each premium increase – for enrollees living closer to either CHCs or Boston Medical Center.

For our second analysis, we report marginal costs for people who drop insurance at each of our RD income thresholds – calculated from average cost RDs and the percent change in enrollment. Because WTP for the marginal enrollees is by definition fixed (it lies between the lower and higher premium), higher marginal costs for a subgroup indicates a larger gap between WTP and costs. Panel B of Figures 19 and 20 show these cost estimates at each income RD. For CHCs, at two of three thresholds, costs are higher for people living within 2 miles of a CHC, though the reverse is true for the 250% FPL threshold. For proximity to BMC, the cost differences are much larger and more consistent; marginal enrollees living nearby BMC have higher costs by at least +30% at every threshold.

**Variation by Income** We also examine how our demand and cost estimates vary by income. We use the fact that our regression discontinuities give us estimates of willingness to pay and average cost curves for three income groups, 150%, 200% and 250% of poverty. In our main analysis, we shifted these groups' line segments to align with 150% of poverty (see Figures 10 and 12 for a visualization). It is straightforward to implement this same method but instead align everything with 200% or 250% of FPL. Figure 21 shows the results. It shows that the 150% FPL group has the lowest WTP and highest cost, and therefore the biggest gap between WTP and costs. This gap shrinks for higher-income groups. This pattern holds outside our sample too: our finding of willingness to pay below

Figure 20: Variation by Proximity to Largest Safety Net Hospital (BMC)



NOTE: The figure shows WTP curves (panel A) and marginal enrollees’ costs (panel B) for different subgroups of enrollees based on their proximity of their residence to Boston Medical Center (the largest safety net hospital in MA) or its affiliated health centers. The analysis is restricted to people living in the Boston area, defined as within 10 miles of the city center. All analyses are based on pooled 2009-2013 data. As discussed in text, the WTP curve is constructed using RD estimates of the percent change in enrollment at each income threshold where premiums increase. The cost estimates are calculated using RD estimates of average costs and the enrollment change.

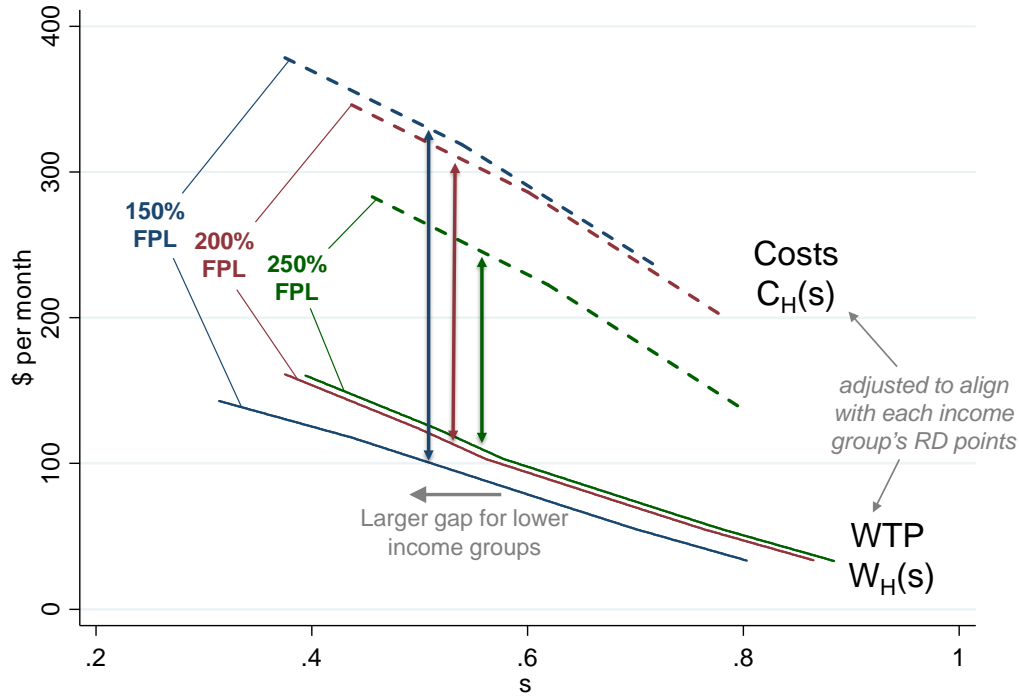
insurer costs for the low-income population in Massachusetts contrasts with Hackmann, Kolstad, and Kowalski (2015)’s estimate that higher-income individuals in Massachusetts (above 300% of FPL) are willing to pay the cost they impose on the insurer.

Both behavioral biases and access to uncompensated care may play a larger role for lower income populations. Behavioral biases may be particularly acute among low-income populations who may be making purchase decisions under greater constraints or stress (Mani et al. (2013); Mullainathan and Shafir (2014); Bhargava et al. (2017)). Lower-income individuals also typically have access to more uncompensated care – both from ex-ante charitable providers and from ex-post bad debt – than higher income individuals (e.g. (Mahoney, 2015; Dranove et al., 2015)). In addition, non-profit hospitals typically have explicit policies that they will give free or discounted care to uninsured patients with incomes below certain thresholds (often around 150-200% of FPL).

Consistent with lower-income groups having more access to uncompensated care, in our data it appears that lower-income marginal enrollees tend to use types of healthcare that is more “amenable” to uncompensated care than higher income marginal enrollees. To see this, we decompose the costs of marginal enrollees at each of our three income RD thresholds. Different types of health care vary in how “amenable” they are to uncompensated care – i.e., how likely uninsured patients can access them at free or discounted fees. Using our underlying claims data, we decomposed claims into categories based on our sense of how amenable they are to uncompensated care. Guided in part by reports like Coughlin et al. (2014) that characterize the nature of uncompensated care, we grouped the data



Figure 21: WTP and Cost Curves, adjusted to different income levels



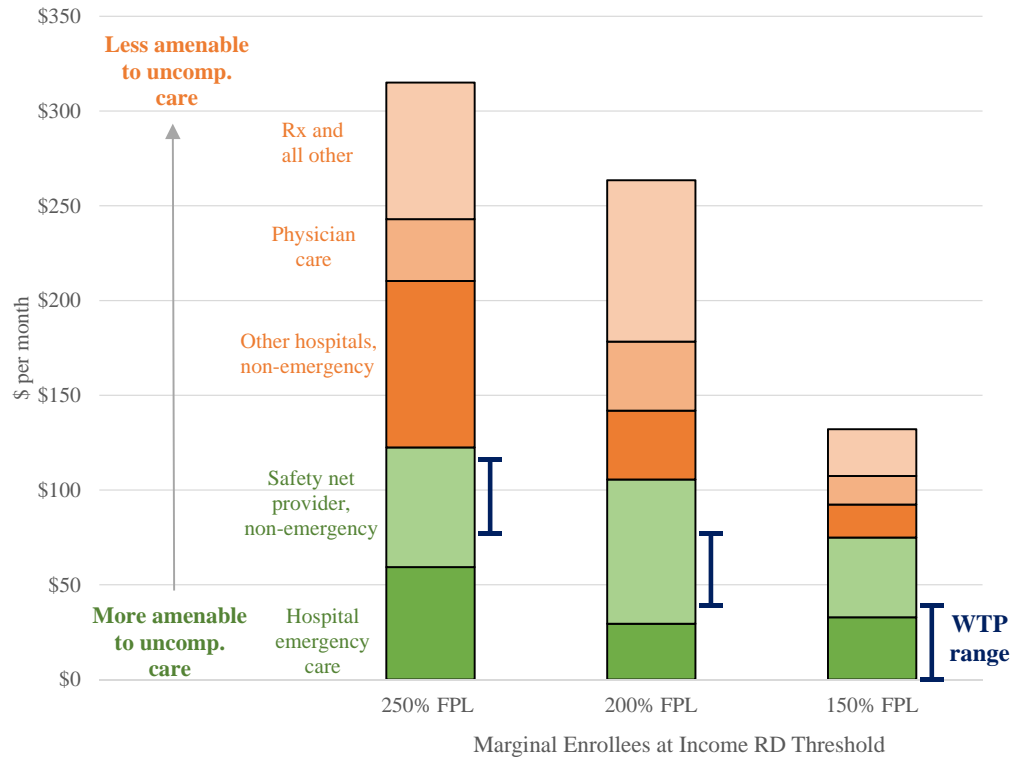
NOTE: These graphs show the adjusted WTP ( $W_H$ , solid lines) and cost curves ( $C_H$ , dashed lines) calculated by adjusting curves to line up with each income group's RD points. Each curve is shown over its in-sample range (no extrapolation).

into the following five categories, in roughly descending order of uncompensated care amenability: (1) hospital emergency care (including ER care and inpatient admissions originating in the ER), (2) non-emergency care (both inpatient and outpatient) provided at a safety net hospital or Community Health Center,<sup>48</sup> (3) non-emergency care provided at other (non-safety net) hospitals, (4) outpatient physician care, and (5) prescription drugs and all other care (where drugs are about 2/3 of this category). Our sense is that categories 1 and 2 are more amenable to uncompensated care, while the remaining categories are less so. For each category, we computed average costs in each income bin and ran RD regressions on the pooled 2009-13 data similar to our main analysis. We used the average cost values just below and above each discontinuity, along with the change in enrollment at the threshold, to calculate costs of the marginal enrollees who drop out when premiums increase.

Figure 22 shows the resulting estimates. The three bars show costs of marginal enrollees at 150%, 200%, and 250% FPL (in reverse order). Next to each bar we show the range of WTP for the marginal population (i.e., the premium below and above each threshold). The results indicate that lower-income (and lower-WTP) groups have a larger share of their costs in more amenable categories. For instance, emergency and safety net care (the green segments) comprise 57% of costs for marginal enrollees at 150% of FPL (whose WTP is between \$0-39) versus 39% of costs at 250% of FPL (whose WTP is between \$77-116). Most of the increment in costs for the 250% FPL vs. 150% FPL marginal enrollees

<sup>48</sup>Following a categorization defined by Massachusetts' Center for Health Information and Analysis, we defined "safety net hospitals" as hospitals with a high share of patients who are uninsured or covered by public payers.

Figure 22: Breakdown of Costs of Marginal Enrollees



NOTE: The graph shows a decomposition of costs of marginal enrollees at each of our three income thresholds (150%, 200%, and 250% FPL) where premiums increase. Costs are broken down into five categories, roughly based on how “amenable” they are to being delivered to the uninsured as uncompensated care. More amenable categories are hospital emergency care and safety net provider non-emergency care (labeled on the graph and shown in green); less amenable categories are other hospital non-emergency care, physician care, and Rx/all other (shown in orange). The bars indicate the range of WTP for marginal enrollees at each income threshold. All analysis is based on the pooled 2009-2013 data.

comes from growth in less amenable (orange) categories.

## Appendix H: Approximating the Moral Hazard Effects of CommCare coverage for the low-income uninsured

We translate the estimates of moral hazard in CommCare from Chandra et al. (2014) into an estimate we can use to estimate the impact of insurance coverage on utilization. Chandra et al. (2014) study healthcare spending for the low-income adult population in MA’s CommCare from 2007-2009; it is thus the same population we study here, although from an earlier time period. They study an increase in co-payments during this period. Based on this, they estimate that a 1% increase in out of pocket costs causes a 0.16% reduction in total spending. We translate this into an estimate of what Commcare coverage does to healthcare spending.

To do so, let  $m$  denote spending and  $x$  denote out-of-pocket payments (which, in their model, is

only copayments). Assume

$$x = pm$$

where  $p = \frac{x}{m}$  is the co-insurance rate. We want to know how  $m$  changes when we change  $p$ ,  $\frac{dm}{dp}$  or  $\frac{d\log(m)}{dp}$ . But, what Chandra et al. (2014) report from their regression is how  $m$  changes with  $x$ . In particular, they report:

$$\log(m) = \alpha + \beta \log(x) + \epsilon$$

and they estimate  $\beta = 0.16$ .

Note that:

$$\beta = -0.16 = \frac{d\log(m)}{d\log(x)} = \frac{dm}{m} \frac{x}{dx} = p \frac{dm}{dx}$$

Now,

$$d\log(p) = d\log(x) - d\log(m)$$

So,

$$\frac{d\log(m)}{d\log(p)} = \frac{1}{\left[\frac{d\log(x)}{d\log(m)} - 1\right]}$$

or

$$\frac{d\log(m)}{dp} = \frac{1}{p} \frac{1}{\left[\frac{d\log(x)}{d\log(m)} - 1\right]}.$$

Therefore, we can plug in our estimate for  $\frac{d\log(x)}{d\log(m)} = \frac{1}{\beta}$  and yield

$$\frac{d\log(m)}{dp} = \frac{-1}{p \left[1 - \frac{1}{\beta}\right]}$$

So, if  $p = 20\%$  (i.e. CommCare corresponds to a 20 percentage point reduction in costs for the insured (because uninsured pay 20% of their costs) and  $\beta = -0.16$  we have

$$\frac{d\log(m)}{dp} = \frac{-1}{.2 * 7.25} = .69$$

So, taking prices from 0.2 to 0 implies a 13.8% ( $=0.69*0.2$ ) reduction in out of pocket spending. Taking a higher price paid by uninsured of 35% implies a 24.2% reduction in prices.

## Appendix I: Willingness to Pay Behind the Veil of Ignorance

One potential concern with comparing willingness to pay to costs is that demand is measured after some information about health risk may potentially have been revealed to the individual. For example, suppose demand is measured after one learns whether or not she has a chronic condition. In this case, observed demand will understate the *ex-ante* value of insurance that would be measured before the individual has learned their risk. Hendren (2017) provides a method for calculating willingness to pay for insurance from behind the veil of ignorance. Instead of using the observed market demand

curve,  $W(s)$ , one uses an “*ex-ante*” demand curve,  $W(s) + EA(s)$ , where  $EA(s)$  captures the value of expanding the size of the insurance market from the perspective of behind the veil of ignorance.

For a linear demand curve, the formula in Hendren (2017) for the *ex-ante* component of willingness to pay is given by  $EA(s) = (1 - s)(C(s) - W(s) - sW'(s))\gamma^{\frac{1-s}{2}}(12 * W'(s))$  where  $\gamma$  is the coefficient of absolute risk aversion and the factor of 12 translates our monthly demand estimates into yearly units. We apply this formula in our context using a conservatively high coefficient of absolute risk aversion of  $5 \times 10^{-4}$  (which corresponds to a coefficient of relative risk aversion of 5 if individuals have \$10,000 of annual consumption). Our estimates suggest that even using an *ex-ante* demand measure and a high value of  $\gamma$ , willingness to pay would still be below own cost. For example, at  $s = 0.50$  we estimate that the marginal welfare impact from behind the veil of ignorance of expanding the size of the insurance market is roughly  $EA(0.5) = 0.5(333 - 103 - 0.5 * (-239))0.0005 * \frac{0.5}{2} * 12 * (-239) = \$63$  higher (i.e., \$163 instead of \$100) than the marginal welfare impact implied by observed demand. Although non-trivial, this is small relative to the approximately \$300 difference between marginal cost and observed demand at  $s = 0.5$ . The intuition for this is that the “risk” of learning that one is a high risk type and must purchase insurance is not exceedingly large when premiums are already heavily subsidized.

## Appendix J: Additional Tables and Figures

We present additional results referenced in the text here. We briefly provide some additional discussion of a few of them.

First, Appendix Figure 23 shows changes in average age of enrollees at the premium discontinuities. The estimated changes in average age are (not surprisingly) more precise than the estimated changes in average costs (Figure 5). An interesting question is how much of the adverse selection observed in Figure 5 is in fact driven by age. Our calculation suggests that age differences can explain only about one-fifth of average cost differences at 150% of poverty, and about one-eighth of cost differences at 200% of poverty. To do this calculation we used the 2009-2013 data to project insurer costs on age (using single year of age dummies). We then used the resulting estimates of expected costs (as a function of age) as the outcome variable in our standard regression discontinuity analysis. We interpret this RD analysis with projected costs as the outcome variable compared to the RD analysis with actual costs as the outcome variable as informing us about the share of adverse selection that can be explained by age.

Second, Appendix Figure 25 shows plan enrollment discontinuities separately by year. In the pooled 2009-2013 data (Panel A of Figure 5) we saw some slight evidence of lower enrollment (relative to the linear slope in income that we fit) to the right of the thresholds. Here, we show results separately by year. The limited bunching (i.e. slightly lower-than-projected enrollment to the right of the threshold) in the pooled figure appears to be driven entirely by 2012 and 2013. This in turn appears to be driven by an annual administrative inflation update to the FPL measure, rather than strategic manipulation by enrollees. Each year in March or April, the state updated the FPL used for calculating income/FPL (our running variable) to reflect the revised HHS value. Because incomes are

Table 5: Premiums by CommCare Plan

CommCare Plan	H / L Plan	Insurer Price (pre-subsidy)	Enrollee Premium (post-subsidy) by Income Group (% of FPL)			
			100-150%	150-200%	200-250%	250-300%
BMC HealthNet	H	\$425	\$11	\$57	\$105	\$146
Fallon	H	\$426	\$12	\$60	\$110	\$151
Neighborhood Health Plan (NHP)	H	\$426	\$12	\$60	\$110	\$151
Network Health	H	\$423	\$10	\$57	\$105	\$146
CeltiCare	L	\$405	\$0	\$39	\$77	\$116

NOTE: The table shows enrollee premiums (by income group range) for each CommCare insurer in the market in fiscal year 2011. The top four plans – which we pool into an “H” plan in our analysis – all have very similar premiums because their (pre-subsidy) price bids were nearly identical, having been constrained by a binding price ceiling.

recorded in nominal terms, a higher FPL automatically reduced incomes as a % of FPL. However, the state only immediately updated the administrative income/FPL variable when it made a difference for subsidies – i.e., when it moved people from just above to just below 150%, 200%, or 250% of FPL. In other cases, they waited for annual income audits to update the income/FPL variable. This administrative update therefore mimics strategic bunching. Consistent with this explanation, in results not shown, we found a sharp increase in bunching among current enrollees in March-April of 2012 and 2013, which fades away to nil over the rest of the year (as other enrollees’ incomes are audited and updated). We see no evidence of bunching among new enrollees (whose income is newly reported so not affected by this policy) in *any* year, including 2012 and 2013. Finally, this administrative update does not affect the data in 2009-2011 for a simple reason: there was no inflation update to the FPL in 2009 or 2010, and the inflation update in 2011 was very small (+0.6%, vs. +2.6-2.9% in 2012-13). We thank Michael Norton of the Connector for alerting us to this policy and helping us reconcile our findings with it.

Table 6: Summary of Estimates, 2011

Variable	150% FPL			200% FPL			250% FPL		
	Below	Above	$\Delta$	Below	Above	$\Delta$	Below	Above	$\Delta$
<b>Sticker Premium (Monthly)</b>									
$P_U$ (Expected)		\$9.5	--		\$28.5	--		\$48.0	--
$P_L$	\$0.0	\$39.0	+\$39	\$39.0	\$77.0	+\$38	\$77.0	\$116.0	+\$39
$P_H$	\$11.0	\$57.9	+\$47	\$57.9	\$106.3	+\$48	\$106.3	\$147.3	+\$41
$P_H - P_L$	\$11.0	\$18.9	+\$8	\$18.9	\$29.3	+\$10	\$29.3	\$31.3	+\$2
<b>Normalized Premium (Monthly)</b>									
$P_L$	-\$9.5	\$29.5	+\$39	\$10.5	\$48.5	+\$38	\$29.0	\$68.0	+\$39
$P_H$	\$1.5	\$48.4	+\$47	\$29.4	\$77.8	+\$48	\$58.3	\$99.3	+\$41
<b>Market Shares</b>									
Any Insurance	0.94	0.70	-0.24	0.76	0.56	-0.20	0.58	0.44	-0.14
H Plan	0.80	0.64	-0.16	0.70	0.50	-0.20	0.52	0.39	-0.12
L Plan	0.14	0.06	-0.08	0.06	0.06	0.00	0.06	0.05	-0.01
<b>Average Cost (Monthly)</b>									
Any Insurance	\$333	\$380	+\$47	\$355	\$386	+\$31	\$328	\$343	+\$15
H Plan	\$361	\$393	+\$32	\$371	\$405	+\$35	\$345	\$365	+\$20
L Plan	\$169	\$242	+\$73	\$170	\$225	+\$55	\$175	\$153	-\$22

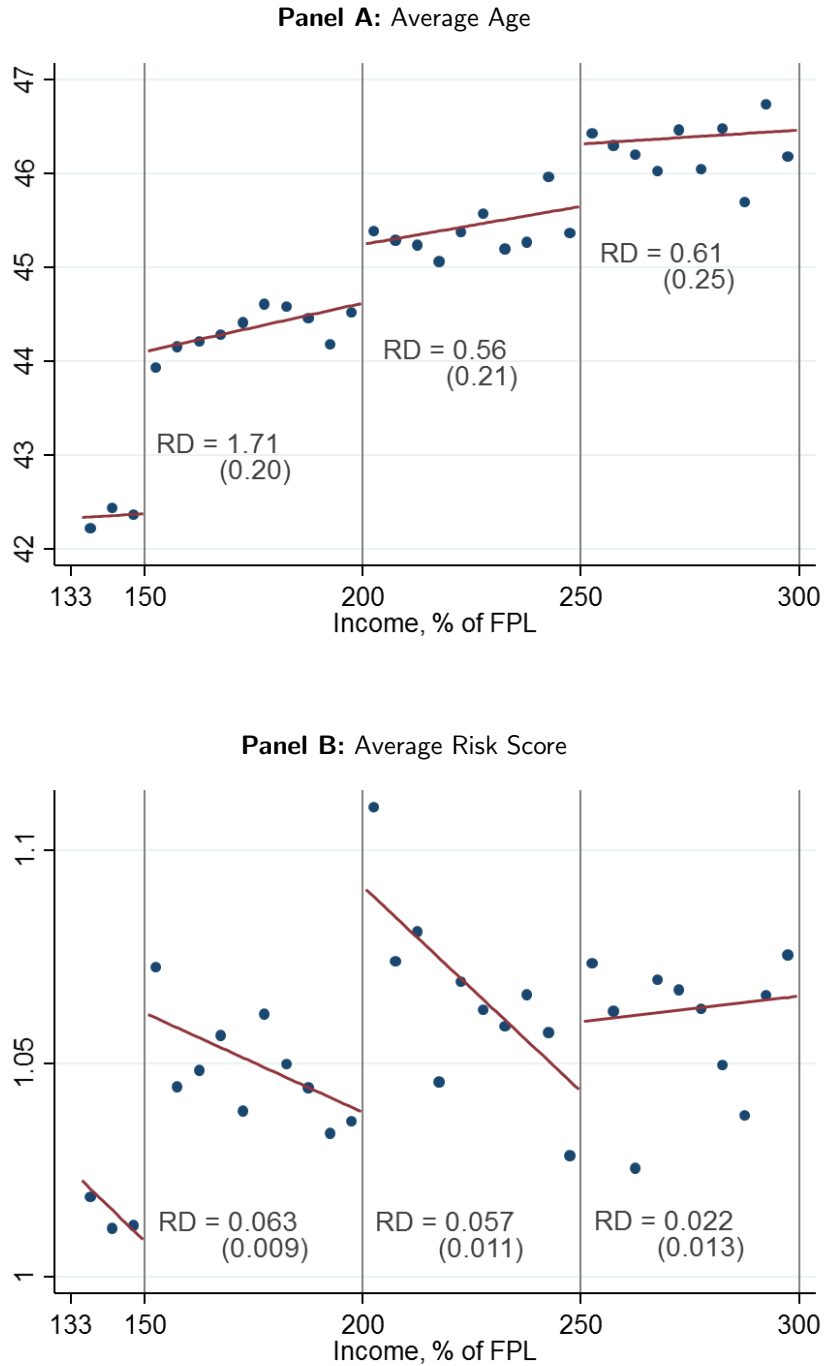
NOTE: This table summarizes the inputs into our estimates of willingness to pay and cost curves. For each income threshold at which premiums change, table shows the monthly enrollee premium, estimated market share, and average monthly insurer costs just below and above the threshold, as well as the change across the threshold. The premiums reported in the first two panels were previously presented in Figure 3. The first panel shows sticker premiums for  $U$  (the expected mandate penalty), the  $L$  plan,  $H$  plan, and the difference  $p_H - p_L$ ; we use these for our main demand estimates. The second panel shows “normalized” premiums, where  $p_U$  has been normalized to \$0, which we use for robustness analysis. The third and fourth panels report changes in market shares and average insurer costs based on RD estimates of equation (1); these results for any insurance and  $H$  plan were previously shown in the main text in Figures (7) and (8), respectively. The results for the  $L$  plan are in Appendix Figure 24.

Table 7: Willingness to Pay and Costs (\$ per month)

Point in WTP Distribution		WTP		Costs	
		$W_L(s)$	$W_H(s)$	$C_H(s)$	$AC_H(s)$
Min In-Sample	(s = 0.94)	\$0	\$5	\$148	\$334
20th Percentile	(s = 0.80)	\$23	\$34	\$203	\$362
40th Percentile	(s = 0.60)	\$58	\$79	\$291	\$400
Median	(s = 0.50)	\$77	\$103	\$333	\$417
60th Percentile	(s = 0.40)	\$105	\$135	\$369	\$434
Max In-Sample	(s = 0.31)	\$131	\$162	\$399	\$448

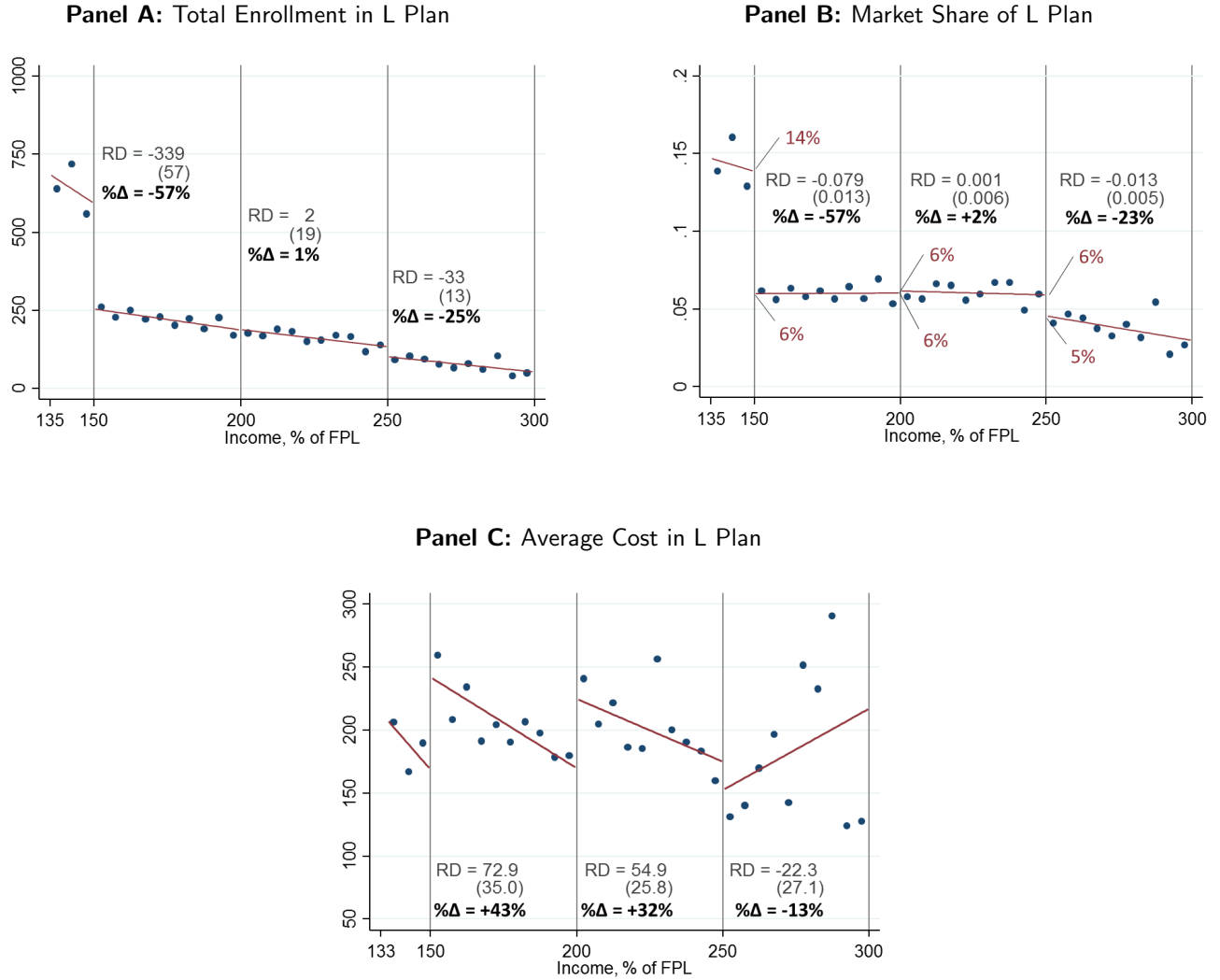
NOTE: Table summarizes our estimates of willingness to pay and costs for individuals at 150 percent of the FPL shown in Figure 13.

Figure 23: RD for Age and Risk Scores for Enrollees in All Plans, 2009-2013



NOTE: These graphs show RD estimates for the average age (panel A) and risk score (panel B) of CommCare enrollees in all plans, pooled over the 2009-2013 period of our data. Risk scores are calculated by CommCare to reflect a person's expected medical spending based on their age, sex, and medical diagnoses. They are used by CommCare to adjust payments to insurers for their enrollees. Risk score values are relative to an average enrollee (whose risk score is 1.0) – e.g., a risk score of 1.05 indicates expected costs 5% above average.

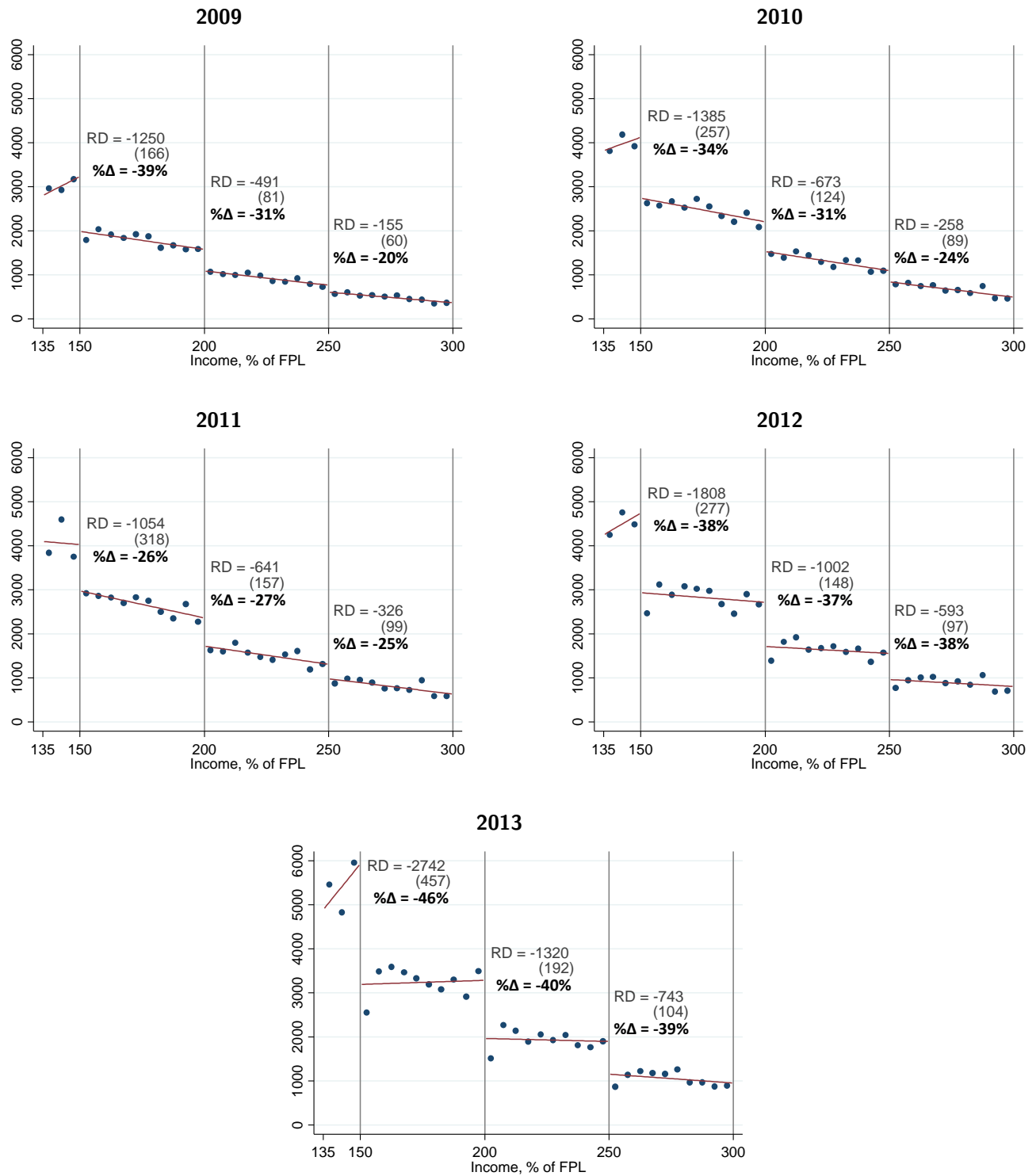
Figure 24: RD Estimates for L Plan, 2011



NOTE: Figures show our RD estimates for total enrollment, market shares, and average costs for the *L* plan in 2011, analogous to the estimates for all plans and the *H* plan in Figures 6-8 of the main text.

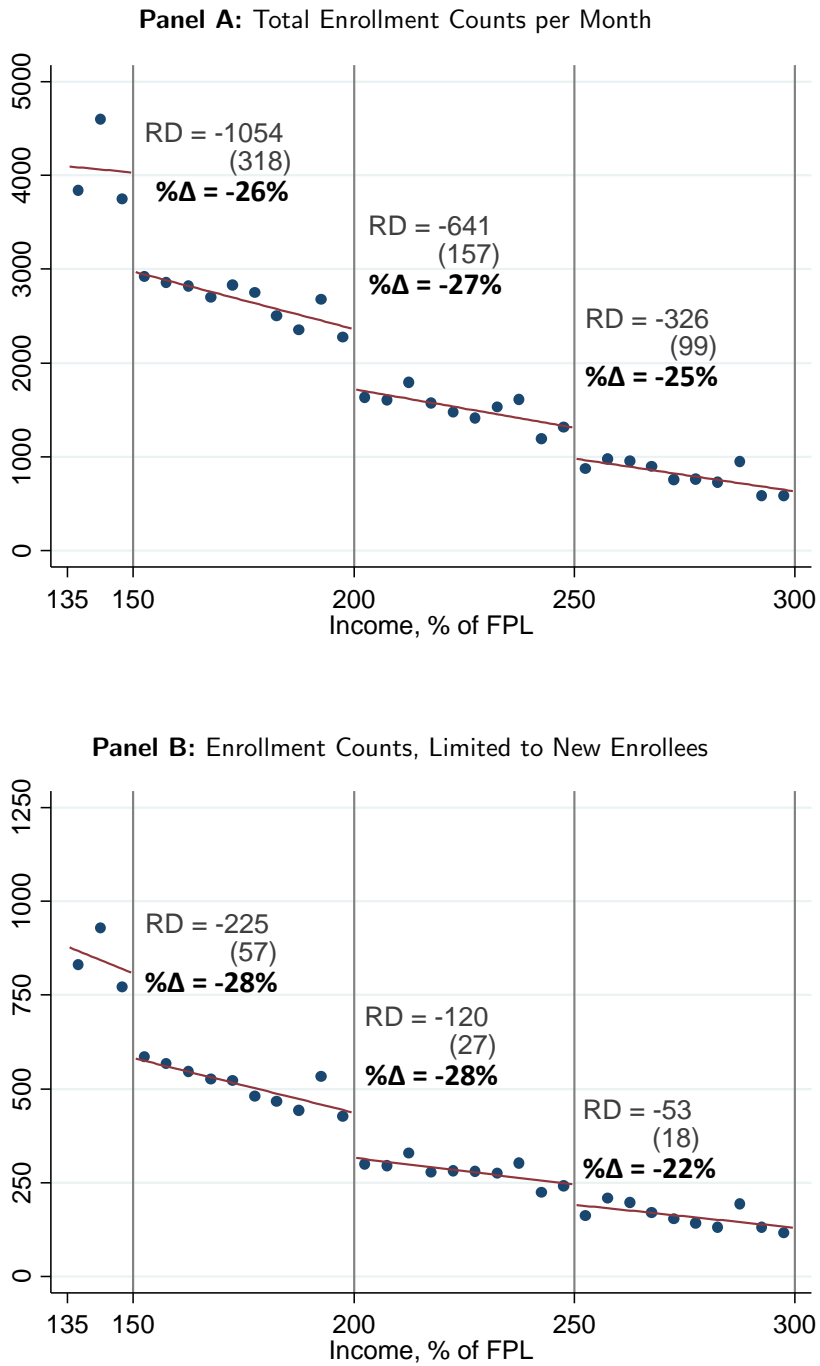


Figure 25: Total Enrollment Counts in CommCare, by Year



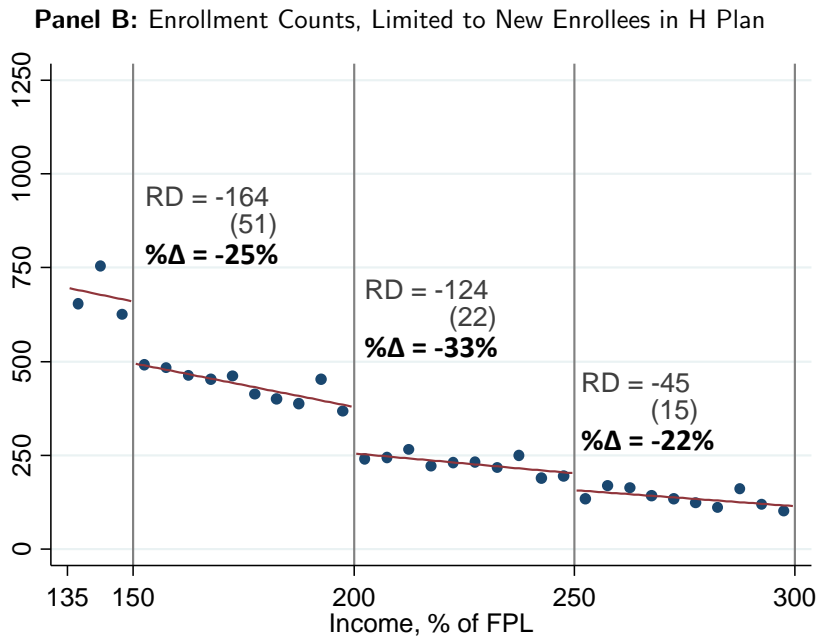
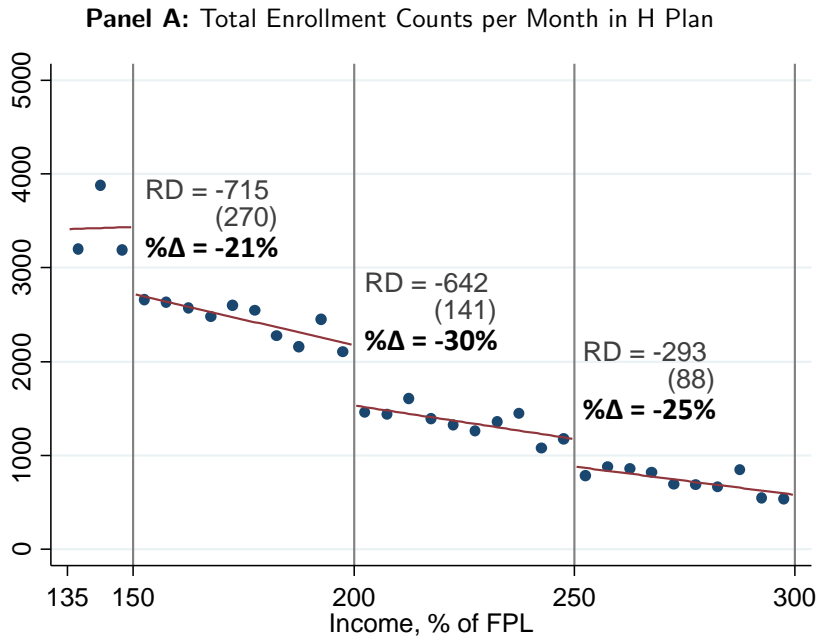
NOTE: The graph shows our baseline regression discontinuity analysis for total enrollment counts per month from Figure (5), Panel A (which showed results pooled for 2009-2013). Here, we show results separately by year.

Figure 26: Enrollment Counts in 2011, by Income



NOTE: These graphs are identical to Figure 25 but applied to counts of enrollees, but Panel B is limited to just new enrollees in CommCare during 2011.

Figure 27: Enrollment Counts in 2011 for *H* Plan, by Income



NOTE: These graphs are identical to Figure 26 but applied to counts of enrollees in the *H* plan only.