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Bankruptcy as Implicit Health Insurance

by

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Abstract

This paper examines the interaction between health insurance and the implicit insurance that people have because they can file (or threaten to file) for bankruptcy. With a simple model that captures key institutional features, I demonstrate that the financial risk from medical shocks is capped by the assets that could be seized in bankruptcy. For households with modest seizable assets, this implicit "bankruptcy insurance" can crowd out conventional health insurance. I test these predictions using variation in the state laws that specify the type and level of assets that can be seized in bankruptcy. Because of the differing laws, people who have the same assets and receive the same medical care face different losses in bankruptcy. Exploiting the variation in seizable assets that is orthogonal to wealth and other household characteristics, I show that households with fewer seizable assets are more likely to be uninsured. This finding is consistent with another: uninsured households with fewer seizable assets end up making lower out-of-pocket medical payments. The estimates suggest that if the laws of the least debtor-friendly state of Delaware were applied nationally, 16.3 percent of the uninsured would buy health insurance. Achieving the same increase in coverage would require a premium subsidy of approximately 44.0 percent. To shed light on puzzles in the literature and examine policy counterfactuals, I calibrate a utility-based, micro-simulation model of insurance choice. Among other things, simulations show that "bankruptcy insurance" explains the low take-up of high-deductible health insurance.

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1 Introduction

There is a large literature in economics evaluating the effects of government policy on health insurance coverage in the United States.[1] The question of why households choose to be uninsured is less well understood.[2] To better understand the insurance coverage decision, this paper examines a mechanism that has received little attention: implicit insurance from the threat-point of personal bankruptcy.

The implicit insurance from bankruptcy arises from the confluence of three factors. First, due to federal law, hospitals are required to provide emergency treatment on credit—and typically provide non-emergency care without any upfront payment as well. Second, under Chapter 7 of the U.S. bankruptcy code, households can discharge medical debt, giving up assets above asset exemption limits in return.[3] Third, because of the deadweight cost of the bankruptcy process, households and creditors have an incentive to negotiate payments without a formal bankruptcy filing.

Bankruptcy, as a result, provides households with a form of high-deductible health insurance. Households are exposed to the financial risk from medical shocks up to the level of assets that can be seized in bankruptcy and insured against financial risk above this level.

Summary data on the uninsured suggest that this mechanism could be important. Figure 1 shows that uninsured households have vastly fewer seizable assets than households with private insurance. Sixty-three percent of the uninsured would give up less than $5,000 in a bankruptcy filing, compared to only 28 percent of the privately insured. Figure 2 shows that payments by the uninsured are substantially lower when receiving a high volume of medical care. While payments by the privately insured scale up proportionally with medical charges, payments by the uninsured are capped on average at just over $5,000.

To more rigorously examine the mechanism, I construct a simple model of bankruptcy, medical billing, and insurance choice. The model predicts that, conditional on wealth, out-of-pocket

[1] See Gruber and Simon (2008) for review of the take-up and crowd-out effects of public insurance expansions. See Gruber (2005) for a review of the impact of tax subsidies on the employer provision of insurance. See Liu and Chollet (2006) for a review of the effects of tax policy on insurance take-up in the non-group market.

[2] In a review of the literature Gruber (2008) concludes, "there are a variety of hypotheses for why so many individuals are uninsured, but no clear sense that this set of explanations can account for the 47 million individuals."

[3] The Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005 was implemented after the period I analyze. It prevents households with more than the state median income from filing under Chapter 7 in most circumstances. The households most affected by the reform are unlikely to be marginal to the mechanism I analyze.

medical payments should be decreasing in the level of seizable assets for a given volume of medical care received. Holding wealth constant, households with fewer seizable assets should be less likely to purchase conventional coverage.

I test these predictions using variation in the state-level asset exemption laws that specify the type and level of assets that can be seized in bankruptcy and detailed asset data from the restricted access Medical Expenditure Panel Survey (MEPS) and the Panel Survey of Income Dynamics (PSID). The degree of cross-state variation in the asset exemption laws in substantial. Kansas, for example, allows households to exempt an *unlimited* amount of home equity and up to $40,000 in vehicle equity. Neighboring Nebraska allows households to keep no more than $12,500 in home equity or a $5,000 wildcard of any type of asset. Both states allow households to keep retirement assets. I construct a simulated instrument that isolates the variation in seizable assets solely due to these laws, mechanically purging variation due to wealth and other household characteristics.

Using this source of variation and cost data from the MEPS, I find that uninsured households with fewer seizable assets make lower out-of-pocket payments for a given level of medical care received. My preferred estimate indicates that a log point drop in seizable assets reduces out-of-pocket payments by 37 percent. Consistent with the high-deductible nature of this insurance, the drop is larger for households that utilize more medical services as the "deductible" of this implicit insurance is more likely to bind.

Using the same source of variation and MEPS and PSID data, I find that households with fewer seizable assets are less likely to have insurance. The estimates suggest that if the bankruptcy laws of the least debtor-friendly state of Delaware were applied nationally, 16.3 percent of the uninsured would buy health insurance. With a take-up semi-elasticity of -0.084 from the literature, achieving the same increase in take-up would require a premium subsidy of 44.0 percent.[4]

I use three strategies to address the concern that asset exemption laws may be correlated with unobserved state-level factors. The first strategy is to use variation due to 1920 homestead exemptions as an instrument. By using homestead exemptions from before the era of widespread health insurance, the instrument alleviates potential bias from factors that might have simultaneously caused changes in asset exemption law and the dependent variables over the course of

[4]The -0.084 estimates is taken from Congressional Budget Office (2005) and is based on premium variation due to state-level community rating and premium compression regulations. As I discuss below, this estimate is in the center of the range in the literature.

the twentieth century. Moreover, historical evidence (e.g., Goodman, 1993) showing that 1920 homestead exemption levels resulted from an idiosyncratic array of nineteenth century historical circumstances diminishes the concern that this variable merely proxies for a persistent state characteristic (such as the strength of a pro-debtor political movement).

The second strategy is to sequentially add fixed effects for Census Regions (e.g., Northeast) and Census Divisions (e.g., New England) to the main specification. If a spatially correlated unobserved factor is driving the findings, the results should change with the inclusion of these covariates. Stable estimates across these specifications mitigate this concern. The third strategy is to add controls for a rich set of potentially relevant legislative factors. The fact that the estimates are uncharged by the inclusion of these covariates provides further support for the case that the identifying variation is uncorrelated with unobserved state-level determinants of costs and coverage.

I take the analysis a step further by calibrating a utility-based, micro-simulation model of insurance choice. The model is based on a nationally representative sample of households. Households face household-specific medical shock distributions that depend on the age and sex of each household member. To maximize their expected utility over wealth, households choose to either purchase conventional insurance at market premiums or rely on the high-deductible insurance from bankruptcy.

I use this model to shed light on puzzles in the health policy literature. One of the puzzles I examine is the low take-up of high-deductible health plans (HDHP) by the uninsured (Fronstin and Collins, 2008). Proponents of these plans have argued that by offering lower premiums, HDHPs would expand coverage among the uninsured. But because the implicit insurance from bankruptcy often resembles a high-deductible policy, HDHPs are relatively more likely to be crowded out by this mechanism. In the micro-simulation model, accounting for bankruptcy reduces the percentage of uninsured households projected to purchase a $1,000 deductible plan by 13 percentage points. For a $5,000 deductible plan, bankruptcy reduces demand by 37 percentage points, or from 43 to 6 percent.

A second puzzle I examine is heterogeneity in the demand for coverage. Without bankruptcy, households with and without insurance coverage are difficult to separate. Using variation in medical risk, tax exemptions, and administrative costs, the model can separate the predicted coverage levels of uninsured and insured households by only 14 percentage points. Because there are large differences in seizable assets across these groups, accounting for bankruptcy has a substantial incremental effect, widening the gap in predicted coverage from 14 to 51 percentage points.

The mechanism I study may be relevant to policy design. On the one hand, the implicit insurance from bankruptcy has obvious inefficiencies. Uninsured households receive a substantial amount of non-emergency medical care in emergency rooms, which are obviously not optimized for this purpose (Delgado et al., 2010). At the same time, these households receive less preventative care than they would with conventional health insurance (Institute of Medicine, 2002). There are deadweight costs to negotiation and collections under the threat-point of bankruptcy. And the fact that uninsured households are not exposed to the social cost of this implicit insurance means that too many households choose to be uninsured.

Yet conventional health insurance has inefficiencies of its own. A particularly interesting inefficiency relative to bankruptcy insurance is moral hazard. With conventional insurance, medical providers and patients often have incentives to supply and demand excess medical care. Under the implicit insurance from bankruptcy, however, physicians are more likely to be exposed to the social cost of their decisions and patients have little leverage to demand excess treatment. The result is that bankruptcy may be a lower moral hazard form of social insurance.[5]

While a comprehensive analysis of the costs and benefits of bankruptcy is overly ambitious, I can examine one key tension between these forms of insurance with the micro-simulation model. In particular, the model allows me to trade off the benefit of bankruptcy as a lower moral hazard form of insurance against the inefficiency due to households not facing the full social cost from being uninsured. This tradeoff suggests a corrective system of "Pigovian penalties" that expose households to the full social cost of the implicit insurance they receive.[6]

With the optimal penalty of $218 per person on average, about 7 percent of the uninsured take up coverage and aggregate surplus increases by a small $4 to $5 per person. Analyzed in this framework, the penalties under the Patient Projection and Affordable Care Act (PPACA), which average $418 per person, are too large, decreasing aggregate surplus by $9 to $13 per person on average. By effectively eliminating the low moral hazard option, the counterfactual of making

[5]Estimates of the moral hazard effects from conventional health insurance, when identified off large medical costs, are incremental to any moral hazard effects from the implicit insurance from bankruptcy.

[6]For this exercise, I assume that uninsured households are not already subsidized through the tax code or some other channel.

medical debt non-dischargeable in bankruptcy reduces surplus by an average of $36 to $43 per person. While the exact welfare numbers should be viewed with some caution, the exercise suggests that dramatically reducing bankruptcy insurance—while having the superficial benefit of increasing conventional coverage—may not be socially desirable.

By studying the interaction between implicit and conventional insurance, this paper is closely related to the literature on long-term care insurance and the implicit insurance from spending down assets and qualifying for Medicare, such as Brown and Finkelstein (2008). Like them, I find that implicit insurance can cause substantial crowd-out. It is more generally related to a literature in macroeconomics that assesses the equilibrium effects of bankruptcy as a form of consumption insurance against a range of different shocks, including those related to earnings, divorce, child-bearing, lawsuits, and medical bills (Livshits, MacGee and Tertilt, 2007; Chatterjee et al., 2007). By examining unpaid care, this paper is also related to Herring (2004) and Rask and Rask (2000), who find a negative association between measures of charity care and insurance coverage. And this paper shares similarities with a literature that examines the effect of medical debt on bankruptcy filings (e.g., Himmelstein et al., 2005; Dranove and Millenson, 2006; Gross and Notowidigdo, 2009), although unlike these papers, I treat bankruptcy as threat-point, not a dependent variable to be explained. In this, my approach more closely resembles the "informal bankruptcy" viewpoint advanced by Dawsey and Ausubel (2004), who show that credit card debt is charged off without a bankruptcy filing in the majority of cases.

The rest of the paper proceeds as follows: Section 2 presents the institutional background and a simple model. Section 3 provides an overview of the data. Sections 4 discusses the identification strategy. The main empirical results are presented in Sections 5 and 6. The micro-simulation model is presented in Section 7. Section 8 discusses puzzles in the literature and policy implications. Section 9 concludes.

2 Bankruptcy as a Form of High-Deductible Health Insurance

2.1 Institutional Background

The implicit insurance from bankruptcy arises from the combination of three institutional features: the fact that most medical care is provided on credit even when repayment is unlikely, the ability of households to discharge this debt in bankruptcy, and the incentive for households and creditors to come to a negotiated solution to avoid the deadweight loss from a formal bankruptcy filing.

The Emergency Medical Treatment and Active Labor Act (EMTALA) requires that hospitals treat patients with emergency medical conditions, and prohibits them from delaying treatment to inquire about insurance status or means of payment.[7] As a matter of practice, most hospitals provide non-emergency medical care on credit as well. Hospitals generally lack the infrastructure to bill patients at the point of service (LeCuyer and Singhal, 2007) and rarely deny service when repayment is unlikely.[8]

Having received medical care on credit, bankruptcy law allows households to write off this debt in exchange for assets or future earnings. Chapter 7 is the most popular form of personal bankruptcy, accounting for about 70 percent of all filings (White, 2007). Under Chapter 7, households can discharge most unsecured debt such as credit card debt, installment loans, and medical bills. In return, creditors can seize assets above exemption levels that vary by asset type and state of residence.

Chapter 13 is the other bankruptcy option. Under Chapter 13, households discharge most unsecured debt in exchange for payments out of disposable income over the following 3 to 5 years. By statute, these payments must be of at least the value that creditors would receive in Chapter 7. They are rarely larger because, in the period I study, all households have the option to file for Chapter 7.[9] Following Fay, Hurst and White (2002), I use seizable assets under Chapter 7 to characterize payments under both chapters of the bankruptcy code.

Households, however, do not have to formally declare bankruptcy to receive the implicit insurance it provides. Under the threat-point of bankruptcy, households and medical providers often resolve payments without an actual bankruptcy filing. There are multiple junctures where this occurs. Discounts on the list price of treatment—known as charity care—are offered at the

[7] U.S.C. 42 §1395dd.

[8] In a survey of nonprofit hospitals, 90 percent reported never denying *any* medical services to patients with no insurance (IRS, 2007). For-profit hospitals seem to operate similarly. For example, Duggan (2000) rejects the hypothesis that for-profit hospitals have a lower preference for charity care. Delgado et al. (2010) find that the majority of emergency departments offer preventative care to uninsured patients.

[9] The Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), effective in October 2005, established a "means test" for Chapter 7. It restricted households earning more than the state median income from filing under Chapter 7 in most circumstances. The households most effected by the reform are unlikely to be marginal to the mechanism I analyze.

point of service to the obviously indigent.[10] After treatment, many hospitals encourage financially strapped households to negotiate discounts, requiring the submission of information on income and assets (e.g., W-2s and mortgage payments) as part of their charity care applications.[11] Even when charity care is not provided, the lion's share of medical debt is charged off in the collection process. Despite contracting with debt collection agencies, providers recover only about 10 to 20 percent of bills submitted to the uninsured (LeCuyer and Singhal, 2007).

Overall, bad debt from the uninsured was estimated at about \$16 to \$18 billion in 2004 (LeCuyer and Singhal, 2007). While the exact proportion of debt discharged without a bankruptcy filing is unknown, Himmelstein et al. (2009) find that the ratio of "medical" to "non-medical" bankruptcies, according to their definition, is the same for households with and without insurance coverage, suggesting that a large portion of the uninsured's medical debt is charged off outside of formal bankruptcy. This is not unique to medical debt. Dawsey and Ausubel (2004) report that the majority of credit card debt is charged off in what they call "informal bankruptcy."

2.2 A Model of Bankruptcy as High-Deductible Health Insurance

To bring together these institutional features, I build a stylized model of households, medical providers, and bankruptcy. Households have a representative agent with expected utility preferences over wealth $w = w^E + w^S$, composed of exempt assets w^E (net wealth that cannot be seized in a bankruptcy filling) and seizable assets w^S (net wealth that can be seized by creditors).[12] They face medical shocks with list price m drawn from distribution M and choose whether to purchase health insurance to protect against this financial risk.

Medical providers are obligated to provide medical services m and then attempt to recover the costs.[13] In doing so they face the difficulty of having imperfect information on household wealth. I assume that the information they have—which can be anything from basic demographics to detailed asset values reported in charity care applications—can be summarized by a predicted

[10] Federal and state laws also influence charity care provision. Nonprofits use charity care to meet their Community Benefit requirement. Some states subsidize care to the indigent through unpaid care pools. I account for these factors in the empirical analysis.

[11] When this information is not provided, hospitals run credit checks on indebted patients, filing suit if they find evidence of a mortgage or savings that could be claimed ("In Their Debt," *Baltimore Sun*, December 12, 2008 to December 24th, 2008).

[12] I discuss endogenizing wealth at the end of this section.

[13] Providers actually outsource many of the functions described below to debt collection companies.

level of seizable assets $\hat{w}^S$. Based on this information, providers submit a bill (s) that can be no more than the medical charge ($s \leq m$). In the event of an actual bankruptcy filing only a fraction $\theta \leq 1$ of seizable assets is recovered.[14]

Model timing proceeds as follows: first, households decide whether to purchase health insurance; second, households receive medical shock m; third, medical providers submit a bill; fourth, households decide whether to declare bankruptcy. I solve the model in reverse order.

2.2.1 Household bankruptcy decision

Conditional on receiving medical bill s, households can either not declare bankruptcy (yielding wealth of $w^E + w^S - s$) or declare bankruptcy (yielding wealth of w^E). Maximizing wealth, households declare bankruptcy if and only if $s > w^S$.[15]

2.2.2 Provider billing decision

Providers choose the bill to maximize

$$\max_{s \leq m} \quad s \cdot \Pr(s < w^S | \hat{w}^S) + \theta \cdot \mathbb{E}_{\hat{w}^S}\left[w^S | s \geq w^S\right] \cdot \Pr(s \geq w^S | \hat{w}^S), \tag{1}$$

where the first term is the submitted bill s multiplied by the probability it does not induce bankruptcy and the second term is recovered assets multiplied by the probability of a formal bankruptcy filing.

Figure 3 depicts the submitted bill $s^* = \min\left\{m, \bar{s}(\hat{w}^S)\right\}$ that maximizes this objective. Moving along the x-axis, the bill increases one-for-one with list price m. It is capped at the value $\bar{s}(\hat{w}^S)$ where the marginal probability of a dollar in increased payments equals the marginal cost in lost assets from pushing a household into formal bankruptcy. Under standard distribution assumptions on seizable assets discussed in Appendix Section A, the following intuitive result obtains:

Prediction 1. *Holding overall wealth constant, the optimal submitted bill s^* is increasing in the level of seizable assets w^S.*

[14]The loss of wealth arises from the legal cost of filing, fees taken by the bankruptcy trustee for selling the assets, competing claims on seizable assets from other creditors, and the depreciation of assets prior to sale, among other costs.

[15]Fay, Hurst and White (2002) find empirical support for this strategic model of bankruptcy in contrast to a nonstrategic model where households file due to unanticipated adverse events.

The formulation allows for formal and informal bankruptcy. If providers overestimate seizable assets, households can be pushed into formal bankruptcy. If providers underestimate seizable assets, households can settle at a discount.

2.2.3 Household insurance decision

The cap on financial risk affects insurance coverage. To see this, consider a stylized health insurance contract with deductible $\bar{m}$ and no other features. Under this contract, households are exposed to medical costs up to deductible $\bar{m}$ and insured above this level.[16] Under bankruptcy, households are exposed to medical costs up to the provider cap $\bar{s}(\hat{w}^S)$ unless it is exceeds seizable assets w^S, in which case households declare formal bankruptcy, limiting their financial risk at this level. A household's willingness to pay v for conventional insurance with deductible $\bar{m}$ is the value that equates the expected utility with conventional insurance to the expected utility with the implicit insurance from bankruptcy:

$$\mathbb{E}_m\left[u(w - v - \min\{m, \bar{m}\}\right] = \mathbb{E}_{m,\hat{w}^S|w^S}\left[u(w - \min\{m, \bar{s}(\hat{w}^S), w^S\}\right] \tag{2}$$

As this formulation makes clear, conventional and bankruptcy insurance are very similar: the only difference is that with conventional insurance the deductible is $\bar{m}$ and with bankruptcy insurance the deductible is the minimum of $\bar{s}(\hat{w}^S)$ and w^S.

Prediction 2. *Holding overall wealth constant, the willingness to pay for insurance v—and therefore insurance coverage—is increasing in the level of seizable assets w^S.*

Because the implicit insurance from bankruptcy is a substitute for conventional health insurance, households with more seizable assets have a higher willingness to pay for insurance and are *ceteris paribus* more likely to be insured. I derive the prediction in Appendix Section A.

The prediction is robust to natural extensions of the model. For example, allowing insured households to receive more or better medical treatment (Doyle, 2005) increases the incentive to purchase coverage, but households with fewer seizable assets are still relatively less likely to insure. Similarly, increasing the cost of bankruptcy to account for factors such as stigma (Gross and

[16] In practice, health insurers negotiate discounts off of medical charges. However, as shown in Figure 2, uninsured households seem to receive these discounts as well. Thus to account for discounts in the model, one could replace m with discounted costs with no impact on the predictions.

Souleles, 2002) or reduced future access to credit (Musto, 1999) does not affect the basic prediction. And endogenizing the level of seizable and exempt assets actually strengthens the relationship between insurance coverage and seizable assets because households that choose to forgo coverage have an additional incentive to reduce their seizable asset holdings.

A more subtle point relates to the information available to households. The model assumes that households know their level of seizable assets w^S and their health risk. Obviously this is an exaggeration. What matters is that households have some knowledge of the financial risk from forgoing insurance. For example, if households learn from the news-media or peers that medical providers in their community frequently seize home equity, then homeowners may be more likely to purchase coverage—even if they know nothing about the mechanism.

3 Data Overview

I use two main data sources to test the predictions of the model. I examine the effect of bankruptcy on medical costs using data from the 2000 to 2005 waves of the Medical Expenditure Panel Survey (MEPS). The survey has detailed information on medical costs and insurance coverage. At the Data Center, encrypted state identifiers and newly edited asset and debt variables are also available.[17]

I examine the effects on coverage using the MEPS data and the 1999 to 2005 waves of the biennial Panel Survey of Income Dynamics (PSID). The survey has public use information on insurance coverage, assets and debts variables, and state identifiers. Because the state of residence is non-encrypted in the PSID, I use this dataset for the primary insurance coverage analysis and replicate the results in the MEPS.

In both data sets, I aggregate the individual-level data to the household level and inflation-adjust monetary variables to 2005 dollars using the CPI-U. I also exclude households with one or more members enrolled in public insurance or a head age 65 or older due to their eligibility for public Medicare insurance.[18] This leaves me with 34,841 observations in the MEPS and 22,844 observations in the PSID.

[17] Bernard, Banthin and Encinosa (2009) find that the estimates of net worth in the MEPS are comparable to those in the Survey of Income and Program Participation (SIPP). My analysis does not go back before 2000 because when I started the project only asset and debt data from the 2000 to 2005 period had been edited.

[18] In the MEPS, I also drop the 3.6 percent of households with missing wealth variables.

3.1 Asset Exemptions

I codify assets exemptions using Elias (2007), a do-it-yourself guide to personal bankruptcy. Table 1 shows these exemptions. Contemporaneous homestead exemptions exhibit substantial variation, ranging from zero in seven states to unlimited in eight others; vehicle exemptions range from zero in 15 states to at least $10,000 in five others; and wildcard exemptions, which can be applied to any asset, show a similar degree of variation. California residents can file under two different exemption systems, and residents of 14 states can file under the federal exemption system if they choose. The last column shows homestead exemptions in the year of 1920 from Goodman (1993).[19]

3.2 Seizable Assets

Let i denote households and j denoted states. Seizable assets are a function of household assets and debts and exemptions laws, denoted by vectors w_i and e_j. Following the general structure of Fay, Hurst and White (2002), seizable asset can be decomposed into assets that can be seized in bankruptcy (gross seizable assets) minus any debt that can be discharged in bankruptcy (dischargeable debt) plus a cost of filing:

$$w^S(w_i, e_j) = Gross\_Seizable\_Assets(w_i, e_j) - Dischargeable\_Debt(w_i) + Filing\_Cost.$$

[19]States that did not exist and states that had only acre-based exemptions are denoted as missing.

Gross seizable assets are calculated as the sum of assets above the exemption level in each asset category:[20,21]

$$
\begin{aligned}
&Gross\_Seizable\_Assets(w_i, e_j) = \max\Big\{ \max\left\{Home\_Equity_i - Homestead\_Exemption_{ij}, 0\right\} \\
&+ \max\left\{Vehicle\_Equity_i - Vehicle\_Exemption_{ij}, 0\right\} \\
&+ \max\left\{Retirement\_Assets_i - Retirement\_Exemption_{ij}, 0\right\} \\
&+ \max\left\{Financial\_Assets_i - Financial\_Exemption_{ij}, 0\right\} \\
&+ Other\_Assets_i - Wildcard_{ij}, 0\right\}\Big\}.
\end{aligned}
$$

For households with multiple options (e.g., state and federal), I calculate seizable assets under each option and assign households the most generous.

Dischargeable debt is defined as non-collateralized debt excluding education loans.[22] Filing costs, which include an estimate of legal fees, are set to $2,000, as estimated by Elias (2007). Neither of these variables vary by state.

Appendix Table A1 shows summary statistics for seizable assets by insurance status. Seizable assets are right skewed with a median of $34,000 and a mean of $217,000 in the baseline sample. Gross seizable assets average $221,000. Due to the large homestead exemptions in many states, seizable home equity accounts for only about a quarter of this amount. Dischargeable debt levels are small, averaging $7,000 per household. More detail on the seizable assets calculations can be found in Appendix Section B.

3.3 Medical Costs

Medical costs variables are shown in Appendix Table A2. Annual medical charges, defined as the list price of medical services used that year, average $6,647 per household. Total payments, defined as the sum of payments received, are less than charges due to both discounts negotiated by

[20]Calculating seizable assets by asset types ignores potential gains from reallocating wealth into asset categories with unused exemptions immediately before a bankruptcy filing. This seems appropriate as such reallocation is explicitly prohibited under bankruptcy law and judges have broad discretion to root out this type of behavior (Elias, 2007).

[21]Following the law, the formulation allows the wildcard exemption to be applied both towards *Other_Assets* and assets in excess of the main asset categories.

[22]As educational debt is not separately identified in either data set, I net out projected educational debt using estimates from the 2004 Survey of Consumer Finances (SCF).

insurance providers and medical care provided as charity care or bad debt. For privately insured households, total payments average $4,480 per household. Ninety-four percent of these payments are either out-of-pocket payments or payments made by private insurance providers. For the uninsured, total payments average $1,267 per household. Fifty-two percent of these payments are out-of-pocket. Miscellaneous payments, such as payments from charity care pools, worker's compensation, or automobile insurance, account for most of the rest.

In the empirical analysis, I use the out-of-pocket payments variable to measure the financial risk faced by the uninsured. While this variable will accurately capture financial risk in most circumstances, it may inaccurately measure financial risk for two reasons. First, out-of-pocket payments overstate financial risk when these payments are put on a credit card that is ultimately discharged in bankruptcy. Because households with fewer seizable assets are more likely to discharge credit card debt, out-of-pocket payments may overestimate financial risk for some low seizable assets households.

Second, out-of-pocket payments may understate financial risk when medical providers break up large bills into installments since households are not prompted to report payments that extend beyond the survey period. Because households with more seizable assets are more likely to make these large, multi-installment payments, out-of-pocket payments may understate financial risk for high seizable assets households. Both overstated financial risk for low seizable assets households and understated financial risk for households with high seizable assets may lead to attenuated estimates of the relationship between seizable assets and financial risk as measured by out-of-pocket payments, suggesting that the empirical estimates should be interpreted as a lower bound of the effect of bankruptcy insurance on household financial risk.

I use Relative Risk Scores to control for medical utilization. As I discuss in Section 4, controlling for utilization is important because the direction of the unconditional relationship between out-of-pocket payments and seizable assets in theoretically ambiguous. To control for utilization, I use the Relative Risk Score variable constructed using the RiskSmart Version 2.2 software created by DxCG Inc.[23] This software uses information on age, sex, and medical diagnoses to project expected medical utilization based on regression models developed by the company. Because the software does not use geographical information to project utilization, the Relative Risk Score is

[23]See form HC-092 on the MEPS website for a full description of the construction of this variable.

orthogonal to asset exemption laws and other state-level factors.

3.4 Insurance Premiums

I conduct additional analysis using data on health insurance premiums in the individual market. In particular, I use data on premium quotes in each state that are listed on eHealthInsurance, a website that aggregates premium quotes from most of the major insurance providers. The data I use were collected in November, 2010. I collect premiums in each state for a 30-year-old non-smoking male. Because premiums quotes are zip code specific, the data are collected for a zip code randomly selected from the 10 most populous zip codes in the state. Along with premiums, I collect data on the insurance provider, plan brand name, deductible, coinsurance rate, and co-payment for a office visit. I define an insurance plan as all observations with the same insurer, brand name, deductible, coinsurance and co-payment. Table A3 shows basic summary statistics for the data. The data set covers 41 states and 1,891 plans. The mean premium is \$103 per month, the mean deductible is \$3,351, and the mean coinsurance rate is 15 percent.

4 Empirical Strategy

In this section, I discuss the instrumental variables strategy I use to test the predictions of the model. I start by presenting the second stage coverage and cost equations and then discuss the instrument and potential threats to validity.

4.1 Coverage Equation

Figure 1, discussed in the Introduction, showed a strong correlation between insurance coverage and seizable assets. To evaluate the impact of bankruptcy more rigorously, I estimate regression models of insurance coverage on seizable assets. Letting i indicate households and j indicate states, the second stage coverage regression takes the form

$$Insured_{ij} = \alpha_w \ln(w_{ij}^S) + X_{ij}'\alpha_X + \epsilon_{ij}, \tag{3}$$

where $Insured_{ij}$ is the percent of household member-months insured, w^S is seizable assets, X_{ij} is a vector of household and state characteristics, and ϵ_{ij} is the error term.[24,25] The crowd-out prediction is that the coefficient on seizable assets is greater than zero ($\alpha_w > 0$).

4.2 Costs Equation

Figure 2, also discussed in the Introduction, showed that out-of-pocket payments by uninsured households are capped on average at $5,000. Figure 4 examines this effect more closely, plotting out-of-pocket payments against charges for uninsured households with low (< $10,000), moderate ($10,000 to $49,999), and high ($\geq$ $50,000) levels of seizable assets. For small charges the three groups make similar out-of-pocket payments, consistent with most households being below the cap. For large charges, out-of-pocket payments sharply diverge. While households with less than $10,000 in seizable assets have their out-of-pocket payments capped, households with more than $50,000 in seizable assets see their out-of-pocket payments continue to scale up with charges, consistent with a cap that is increasing in seizable assets.

To test the capping-of-cost prediction more rigorously, I estimate regression models of out-of-pocket payments on seizable assets, conditioning on the level of medical care received. Controlling for medical utilization is important because the sign of the unconditional effect of seizable assets on out-of-pocket payments is theoretically ambiguous. To see this, consider the effect of reducing a household's level of seizable assets. Due to the mechanical effect of the implicit insurance from bankruptcy, out-of-pocket payments should decrease. On the other hand, due to moral hazard, households may increase their medical utilization, raising out-of-pocket costs and potentially offsetting the mechanical effect in the opposite direction.

For the analysis, I restrict the sample to uninsured households with positive medical utilization. Letting i denote households and j denote states, the second stage cost equation takes the

[24] Using probit or logit functional forms for this equation does not have noticeable effects on the findings.

[25] The log function form is a convenient way to deal with the long tail of seizable assets in the data. In the preferred specification, I bottom-code seizable asset at the filing cost of $2,000 and include an indicator for bottom-coding as a control. This prevents small fluctuations in seizable assets above zero, due to, for instance, whether a household recently deposed a paycheck in their checking account, from driving the results. The qualitative findings are robust to bottom-coding at 1 and to a linear functional form.

form

$$\ln(OOP_{ij}+1) = \beta_w \ln(w^S_{ij}) + f(RRS_i;\beta_{RRS}) + X_{ij}\beta_X + \nu_{ij}, \tag{4}$$

where the dependent variable is log out-of-pocket payments, w^S_{ij} is seizable assets, $f(RRS_i;\beta^k_m)$ is a fourth-order polynomial in the Relative Risk Score, X_{ij} is a vector of household and state characteristics, and ν_{ij} is the error term.[26] The capping of cost prediction is supported by a positive coefficient on seizable assets ($\beta_w > 0$).

4.3 Cross-State Variation

Consistently estimating the parameters of interest poses four distinct identification problems. The first issue is omitted variables: that coverage or costs and seizable assets may be jointly determined by unobserved factors. For instance, in the coverage equation, unobserved risk preferences could generate positive bias if more risk adverse households are more likely to accumulate precautionary savings and purchase insurance. Unobserved health shocks could generate negative bias by depleting assets and increasing preferences for coverage.

The second concern is reverse causality: that households that choose bankruptcy insurance might strategically reduce their seizable assets to lessen their financial losses in the event of a bankruptcy filing. The third concern is measurement error: that because the measurement of assets is notoriously difficult, the coefficient on seizable assets might be attenuated towards zero.

The fourth concern is endogenous asset exemption laws: that the state-level laws that specify the type and level of assets that can be seized in bankruptcy may be correlated with unobserved state-level factors. For instance, in the coverage equations one might be worried that a high-profile incident of medical bankruptcy in a state both increased insurance take-up and provided a legislative impulse for larger asset exemptions, biasing the estimates towards zero.

I address the first three issues by constructing a simulated instrument that isolates variation in seizable assets solely due to cross-state differences in asset exemption law. (I discuss the fourth concern below.) The instrument is analogous to the Currie and Gruber (1996) instrument for Medi-

[26]The depend variable is rarely zero. In the sample analyzed, less than 4 percent of households make zero out-of-pocket payments.

caid eligibility. In that paper, they construct their instrument by taking a nationally representative sample of individuals and running them through the eligibility laws of each state. They think of this instrument as a "convenient parameterization" of the legislative differences across states, purged of any contamination from the actual characteristics of each state's residents. In this context, I construct a simulated instrument by taking a constant, nationally representative sample of households (I use the entire sample) and running them through the asset exemption laws of each state. The baseline instrument for state j is given by:

$$Baseline\_Instrument_j = \frac{1}{|I|} \sum_{k \in I} \ln(w^S(w_k, e_j)), \tag{5}$$

where I is the entire set of households in the data. The first stage equation for household i that actually resides in state j is therefore:

$$\ln(w^S_{ij}) = \gamma_{IV} Baseline\_Instrument_j + X'_{ij}\gamma_X + \mu_{ij} \tag{6}$$

Figure 5 plots the baseline instrument in each state. For the constant, nationally representative sample of households, there is an almost 2 log point difference in seizable assets across states. Even excluding the extremes, there is more than a log point difference.

It is well known that instrumental variables estimates are identified by the response of households local to the instrument (Imbens and Angrist, 1994; Heckman and Vytlacil, 1998). Figure 6 examines these households by plotting the 20th through 50th percentiles of log seizable assets by state for the constant, nationally representative sample. The figure reveals two things. First, even at the 30th percentile of seizable assets there is substantial variation in log seizable assets across states. In creditor-friendly states such as Delaware, Michigan, and South Carolina seizable assets are a log point higher than in debtor-friendly states such as Rhode Island, Minnesota, and Texas. Second, the figure shows that the difference in log seizable assets between states is fairly constant across much of the relevant range of the distribution. Households in Kansas, to give a concrete example, have approximately 1.5 log points more seizable assets than households in Nebraska in the 30th, 40th, and 50th percentiles of the seizable asset distribution. This means that the simulated instrument is capturing variation across a substantial range of seizable assets levels, reducing concerns that the instrumental variables estimate is local to households with particularly high or low levels of wealth.

4.4 Historical Homestead Exemptions

I use three strategies to to address the fourth concern that asset exemption laws may be correlated with unobserved state-level determinants of insurance coverage. My main strategy is to construct an instrument that isolates variation solely due to 1920 homestead exemptions. By using homestead exemptions from before the era of widespread health insurance, this strategy eliminates potential bias from factors that might have simultaneously caused changes in asset exemptions and out-of-pocket costs or coverage over the course of the twentieth century. Moreover, historical evidence shows that 1920 homestead exemption levels resulted from an idiosyncratic array of nineteenth century historical circumstances. Describing the key factors driving the establishment of homestead exemptions in the nineteenth century, Goodman (1993) cites no less diverse a list than "Texas colonizers and western developers, labor and land reformers, antimonopoly Jacksonian egalitarians, defenders of family security and women's property rights, southern planters and yeomen devastated by the Civil War." These heterogenous causes reduce the concern that historical homestead exemptions merely proxy for a persistent state-level characteristic such as the strength of the pro-debtor political movement.

Importantly, historical homestead exemptions are also a good predictor of contemporaneous exemptions values.[27] Figure 7 shows this graphically, plotting the average level of seizable home equity for a constant, nationally representative sample of households under 2005 homestead exemptions (y-axis) and inflation-adjusted 1920 homestead exemptions (x-axis) in each state. The plot also shows the fitted line from a bivariate regression. As the slope coefficient indicates, homestead exemptions have become less generous over time, with seizable assets increasing on average by 90 percent. The R-squared value is 0.43, with the New England states in the lower right corner being the most prominent outliers.[28]

I take two further approaches to reduce the concern that unobservable factors are driving the

[27]Many of the changes since 1920 have simply been inflation updates passed by individual state legislatures (Skeel, 2001).

[28]A keyword search of newspaper articles in a six-month window around major changes in Massachusetts and Connecticut assets exemptions failed to reveal any information on the reasons for these increases.

effect. The first is to sequentially add controls for Census Regions (e.g., Northeast) and Census Divisions (e.g., New England) to the main specification. Stable results across these specifications should address the concern that the effects are being driven by a spatially-correlated, unobserved factor.

The second is to control for a rich set of state-level legislative covariates. In the coverage equations, I control for insurance market regulations (e.g., community rating requirements, coverage mandates) that may affect premiums.[29] While the publicly insured are excluded from the baseline sample, correlation between asset exemption laws and eligibility thresholds for public insurance programs might bias the estimates though sample selection. To assuage this concern, I estimate the regression models on samples excluding and including the publicly insured. I also control for the presence and generosity of Medicaid Medically Needy programs that provide an alternative form of safety net coverage.[30] In the cost equations, I control for hospital characteristics and other state-level factors (e.g., share of private hospitals) that may affect out-of-pocket payments.[31]

5 The Effect on Insurance Coverage

5.1 First Stage Estimates

Table 2 shows implied first stage regressions of log seizable assets on different instrumental variables. Column 1 shows estimates with the baseline instrument. Columns 2 and 3 show estimates with instruments that isolate the variation due to seizable homestead equity and seizable non-homestead assets. These instruments are calculated by taking a constant, nationally representative of households and calculating their level of seizable homestead and non-homestead equity as though they lived in each state. Column 4 shows estimates using the instrument that isolates variation due to 1920 homestead exemptions. All the specifications include demographic controls (age group, family structure, race, education, and income), state controls (mean income, percent

[29] The data on these regulations was taken from a Blue Cross Blue Shield (2002) compilation gracious shared by Amanda Kowalski.

[30] I thank Jay Bhattacharya for alternating me to the presence of these programs. I use 2003 data on these programs taken from Crowley (2003).

[31] In particular, I control for the share of private and nonprofit hospitals, taken from the Hospital Statistics 2005 published by the American Hospital Association. I control for Disproportionate Share Hospital payments per 1,000 residents taken from the Kaiser Family Foundation. I control for the number of Federally Qualified Health Centers per 100,000 residents.

unemployed, percent covered by Medicaid), and year fixed effects. Standard errors in all specifications here and throughout the paper are clustered at the state level. The instruments have substantial power. The baseline instrument has an F-statistic of nearly 500 (column 1) and even the instrument based on 1920 homestead exemptions has an F-statistic over 20 (column 4).

5.2 Baseline Coverage Estimates

Before turning to the regression estimates, Figure 8 presents visual evidence on the crowd-out prediction. Plots on the same row show the exact same data. Datapoints are indicated with state abbreviations in the plots in the left column and with circles proportional to the number of observations in the plots in the right column. Panels A and B plot insurance coverage against seizable assets averaged by state. In the raw data, there is a strong upward-slopping relationship. The relationship is consistent across most states, with the outliers mainly states with very few observations. Panels C and D plot insurance coverage against the baseline instrument averaged by state—the graphical analogue to a bivariate reduced form regressions. The upward-sloping relationship is similar although the figures are more noisy. (I discuss Panels E and F below.)

Table 3 presents the baseline regression specifications. The first four columns show OLS estimates. Column 1 only has controls for year fixed effects. Column 2 adds the demographic and state controls. Columns 3 and 4 add controls for wealth and premiums.[32] Since wealth and premiums may be directly affected by asset exemption laws, the parameter estimates with these controls are inappropriate for counterfactuals involving changes in these exemptions. The coefficient on log seizable assets is 6.13 in column 1 and about 2.5 across the other specifications. The similar estimates with the wealth and premium controls suggest that the effect is not mediated through these channels.[33]

Columns 5 to 8 show the 2SLS estimates with the baseline instrument (column 1 of Table 2), adding controls in the same manner as columns 1 through 4. The coefficient on log seizable assets is 5.43 in the preferred specification with demographic and state controls (column 6) and significantly positive at more than the 0.1 percent level. Like the OLS specifications, adding controls

[32]The premium index is state fixed effects from a regression of log premiums on plan and state fixed effects.

[33]The slight increase in columns 4 and 8 is due to the fact that premium data is only available for a subset of states. When compared to a specification without this control estimated on the same sample, controlling for premiums very slightly reduces the coefficient on log seizable assets. This is consistent with a negative correlation between asset exemption levels and insurance premiums.

for wealth (column 7) and premiums (column 8) has little effect. The larger 2SLS estimates are consistent with measurement error attenuating the coefficient of interest in the OLS specifications.

The reduced form panels of Figure 8, discussed above, suggested that Texas might be important to the 2SLS results. Figure 9 examines the robustness of the estimates to this type of concern by showing the coefficient on log seizable assets from 51 separate regressions of the preferred specification (column 6 of Table 3) that sequentially drop households from the indicated state. The figure shows that neither Texas—nor any other state for that matter—is driving the results. Dropping Texas does slightly reduce the coefficient on log seizable assets. However, the estimate without Texas is significantly greater than zero and slightly larger than the estimate that excludes the state of Arizona.

5.3 Sensitivity Analysis

As discussed above, I address the potential bias from endogenous asset exemption laws with three strategies. I include controls for state legislative factors. I add controls for Census Regions (e.g., Northeast) and Census Divisions (e.g,. New England). And I show specifications that use variation due to 1920 homestead exemptions as an instrument.

Column 1 of Table 4 presents estimates of the preferred specification on a sample that includes households with public insurance and column 2 adds controls for state insurance regulations and Medicaid Medically Needy programs to the preferred specification. Columns 3 and 4 sequentially add fixed effects for Census Regions and Census Divisions. The coefficient on log seizable assets is stable across these specifications, reducing concerns that the estimates are driven by unobserved state level factors.

Column 5 applies a variant of the baseline instrument that is calculated by averaging log seizable assets for the constant, nationally representative sample of households by age-by-educations groups rather than at the population level. The coefficient on log seizable assets is very similar with this instrument. Columns 6 and 7 apply instruments that isolate the variation due to seizable homestead equity and seizable non-homestead assets respectively. The coefficient is a smaller 4.53 (p-value < 0.05) when estimated using variation in homestead exemptions and a larger 6.16 (p-value <0.01) when estimated using variation in non-homestead seizable assets.

Before discussing the eighth column, I return to Panels E and F of Figure 9. These panels show reduced form plots of insurance coverage against log seizable home equity under inflation-adjusted 1920 homestead exemption laws averaged by state. The historical instrument plots show a similar upward-sloping relationship and are somewhat less noisy than the baseline instrument plots in the row above. One reason for this is that the New England states—which are outliers in Panels C and D—have greater seizable assets levels under the historical exemptions and are closer to the regression line.

Column 8 of Table 4 shows the 2SLS estimates with the historical instrument. With the historical instrument, the coefficient on log seizable assets is slightly larger than the preferred estimate (6.39 versus 5.43). A Hausman test cannot reject the validity of the baseline instrument. Given that the historical instrument has lower power in the first stage, it seems prudent to maintain the baseline instrument parameter of 5.43 as the preferred estimate.

5.4 Heterogeneity in the Effect on Coverage

Table 5 examines heterogeneity in the coefficient on log seizable assets by estimating the preferred specification on subsamples of the data. The 2SLS estimate is somewhat larger when estimated on the sample of younger versus older households (defined by a household head younger than 35) and the sample of renters versus homeowners. Households earning less than the median income are significantly more responsive to seizable assets levels (8.18 in column 5 versus 2.79 in column 6). This is consistent with Gruber and Poterba (1994), who find that low income households are more premium elastic in their demand for health insurance. The coefficient on log seizable assets is larger for households with seizable assets below the median value (8.24 in column 7 versus 4.87 in column 8).

5.5 The Effect on Wealth and Premiums

Table 3 showed that including controls for wealth and premiums did not have much of an effect on the parameter of interest. Tables 6 and 7 examine the effects of asset exemption law on these variables on their own.

Table 6 shows OLS and 2SLS estimates of assets on state-level measures of asset exemption law (the instruments). Columns 1 to 6 examine the effects of exemptions for specific asset categories (home equity and vehicle equity). In these specifications, the dependent variable is an indicator for positive assets or the log asset value. All specifications include households controls—including a fourth-order polynomial in wealth—and the baseline instrument to control for the overall generosity of asset exemption laws in that state. Columns 1 and 2 show estimates of home equity on the measure of homestead exemptions laws. Columns 3 and 4 show similar specifications with homestead exemptions from 1920 used as an instrument. Columns 5 and 6 show estimates with a measure of vehicle equity as the dependent variable. None of the specifications show a statistically significant relationship between asset exemption laws and assets.

Columns 7 and 8 of Table 6 examine the effect of asset exemption law on overall wealth. In these specifications, the dependent variable is an indicator for positive wealth or the log wealth value. The parameter on the baseline instrument—which is simply a measure of the generosity of asset exemption laws—is the coefficient of interest. The specifications include the standard set of demographic controls except for the polynomial in wealth. Like the estimates for specific asset categories, there is no evidence of relationship between asset exemption laws and wealth levels.

Table 7 examines the effect of asset exemption law on health insurance premiums by showing estimates of log premiums on the baseline instrument. Observations in these regressions are monthly premiums for a 30-year-old non-smoking male. All specifications include plan fixed effects so that the parameters are identified off differences in premiums for the same insurance product across different states.

The estimates show a marginally significant, negative relationship between asset exemption laws and insurance premiums, consistent with higher asset exemptions inflating hospital costs. Columns 1 to 3 show OLS specifications of log premiums on the baseline instrument. Column 1 has only plan fixed effects. Column 2 adds state demographic factors. Column 3 includes controls for state insurance market regulations. The estimates are quite similar across specifications and indicate that a log point increase in seizable assets is associated with a 7 to 10 percent decrease in premiums, although the effect is only significantly less than zero at the 10 percent level. Columns 4 to 6 shows estimates where seizable home equity under 1920 asset exemption laws is used as an instrument for contemporaneous asset exemptions. Controls are added analogously to columns 1 to 3. The estimates are slightly more negative but less precisely estimated. Column 6, which includes the full set of controls, indicates that a log point increase in asset exemptions decreases premiums by 16 percent and is significantly negative at the 5 percent level.

5.6 Summary and Interpretation

Supporting the crowd-out prediction, the estimates show a robust positive relationship between insurance coverage and seizable assets. The preferred estimate indicates that a log point increase in seizable assets raises insurance coverage by 5.43 percentage points. The effect is similar when identified using variation due to 1920 homestead exemptions, and is stable to the introduction of controls for Census Regions and Census Divisions and well as relevant state level legislative factors.

There are a number of ways to put this estimate in context. Perhaps the most natural way—given the source of identifying variation—is to consider counterfactuals involving cross-state variation in asset exemption law. In the sample, 77.3 percent of individuals are insured (recall that the sample excludes the elderly and those with public insurance). If the exemption laws of the most debtor-friendly state (Texas) were applied nationally, the estimates suggest that the number of uninsured would be increased by 30.0 percent (6.8 percentage points).[34] If the exemptions laws of the least debtor-friendly state (Delaware) were applied nationally, 16.3 percent (3.7 percentage points) of the uninsured would take-up insurance.[35] Take-up under the least debtor-friendly laws is smaller in magnitude because most uninsured household have little wealth and are thus not exposed to substantially more financial risk under these laws.

Achieving the same increase in coverage as implied by the Delaware laws would require a large premium subsidy. Too see this, I use the -0.084 take-up premium semi-elasticity for the uninsured estimated by the Congressional Budget Office (2005).[36] With this elasticity, inducing a 3.7 percentage points increase in coverage requires a premium subsidy of 44.0 ($= 100 \times (0.037/0.084)$) percent.

[34]Couples filing jointly in Texas can exempt all of their home equity, an unlimited amount of retirement assets, and up to $60,000 of any asset of their choose. See Table 1 for details.

[35]Delaware gives couples filing jointly an unlimited exemption for retirement assets and a $500 wildcard exemption. Households cannot exempt any home or vehicle equity in excess of the $500 wildcard. See Table 1 for details.

[36]The Congressional Budget Office (2005) estimate of -0.084 is identified off premium variation due to state-level community rating and premium compression regulations. The estimate is central to the small number of estimates in the literature. It is smaller than the estimate of Gruber and Poterba (1994), who use the introduction of a tax subsidy for insurance purchases by the self-employed, and is larger than the estimate from Marquis and Long (1995). See Liu and Chollet (2006) for a review of estimates in the literature.

The effect does not seem to be driven by an endogenous response of either wealth or premiums. Assets are completely unresponsive to asset exemption laws. And while a log point increase in asset exemptions is associated with a (marginally significant) 7 percent decrease in insurance premiums, controlling for premiums does not impact the coefficient on seizable assets. This is consistent with findings in the literature that the demand for health insurance is highly premium inelastic. For example, with the -0.084 premium semi-elasticity discussed above, a 7 percent decrease in insurance premiums is projected to increase insurance coverage by only 0.6 (=-0.084 $\times$ -0.07) percentage points.

6 The Effect on Costs

6.1 Baseline Estimates

Table 8 presents the baseline OLS and 2SLS estimates of the effect on costs. The sample includes all uninsured households with positive medical utilization. Standard errors are clustered at the state level in all specifications. In the OLS specification without controls (column 1), the elasticity of out-of-pocket payments with respect to seizable assets is 0.56. Including controls for household demographics and utilization reduces this coefficient to 0.22 (column 2). Controlling for wealth has little incremental effect (column 3).

The 2SLS estimates using the baseline instrument are shown in columns 4 to 6, adding controls in the same manner as columns 1 to 3. With controls, the 2SLS point estimates are slightly larger than the corresponding OLS specifications. In the preferred specification with controls for demographics and utilization (column 5), the elasticity of out-of-pocket payments with respect to seizable assets is 0.37. As before, controlling for wealth (column 6) has little effect.

6.2 Sensitivity Analysis

Table 9 examines the sensitivity of these results to concerns about potential bias from endogenous asset exemptions. Column 1 adds controls for hospital and state characteristics. Because hospitals with different ownership structures may have different incentives and preferences for charity care, I include controls for the share of public and nonprofit hospitals in each state (private hospitals are the omitted category). I control for Disproportionate Share Hospital (DSH) payments per 1,000 residents as these may affect incentives to provide unpaid care, the presence of state charity care pools, and the number of Federally Qualified Health Centers per 100,000 people. The parameters of interest are virtually unchanged in these specifications and none of the covariates have coefficients that are statistically distinguishable from zero.

Column 2 uses the instrument that isolates variation due to contemporaneous homestead exemptions and column 3 uses the instrument that isolates variation due to exemptions for non-homestead assets with no effect on the parameter of interest. Column 4 applies the instrument that isolates variation due to 1920 homestead exemptions. Using this source of variation addresses concerns that contemporaneous asset exemptions may be influenced by unobserved state-level factors such as the strength of the hospital lobby or state-level attitudes towards charity care. The estimates are very similar with this instrument.

The final two columns of Table 9 examine heterogeneity in the effect by utilization level. The capping-of-cost prediction and the simple descriptive evidence shown in Figures 2 and 4 suggest that seizable assets should have a larger impact on households with high utilization, as the "deductible" of bankruptcy insurance is more likely to bind for these households. Columns 5 and 6 allow the effect to vary by whether utilization—as measured by the Relative Risk Score—is above the 90th percentile (high utilization) or below this level (low utilization). The elasticity parameter is 0.51 for high utilization and about 0.37 for low utilization, consistent with a high deductible structure for this insurance.

6.3 Summary and Interpretation

Figures 2 and 4 showed that uninsured households with fewer seizable assets have their out-of-pocket payments capped in the raw data. The regression estimates show that this effect is robust to demographic controls and variation in seizable assets solely due to cross-state differences in asset exemption law. The preferred estimate indicates that a log point increase in seizable assets raises out-of-pocket payments by 37 percent, conditional on medical utilization. Consistent with the high-deductible structure of this insurance, the elasticity is larger for households with high utilization.

7 Micro-Simulation Model

To shed light on puzzles in the literature and examine policy implications, I calibrate a micro-simulation model of insurance choice. The model is based on the set of uninsured and privately insured households in the 2005 PSID. Households face household-specific medical cost distributions that depend on the age and sex of each household member. Premiums for conventional health insurance are based on these costs, scaled to account for moral hazard, administrative costs, and the cross-subsidization of unpaid care to the uninsured. Following closely the formulation in Section 2, the model uses an expected utility framework to implicitly define each household's willingness to pay for conventional health insurance. Households purchase coverage if and only if their willingness to pay is greater than their calibrated premium.

With bankruptcy, the willingness to pay v for an insurance contract with deductible $\bar{m}$ is the value that equates the expected utility with health insurance and bankruptcy insurance:

$$\mathbb{E}_m\Big[u(w - v - \min\{m, \bar{m}\}\Big] = \mathbb{E}_m\Big[u(w - \min\{m, w^S\}\Big],$$

where as before w is wealth, w^S is seizable assets, and m are medical shocks drawn from distribution M. Slightly departing from the model in Section 2, I assume that uninsured households have their risk capped at seizable assets w^S rather than the minimum of this value and the provider determined level $\bar{s}(\hat{w}^S)$. This leads me to understate the generosity of bankruptcy insurance. To model the counterfactual in which medical debt cannot be discharged in bankruptcy, I calculate the willingness to pay that equates the expected utility with health insurance to the expected utility with no cap on financial risk.

Premiums are based on expected costs above the deductible. To allow for moral hazard, administrative loading, and the cross-subsidization of unpaid care, I scale up these costs by three factors.[37,38] For a given deductible, premiums are given by:

$$p = (1+\mu_1)(1+\mu_2)(1+\mu_3)\mathbb{E}_m\Big[\max\{m-\bar{m},0\}\Big]$$

where μ_1 accounts for moral hazard, μ_2 for administrative loading, and μ_3 for the cross-subsidization of the uninsured.

In the baseline calibrations, each household is represented by a single member with CARA utility.[39] I show results with risk aversion parameters of $\alpha = 2.5 \times 10^{-5}$ (low risk aversion), $\alpha = 5.0 \times 10^{-5}$ (moderate risk aversion), and $\alpha = 7.5 \times 10^{-4}$ (high risk aversion). Dividing by the median wealth level of $40,318, these parameters can be interpreted as relative risk coefficients of γ = 1, 2, and 3. Household-level medical cost distributions are constructed using individual-level medical cost distributions for age-by-sex-by-insurance status cells in the 2005 MEPS. The markup for moral hazard is $\mu_1 = 0.56$, the value implied by the RAND health insurance experiment price elasticity of -0.22 in an arc elasticity framework (Manning et al., 1987). The administrative load factor is set to $\mu_2 = 0.1$ for households with employer sponsored insurance and $\mu_2 = 0.5$ for the uninsured and households in the non-group market.[40] I solve for the cross-subsidization parameter μ_3 endogenously using the cost distributions of uninsured households in the model. In Appendix Section C, I discuss the construction of the medical cost distributions and premiums in more detail. I show that the calibrated premiums closely match quoted premiums in the individual market.

[37] This formulation for moral hazard assumes that households behave as though they face the full price of medical care when expenditure is below the deductible and a price of zero above the deductible level (i.e., they behave myopically). In actuality, households may anticipate exceeding the deductible and therefore behave as though they have a marginal price of less than 1 below the deductible (i.e., they may exhibit foresight). Because most of the empirical literature makes the myopic assumption and I calibrate my model to estimates from this literature, it is most convenient to make assumption here as well. (See Kowalski (2010) for a in-depth discussion of this issue.)

[38] By allowing moral hazard and administrative costs to affect premiums but not utility, I am implicitly normalizing the willingness to pay for these factors to zero.

[39] Using a CARA specification avoids the problems associated with non-positive wealth. Calibrations with CRRA utility and a consumption floor generate stronger results.

[40] This values are take from Pauly and Nichols (2002).

8 Puzzles and Policy

In this section of the paper, I use the micro-simulation model to investigate how bankruptcy insurance sheds light on puzzles in the health policy literature and to examine implications of this mechanism for the design of health insurance policy.

8.1 Puzzles

Puzzle 1: Why are 47 million individuals uninsured?

Explaining why households are uninsured is a central puzzle for scholars of health insurance. In his review of the literature Gruber (2008) writes, "there are a variety of hypotheses for why so many individuals are uninsured, but no clear sense that this set of explanations can account for the 47 million individuals." Bankruptcy insurance is a compelling additional explanation. I used regression analysis to quantify the importance of this mechanism in the sections above. I use the micro-simulation model for an alternative perspective.

Table 10 shows the percent of insured and uninsured individuals predicted by the model to purchase a $2,000 deductible plan. Column 1 shows these predicted values from a simulation where there is no bankruptcy insurance. Column 2 adds bankruptcy insurance to the model. Without bankruptcy, insured and uninsured individuals are difficult to separate. Using the variation in health risk, administrative costs, and tax preferences, the model can only separate predicted coverage by 8 to 28 percentage points. Because there are large differences in seizable assets between these groups, accounting for bankruptcy substantially improves the explanatory power of the model, expanding the gap in predicted coverage to 43 to 54 percentage points. Bankruptcy insurance thus to increases the gap in predicted coverage by 14 to 46 percentage points.

Puzzle 2: The low take-up of high deductible plans

A second puzzle is the low take-up of high deductible health plans (HDHP) by the uninsured. HDHPs were intended by their proponents to expand insurance coverage, yet despite offering low premiums they have not been successful in this regard (Fronstin and Collins, 2008). Crowd-out from implicit insurance is an appealing explanation for this failure. Because the median uninsured household has less than $5,000 in seizable assets, HDHPs are largely redundant to the implicit insurance they already hold. Figure 10 makes this case quantitatively, plotting the percent of uninsured households projected to purchase insurance by deductible level. Without bankruptcy, the probability of purchase increases sharply from 19 percent for a $1,000 deductible plan to 43 percent for a $5,000 deductible plan, as the concavity of utility makes insurance more valuable at higher deductible levels. With bankruptcy, this increase is virtually eliminated, rising from 2 percent for a $1,000 deductible plan to only 6 percent for a $5,000 deductible contract, a full 37 percentage points below the projected value without bankruptcy.

Puzzle 3: Rising risk, falling coverage

A third puzzle is the association between rising health insurance costs and falling coverage. Chernew, Cutler and Keenan (2005) show that more than half the decrease in insurance coverage over the 1990s can be explained by rising premiums. Yet as the authors explain, from the standpoint of economic theory this is counterintuitive. With standard risk preferences, rising underlying costs should lead to *increased* insurance coverage. Taking bankruptcy into account, however, reverses this intuition. The decrease in coverage can be explained by households substituting conventional health insurance for bankruptcy insurance that is increasing in actuarial value without increasing in price.

Puzzle 4: The insurance generosity gap

A fourth puzzle is the insurance generosity gap. In his review of the literature, Gruber (2008) asks why most U.S. households appear to be either under-insured or over-insured but rarely in-between. Implicit insurance from bankruptcy can explain this finding. To illustrate how bankruptcy insurance creates a generosity gap, Figure 11 presents a stylized budget set. Without bankruptcy, households face the standard continuous tradeoff between insurance generosity (y-axis) and other goods (x-axis). Implicit insurance generates a notch: households receive some implicit insurance without giving up other goods. Convex preferences give rise to an insurance generosity gap, with households sorting into the more generous conventional health insurance and the less generous implicit insurance from bankruptcy.

8.2 Policy Implications

I use the micro-simulation model to examine welfare implications of this mechanism. From a policy design perspective, bankruptcy insurance has many potential drawbacks: It forces the uninsured to receive care in emergency rooms, which are often not the most appropriate settings (Delgado et al., 2010), and may lead to inefficiently low levels of preventative care, inflating overall costs (Institute of Medicine, 2002). Negotiation under the threat-point of bankruptcy is probably not the most efficient way of processing payments and there are deadweight costs and externalities to formal bankruptcy.

For this exercise, however, I focus on a single problem: because bankruptcy insurance has a price of zero but cross-subsidized costs, too many households choose to be uninsured. I find this inefficiency particularly interesting because it directly relates to the insurance coverage decision and because the problem is naturally addressed with penalties for being uninsured—a key and controversial element of PPACA.[41]

Of course, conventional health insurance has well-documented inefficiencies as well. Relative to bankruptcy insurance, moral hazard is particularly relavent.[42] With conventional health insurance it is well known that medical providers and patients often have incentives to supply and demand excess medical care. With bankruptcy insurance, on the other hand, physicians are more likely to be exposed to the social cost of their decisions and patients have little leverage to demand excess treatment. Thus, for the optimal "Pigovian penalties," low moral hazard bankruptcy insurance may be the efficient choice for some households.

Table 11 shows the welfare effects of different penalty systems. For each penalty system, I allow households to choose between conventional insurance at the calibrated premiums and bankruptcy insurance at the cost of the penalty.[43] The results are shown relative to a baseline in which households can choose bankruptcy at no cost. The first set of rows shows coverage and welfare under the optimal Pigovian penalties—defined as the household-specific actuarially fair cost

[41]For this exercise, I assume that uninsured households are not already subsidized through the tax code or some other channel.

[42]Empirically, adverse selection does not seem to affect insurance choice on the extensive margin (Cutler and Zeckhauser, 2000; Cardon and Hendel, 2001).

[43]Recall that calibrated premiums are calculated using costs scaled up for moral hazard, administrative loading, and the cross-subsidization of the uninsured.

of the implicit insurance from bankruptcy.[44] The optimal penalties average $218 per person and induce 7 to 8 percent of the uninsured to take-up coverage. As indicated by the higher willingness to pay, these households purchase more generous coverage than they had from bankruptcy. Due to the increased moral hazard, however, costs rise by almost as much. The net effect is an increase in surplus of only $4 to $5 per person.

The second panel shows the welfare effects of the PPACA penalty system. When fully implemented in 2016, these penalties will equal the greater of $625 or 2.5 percent of income per household, up to a maximum of $2,085. Under these penalties, deflated to 2005 levels assuming trend inflation, take-up ranges from 50 to 64 percent. The generosity of coverage does not change much on average while—due to higher moral hazard—costs increase by a significant amount. The net effect is a decrease in surplus of $9 to $13 per person.

The third panel considers the welfare effects of preventing households from discharging medical debt in bankruptcy—the exact exercise performed in coverage and cost counterfactuals. Without bankruptcy, all households purchase conventional insurance. As indicated by the lower willingness to pay, these plans are less generous on average. Because of the higher moral hazard from conventional insurance, costs do not shrink by a commensurate amount. The net effect is a reduction in surplus of $36 to $43 per person. While the exact numbers, of course, are a function of the particular calibration parameters, the takeaway point from this last exercise is a simple message: despite increasing insurance coverage, eliminating bankruptcy insurance may not be socially desirable.

9 Conclusion

Understanding why households choose health insurance is fundamental to positive and normative analysis of health insurance policy—yet the insurance coverage decision is not well understood. The objective of this paper is to describe and evaluate how the implicit insurance from bankruptcy bears on this decision. In the first part of the paper, I argued that the fact that most medical care is provided on credit coupled with the ability of households to discharge this debt for seizable assets in bankruptcy provides households with a form of high-deducible health insur-

[44] That is, expected medical costs above seizable assets.

ance.

I next evaluated the quantitative significance of this bankruptcy insurance. Exploiting variation in seizable assets that is orthogonal to wealth and other household characteristics, I found that households with more seizable assets make higher out-of-pocket payments and are substantially more likely to be insured. The estimates suggest that if medical debt could not be discharged in bankruptcy, 16.3 percent of the uninsured would purchase coverage. Achieving the same increase in coverage would require a premium subsidy of approximately 44.0 percent.

The final part of the paper examined ways in which this mechanism might inform our understanding of puzzles in the health policy literature and the design of health insurance policy. Using a utility-based, micro-simulation model of insurance choice, I showed that bankruptcy insurance explains the low take-up of high-deductible health plans. In a narrowly designed calibration, I found that the counterfactual of making medical debt non-dischargeable sharply decreases welfare. The welfare analysis was by no means comprehensive—as important costs and benefits of bankruptcy insurance are not understood. Filling in some of the missing pieces may be a fruitful area for future research.

A Model Predictions

A.1 Derivation of Prediction 1

Recall that medical providers have imperfect information on seizable assets w^S that can be summarized by a predicted level of seizable assets $\hat{w}^S$. Assume that the prediction error $\epsilon^S = w^S - \hat{w}^S$ is distributed according to F_ϵ. Using this notation, the provider objective function can be written as

$$\max_{s \leq m} s \cdot (1 - F_\epsilon(s - \hat{w}^S)) + \theta \cdot \int_{-\hat{w}^S}^{s - \hat{w}^S} \left(\hat{w}^S + \epsilon\right) dF_\epsilon$$

The first order condition of the Lagranian is

$$(1 - F_\epsilon(s - \hat{w}^S)) - (1 - \theta) \cdot s \cdot f_\epsilon(s - \hat{w}^S) \geq 0 \qquad \text{with equality if } s < m.$$

The optimal bill is then $s^* = \min\left\{m, \bar{s}(\hat{w}^S)\right\}$, where $\bar{s}(\hat{w}^S)$ is the implicit solution to the first order condition. Rearranging the first order condition yields

$$s = \frac{1}{(1-\theta)} \frac{1 - F_\epsilon(s - \hat{w}^S)}{f_\epsilon(s - \hat{w}^S)} = \frac{1}{(1-\theta)} \frac{1}{h_\epsilon(s - \hat{w}^S)},$$

where $h_\epsilon(\cdot)$ is the hazard function of the prediction error. Differentiating with respect to predicted seizable assets gives

$$\frac{\partial s}{\partial \hat{w}^S} = \frac{1}{(1-\theta)} \frac{1}{h_\epsilon(s - \hat{w}^S)} h'_\epsilon(s - \hat{w}^S).$$

It follows that the submitted bill is increasing in seizable assets if the hazard of the prediction error is increasing. This condition is satisfied by most standard distributions such as the uniform, normal, and exponential (Bolton and Dewatripont, 2005).

A.2 Derivation of Prediction 2

Denote equation (2) by $f(v) = g(w^S)$, where v is willingness to pay and w^S is seizable assets. Because $\partial f(v), / \partial v = -\Pr(m > \bar{m}) u'(w - v(\bar{m}) < 0$, the function $f(v)$ and therefore its inverse $f^{-1}(v)$ is strictly decreasing in v. Since $g(w^S)$ is strictly decreasing in w^S, it follows that $v = f^{-1}(g(w^S))$ is strictly increasing in w^S.

B Seizable Assets Calculation Details

In the PSID, home and vehicle equity are defined as these variables; retirement assets are defined as the value in private annuities or IRAs; financial assets are defined as wealth in checking and saving accounts and in stock; other assets are defined as farm/business wealth, equity in other real estate, and other savings or assets. In the MEPS, home equity and vehicle equity are defined as these variables; retirement assets are defined as the value in IRA, Keogh, and 401K accounts; financial assets as defined as the equity in farms or businesses, equity in other real estate, equity in a second home, equity in recreational vehicles, the value of CDs, stocks, government or corporate bonds or mutual funds, the value in checking or savings accounts, and other assets.

One weakness of both data sets is the coarse decomposition of debt. Under bankruptcy law, dischargeable debt is defined as non-collateralized debt excluding education loans. While the PSID and MEPS distinguish remaining housing and vehicle principle from other debts, these other debts are not further decomposed.[45] The leading potential concern is that these other debts include a substantial amount of education debt—particularly for households with recent college graduates who may also be on the margin of insurance coverage. To overcome this issue, I estimate the share of education debt in total unsecured debt in the 2004 Survey of Consumer Finances (SCF) and use this estimate to project education debt in the PSID and MEPS. In particular, I use parameter estimates from a probit regression of the share of education debt in total unsecured debt on income, family structure, age of the household head, and unsecured debt level fully interacted with a categorical variable for educational attainment of the head to project education debt values.

C Micro-Simulation Details

C.1 Medical Cost Distributions

I construct the household-level medical cost distributions using individual-level medical cost data from the 2005 MEPS for age-by-sex-by-insurance status cells.[46] For insured individuals, costs are defined as total payments. For uninsured individuals, my measure of costs in construct in the following way: I start with medical charges as this variable accounts for medical services written off as charity care or bad debt. I then scale down charges by the cost-charge ratio (CCR) for the privately insured population to account for the discount typically extended to the uninsured.[47] Finally, I subtract out payments made by workman's compensation, the Veterans Administration, and other such sources as the uninsured are not exposed to these costs. Household-specific medical cost distributions are constructed numerically by summing over 10,000 independent draws from the appropriate individual-level distributions.

[45] The debt variable in the PSID is based on the question "Aside from the debts that we have already talked about, like any mortgage on your main or vehicle loans – do [you/you or anyone in your family] currently have any other debts such as credit card charges, student loans, medical or legal bills, or loans from relatives?" In the MEPS it is based on the question "Does anyone in the family have any debts that we haven't asked about, such as credit card balances, medical debts, life insurance policy loans, loans from relatives, and so forth?" While both these variables may include additional non-dischargeable debt (e.g., department store loans collateralized by durable goods, unpaid taxes), the bias introduced by this is likely to be small.

[46] The age-by-sex groups are no more than 18 years old, male age 19 to 34, female age 19 to 34, male age 35 to 64, and female age 35 to 64.

[47] Recall from Figure 2 that privately insured and uninsured households make similar payments for low charges.

C.2 Premiums

I calculate the household-specific premiums by scaling up these costs to account for moral hazard $(1+\mu_1)$, administrative loading $(1+\mu_2)$, and the cross-subsidization of unpaid care to the uninsured $(1+\mu_3)$.

- The moral hazard factor of $\mu_1 = 0.56$ is constructed using the RAND health insurance experiment price elasticity of -0.22 (Manning et al., 1987) and the arc elasticity formula. The arc elasticity formula is given by $\varepsilon = \left(\frac{q_2-q_1}{(q_2+q_1)/2}\right)/\left(\frac{p_2-p_1}{(p_2+p_1)/2}\right)$ where ε is the price elasticity and q_i and p_i are quantity and price. For a price change from 1 to 0, the arc elasticity formula simplifies to $\varepsilon = -\frac{q_2-q_1}{q_2+q_1}$. Rearranging yields $\frac{q_2}{q_1} = \frac{1+\varepsilon}{1-\varepsilon}$. Plugging in $\varepsilon = -.22$ yields $(1+\varepsilon) = \frac{q_2}{q_1} = \frac{1+.22}{1-.22} = 1.56$ and $\mu_1 = 0.56$.

- The administrative markup is set to $\mu_2 = 0.1$ for households with employer-sponsored insurance and $\mu = 0.5$ for households with non-group or no coverage. These values are taken from Pauly and Nichols (2002).

- The cross-subsidy for uninsured households is calculated endogenously by assuming that medical costs for the uninsured seizable assets are evenly distributed across expenditure by insured and uninsured households. That is:

$$\mu_3 = \frac{\sum_i \mathbb{E}_{m_i}\left[1(uninsured_i)\max\{m_i - w_i^S, 0\}\right]}{\sum_i \mathbb{E}_{m_i}\left[1(insured_i)(1+\mu_1)(1+\mu_2)m_i + 1(uninsured_i)\max\{m_i, w_i^S\}\right]},$$

  where $1(\cdot)$ is an indicator of insurance status, m is medical costs, and w^S is seizable assets.

- I convert premiums for households with employer-sponsored insurance into after-tax dollars using federal, state, and payroll tax information from NBER's TaxSim program.

Appendix Table A4 shows the resulting distributions of medical costs and premiums normalized by household size for comparison. Costs have a long right tail: while 91 percent of persons incur less than \$1,000 in a given year, about 1 in 36 incur more than \$5,000 and 1 in 69 incur more than \$10,000 in medical costs. Calibrated premiums drop steeply from \$2,126 per person for a plan with first dollar coverage to \$1,009 per person for a \$10,000 deductible plan.

As a reality check, Appendix Table A4 compares these premiums to quoted individual market premiums for the median uninsured individual in the data (a 32-year-old male), adjusted for inflation and cost-sharing.[48] The calibrated and market premiums are quite similar. The calibrated premiums are slightly less expensive for low deductible levels and somewhat more expensive for high deductibles. This difference could be explained by selection or by heterogeneity in the moral hazard parameter across the expenditure distribution.

[48]The individual market premiums, from www.ehealthinsurance.com, are for a non-smoking 32-year-old male. The policies are issued by Aetna and start in May 2010. They are adjusted for inflation using the Medical Care component of the CPI-U.

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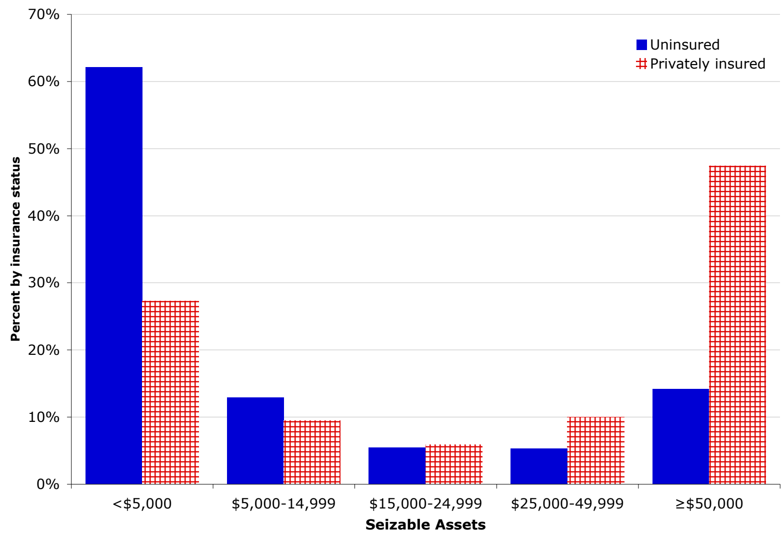
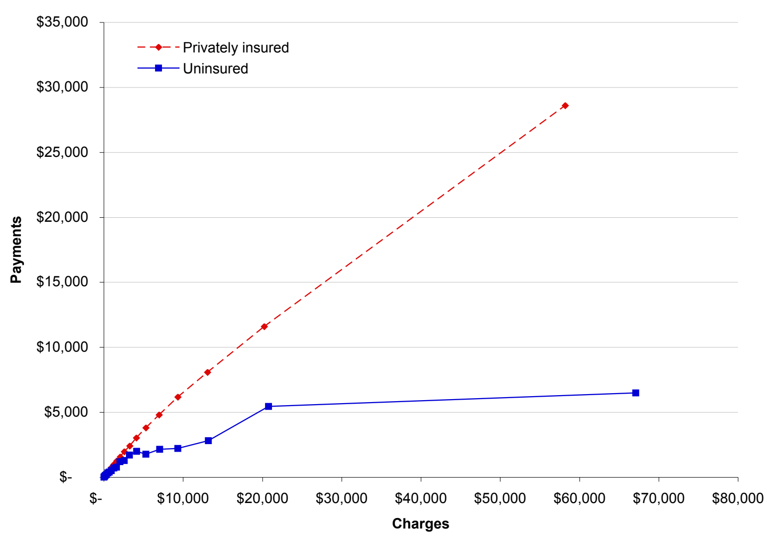
Figure 1: Histogram of Seizable Assets by Insurance Status



Notes: Histogram of seizable assets for uninsured and privately insured households, excluding households with a head age 65 or older. Pooled data from 1999 to 2005 PSID, inflation-adjusted to 2005 using the CPI-U. Household-level estimates weighted by number of individuals per household for interpretation at the individual level. See text for details on the seizable assets calculation.

Figure 2: Payments vs. Charges by Insurance Status



Notes: Payments versus medical charges for uninsured and private insured households. Payments are the sum of out-of-pocket payments and payments from private insurers. The plot is created by averaging payments and charges at 20ths of the charge distribution. Pooled 2000 to 2005 MEPS, inflation-adjusted to 2005 using the CPI-U. Excludes households with a head age 65 or older. Household-level estimates weighted by number of individuals per household for interpretation at the individual level.

Figure 3: Provider Billing Decision: Submitted Bill vs. List Price of Medical Care

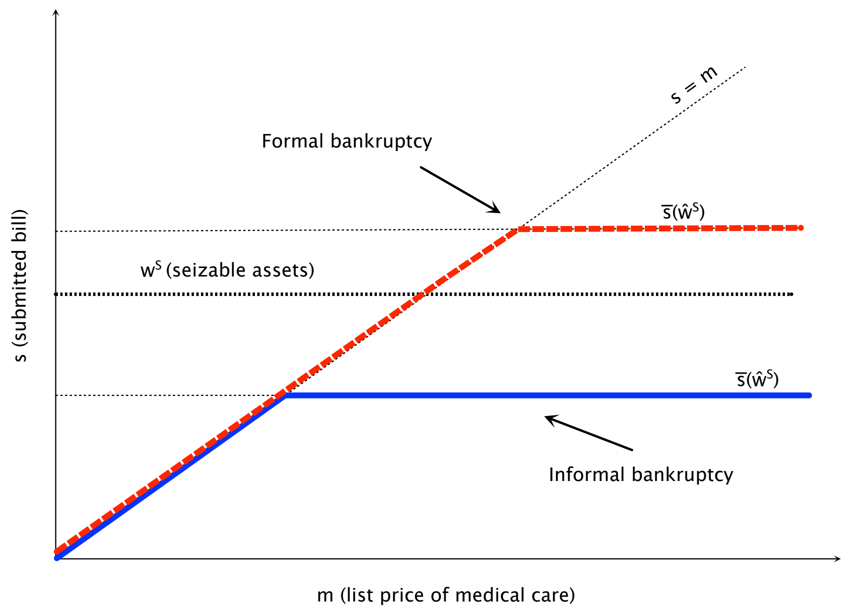
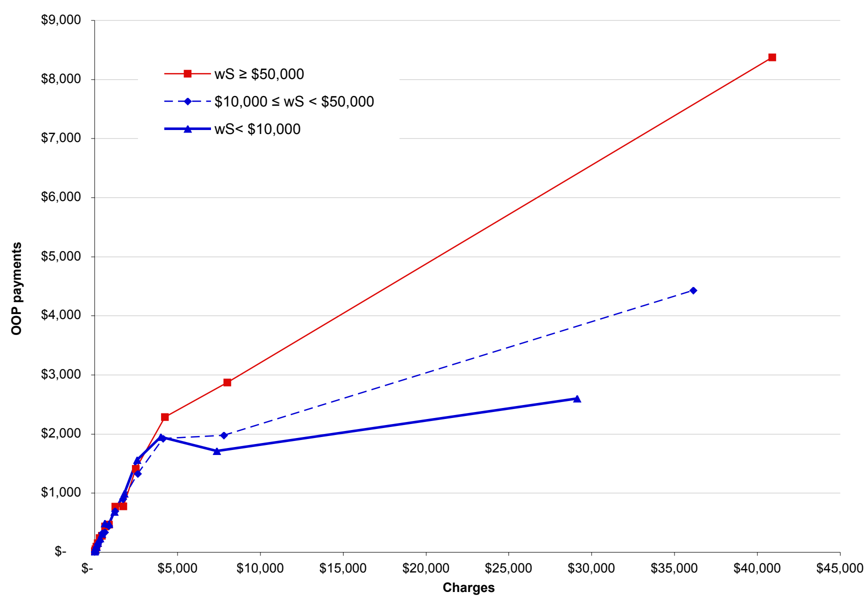
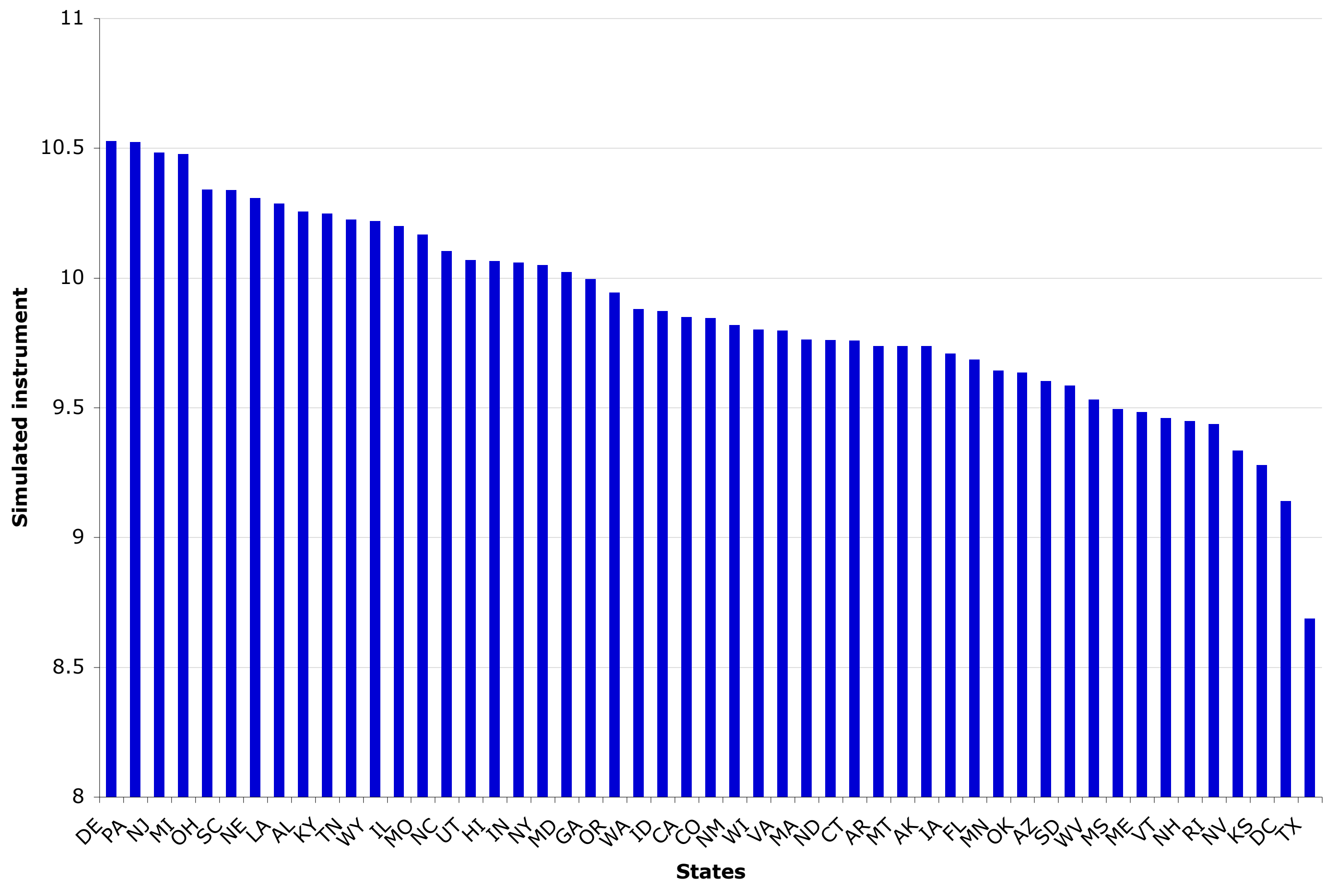


Figure 4: Payments vs. Charges by Seizable Assets



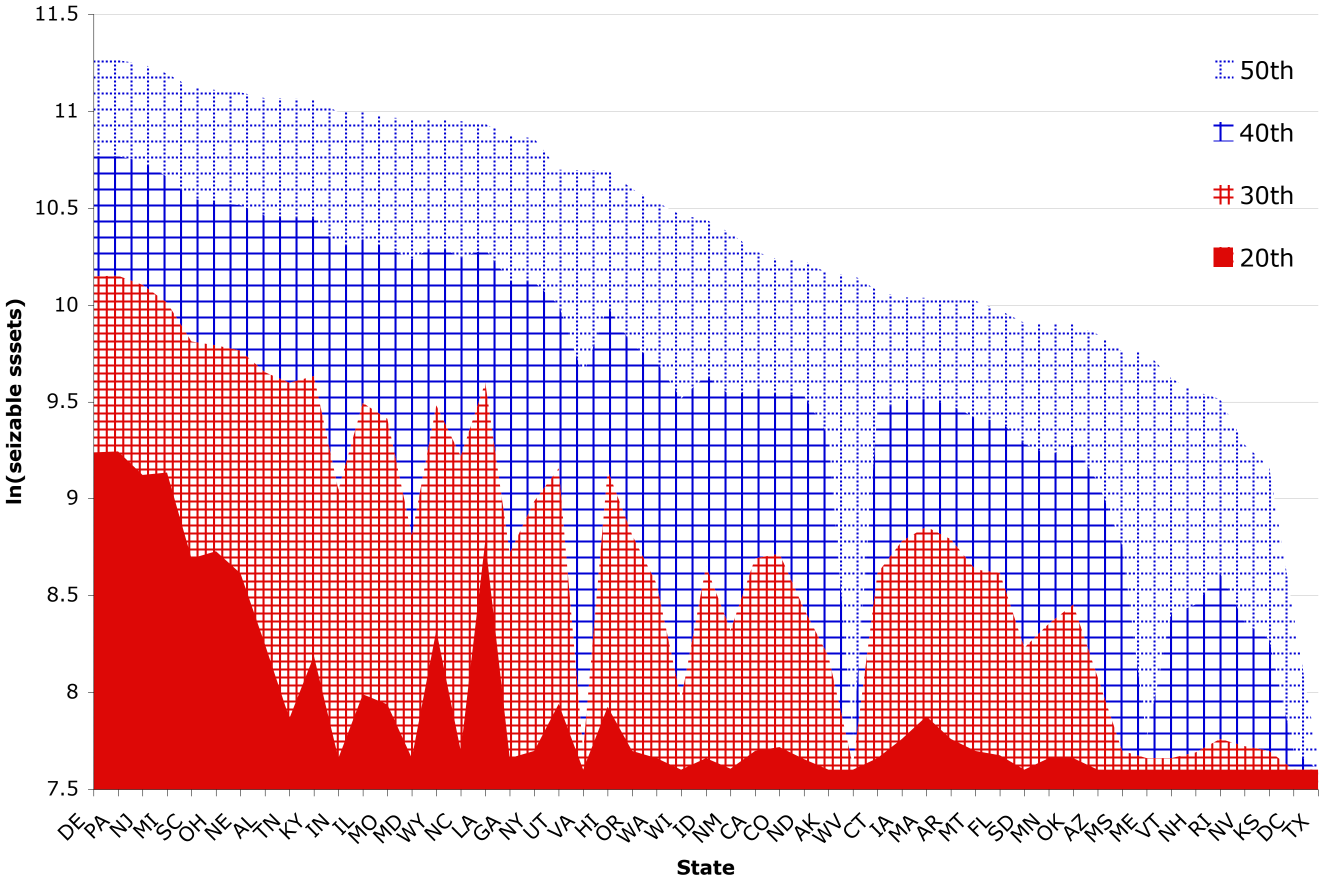
Notes: Out-of-pocket payments versus medical charges for uninsured households with low (< $10,000), moderate ($10,000 to $50,000), and high ($\geq$ $50,000) levels of seizable assets. The plot is created by averaging payments and charges at 20ths of the charge distribution. Pooled 2000 to 2005 MEPS, inflation-adjusted to 2005 using the CPI-U. Excludes households with a head age 65 or older. Household-level estimates weighted by number of individuals per household for interpretation at the individual level.

Figure 5: Simulated Instrument by State



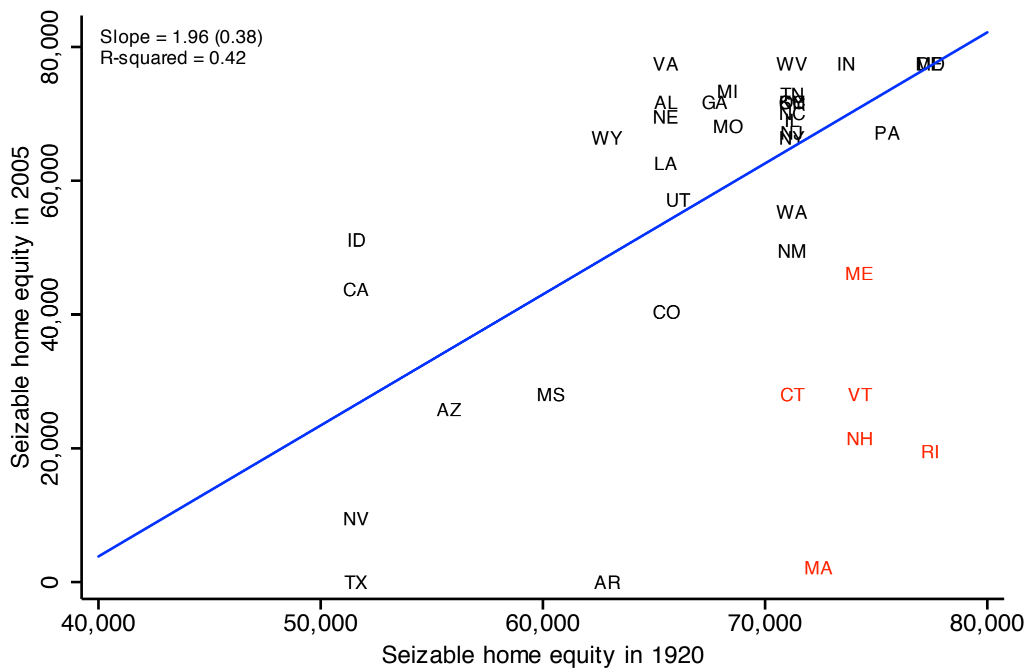
Notes: The simulated instrument is log seizable assets for a constant, nationally representative sample of households as though they lived in each state. The sample is made up of uninsured and privately insured households, excluding households with a head age 65 or older. Pooled 1999 to 2005 PSID, inflation-adjusted to 2005 using the CPI-U. See text for details on the seizable assets calculation.

Figure 6: Log Seizable Assets Percentiles by State for a Constant Sample of Households



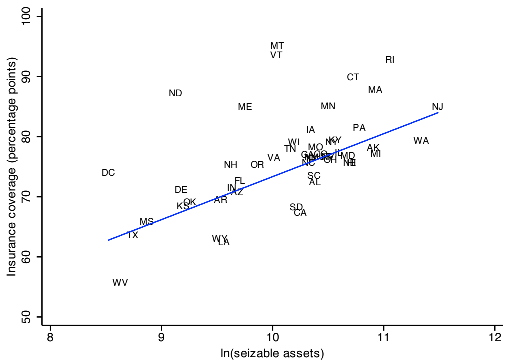
Notes: Percentiles of log seizable assets for a constant, nationally representative sample of households as though they lived in each state. The sample is made up of uninsured and privately insured households, excluding households with a head age 65 or older. Pooled 1999 to 2005 PSID, inflation-adjusted to 2005 using the CPI-U. See text for details on the seizable assets calculation.

Figure 7: Seizable Homestead Equity in 2005 vs. 1920 for a Constant Sample of Households

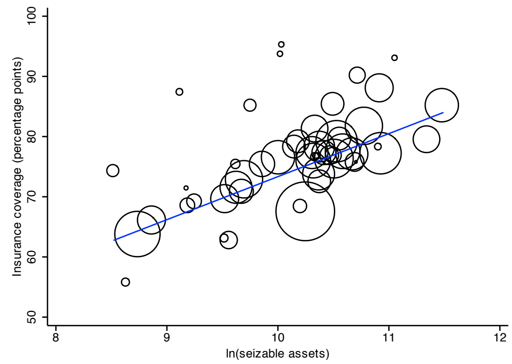


Notes: Mean seizable home equity for a constant, nationally representative sample of households under 2005 and inflation-adjusted 1920 homestead exemption laws as they lived in each state. The New England states are shaded red. The sample is made up of uninsured and privately insured households, excluding households with a head age 65 or older. Slope coefficient from a bivariate regression weighted by population, with a robust standard error in parentheses. Pooled 1999 to 2005 PSID, inflation-adjusted to 2005 using the CPI-U. States that did not exist or had acre-based homestead exemption laws are excluded. Household-level estimates weighted by number of individuals per household for interpretation at the individual level.

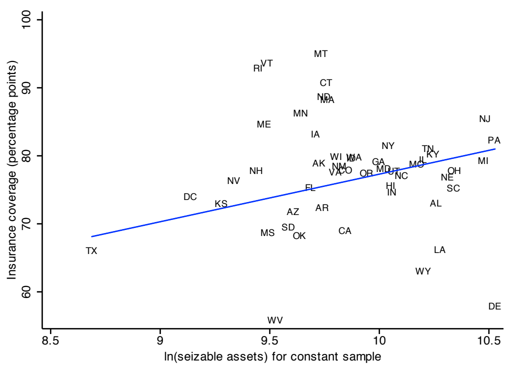
Figure 8: Insurance Coverage vs. Seizable Assets



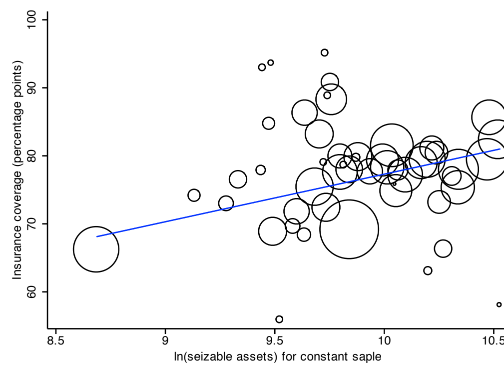
(a) Insurance Coverage vs. Seizable Assets



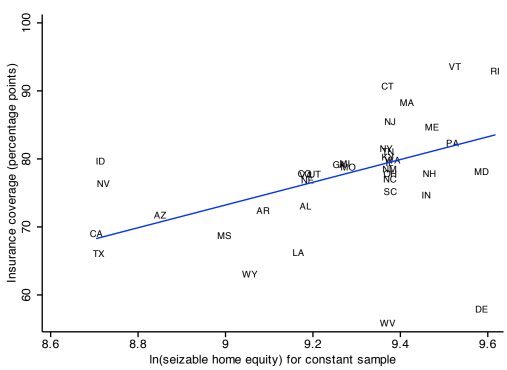
(b) Insurance Coverage vs. Seizable Assets



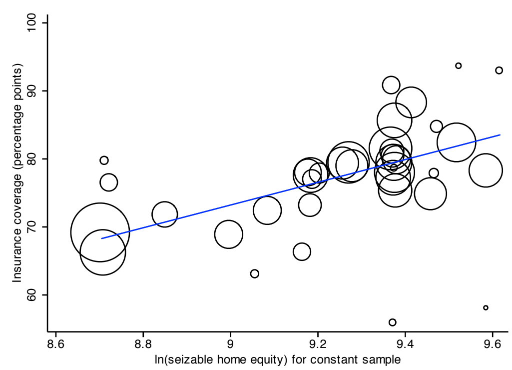
(c) Insurance Coverage vs. Simulated Instrument



(d) Insurance Coverage vs. Simulated Instrument



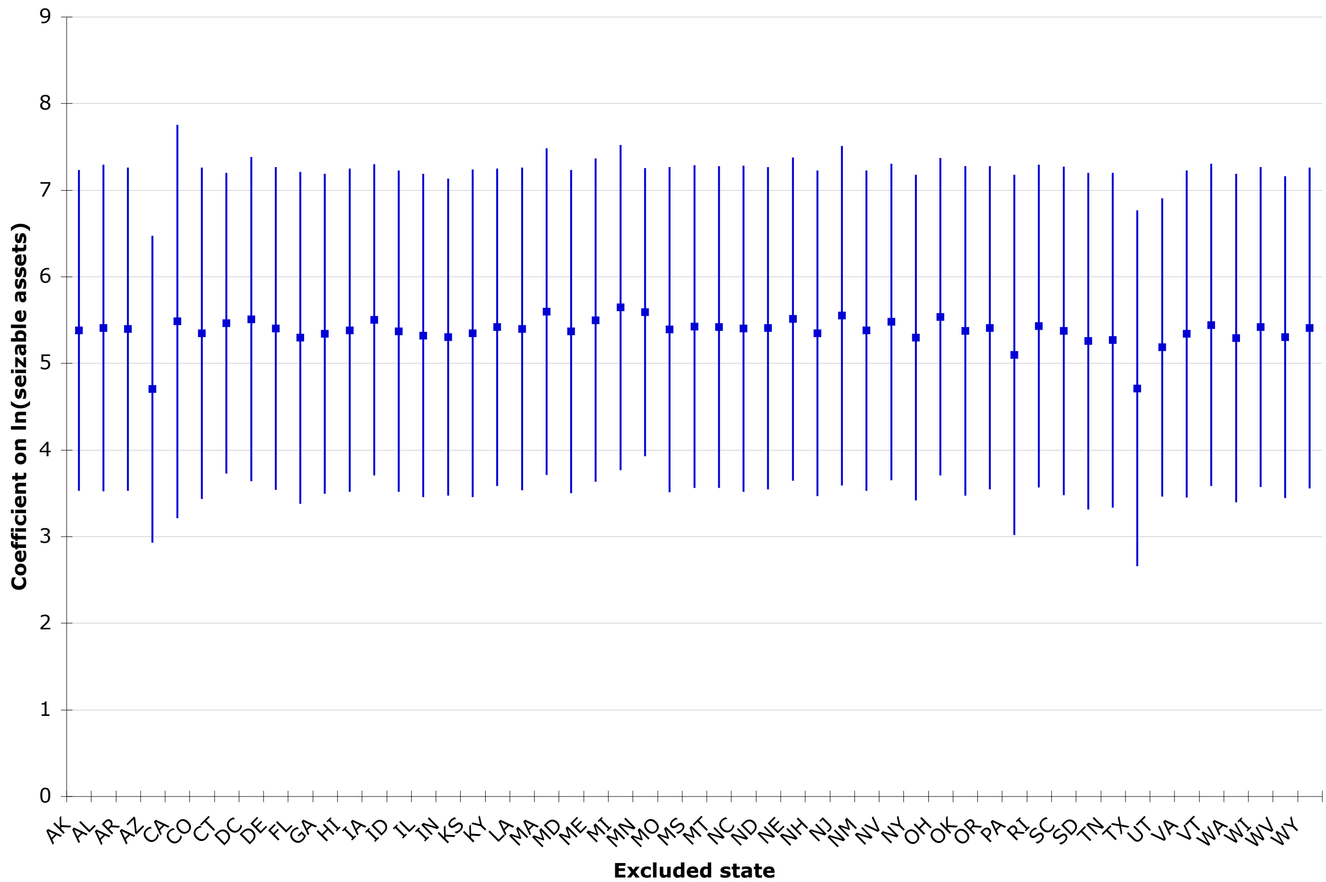
(e) Insurance Coverage vs. Historical Instrument



(f) Insurance Coverage vs. Historical Instrument

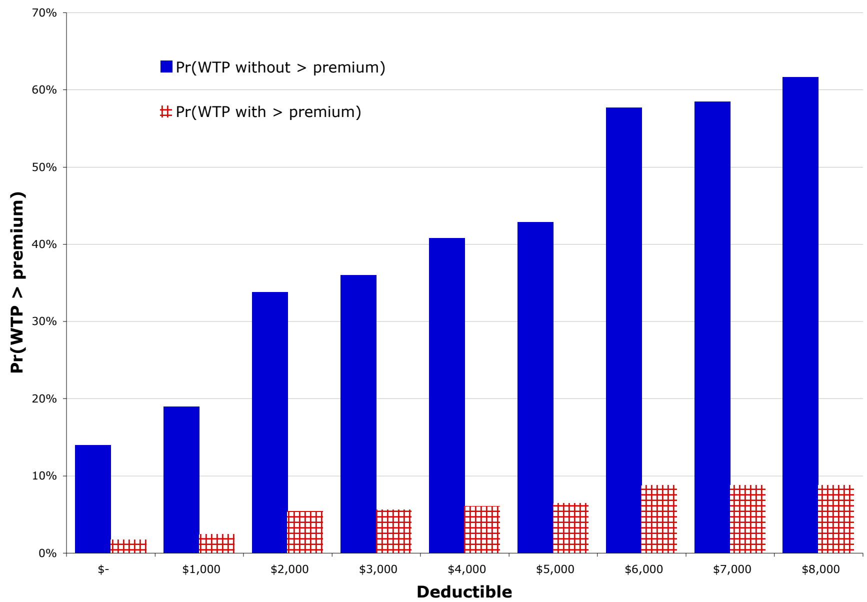
Notes: Figures on the same row show the exact same data. In the left column, data points are indicated with state abbreviations. In the right column, states are indicated with circles proportional to the number of observations from that state. Panels A and B plot the raw data: insurance coverage against log seizable assets averaged by state. Panels C and D plots the reduced form: insurance coverage against the instrument by state. The simulated instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. Panels E and F plots the reduced form with the historical instrument. The historical instrument is constructed similarly to the simulated instrument using seizable home equity under inflation-adjusted 1920 homestead exemption laws. The sample is made up of uninsured and privately insured households, excluding households with a head age 65 or older. Pooled data from the 1999 to 2005 PSID, inflation-adjusted to 2005 using the CPI-U.

Figure 9: Effect on Coverage on Samples Excluding Each State



Notes: Figure shows the coefficients and 95 percent confidence intervals from the baseline 2SLS specification excluding the indicated state. The specification is the same as column 6 of Table 3. The 95 percent confidence intervals are constructed using robust standard errors clustered at the state level. See the Table 3 note for more details.

Figure 10: Micro-Simulation Estimates of Percent Covered Without and With Bankruptcy Insurance by Deductible



Notes: Micro-simulation estimates of the probability the willingness to pay (WTP) exceeds the premium without and with bankruptcy by deductible level. Willingness to pay is calculated using CARA utility with parameter of 2.5×10^{-5}. Premiums calculated as the expected value of medical costs above the deductible scaled up to account for moral hazard (elasticity of -0.22) and administrative loading (50 percent). Household-level estimates weighted by number of individuals per household for interpretation at the individual level.

Figure 11: The Insurance Generosity Gap

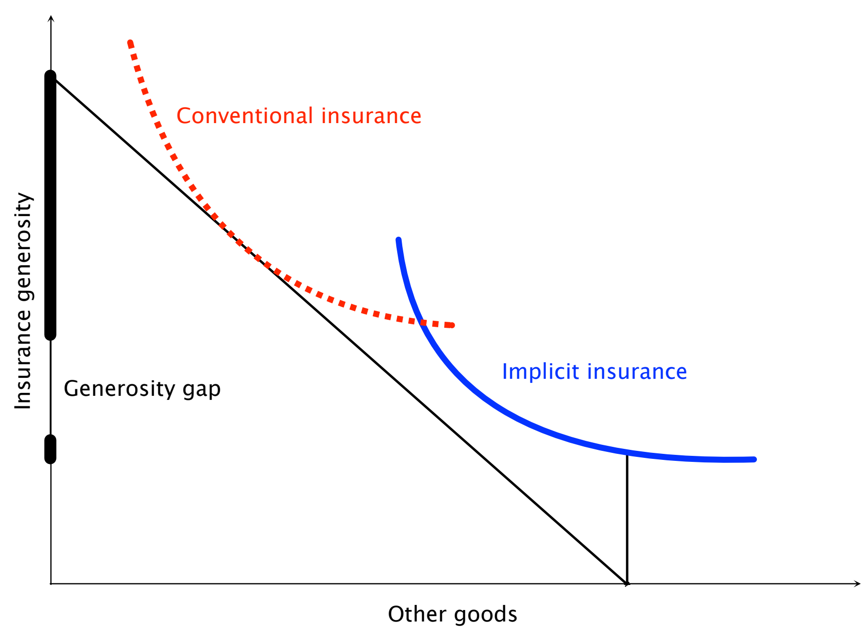


Table 1: Asset Exemption Laws by State

State	Homestead	Vehicle	Retirement	Other financial assets	Wildcard	Wildcard no homestead	Federal available	Homestead exemptions for town lots in 1920
	Contemporaneous exemptions							
Alabama	10,000	0	Unlimited	0	6,000	6,000	No	2,000
Alaska	67,500	7,500	Unlimited	3,500	0	0	No	n/a
Arizona	150,000	10,000	Unlimited	300	0	0	No	4,000
Arkansas	Unlimited	2,400	40,000	0	500	500	Yes	2,500
California--system 1	75,000	4,600	Unlimited	1,825	0	0	No	5,000
California--system 2	0	2,975	Unlimited	0	19,675	19,675	No	n/a
Colorado	90,000	6,000	Unlimited	0	0	0	No	2,000
Connecticut	150,000	3,000	Unlimited	0	2,000	2,000	Yes	1,000
Delaware	0	0	Unlimited	0	500	500	No	0
District of Columbia	Unlimited	5,150	Unlimited	0	17,850	17,850	Yes	n/a
Florida	Unlimited	2,000	Unlimited	0	2,000	2,000	No	n/a
Georgia	10,000	7,000	Unlimited	0	11,200	11,200	No	1,600
Hawaii	40,000	5,150	Unlimited	0	0	0	Yes	n/a
Idaho	50,000	6,000	Unlimited	0	1,600	1,600	No	5,000
Illinois	15,000	2,400	Unlimited	0	4,000	4,000	No	1,000
Indiana	0	0	Unlimited	0	20,000	20,000	No	600
Iowa	Unlimited	1,000	Unlimited	0	200	200	No	n/a
Kansas	Unlimited	40,000	Unlimited	0	0	0	No	n/a
Kentucky	10,000	5,000	Unlimited	0	2,000	2,000	No	1,000
Louisiana	25,000	0	Unlimited	0	0	0	No	2,000
Maine	70,000	10,000	Unlimited	0	12,800	12,800	No	500
Maryland	0	0	Unlimited	0	22,000	22,000	No	0
Massachusetts	1,000,000	1,400	Unlimited	1,250	0	0	Yes	800
Michigan	7,000	0	Unlimited	0	0	0	No	1,500
Minnesota	200,000	7,600	Unlimited	0	0	0	Yes	n/a
Mississippi	150,000	0	Unlimited	0	10,000	10,000	No	3,000
Missouri	15,000	6,000	Unlimited	0	1,250	1,250	No	1,500
Montana	200,000	5,000	Unlimited	0	0	0	No	n/a
Nebraska	12,500	0	Unlimited	0	0	5,000	No	2,000
Nevada	400,000	30,000	1,000,000	0	0	0	No	5,000
New Hampshire	200,000	8,000	Unlimited	0	8,000	8,000	Yes	500
New Jersey	0	0	Unlimited	0	2,000	2,000	Yes	1,000
New Mexico	60,000	8,000	Unlimited	0	1,000	4,000	Yes	1,000
New York	20,000	0	Unlimited	0	10,000	10,000	No	1,000
North Carolina	13,000	3,000	Unlimited	0	8,000	8,000	No	1,000
North Dakota	80,000	2,400	200,000	0	0	15,000	No	n/a
Ohio	10,000	2,000	Unlimited	800	800	800	No	1,000
Oklahoma	Unlimited	6,000	Unlimited	0	0	0	No	n/a
Oregon	33,000	3,400	15,000	15,000	800	800	No	n/a
Pennsylvania	0	0	Unlimited	0	600	600	Yes	300
Rhode Island	200,000	20,000	Unlimited	0	0	0	Yes	0
South Carolina	10,000	2,400	Unlimited	0	0	2,000	No	1,000
South Dakota	Unlimited	0	500,000	0	4,000	4,000	No	n/a
Tennessee	7,500	0	Unlimited	0	8,000	8,000	No	1,000
Texas	Unlimited	0	Unlimited	0	60,000	60,000	Yes	5,000
Utah	40,000	5,000	Unlimited	0	0	0	No	2,000
Vermont	150,000	5,000	Unlimited	1,400	8,400	8,400	Yes	2,000
Virginia	0	4,000	35,000	0	32,000	32,000	No	500
Washington	40,000	5,000	Unlimited	0	4,000	4,000	Yes	1,000
West Virginia	0	4,800	Unlimited	0	51,600	51,600	No	1,000
Wisconsin	40,000	0	Unlimited	2,000	10,000	10,000	Yes	n/a
Wyoming	20,000	4,800	Unlimited	0	0	0	No	2,500
Federal	18,500	5,900	Unlimited	0	20,450	20,450	n/a	n/a
Averages*	58,821	4,884	298,333	501	6,592	7,073	27%	1,679

Notes: Contemporaneous exemptions for couples filing jointly from Elias (2007) and historical exemptions for couples filing jointly from Goodman (1993). Under contemporaneous law, California residents can choose between system 1 and 2 and residents can choose federal exemptions in states where federal exemptions are available. Wildcard no homestead exemption is available to households which do not take the homestead exemption. For the historical exemptions, states that did not exist and states that had acre-based exemptions are denoted as n/a. States that did not have homestead exemptions are assigned a value of zero.
*Excludes states with unlimited or n/a exemptions.

Table 2: Implied First Stage Estimates

	Dependent variable: ln(w^S)			
	(1)	(2)	(3)	(4)
Instruments				
Baseline instrument	1.00			
	(0.04)			
Homestead instrument		0.38		
		(0.06)		
Non-homestead instrument			1.10	
			(0.10)	
Historical homestead instrument				1.41
				(0.31)
Age group				
35-44	-0.14	-0.14	-0.13	-0.12
	(0.02)	(0.02)	(0.02)	(0.02)
45-54	-0.20	-0.20	-0.20	-0.20
	(0.03)	(0.03)	(0.03)	(0.04)
55-64	-0.23	-0.23	-0.21	-0.22
	(0.04)	(0.04)	(0.04)	(0.04)
Family structure				
Couple	-0.21	-0.21	-0.20	-0.22
	(0.03)	(0.03)	(0.03)	(0.03)
Single parent	-0.02	-0.02	-0.02	0.00
	(0.03)	(0.03)	(0.03)	(0.03)
Couple with children	-0.27	-0.26	-0.26	-0.26
	(0.03)	(0.03)	(0.03)	(0.04)
Race				
Non-white	0.00	-0.01	0.01	0.02
	(0.02)	(0.03)	(0.02)	(0.02)
Education				
High school to some college	0.02	0.03	0.03	0.05
	(0.03)	(0.03)	(0.03)	(0.02)
College or greater	-0.01	0.00	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Income polynomial (4th order)	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes
R-squared	0.89	0.88	0.88	0.89
N	20,265	20,265	20,265	17,418
F-statistic on excluded instrument	494.06	36.16	116.93	20.95
Prob > F	0.00	0.00	0.00	0.00

Notes: The baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. The homestead, non-homestead, and historical homestead instruments are constructed similarly using seizable home equity, non-homestead seizable assets, and seizable home equity under inflation-adjusted 1920 homestead exemption laws. The excluded demographic groups are age 18-34, single, less than high school, and white. The state controls are mean income, percent unemployed, and percent covered by Medicaid. Robust standard errors clustered at the state level in parentheses. Pooled 1999 to 2005 PSID excluding households with public insurance or a head age 65 or older. Inflation-adjusted to 2005 using the CPI-U.

Table 3: Baseline Coverage Estimates

	Dependent variable: Percent of household insured							
	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(w^S)$	6.13	2.45	2.36	2.63	8.80	5.43	5.38	6.15
	(0.37)	(0.20)	(0.53)	(0.25)	(2.27)	(1.16)	(0.95)	(0.87)
Age group								
35-44		4.48	3.98	4.48		3.49	4.28	3.32
		(0.97)	(0.93)	(1.13)		(1.10)	(0.88)	(1.60)
45-54		3.08	2.48	2.91		1.22	2.94	0.78
		(1.04)	(1.02)	(1.34)		(1.27)	(0.98)	(2.39)
55-64		8.03	7.44	8.48		4.53	7.79	4.42
		(1.08)	(1.05)	(1.44)		(1.81)	(1.01)	(3.63)
Family structure								
Couple		5.38	4.76	6.55		5.05	5.29	5.89
		(1.55)	(1.43)	(1.92)		(1.48)	(1.42)	(1.95)
Single parent		3.04	3.00	4.72		3.29	3.13	5.01
		(1.55)	(1.51)	(1.92)		(1.52)	(1.48)	(2.00)
Couple with children		11.41	10.51	12.53		11.16	11.14	12.25
		(1.51)	(1.38)	(1.96)		(1.41)	(1.37)	(1.83)
Race								
Non-white		-6.34	-6.06	-5.85		-4.95	-5.86	-4.10
		(0.76)	(0.77)	(1.01)		(0.88)	(0.82)	(1.26)
Education								
High school to some college		9.86	9.83	8.65		9.12	9.51	7.77
		(1.88)	(1.86)	(2.37)		(1.81)	(1.83)	(1.70)
College or greater		11.79	12.03	10.76		10.35	11.94	8.91
		(1.77)	(1.73)	(2.10)		(1.68)	(1.70)	(1.86)
Income polynomial (4th order)		Yes	Yes	Yes		Yes	Yes	Yes
Wealth polynomial (4th order)			Yes				Yes	
State controls		Yes	Yes	Yes		Yes	Yes	Yes
State premium index (log points)				-1.15				-1.47
				(0.91)				(0.93)
Instrument								
Baseline instrument					Yes	Yes	Yes	Yes
R-squared	0.13	0.27	0.28	0.27	-	-	-	-
N	20,265	20,265	20,265	14,510	20,265	20,265	20,265	14,510

Notes: The dependent variable is the percent of household member-months insured. In the 2SLS specifications, the baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. The excluded demographic groups are age 18-34, single, less than high school, and white. The state controls are mean income, percent unemployed, and percent covered by Medicaid. See text for a description of the premium index. All specifications include an indicator for the bottom-coding of seizable assets. Robust standard errors clustered at the state level in parentheses. Pooled 1999 to 2005 PSID excluding households with public insurance or a head age 65 or older. Inflation-adjusted to 2005 using the CPI-U.

Table 4: Sensitivity Analysis of the Effect on Coverage

	Dependent variable: Percent of household insured							
	Publicly insured	Ins mkt regs	Census region	Census division	Baseline IV by group	Homestead IV	Non-homestead IV	Historical IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(w^S)$	6.30	4.71	5.01	4.23	4.71	4.53	6.16	6.39
	(1.11)	(1.23)	(1.83)	(0.72)	(1.17)	(1.29)	(0.67)	(0.82)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional state legislative factors		Yes						
Census region FE			Yes					
Census division FE				Yes				
Instrument								
Baseline instrument	Yes	Yes	Yes	Yes				
Baseline instrument by group					Yes			
Homestead instrument						Yes		
Non-homestead instrument							Yes	
Historical instrument								Yes
N	25,450	20,265	20,265	20,265	20,265	20,265	20,265	17,418

Notes: The dependent variable is the percent of household member-months insured. The baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. Means are taken by age and education group for the baseline instrument by group variable. The homestead, non-homestead and historical homestead instruments are constructed similarly to the baseline instrument using seizable home equity, non-homestead seizable assets, and seizable home equity under inflation-adjusted 1920 homestead exemption laws. Demographic controls are dummies for age group, family structure, race, and education. State controls are mean income, percent unemployed, and percent covered by Medicaid. Additional state legislative factors are insurance market regulations and Medicaid Medically Needy program parameters. See text for details. All specifications include an indicator for the bottom-coding of seizable assets. Robust standard errors clustered at the state level in parentheses. Pooled 1999 to 2005 PSID excluding households with public insurance or a head age 65 or older. Inflation-adjusted to 2005 using the CPI-U.

Table 5: Heterogeneity in the Effect on Coverage

	Dependent variable: Percent of household insured							
	Younger household head(<35)	Older household head (≥35)	Non-homeowner	Homeowner	Lower income (< median)	Higher income (≥ median)	Lower seizable assets (< median)	Higher seizable assets (≥ median)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(w^S)$	7.67	3.02	6.98	4.98	8.18	2.79	8.24	4.87
	(1.90)	(0.98)	(1.06)	(1.48)	(1.70)	(1.16)	(1.41)	(0.91)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrument								
Baseline instrument	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.24	0.23	0.22	0.17	0.19	0.13	0.25	0.13
N	12,460	7,805	7,573	12,692	9,859	10,406	10,091	10,174

Notes: 2SLS regressions on samples partitioned by household characteristics. The dependent variable is the percent of household member-months insured. The baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. Demographic controls are dummies for age group, family structure, race, and education. State controls are mean income, percent unemployed, and percent covered by Medicaid. All specifications include an indicator for the bottom-coding of seizable assets. Robust standard errors clustered at the state level in parentheses. Pooled 1999 to 2005 PSID excluding households with public insurance or a head age 65 or older. Inflation-adjusted to 2005 using the CPI-U.

Table 6: The Effect on Assets

	Dependent variable:							
	1(homeowner)	ln(home equity)	1(homeowner)	ln(home equity)	1(vehicle owner)	ln(vehicle equity)	1(wealth > 0)	ln(wealth)
	OLS		2SLS		OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Homestead instrument	-0.009	0.000	0.066	0.000				
	(0.014)	(0.000)	(0.149)	(0.000)				
Vehicle instrument					-0.088	-0.288		
					(0.064)	(0.149)		
Baseline instrument	0.008	0.000	-0.078	0.000	-0.025	-0.047	-0.011	-0.011
	(0.031)	(0.000)	(0.178)	(0.000)	(0.014)	(0.041)	(0.007)	(0.083)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income polynomial (4th order)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth polynomial (4th order)	Yes	Yes	Yes	Yes	Yes	Yes		
Instrument								
Historical homestead			Yes	Yes				
R-squared	0.47	1.00	-	-	0.16	0.35	0.10	0.43
N	20,265	17,293	17,418	14,836	20,265	17,699	20,265	17,293

Notes: Regressions of assets (indicators for positive values and log values) on state-level measures of asset exemption law (the instruments). The homestead instrument is mean log seizable home equity for a constant, nationally representative sample of households as though they lived in each state. The historical, vehicle, and baseline instruments are constructed similarly using seizable home equity under inflation-adjusted 1920 homestead exemption laws, seizable vehicle equity, and seizable assets. Demographic controls are dummies for age group, family structure, race, and education. Pooled 1999 to 2005 PSID excluding households with public insurance or a head age 65 or older. Inflation-adjusted to 2005 using the CPI-U. Homeownership rate is 72.5 percent. Vehicle ownership rate is 91.0 percent.

Table 7: The Effect on Premiums

	Dependent variable: ln(premium)					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline instrument	-0.098	-0.098	-0.074	-0.093	-0.111	-0.160
	(0.059)	(0.053)	(0.038)	(0.106)	(0.107)	(0.076)
State controls						
Medicaid (share)		-0.354	-0.289		-0.417	-0.617
		(1.004)	(0.794)		(1.185)	(0.890)
Income		0.000	0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Unemployment (share)		-0.065	-0.540		1.120	-0.333
		(2.675)	(1.850)		(3.060)	(1.767)
Additional state legislative factors						
Coverage mandates			0.003			0.000
			(0.004)			(0.004)
Any willing phamacists			0.058			0.031
			(0.051)			(0.058)
Any willing provider			-0.026			-0.050
			(0.060)			(0.067)
Community rating			0.532			-0.016
			(0.089)			(0.070)
Guarenteed issue			-0.450			0.091
			(0.133)			(0.135)
Charity care pool			-0.140			-0.207
			(0.060)			(0.064)
Plan FE	Yes	Yes	Yes	Yes	Yes	Yes
Instrument						
Historical instrument				Yes	Yes	Yes
R-squared	0.833	0.834	0.865	-	-	-
N	1,891	1,891	1,891	1,420	1,420	1,420

Notes: The dependent variable is the monthly premium for a 30-year-old non-smoking male for plans offered by eHealthInsurance. The baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in that state. In the 2SLS specifications, mean seizable home equity under 1920 homestead exemptions laws is used as an instrument. Robust standard errors clustered at the state level in parentheses. Premiums inflation-adjusted to 2005 using the CPI-U.

Table 8: Baseline Costs Estimates

	Dependent variable: ln(out-of-pocket+1)					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(w^S)$	0.561	0.219	0.271	0.572	0.368	0.350
	(0.014)	(0.030)	(0.037)	(0.014)	(0.040)	(0.038)
Age group						
35-44		-0.118	-0.092		-0.237	-0.123
		(0.119)	(0.120)		(0.128)	(0.121)
45-54		-0.136	-0.075		-0.255	-0.088
		(0.136)	(0.133)		(0.146)	(0.134)
55-64		-0.210	-0.088		-0.368	-0.089
		(0.155)	(0.158)		(0.162)	(0.158)
Family structure						
Couple		0.226	0.298		0.245	0.335
		(0.103)	(0.096)		(0.107)	(0.098)
Single parent		0.009	0.026		0.083	0.065
		(0.121)	(0.121)		(0.113)	(0.119)
Couple with children		-0.217	-0.135		-0.138	-0.072
		(0.146)	(0.141)		(0.153)	(0.139)
Race						
Non-white		0.011	-0.043		-0.049	-0.092
		(0.119)	(0.122)		(0.122)	(0.120)
Education						
High school to some college		0.205	0.173		-0.001	0.095
		(0.113)	(0.116)		(0.115)	(0.115)
College or greater		0.219	0.254		-0.067	0.167
		(0.175)	(0.176)		(0.179)	(0.181)
Income polynomial (4th order)		Yes	Yes		Yes	Yes
Wealth polynomial (4th order)			Yes			Yes
Relative Risk Score polynomial (4th order)		Yes	Yes		Yes	Yes
Instrument						
Baseline instrument				Yes	Yes	Yes
R-squared	0.856	0.881	0.882	-	-	-
N	3,401	3,401	3,401	3,401	3,401	3,401

Notes: Regressions of out-of-pocket payments on seizable assets in the sample of uninsured households with positive medical utilization. In the 2SLS specifications, the baseline instrument is mean log seizable assets for a constant, nationally representative sample of households as though they lived in state state. The excluded demographic groups are age 18-34, single, less than high school, and white. The Relative Risk Score is a measure of utilization based on medical diagnoses. All specifications include an indicator for the bottom-coding of seizable assets. Robust standard errors clustered at the state level in parentheses. Pooled 2000 to 2005 MEPS inflation-adjusted to 2005 using the CPI-U.

Table 9: Sensitivity Analysis of the Effect on Costs

	Dependent variable: ln(out-of-pocket+1)					
	Hospital controls	Homestead IV	Non-homestead IV	Historical IV	High/low utilization, baseline IV	High/low utilization, historical IV
	(1)	(2)	(3)	(4)	(5)	(5)
$\ln(w^S)$	0.380	0.377	0.382	0.375		
	(0.066)	(0.038)	(0.039)	(0.039)		
$\ln(w^S)$ X 1(High utilization)					0.512	0.506
					(0.044)	(0.046)
$\ln(w^S)$ X 1(Low utilization)					0.360	0.372
					(0.038)	(0.037)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
State hospital factors						
Nonprofit share	-0.123					
	(0.439)					
Forprofit share	0.913					
	(0.694)					
DSH payments per 1,000	0.000					
	(0.000)					
Charity care pool indicator	0.009					
	(0.214)					
FQHC per 100,000	0.043					
	(0.043)					
Relative Risk Score polynomial (4th order)	Yes	Yes	Yes	Yes	Yes	Yes
Instrument						
Baseline instrument	Yes				Yes	
Homestead instrument		Yes				
Non-homestead instrument			Yes			
Historical instrument				Yes		Yes
N	3,401	3,401	3,401	2,839	3,401	2,839

Notes: Regressions of out-of-pocket payments on seizable assets in the sample of uninsured households with positive medical utilization. The baseline instrument is mean log seizable assets by state for a constant, nationally representative sample of households as though they lived in each state. The homestead, non-homestead, and historical homestead instruments are constructed similarly using variation in seizable home equity, non-homestead seizable assets, and seizable home equity under inflation-adjusted 1920 homestead exemption laws. Demographic controls are dummies for age group, family structure, race, and education. The Relative Risk Score is a measure of utilization based on medical diagnoses. All specifications include an indicator for the bottom-coding of seizable assets. Robust standard errors clustered at the state level in parentheses. Pooled 2000 to 2005 MEPS inflation-adjusted to 2005 using the CPI-U.

Table 10: Micro-Simulation Estimates of Percent Covered Without and With Bankruptcy Insurance by Insurance Status

	Pr(WTP > premium)		
	Without bankruptcy	With bankruptcy	Difference
Low risk aversion			
Uninsured	34%	5%	28%
Insured	62%	48%	14%
Difference	-28%	-43%	14%*
Moderate risk aversion			
Uninsured	71%	11%	60%
Insured	85%	62%	23%
Difference	-14%	-51%	37%*
High risk aversion			
Uninsured	91%	21%	70%
Insured	99%	75%	24%
Difference	-8%	-54%	46%*

Notes: Micro-simulation estimates of the probability that the willingness to pay exceeds the premium by insurance status for a $2,000 deductible plan. Willingness to pay (WTP) calculated using CARA utility with parameters of 2.5 x 10^-5 (low risk aversion), 5.0 x 10^-5 (moderate risk aversion), and 7.5 X 10^-5 (high risk aversion). Premiums calculated as the expected value of medical costs above the deductible scaled up to account for moral hazard (elasticity of -0.22), administrative loading (10 and 50 percent), and the cross subsidization of unpaid care (endogenously determined). Household-level estimates weighted by the number of individuals per household for interpretation at the individual level.
*Difference-in-differences.

Table 11: Policy Counterfactuals

	Penalty	Take-up	Δ WTP	Δ Cost	Δ Surplus
Pigovian penalty					
Low risk aversion	$218.21	7.5%	$10.02	$6.06	$3.95
Moderate risk aversion	$218.21	7.3%	$11.02	$6.83	$4.19
High risk aversion	$218.21	7.9%	$12.30	$7.72	$4.58
PPACA penalty					
Low risk aversion	$481.43	63.6%	-$7.38	$5.34	-$12.72
Moderate risk aversion	$481.43	56.4%	$3.02	$14.40	-$11.38
High risk aversion	$481.43	49.7%	$11.09	$20.24	-$9.15
Medical debt non-dischargeable					
Low risk aversion	n/a	100.0%	-$48.26	-$12.12	-$36.14
Moderate risk aversion	n/a	100.0%	-$28.18	$12.75	-$40.93
High risk aversion	n/a	100.0%	-$6.43	$36.74	-$43.17

Notes: Micro-simulation estimates of insurance take-up, willingness to pay, costs, and social surplus from different penalty systems relative to a baseline in which households can choose bankruptcy at no cost. The Pigovian penalty is the household-specific social cost of the implicit insurance from bankruptcy. PPACA is the inflation-adjusted, fully phased-in penalty under this legislation, defined as the greater of $625 or 2.5 percent of income, up to a maximum of $2,085 per household. Medical debt non-dischargeable exposes households to the full financial risk when uninsured. Take-up is the percent of uninsured individuals that take up coverage. Willingness to pay (WTP) is calculated using CARA utility with parameters of 2.5 x 10^-5 (low risk aversion), 5.0 x 10^-5 (moderate risk aversion), and 7.5 x 10^-5 (high risk aversion). Household-level estimates weighted by number of individuals per household for interpretation at the individual level.

Table A1: Summary Statistics: Seizable Assets by Insurance Status

	Mean	Std. Dev.	Percentile 5th	25th	50th	75th	95th
Panel A: All (n = 22,844)							
Seizable assets	$216,943	$1,105,939	-$10,148	$2,344	$34,328	$155,219	$796,366
Gross seizable assets	$221,434	$1,106,139	$0	$3,500	$38,400	$158,699	$797,593
Seizable home equity (70.4% homeownership)	$52,487	$134,239	$0	$0	$0	$53,760	$249,205
Other seizable assets	$168,948	$1,054,503	$0	$1,010	$18,000	$81,180	$616,680
Dischargeable debt	$6,659	$15,675	$0	$0	$1,024	$7,305	$28,678
Filing costs	$2,000	$0	$2,000	$2,000	$2,000	$2,000	$2,000
Panel B: Privately Insured (n = 20,197)							
Seizable assets	$233,241	$1,153,125	-$9,880	$3,423	$42,809	$168,945	$849,475
Gross seizable assets	$237,970	$1,153,292	$0	$5,860	$46,294	$172,870	$852,001
Seizable home equity (73.3% homeownership)	$56,416	$139,145	$0	$0	$0	$60,320	$260,000
Other seizable assets	$181,554	$1,099,952	$0	$2,308	$21,500	$90,649	$654,239
Dischargeable debt	$6,898	$15,979	$0	$0	$1,297	$7,684	$29,511
Filing costs	$2,000	$0	$2,000	$2,000	$2,000	$2,000	$2,000
Panel C: Uninsured (n = 2,647)							
Seizable assets	$41,658	$207,719	-$13,305	$2,000	$2,344	$14,937	$212,000
Gross seizable assets	$43,586	$207,884	$0	$0	$637	$16,000	$218,871
Seizable home equity (38.5% homeownership)	$10,222	$40,560	$0	$0	$0	$0	$75,000
Other seizable assets	$33,364	$197,079	$0	$0	$0	$9,348	$158,089
Dischargeable debt	$4,095	$11,615	$0	$0	$0	$3,264	$20,304
Filing costs	$2,000	$0	$2,000	$2,000	$2,000	$2,000	$2,000

Notes: Household-level statistics from the pooled 1999 to 2005 PSID inflation-adjusted to 2005 using the CPI-U. Excludes households with a head age 65 or older and those with public insurance. See text seizable assets calculation for details.

Table A2: Summary Statistics: Medical Costs by Insurance Status

	Mean	Std. Dev.	Percentile 5th	25th	50th	75th	95th
Panel A: All (n = 34,841)							
Charges	$6,647	$17,781	$0	$420	$1,836	$6,099	$27,029
Total payments	$4,085	$9,704	$0	$309	$1,388	$4,275	$15,859
Private payments	$2,974	$8,648	$0	$37	$661	$2,701	$12,448
Public payments	$85	$1,094	$0	$0	$0	$0	$78
Misc payments	$243	$2,102	$0	$0	$0	$0	$715
Out-of-pocket payments	$783	$1,565	$0	$76	$340	$907	$2,934
Panel B: Insured (n = 31,753)							
Charges	$7,201	$18,437	$0	$590	$2,201	$6,860	$28,617
Total payments	$4,480	$10,131	$0	$455	$1,678	$4,786	$16,767
Private payments	$3,391	$9,157	$0	$190	$954	$3,209	$13,528
Public payments	$83	$1,078	$0	$0	$0	$0	$89
Misc payments	$204	$1,673	$0	$0	$0	$0	$567
Out-of-pocket payments	$801	$1,474	$0	$103	$375	$943	$2,939
Panel C: Uninsured (n = 3,088)							
Charges	$2,691	$11,353	$0	$0	$232	$1,429	$11,022
Total payments	$1,267	$4,966	$0	$0	$136	$858	$5,231
Private payments	$0	$0	$0	$0	$0	$0	$0
Public payments	$96	$1,200	$0	$0	$0	$0	$0
Misc payments	$515	$3,989	$0	$0	$0	$40	$1,678
Out-of-pocket payments	$657	$2,097	$0	$0	$80	$543	$2,906

Notes: Household-level statistics from the pooled 2000 to 2005 MEPS inflation-adjusted to 2005 using the CPI-U. Charges are the list price of medical care received. Private payments are from private insurance providers (e.g., employer sponsored insurance, individual market insurance), public payments are from public insurance (e.g, Medicaid), miscellaneous payments are from other sources (e.g. Workman's Compensation), and out-of-pocket payments are from households. Total payments are the sum of the payment values.

Table A3: Summary Statistics: Premiums

	N	Mean	Std. Dev.	Min.	Max.
Premium (per month)	1,891	103	46	30	503
Deductible	1,891	3,351	2,229	0	8,963
Coinsurance (%)	1,891	15	12	0	50

Notes: Plan characteristics for all plans offered to a 30-year-old non-smoking male in each state on eHealthInsurance. Values inflation-adjusted to 2005 using the CPI-U.

Table A4: Costs and Premiums by Deductible Level

		Premium	
Deductible	Pr(Costs > deductible)	Calibrated	Individual Market
$0	46.0%	$2,126	$2,140
$1,000	10.4%	$1,735	$2,061
$2,000	5.9%	$1,546	N/A
$5,000	2.7%	$1,259	$874
$10,000	1.5%	$1,009	N/A

Notes: Costs are medical costs when uninsured. Calibrated premiums are calculated as the expected value of medical costs above the deductible scaled up to account for moral hazard (elasticity of -0.22) and administrative loading (50 percent). Individual market premiums are for policies starting in May 2010 issued by Aetna. They are adjusted for inflation using the Medical Care component of the CPI-U. See Appendix D for details.