Long-Term Care and the Elderly

By

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Abstract

Long-term care expenditures represent one of the largest uninsured financial risks facing the elderly. Medicaid provides incomplete insurance against these costs: unlimited nursing home benefits with a deductible equal to the savings and income above the means-testing limits. While private insurance is available, fewer than 10 percent of the elderly are currently covered. This thesis explores how the elderly prepare for future nursing home use and the interactions between the private and public insurance systems.

Chapter one exploits the state-variation in Medicaid generosity to study the financial response of the elderly to perceived future nursing home needs. I find that the elderly shift their consumption and savings decisions in response to Medicaid. Single households have lower net worth through the median of the distribution due to Medicaid policy. On the other hand, I find that married households do not lower total net worth, but they change their relative holdings of protected and non-protected assets.

Chapter two explores the crowd-out effect of the public Medicaid program on demand for private long-term care insurance coverage. We estimate the impact of Medicaid program rules on private long-term care insurance coverage for the elderly. We find small but statistically significant marginal crowd-out effects. Our estimates imply that even a $67,000 decrease in the asset disregard for couples would only increase private long-term care insurance ownership among the elderly by 1.9 percentage points. These findings underscore that marginal reforms to the existing Medicaid program are unlikely to be an effective way of increasing private long-term care insurance coverage among the elderly.

Chapter three explores individuals' expectations for future nursing home use. I compare self-reported probabilities to the statistical probability computed with a state-of-the-art model used by the long-term care insurance industry. I find that respondents tend to overestimate unlikely outcomes and underestimate likely outcomes. On average, though, the expectations are very accurate. I find that expectations for nursing home use evolve with health conditions in similar ways as the statistical probability. While I find that expectations include private information, they do not account for all information available to the individual, especially the individual's demographic characteristics.

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Chapter One

Financing Nursing Home Care: New Evidence on Spend-Down Behavior

1.1 Introduction

This paper examines how Medicaid coverage of nursing home care affects wealth accumulation decisions by the elderly. Long-term care represents a large, and largely uninsured, expenditure facing the elderly, averaging over $50,000 a year in 2000. Medicaid covers long-term care, but only after most private savings is exhausted. Hubbard, Skinner, and Zeldes (1995) model the role of a means-tested social safety net on savings, but to date their findings have not been widely tested (See Powers (1996), Gruber and Yelowitz (1999)). The literature thus far has largely ignored the potential impact of Medicaid on the savings of the elderly. The implications of the model are concrete: a means-tested program can lead to lower savings for those who might qualify for the program.

I use the 1995-2000 waves of the Asset and Health Dynamics of the Oldest Old (AHEAD) cohort of the Health and Retirement Survey (HRS). I supplement the public-use files by adding restricted state-of-residence information. I have collected a panel of Medicaid eligibility and estate recovery rules for every state during this time period, and match these rules to the household. I construct three measures of state Medicaid generosity: the number of days until one would pass the means-test, the percent of a one-year stay in a nursing home that a Medicaid recipient would have to pay out-of-pocket, and the percent of a five year stay that one would have to pay out-of-pocket. To purge these variables of their endogeneity, I take two approaches. The first is similar to the Currie and Gruber (1996) simulated eligibility measure, where I apply the state-median Medicaid generosity to everyone in the state. The second consists of using quantile IV estimation as proposed in Chernozhukov and Hansen (forthcoming).

I explore two major avenues available to households to shift more of the cost of a nursing home stay to the government. The first is available to all households, and it is to simply lower your net worth. The second is available to single households in select states and all married

couples, and that is to put more money in housing assets, which are protected from the Medicaid program. I find that single households use both methodologies; the net worth is lower in the bottom half of the distribution, and the lowest quantiles lower their housing wealth if it is not protected. On the other hand, married households do not seem to be lowering their overall net worth. Instead, I find that married households shift assets from non-protected to protected forms.

The structure of the rest of the paper is as follows: Section 1.2 gives a brief background of Medicaid and long-term care. Section 1.3 examines the state of the current literature. Section 1.4 outlines the economic model. I describe the data and my empirical strategy in detail in Section 1.5. Section 1.6 presents the results. My conclusions are presented in section 1.7.

1.2: Brief Background on Medicaid and Long-Term Care

1.2.1 Who Uses and Who Pays For Long-Term Care

Over a lifetime, the probability of using a nursing home is quite high. While there is approximately a 40% chance for a 65-year-old to use a nursing home, the financial risk is far from uniform. Dick et al. (1994) estimate that while one-third of people entering nursing homes will spend less than three months there, 40 percent will spend at least a year in care, and 12 percent will spend five or more years. At over $50,000 a year on average, this stay would represent a substantial drain on a household's budget. Despite this risk, there remains little purchase of private long-term care insurance. (See Brown and Finkelstein 2004.) Finkelstein and McGarry (2003) estimate that only 10 percent of those aged 60 and older had private long-term care insurance in 2000. In fact, of the nearly $71 billion that the US paid towards institutional care for the elderly in 2000, only $300 million, or less than .5%, came from private insurance.[1]

The Federal and state governments bore almost 60% of the institutional costs for the elderly through Medicaid and Medicare in 2000. Medicare, health insurance for the elderly, provides very limited nursing home coverage and is targeted to those with temporary needs that can be met more cheaply in a nursing home than through an extended hospital stay. If the patient needs short-term daily skilled nursing home care or rehabilitation after a minimum 3-day hospital stay, Medicare will pay 100% of the nursing home costs for the first 20 days, and 80%

[1] 2000 Greenbook, US House of Representatives.

of the costs for the next 80 days, providing that the transfer to a Medicare certified nursing facility takes place within 30 days of the hospital discharge. Thus, patients with degenerative cognitive dysfunction who are otherwise healthy would not qualify for Medicare nursing facility coverage. Because of the specific targeting of the insurance and its limited duration, Medicare paid only 15% of the institutional care costs for the elderly in 2000.

Medicaid, on the other hand, will pay for an unlimited amount of nursing home care, regardless of the underlying cause or the ability to recuperate. This insurance is not free: Medicaid is means-tested, and generally speaking, the eligibility rules require spending most of a household's accumulated assets before coverage can start. Even once covered, a patient must still contribute any "excess income," as determined by the Medicaid rules, to their own care. Still, Medicaid paid $31 billion dollars in 2000 for nursing home care for the elderly. The remaining 40% was paid out-of-pocket by the patients themselves – an average of over $17,000 per nursing home resident per year.

Despite the decreasing morbidity measures for the elderly, the aging of the population, increased longevity, and real cost growth has led to concerns about this mounting public liability. Medicaid spending on nursing facility care almost doubled between 1990-1997. Real expenditures are projected to triple by 2040 (Congressional Budget Office, 1999). Zedlewski and McBride (1992) predict that not only will the number of elderly increase from 1.8 million in 1990 to between 3 to 3.4 million in 2010, but that the *proportion* of elderly needing nursing home care will increase from 5.7% to 7% over the same time period. This percentage will continue to rise over time, due to decreasing fertility and increasing numbers of elderly living alone, thereby limiting the options for informal care. Even with the projected decrease in disability rates in Manton and Land (2000), Tilly et al. (2001) estimate that the number of elderly with disabilities will double between 2000 and 2050. They also estimate that there will be 4.5 million adults (10.5 million) aged 85 and older in 2050 in institutional care (home health care), compared to 2 million (5.4 million) in 2000.

The current state fiscal crises exacerbate these concerns. Medicaid is a cost borne by both the state (42%) and federal (58%) governments. The Medicaid program represents over 20 percent of state budgets in fiscal year 2000 (State Health Care Expenditure Report 2003), second only to elementary and secondary education. The nursing home component alone cost the states over $25 billion annually. Medicaid had an average annual growth rate of 13 percent in 2002

(Fiscal Survey of States, Table 5), and has been a widely discussed option for budget cutting. According to the Kaiser Commission report, *The Continuing Medicaid Budget Challenge: State Medicaid Spending Growth and Cost Containment in Fiscal Years 2004 and 2005: Results from a 50-State Survey*, every state and the District of Columbia instituted cost containment measures in both FY 2003 and FY 2004. Additionally, every state has specific plans to continue cost containment in FY 2005. An increasing number of states are opting to cut long-term care: seven cut benefits in 2002, and 17 have adopted measures for 2005.

1.2.2: Medicaid Income Eligibility Rules

Medicaid eligibility for nursing home care is a complicated calculation due to the myriad state and federal rules. Below I outline only those rules that apply to the elderly and to nursing home coverage. Income and assets tests are present universally, but how they are applied depends on the state of residence, the marital status of the applicant, the residence of any disabled or minor dependents, the type of assets the applicant holds, as well as the cost of the nursing facility itself. Table 1.1 details the states' Medicaid eligibility rules and income and asset limits for 2001.

There are five main avenues for an elderly institutionalized person to qualify for Medicaid (in order of generosity): (a) the Medically Needy Program, (b) the special-income rule, (c) 209(b) states, (d) through another program, such as Supplemental Security Income (SSI) or the State Supplementation Payment (SSP), or (e) income-test states.

The Medically Needy program was used by 29 states and the District of Columbia in 2000. This is the most generous way to qualify for Medicaid in an institutional setting. Not only can you deduct your medical costs from your income before applying the income test, but the income and asset test limits are generally much higher than for the other avenues to Medicaid coverage.

The special-income rule was used by 35 states in 2000, 16 of which also use the Medically Needy program. The special-income rule is only applicable to nursing home residents, distinct from those seeking other types of care. This allows your income to be higher than the normal Medicaid rules allow, up to 300% of the SSI benefit, while still qualifying for Medicaid. All states have opted for the full 300% threshold, except Delaware (250%), Missouri

(175%) and New Hampshire (244%). The asset test, however, is more stringent than the Medically Needy asset test, and is the same as the SSI asset rules.

States have the option of not using the indexed Federal income standards for determining SSI eligibility, but rather using their 1972 income standards, resource standards, and/or methodologies to determine eligibility instead. These are called 209(b) states. As of 2003, 11 states have opted to keep their more restrictive 1972 tests. [CT, HI, IL, IN, MN, MO, NH, ND, OH, OK, VA] These states are required to allow individuals to deduct medical expenses from their income in order to meet the income test for Medicaid – a potentially sizable exclusion when dealing with nursing home expenses. The asset test remains at the normal Medicaid level, thus lower than either of the other aforementioned options.

Those states not opting for 209(b) status are required to provide Medicaid benefits to anyone receiving cash assistance through the Federal Supplemental Security Income (SSI) program. Some states provide their own State Supplementation Payment (SSP) to SSI recipients, and in some cases to those who do not qualify for SSI. As of January 2000, 36 states provide an SSP, all of which also extend Medicaid coverage with the benefit.

States without a medically needy program or the 209(b) designation are called "income-test" states, and are the most stringent states in terms of patient eligibility. Twenty-one states fell into this category in 2000. They do not allow medical spend-down to meet their income test, but are required by Federal law to allow the use of Qualified Income Trusts (QIT), formerly known as Miller Trusts, in order to circumvent the income test. A QIT is a "sheltering" device, but it only shelters income to meet the eligibility criteria. The income generated from a QIT will not be considered income for the income test, but will be considered income in calculating how much the applicant can pay towards his or her own care. QIT's must also be set up to allow the state to recover any assets left upon the death of the Medicaid beneficiary.

For the income determination, all states, except two, divide income using a "name-on-the-check" rule. Joint income, such as income on rental property held in both names, is divided equally. The exceptions, California and Washington, divide all income evenly.

1.2.3 Medicaid Resource Eligibility

Resources for which the asset test applies are defined as "any asset that can be utilized as income." There are, of course, exclusions. The largest is the (uncapped) value of the primary

residence. This can be excluded if the applicant plans on returning home, or if a spouse or a disabled or minor dependent is living in the home. Some states use liens, however, to recover these assets after the death of the Medicaid recipient, sale of the house, or death of the spouse or disabled minor. Thus this exclusion is temporary since it is excluded for eligibility purposes, but may still be used to retroactively pay for care.

Any money invested in an income annuity (like a QIT) is excluded from assets, as is the value of a personal vehicle if there is a community spouse or if the applicant plans on returning to the residence (capped between $4,000 and $10,000 depending on the state). Irrevocable trusts are also excluded.

In addition to the exclusions, there are also income and asset allowances for a community spouse. A minimum and maximum for each allowance are set each year by the Federal government, and indexed for inflation. States then choose a community spouse resource allowance (CSRA) and a community spouse income limit (CSIL) within the appropriate range.

For the asset test for couples, all non-excluded assets are added together, regardless of the name on the asset. Half of this is then attributed to each spouse. If this amount is greater than the federally mandated maximum, then the community spouse gets to keep the federally mandated maximum. If this amount is between the CSRA and the Federally mandated maximum standard, then the community spouse gets to keep half of the assets. If this amount is less than the CSRA, the community spouse gets to keep up to the CSRA level. Any assets not allocated to the community spouse are allocated to the institutionalized spouse, who must spend them down to the state resource limit for a single individual before becoming eligible for Medicaid.

For example, the CSRA in Texas is set at the minimum allowed in 2000, at $16,824, while their asset test for single individuals is set at $2,000. The Federal maximum CSRA is $84,120. If a couple with $200,000 in non-protected assets and one spouse in need of care were to apply for Medicaid nursing home coverage, the community spouse would be able to keep $84,120, or the Federal maximum, which is less than half of the couple's assets. The infirm spouse would keep and additional $2,000, and the remaining $113,880 would need to be "spent-down" before the Medicaid benefits would to start. If the same couple, now with only $90,000 in non-protected assets were to apply, now the community spouse would be able to keep half of the assets, or $45,000. Again, the infirm spouse would keep $2,000, and now $43,000 would

need to be spent down in order to qualify. Finally, if the couple had only $30,000 in non-protected assets, the community spouse would now keep $16,824, since that is greater than half of the assets. The infirm spouse would be able to keep $2,000, and the remaining $11,176 would need to be spent before the Medicaid program would cover the bill.

This system, while designed to give states more flexibility in the implementation and generosity of their Medicaid program, sets up an unusual marginal tax scheme, illustrated in Figure 1.1. If your total assets are greater than the Federal Maximum ($84,120 in 2000), there is a 100% implicit marginal tax on the assets over the limit. There is a 50% marginal tax rate when assets are higher than the state standard but less than twice the state standard. A couple in a state that sets their CSRA at the Federal minimum and whose assets are between $33,648 and $168,240 in 2000 is in this portion of the tax schedule. If the state limit is less than half of the Federal maximum, and if the household assets fall between the state standard and twice the state standard, then the household faces a 100 percent marginal tax rate. This portion of the schedule is where couples in the states that set their CSRA at the Federal minimum with non-protected assets between $16,824 and $33,648 fall. Finally, there is a zero percent marginal tax rate on households whose total assets are less than the state standard, since they do not have to spend any assets to qualify for Medicaid.

1.2.4 Spend-down

There are limits to how one may eliminate assets to qualify for Medicaid. The Medicare Catastrophic Coverage Act of 1988 (MCCA) and the Omnibus Budget Reconciliation Act of 1993 (OBRA93) set up and strengthened a uniform "look-back" period and sanction regime for all states. The state has the right/obligation to see if there are any transfers of assets at below market value in the look-back period – 36 months prior to a nursing home stay, or 60 months for revocable trusts or any other arrangement where the beneficiary has a "life interest." The value of any gift found within the look-back period is then divided by the average Medicaid reimbursement rate in the state. This is then the number of months that the individual is "sanctioned" and prevented from receiving Medicaid benefits, starting with the date of transfer. Example: Joan gives $240,000 to her able-bodied, non-dependent son. Joan goes into a nursing facility 2 years later, and would qualify for Medicaid 4 months later. If the average reimbursement rate was $4,000 a month, Joan would not be eligible for Medicaid benefits until 5

years after the transaction, or 3 years after living in the nursing home. In this example her son could give back the gift to prevent the sanction, or someone will have to pay for her care until the Medicaid sanction is expires.

After qualifying for Medicaid, beneficiaries are required to contribute their income, including any income from a QIT, after allowances, to their own care. The first allowance filled is a state-specific personal needs allowance (PNA) (Federal minimum set at $30 a month, maximum is $90). Second, if the income of the community spouse is less than the spouse protection income standard, income from the institutionalized spouse is given to the community spouse until the void is filled. After these allowances are filled, the "excess" income is used to pay a portion of the institutional care. Medicaid picks up the remainder of the bill as the payer of last resort.

While this set-up is done to minimize the government's burden for nursing home care, it does set up an interesting incentive scheme. If one enters a nursing home and cannot self-fund the entire cost and therefore needs to go on Medicaid, there is an implicit 100% tax on all income and assets over the protected limit. If there is no difference, psychological or in actual care between having public funds or private funds pay for a nursing home, the optimal decision is to consume all wealth over the protected amount in the previous period and then let Medicaid pay for all nursing home costs.

1.3: Literature Review

Most studies that examine the effect of the Medicaid rules focus on the non-elderly and non-disabled population (see Gruber 2000), despite the fact that long-term care spending is almost half of Medicaid expenditures. While there is a large literature on the savings and asset allocation decisions of the elderly, few studies have examined the effect of Medicaid on these decisions.

1.3.1 Spend-down

There is a perceived phenomenon that the middle-class elderly are shielding their assets from the state through various financial transactions to qualify for Medicaid (Moses, 1990; Sloan and Shayne, 1993). There is a substantial literature measuring the phenomenon known as Medicaid spend-down, or the number of people who enter nursing homes as private payers and

eventually become dependent on Medicaid. The results are very sensitive to the data and the methodology used. (See Weiner et al (1996) for a summary.) For example, Norton (2000) reports that less than 20 percent of nursing home patients admitted as private-payers eventually spend-down during their time in the nursing home. Spillman and Kemper (1995), on the other hand, estimate that only 44% of those entering a nursing home as private payer remain so for the duration of their stay.

1.3.2 Long-term care decisions

Medicaid can influence the demand for long-term care by lowering the price of care. If the demand is price-sensitive, then increasing the amount of assets protected under Medicaid, i.e. lowering the price, can increase the demand for nursing facility services. Hoerger, Picone, and Sloan (1996), using the 1982-1989 waves of the National Long Term Care Survey (NLTCS), find that the elderly are price sensitive and that state policies that affect nursing home price or supply have a substantial affect on the institutionalization of the elderly. Further, they find that subsidies to community living have little effect on the institutionalization rate, but do increase the probability of living independently. Thus subsidies to formal home care crowd out informal care, not institutional care. Cutler and Sheiner (1994) report similar results, and also find that higher reimbursement rates draw people into nursing homes that would otherwise live with their children. Using three waves of the National Long-Term Care Survey, Noguchi (1997) finds that the presence of a medically needy program increases an elderly person's probability of entering a nursing home by approximately 30 percent. Auerbach (2002) uses the state variation in Medicaid rules with two waves of AHEAD data and finds that only single elderly are responsive to the Medicaid subsidy level, and estimates an elasticity of -0.5.

1.3.3 Savings decisions

Hoerger, Picone, and Sloan (1996) and Hubbard, Skinner, Zeldes (1995) present the theoretical framework explaining why Medicaid nursing home coverage could have substantial negative effects on savings. There has been very little empirical work thus far to test these predictions. Gruber and Yelowitz (1999) find a negative effect of the Medicaid asset tests using the Survey of Income and Program Dynamics (SIPP) by utilizing Medicaid expansion to children as a natural experiment. Powers (1997) also finds a negative effect of Medicaid asset tests on

wealth accumulation of female-headed households using the National Longitudinal Survey – Young Women. Because of the very different populations in question, their findings may not be applicable to the elderly facing nursing home stays.

Feinstein and Ho (2000) look at asset management and health, but do not look at Medicaid directly. They find that negative health changes dramatically increase the likelihood of spending out of assets. They also find that while higher income leads to higher savings for those in good health, it has no discernable impact on the spending/savings decision for those in poor health.

1.3.4 Inter Vivos Transfers

Basset (1999) and Gilchrist (1999) use a Heckman two-step procedure to predict the probability of an inter vivos transfer, and the size of that transfer, using the self-reported probability of using a nursing home variable that I will describe in detail in the data section. She finds that a one percent increase in the probability of needing a nursing home leads to a .05 percent increase in the probability of making an inter vivos transfer.

1.3.5 Trust Formation

Hoerger, Picone and Sloan (1996) use the National Long Term Care Survey (NLTCS) and found that the Medicaid availability did not have any effect on asset accumulation decisions. Taylor, Sloan and Norton (1999), using the first wave of the AHEAD data, find that avoiding probate and keeping control of their assets is a larger factor in trust creation than Medicaid eligibility rules. They find that while 40 percent of the elderly could be potentially eligible for Medicaid with the creation of a trust, less than 10 percent of the sample had one.

1.3.6 Asset Allocation and Spend-down

None of the studies above look at the savings and asset allocation decisions before entry to a nursing home, primarily because of data limitations. Stum (1998) conducted in-depth interviews using open-ended questions to understand how the family members view and experience the reality of financing long-term care, including the spend-down process. She found that buying prepaid burial trusts and one-time gifts to children ranging from $500 to $8,000 were the most common behavioral responses to imminent spend-down. Norton (1995) uses data from

two different samples of the elderly, the PSID for a non-institutionalized sample and the National Nursing Home Survey (NNHS) for the institutionalized elderly, and finds that the actual time to spend-down to Medicaid eligibility is actually *slower* than the predicted time absent behavioral effects. This indicates that the elderly are not shielding assets from Medicaid, but perhaps using protected assets or transfers from others to *avoid* Medicaid.

There is one paper that looks at both asset allocation and spend-down decisions. Bryant (2002) takes a structural approach, modeling the decisions for insurance, care choice, and spending decisions using a dynamic behavioral model. She measures generosity as the likelihood of becoming eligible, and multiplies that by the average cost of care in that state. She finds that the average person in a state with higher expected Medicaid benefits saves more money.

I am taking a very different approach. First, I am using a reduced form model. This allows me to use the self-reported probability of using a nursing home, which was shown an important predictor of future care (Finkelstein and McGarry (2004)) and determinant of inter vivos transfers (Gilchrist (1999)). Second, I allow behavior to differ between married and single households by splitting the sample, as was shown to be important in Aeurbach (2002). Finally, I look at asset accumulation and allocation directly. Bryant focuses on non-protected assets since that is the metric for Medicaid eligibility rules, while I examine total net worth, which may be of more policy concern. Finally, I use quantile regression methodology, to examine the effect of Medicaid eligibility and generosity through the wealth distribution, not just at the mean. This measures the overall effect of the policy, as well as addressing policy questions of interest, such as elderly poverty rates.

1.4: Model

The theoretical framework for this paper is laid out in Hubbard, Skinner, and Zeldes (HSZ, 1995). They take the basic life-cycle model and add a means-tested government transfer program to the model. Because of the means-testing, they find that with the standard two-period model, at some critical point in the asset distribution, consumption in period 1 will increase in order to induce eligibility for the transfer program in period 2. I modify the basic model slightly to take into account the specifics of Medicaid coverage of nursing homes: specifically, I

introduce unknown health status in period 2, a multiple-kinked budget constraint, and different budget constraints for each health status.

I start with a two-period model. The household is healthy in period 1. There is some probability, p, of needing a nursing home in period 2. Medicaid will help pay for the cost of a nursing home, if the household qualifies for the program. The household dies at the end of period 2, and there is no bequest motive. I assume additive separability of utility between periods. For simplicity, I set the discount rate and the interest rate to zero.

At the beginning of the first period, the household decides on consumption today and tomorrow in either the sick (S) or the healthy (H) state. There is an endowment of assets (A) today, and no other resources either today or tomorrow. The maximization problem is:

$$\begin{aligned} \underset{C_1, C_{2H}, C_{2S}}{Max} \quad & Z = U(C_1) + pU(C_{2S}) + (1-p)U(C_{2H}) \\ S.T. \quad & A \geq C_1 \\ & A - (1-\beta)NH - C_1 \geq C_{2S} \\ & A - C_1 \geq C_{2H} \end{aligned} \tag{1}$$

Where NH is the price of a nursing home, and (1-β) is the fraction of the nursing home price you have to pay out of pocket. β will vary between zero and one. At zero, one is not eligible for Medicaid, thus you will pay all of the nursing home expense. At β equal one, Medicaid completely covers the entire nursing home stay. When β is between zero and one, you qualify for Medicaid but must contribute assets to help cover the nursing home costs. Thus β can be thought of as the generosity of the Medicaid program parameter.

According to the first constraint, borrowing is not allowed in period 1. The second constraint indicates that all assets are used for consumption in period 1, period 2, or to pay the nursing home costs.

The Lagrangian becomes:

$$\begin{aligned} \underset{C_1, C_{2H}, C_{2S}}{Max} \quad & Z = U(C_1) + pU(C_{2S}) + (1-p)U(C_{2H}) + \mu(A - C_1) \\ & + \lambda[A - C_1 - C_{2S} - (1-\beta)NH] + \gamma[A - C_1 - C_{2H}] \end{aligned} \tag{2}$$

where μ is the shadow price of the borrowing constraint, and λ and γ are the marginal utility of income in each state.

Normal maximization yields the first order conditions:

$$\begin{aligned} &U'(C_1) - \mu - \lambda(1 - \frac{\partial \beta}{\partial C_1} * NH) - \gamma = 0 \\ &pU'(C_{2S}) - \lambda = 0 \\ &(1-p)U'(C_{2H}) - \gamma = 0 \end{aligned} \qquad (3)$$

Due to the non-convexities in the budget set imposed by the Medicaid program, there exist multiple local maxima for equation 2, depending on the Medicaid program's generosity (β). But clearly β is endogenous. Finding the global maximum requires solving all the local maxima and choosing the largest. This will yield an optimal consumption function, denoted $C_1^*(\beta, A, p)$. From this, we can determine a (A*,p*) locus, above which it would be optimal to self-fund, below which it would be optimal to use Medicaid.

The HSZ model also predicts the sign of the effect on consumption resulting from a change in the generosity of Medicaid. An increase in Medicaid benefits is similar to a shift in the budget constraint, as illustrated in Figure 2. Those who are already planning on using Medicaid no longer have to consume as much in period 1 in order to qualify; thus $\frac{\partial C_1^*}{\partial \beta} < 0$. The HSZ model also predicts that the (A*,p*) locus would shift outwards, thus people higher in the A distribution (or lower in the p distribution) would decide it is optimal to use Medicaid. For these people, $\frac{\partial C_1^*}{\partial \beta} > 0$. Since I examine asset allocation and accumulation decisions, not consumption directly, it's important to transform these derivatives in terms of assets in period 2 ($A-C_1$). The implication of this model is that for people lower in the asset distribution (or higher in the p distribution), $\frac{\partial (A - C_1)}{\partial \beta} > 0$, thus increasing the generosity of the program would increase net worth in period 2. For people higher in the asset distribution (or lower in the p distribution),

$\frac{\partial(A-C_1)}{\partial\beta} < 0$, so increasing generosity would decrease net worth in period 2 as they now qualify for Medicaid.

1.5: Data and Empirical Approach

A data set that meets all the data requirements for this project is somewhat unique. I need detailed information about wealth and how the wealth is held. I also need information on a person's state of residence. Thirdly, I need *perceived* probabilities of needing a nursing home in the future. Self-reported probabilities are better than average probabilities based on individual or family characteristics because it is the perceived need that will cause a behavioral response. If there is a disconnect between the perceived need and the average need for any reason, then any potential behavioral responses will be mis-measured using averages. Finally, I need a large enough sample of the elderly to be able to measure a response.

The data I use for this project are the 1995-2000 waves of the Assets and Health Dynamics of the Elderly (AHEAD). The AHEAD is a nationally representative panel survey of households with heads at least age 70 in 1993. By design, the AHEAD over samples African-Americans, Mexican-Americans, and Floridians. The AHEAD follows people over time regardless of institutionalization, divorce, or remarriage. The 1993 wave consisted of 8222 individuals, or 6047 households. I do not use the 1993 wave because of differences in asset definitions, top-coding practices, and the questionnaire between 1993 and the other waves. The dataset contains 13,582 household/year observations interviewed in years 1995-2000.

1.5.1 Assets

The AHEAD asked detailed information about wealth in a variety of forms. The methodology of the survey, known as unfolding brackets, reduces the non-response rate for the wealth and income measures. This method asks repeated bracket questions of respondents who could not answer the exact value of an asset or income stream. This allows the AHEAD survey to then impute the exact value through a hot-decking procedure. While I do use the AHEAD imputes, I do not use the asset information for households who do not report any bracket information. This eliminates 2,618 observations.

1.5.2 Health

The AHEAD also asks detailed information about health and expectations. The question: "What is your probability of needing a nursing home in the next 5 years?" is perfectly suited to this situation. Finkelstein and McGarry (2003) find that this question has predictive power above and beyond simple models that include health, age, and other demographic variables.

There are two downsides to using a self-reported probability measure. The first is the problem of focal answers. As is evident in Figure 3, this data has this property. There are high frequencies reported at 0, 25, 50, 75, and 100 percent. To address this, I use a dummy variable for a high probability, defined as reporting a greater than 50 percent probability of using a nursing home.

The second downside is a possible endogeneity problem. If someone cannot afford extensive home-health care, they may report having a higher probability of entering a nursing home than someone of the same health and different financial means. Thus there could be a relationship between self-reported future nursing home use and wealth separate from the spend-down to eligibility issue. To test for this, I also use a predicted probability of using a nursing home in the future, based on health and other observable characteristics as developed in Finkelstein and McGarry (2003). In results not shown, I find very similar results using this predicted probability of needing a nursing home, although the regressions are a much worse fit, as measured by the r-square.

1.5.3 State of Residence

In addition to the public access data, I have added state-of-residence restricted data with special permission from the HRS administration, and access gained through the National Bureau of Economic Research (NBER) in Cambridge, MA. Thus I can accurately assign the state-specific Medicaid rules to each household. Since the asset limit varies by as much as $75,000 depending on the year and the state of residence for a married couple, this matching is key to the identification of the incentives the household faces.

1.5.4 Nursing Home Price

For each state, I use the semi-private room average daily price of a nursing home, as reported in Kiplinger's Retirement Report (1999). I use the CPI index for medical care services to deflate costs over the time period.

1.5.5 Medicaid Policy Variables

There is no central database for the state-specific Medicaid eligibility rules. I have accumulated data from various printed sources[2] over the 1993-2000 period to determine the correct eligibility rules that a household would face in each wave of the survey when making asset allocation decisions. This is critical because there were many state changes over this time period.

Over the 1993-2000 period, 26 states and the District of Columbia changed their PNA. While most states kept their CSRA pegged at either the Federal minimum or the Federal maximum, 20 states did change their policy over the time period, including New York, Michigan, Massachusetts, and Virginia. 13 states introduced estate recovery plans (mandated in OBRA93) during this period, and 4 states were still noncompliant and had not introduced a plan by 1998. In total, 39 states and the District of Columbia changed at least one of their eligibility or estate recovery practices during the survey. Thus inter-state variation and intra-state variation in plan rules are both important dimensions.

1.5.6 Construction of the Medicaid Variables

The Medicaid rules are intricate and interact with each other to create variations in eligibility and benefit generosity. Therefore it is difficult to examine the effects of Medicaid on behavior using each rule independently, or looking at only one aspect of the plan, such as the presence of a Medically Needy program or the value of the CSRA. Instead, it is necessary to use a summary measure for the overall generosity of the state's Medicaid program. I use three different summary measures in the following work.

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[2] See Medicaid Source Book, 1993; Price (1996); Bruen et al (1998); Kassner and Shirley (1998); Sabatino and Wood (1996); 1997 North Carolina Survey of Estate Recovery Programs; the National Association of Medicaid Directors; Schneider et al (1999).

The first measure follows Norton (1995). I calculate the days one would have to pay out-of-pocket before Medicaid eligibility. The formula is as follows:

$$Days_i = \begin{cases} 0 & if \quad Assets_i \le Limit_s \\ \dfrac{Assets_i - Limit_s}{NH_s - income_i} & if \quad NH_s \le income_i \quad and \quad Assets_i \ge Limit_s \end{cases} \tag{4}$$

where Assets are the assets not protected from the Medicaid program. For households in states employing liens, I include the equity in the primary residence in the non-protected assets. NH is the daily price of a nursing home in that state. Income is household income net of Medicaid allowances, calculated on a daily basis. The subscripts, *i* and *s*, indicate whether the variable is at the individual- or state-level.

While this measure captures the generosity of the eligibility criteria, it ignores the differences in generosity once on Medicaid. Since one is required to contribute all income above the state income limits (through the PNA and CSIL) towards their own care, the benefit of Medicaid can vary greatly between households with the same number of days until eligible, but who face different state rules or have different incomes.

To account for both the eligibility and generosity of the benefit once receiving Medicaid, I use a second measure. I calculate the fraction of nursing home costs that one would have to pay out-of-pocket if they were to enter a nursing home and apply for Medicaid immediately. For states employing liens, I again include the equity of the primary residence. I calculate this measure for both a 1-year and a 5-year stay. This corresponds directly to the (1-β) measure in the model section. The formula is as follows:

$$OOP_i = \min\{1, \frac{\max[0,(Assets_i - Limit_s)] + \max[0,(time * income_i)]}{NH_s * time}\} \tag{5}$$

Where *Assets*, *Limit*, *Income*, and *NH*, and the subscripts are as defined above. Time is the time in days spent in a nursing home, either 365 for the 1-year measure or 1825 for the 5-year measure. This measure captures not only the assets that exceed the means testing, but also the "excess income" that one must contribute to their own care once on Medicaid.

While these measures are clearly related, they measure different concepts. Figure 1.4 illustrates this point. The Norton statistic captures the distance between points A and B. The second and third measures, OOP, are the ratio between the shaded area and the total costs, the area ACDE. Thus the OOP, in essence, includes the information captured in the DAYS measure.

1.5.7 Endogeneity Issues

Clearly, if there is an effect of the Medicaid program on savings, all of these generosity measures are endogenous. If people are trying to become Medicaid eligible, then the number of days until Medicaid eligible, or the fraction of a stay in a nursing home they must pay out of pocket will be lower through their own actions, and not just through state policy. To purge the endogeneity, I follow Currie and Gruber (1996) methodology, and run everyone in the sample through each state's Medicaid rules in that year. I then give everyone in each state the median of each measure to capture the state-generosity without any behavioral effects. This purges the measure of characteristics of the household that may be correlated with assets, and achieves identification solely through the legislative differences between states.

In 2000, the state with the fewest DAYS, thus the most generous, is Alaska, with 208.5 days, as illustrated in Figure 5. This is an outlier, partially because of the much higher nursing home care costs (an average of $430 a day, compared to the national average of $140 a day in 2000). The next most generous state is New Hampshire, with 482 days. The state with the most DAYS, thus the least generous, is Oklahoma, with 886 days. Even excluding the outlier, this measures a significant dispersion in state policy; bear in mind, the underlying sample of people is the same.

In 2000, the state with the smallest percentage of a year's stay in nursing home one would have to pay out-of-pocket, the most generous, is again Alaska, where you would pay 22% of a year's stay. Again this is an outlier. The second most generous state under this measure is New Jersey, where you would expect to pay 43% of your stay. Fourteen states share the position of least generous state. These states all employ liens, so even at the median people would be paying for the entire year's care out of pocket.

If we turn to the 5-year measure, Alaska is again the most generous state, with 11 percent of costs expected to be paid out-of-pocket. The second most generous state is once again New Hampshire, with 23.5% followed closely by New Jersey at 24%. Oklahoma is no longer the

least generous state, but drops to 38th. The least generous state is now Alabama, where you can expect to pay over 81% of a 5-year nursing home stay out-of-pocket.

Figure 6 illustrates that these measures indeed give us different generosity measures for the state. I plot the DAYS measure versus the 5-year OOP measure: if the states are ranked in the same order, than this would be a perfectly straight line. It is not, and indeed, there is a lot of variation in the 5-year measure between states that have very similar DAYS measures. (I took Alaska, the outlier, out of this figure for illustrative purposes.) For example, Nevada, Delaware, and Tennessee are nearly identical on the DAYS measure, at 659, 663, and 668 respectively. They are worlds apart when we compare them on the 5-year OOP measure, at .37, .62, and .38 respectively. Again, this is all due to policy variation since the same people went into calculating each of these statistics.

1.5.8 Empirical Approach

The goal of this paper is to determine if the elderly are responding to the incentives implicit in the Medicaid nursing home benefit. To do so, I compare differences in household wealth, both accumulation and allocation, based on the differences in states' Medicaid generosity. Because there are potentially different responses to Medicaid in different parts of the wealth distribution, I use quantile regressions.

The basic regression specification is:

$$A_{i,t} = \alpha + \beta_1 Hi_{i,t} + \beta_2 Medicaid_{i,t} + \beta_3 (Medicaid_{i,t} * Hi_{i,t}) + \beta_4 D_{i,t} + \beta_5 (D_{i,t} * Hi_{i,t}) + \tau_t + \varepsilon_{i,t} \quad (6)$$

where A_i is the household asset of interest (net worth, financial assets, housing equity[3]), $Hi_{i,t}$ is a dummy variable equal to 1 if the self-assessed probability of entering a nursing home is greater than 50 percent, and $Medicaid_{i,t}$ is the household Medicaid benefit, as measured in the variables DAYS, 1-year OOP, and 5-year OOP. D_i is a vector of household-level demographic characteristics and wealth controls. I fully-interact the model to allow the demographic controls

[3] I have also examined trusts and irrevocable trusts, but have found no results. About 10 percent of the sample has a trust, while only 2 percent have an irrevocable trust.

to affect asset accumulation differently based on one's perception of future long-term care needs. All regressions are weighted by the household weights.

The dependent variables for these regressions are net worth, financial assets, and housing equity in the primary home. As expected, all of these measures are very skewed, as illustrated in Table 1.2. Thus I use the natural log of these variables in the regressions. Further, the distributions vary by marital status. Singles have only 4 percent of the net worth of married households at the 20^{th} percentile of the distribution, which climbs to 42 percent at the median, and almost 60 percent at the 95^{th} percentile. Due to these differences, and the difference in asset limits in the Medicaid program, I break the sample by marital status for all regressions. It is important to note that for single households, even those at the fifth percentile would not automatically qualify for Medicaid coverage because of the inability to protect the primary house. For married households, the asset limit would fall between the 20^{th} percentile and the median of the distribution.

The choice of demographic controls is an important issue. Ideally, one would want all of the determinants of savings and spending for the elderly: lifetime earnings, expected life span, risk aversion, the outside option of not using a nursing home and its price (i.e. home health care nurse vs. family), and the strength of the bequest motive. Instead, I select exogenous control variables for each of these determinants.

While it is possible to match the HRS data to social security records, one cannot use both the state-identifier restricted data set and the social security records together. Since the state-variation in Medicaid eligibility is key to my identification, I use the state-identifiers. I use education categories and household income deciles reported in 1993 as controls for lifetime earnings. I also include an indicator variable for whether or not the household invested in stocks in 1993 as a proxy for both financial savvy as well as tastes for risk and saving. I add a 25-year housing price index to the regressions to control for differences in returns to assets that are state-specific.

The price of the outside option of not using a nursing home varies by household situation. The presence of a spouse, daughters, and children living within 10 miles has previously been used in the literature as proxies. I include information on holding long-term care insurance policies as well as if any of their children live within 10 miles. Table 1.3a shows that for both married and single households, those who report having a high probability of needing a nursing

home are also less likely to have children living within 10 miles of their current residence. To measure the bequest motive, I use a dummy variable for whether or not the household has any children.

In addition to all these controls, I interact age and education, marital status and gender, and I allow for a fully interacted model with the self-reported probability of needing nursing home care. This allows the control variables to have a differential impact on the different populations.

This specification suffers from the endogeneity problem discussed earlier. Instead, I can substitute my state-level Medicaid generosity variable into equation 6, turning it into:

$$A_{i,t} = \alpha + \beta_1 Hi_{i,t} + \beta_2 Medicaid_{s,t} + \beta_3 (Medicaid_{s,t} * Hi_{i,t}) + \beta_4 D_{i,t} + \beta_5 (D_{i,t} * Hi_{i,t}) + \tau_t + \varepsilon_{i,t} \quad (7)$$

where $Medicaid_{s,t}$ is now the state-level median Medicaid generosity level. The coefficient of interest is β_3, on the interaction between the probability of needing a nursing home and the state's generosity measure.

I also examine housing wealth decisions. As stated earlier, housing assets are generally protected from the Medicaid program if the beneficiary has a spouse or a dependent child living in the home. They are not protected, even under these circumstances, if the state employs liens in their estate recovery program. These liens are placed on the house while the Medicaid recipient is living in the nursing home, and are collected upon their death, the death of any dependents, or the sale of the house. Therefore for some people the house is classified as a protected asset, and for others it is not. I change my specification slightly in order to allow for different behavioral effects by the state classification. The equation becomes:

$$H_{i,t} = \alpha + \beta_1 Hi_{i,t} + \beta_2 Medicaid_{s,t} + \beta_3 (Medicaid_{s,t} * Hi_{i,t} * I_{L=0}) + \beta_4 (Medicaid_{s,t} * Hi_{i,t} * I_{L=1}) + \beta_5 D_{i,t} + \beta_6 (D_{i,t} * Hi_{i,t}) + \tau_t + \varepsilon_{i,t} \quad (8)$$

where H_i is a measure of housing wealth or mortgage debt, and $I_{L=1}$ is an indicator variable for states that employ liens, and $I_{L=0}$ indicates states that do not. I also use probit regressions to look

at the probability of having a mortgage or owning a house. Mortgage debt is relatively rare among the elderly; approximately 10 percent of the sample reports having a mortgage.

I also model the above equations using the instrumental variables for quantile regression technique (IV-QR), as described in Chernozhukov and Hansen (forthcoming). I use the state-specific median measures described above as instruments for the individual-level measure of Medicaid generosity.

1.6 Results

Tables 1.3a and 1.3b present the summary statistics for the final dataset used in the analysis. I have 3,964 observations on single households; 77 percent are women. Of the women, the majority are widows (87 percent), while the rest are divorced (8 percent) or never married (5 percent). The men are slightly less likely to be widowers (71-75 percent), and more likely to be divorcees (16-21 percent). These characteristics are very similar regardless of self-reported probability of needing a nursing home. While the reported sick are slightly older, their education breakdown is virtually identical.

One striking difference between single households expecting care is the probability of owning a home. 61 percent of low probability singles own a home, while less than half of those expecting care do. Table 1.2b also shows that they also have less housing wealth in the bottom of the distribution, conditional on owning a home.

I have 2,717 observations on married households over the 3-wave sample. Those households who report a high probability of needing a nursing home are, on average, older and wealthier than their healthier counterparts. The increased wealth appears to be coming from housing wealth in the bottom twenty percent of the distribution, and through higher financial assets throughout the distribution of assets.

1.6.1 Net Worth

The easiest way to respond to Medicaid incentives is to save less and lower net worth, making it easier to qualify for Medicaid nursing home coverage. Table 1.4 reports the results from estimating equation 7, using the natural log of Net Worth as the dependent variable. Panel A is for married households, Panel B for singles. Each column is for a different Medicaid generosity measure: DAYS, 1-year OOP, and 5-year OOP. I measure net worth as assets-debts-trusts due to the structure of the questionnaire

in the AHEAD survey.

At the median, Medicaid means-testing has a negative impact on net worth for single households, regardless of which measure I use. The control variables enter much as expected. The more education attained, the more net worth accumulated. For single individuals, there does seem to be a differential effect of education on net worth if there is a high self-perceived probability of needing a nursing home. Divorcees seem to have the least net worth compared to widow(er)s and those who never married. Having children has a negative impact on net worth, and again there is a differential response if there is a perceived need for a nursing home. This may be capturing the ability to give gifts. Women, once controlling for all the other demographic characteristics, do not have a significant different net worth than men.

I do not measure an effect of Medicaid on net worth for married households at the median. Education still has a positive effect on net worth holdings, but now there does not seem to be a differential response for those preparing for a future nursing home stay. Children do not seem to have an effect on the wealth of couples. In only the 1-year out-of-pocket measure does the state generosity main effect seem to impact net worth for either married or single households.

Table 1.5 examines the effects of Medicaid on the distribution of net worth. I examine the 5, 20, 35, 50, 65, 80, and 95th percentiles. All three measures of generosity find that Medicaid causes single households to lower their net worth in the bottom portion of the asset distribution. The effect peaks between the 20th and the 35th percentile, depending on which measure is used, and is mitigated by the 65th percentile. The skewness of the distribution of net worth, plus this differential effect at the bottom- of the distribution, explains why no effect is found with mean regressions (results not shown), and why quantile regression techniques are imperative to measure the effect of this policy.

The 5-year measure indicates that a 1 percentage point decrease in the generosity of a state would lead to a 3 percent decrease in net worth of singles at the 20th percentile, and a 1 percent decrease in net worth at the median. The 1-year measure shows the effect peaking higher in the distribution, near the 35th percentile instead of the 20th. A 1 percentage point decrease in state generosity would lead to a .93 percent decrease in net worth at the 20th percentile, and a .75 percent decrease at the median. The days measure also shows decreases in net worth, of .002 at the 20th percentile and the median for a 1 day decrease in out of pocket expenditures.

To make these estimates more comparable across the different generosity measures, I put this in dollar terms. A one-percentage point decrease in generosity over 5 years is approximately 2,375. At the 20th decile, the average wealth for a single household is 13,300. So for a $1,000 increase in benefits over the course of 5 years, this would lead to an increase in savings of approximately $176 at the 20th decile. The one-year measure yields an estimate of increasing savings by $262, and the days measure yields an increase of $200 at the 20th percentile. At the median, while the coefficients are smaller, the dollar-effect is larger because of the higher asset levels. I get estimates of $390, $1,217 and $1,232 for a $1,000 increase in benefits using the 5-year, 1-year, and days measures, respectively. Both the 1-year and the days measure indicate a crowd-out of over 100% at the median of the distribution for single households.

Married households, on the other hand, do not seem to be responding in the same manner as single households. This could be for a variety of reasons. The first could be due to the different treatment of married versus single household within the Medicaid program itself, as highlighted earlier. The higher asset limits cut into a different segment of the population, where a stigma effect might be more pronounced. Other determinants of the differing behavior could be the strength of the bequest motive, or the joint-decision making that occurs in a couple. Further, the ability to shield assets in the form of housing that many single households do not have may mean that there is more asset shifting rather than actual net worth spend-down.

I only measure a significant response to the Medicaid nursing home benefit at the 5th percentile of the distribution, and only using the 5-year measure. Since I only measure this result using one generosity measure, I am reluctant to call this conclusive evidence of a behavioral response, although it is reassuring that the effect is positive, as theory would predict. At the 5th percentile of the distribution, or $12,368, this is below the asset-test threshold in every state. If the household's goals are to maximize the amount of assets available to the community spouse, they should be saving more money, up to the asset test. The size of this effect is rather small; a coefficient of 1.46 indicates that a $1,000 increase in Medicaid benefits would lead to a decrease in savings of approximately $76 at the 5th percentile in wealth.

1.6.2 Non-Housing Assets

I then look at the asset allocation decision. I break net worth into two components: non-primary housing assets, and primary housing. The first category is always subject to the

Medicaid "tax," while the second is protected in some states and for married households. Table 1.5 looks at the effect of Medicaid on the distribution on non-housing assets. The coefficients on the control variables are almost identical to when Net Worth is the dependent variable (results not shown).

This break-down tells quite a different story than just examining net worth, as shown in table 1.6. Single households appear to be decreasing financial wealth, although at higher points in the distribution. The days measure indicates a negative effect on savings from the 20th to the 65th percentile of the distribution, while the 1-year measure only indicates significant effects from the 50th-80th percentile. While nothing is significant using the 5-year measure, the patterns of the coefficients are very similar. At the median, these coefficients indicate that a $1,000 increase in Medicaid benefits would lead to increased saving of $740 ($673) using the days (1-year) measure.

Unlike the net worth margin, married couples do seem to be responding to the incentives in Medicaid on the financial wealth margin. I am surprised by the negative coefficient at the 5th percentile of the distribution: this is below the asset test of any state so I would not have expected an effect. The magnitude of the effect I find, though, is small; a $1,000 increase in Medicaid benefits would lead to an increase of financial wealth of $75 ($25) at the 5th percentile using the 1-year (5-year) measure.

It is also interesting to note that I do not find an effect of the Medicaid rules at the 35th percentile of the distribution. This is a point in the distribution between the minimum and the maximum protected asset levels for a married couple. Households facing different asset tests may be exhibiting different behavioral responses as the theory would predict, which is canceling each other out in the empirical findings.

I measure a more substantial effect at the median and 65th percentile of the distribution; a $1,000 increase in Medicaid benefits would lead to an increase in financial wealth of $2,050 ($3,417) using the 1-year measure. I get much smaller estimates of crowd-out using the 5-year measure, $523 at the median and $966 at the 65th percentile.

1.6.3 Housing Assets

As mentioned above, housing is sometimes protected from Medicaid. Thus I look at housing wealth[4], changing the specification to equation 8 in order to allow for a differential response. Since a house is always protected for a surviving spouse, they could be considered a type of control group for the single households, to see what might occur without the Medicaid incentives. The results are shown in table 1.7.

For single households, there is a negative effect on housing wealth in the bottom portion of the distribution. Since the sample is of homeowners, this could be done through different channels, such as moving to smaller places or through lack of up-keep (see Davidoff (2004)). The 5-year generosity measure yields a negative effect on housing wealth through the 35th percentile of the distribution, while both the days and the 1-year measure pick up sporadic effects higher in the distribution as well.

Married households also seem to be affected by the Medicaid rules in their housing decisions, but in the opposite way one would expect. Since the house is protected for the spouse in states that employ liens and those that do not, one would not expect a differential effect on housing wealth for married individuals. For the most part, I do not find married households changing their housing wealth in response to Medicaid rules, although when I do, I find that they are actually putting more money into housing assets when their state employs liens. This may be a short-term method of protecting assets for a spouse, and the spouse can later spend the money through mortgage debt. There may be a differential effect if states using liens are also more diligent states in determining income, or if there is simply more Medicaid-planning done in states that employ liens.

1.6.4 Instrumental Variables

Another way to purge the data of the endogeneity problem is to use instrumental variable techniques. Panel A of Table 1.8 reports the median results from this technique. I have also added the median results reported earlier in Panel B for ease of comparison. I report confidence intervals here instead of pseudo-standard errors, as recommended in Chernozhukov and Hansen (mimeo). Since there has been little estimated response on

[4] I also examined the homeownership decision, and found no effect (results not shown).

the part of married households, I am only reporting the results for single households[5]. In each case, the point estimates are of a higher magnitude when we compute the IV estimation. The DAYS measure remains insignificant while the 5-year OOP measure remains significant at the median. It is important to note, though, that while these are statistically significant from zero, the estimates are not statistically significant from each other in each methodology. I cannot reject the point estimate using the reduced form with the IV estimate.

1.6.5 Policy Simulations

Another way to gauge the impact of the Medicaid generosity is through policy simulations. Table 1.9 reports counter-factual distributions of net worth and financial wealth. For each percentile of the distribution, I report three cases: the base case, the simulation of every state having the least generous Medicaid rules, and every state having the most generous. All cases are the prediction of assets from the regression results above, evaluated at the mean characteristics of a person who reports needing a nursing home in the next 5 years. I use the 5-year measure of generosity for this exercise since it consistently yields the most conservative effects.

The results are striking, especially for single households. For example, the average person who thinks they are going to need a nursing home holds $14,500 in net worth at the 20th percentile in the base case. If every state had the most generous Medicaid policy, the net worth would jump to $37,000. If every state had the least generous policies, the net worth would fall to $4,000. There would be virtually no difference in net worth for those not anticipating a nursing home stay.

1.7 Conclusions

Long-term care is a large, and largely uninsured, potential expense facing the elderly. For many, what insurance is available to them is through the Medicaid program, which requires the spend-down of much of the household's accumulated assets before benefits will start. This means-testing, while keeping expenditures down, also creates incentives for the elderly

[5] Results for married households will come in a later draft.

expecting nursing home care to change their consumption and savings decisions in order to qualify for Medicaid coverage.

I find that single elderly households that anticipate future nursing home needs respond to these incentives by lowering their overall net worth. This effect is prevalent through the bottom 50 percent of the distribution. I estimate between a 40% and 120% crowd-out at the median. I find that most of this crowd-out is coming through lowering housing wealth.

Married households face different incentives than single households through higher asset tests and more assets protected from the Medicaid tax. Thus I find different effects for married households; they do not lower total net worth, but do shift assets between housing (protected) and financial (non-protected) assets.

This is an important step in understanding the larger picture of how public insurance programs affect the finances of the elderly. This is only one application, however. Discussions of means-testing social security benefits should consider the impact such policies would have on the accumulation and distribution of assets of the elderly. This could have a large impact on the poverty rate of the elderly, especially widows, based on the estimates of crowd-out I show here.

This paper also contributes to the fiscal federalism literature. My estimates indicate that cutting costs to the state by cutting Medicaid eligibility could lead to higher costs in other-means tested programs, such as SSI. This may be an effective way for states to trim their budget outlays, while increasing the burden on the Federal government. Future research quantifying states' ability to shift these burdens, and the frequency with which they do so, is fundamental. It is imperative, though, to also quantify the effects of these actions on an individual level, examining the effects on the distribution of income and assets.

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Table 1.1: Medicaid Eligibility Rules by State - 2001

	209(b)		SSP	Poverty Expansion	Medically Needy		Special Income Rule	PNA	Community Spouse Protection	
	Income	Asset			Income	Asset			Income	Asset
AL							300% SSI	30	Min	25,000
AK			Y				300% SSI	75	Max	Max
AZ							300% SSI	76.65	Max	Min
AR					108.33	2,000	300% SSI	40	Max	Max
CA			Y	100%FPL	600	2,000		35	Max	Max
CO							300% SSI	50	Max	Max
CT	[6]	1,600	Y		[1]	1,600	300% SSI	54	Max	Min
DE			Y				250% SSI	44	Max	Max
DC			Y	100% FPL	377	2,600		70	Max	Min
FL				90% FPL	180	5,000	300% SSI	35	Max	Max
GA					317	2,000	300% SSI	30	Max	Max
HI	825[7]	2,000	Y	100% FPL	418	2,000		30	Max	Max
ID			Y				300% SSI	40	Max	Min
IL	[8]		Y	85% FPL	283	2,000		30	Max	Max
IN	545	1,500	Y					50	Max	Min
IA			Y		483	10,000	300% SSI	30	Max	24,000
KS					475	2,000	300% SSI	30	Max	Min
KY			Y		217	2,000	300% SSI	40	Max	Max
LA[9]					100	2,000	300% SSI	38	Max	Max
ME			Y	100% FPL	315	2,000	300% SSI	40	Max	Max
MD			Y		350	2,500	300% SSI	40	Max	Max
MA			Y	100% FPL	100% FPL	2,000		60-65	Max	Max
MI			Y	100% FPL	408[10]	2,000	300% SSI	60	Max	Max
MN	482	3,000	Y	95% FPL	482	3,000	300% SSI	69	Max	24,247
MS				135% FPL			300% SSI	44	Max	Max
MO	545	999.99	Y				952[11]	30	Max	Min
MT			Y		525	2,000		40	Max	Min
NE			Y	100% FPL	392	4,000		50	Min	Min
NV							300% SSI	35	Max	Max
NH	544	1,500	Y		544	2,500	236% SSI	50	Max	Min
NJ			Y	100% FPL	367	4,000	300% SSI	40	Max	Min
NM							300% SSI	47	Max	31,290
NY			Y		625	3,750		50	Max	74,820

[6] The income standard is $574.86 in Region A and $476.19 for the rest of the state for individuals under both the standard 209(b) rules and the Medically Needy expansion.

[7] HI sets lower income test for the blind: $535.90 for individuals.

[8] There is no single income standard. 300% of the FPL is the maximum allowed. The actual standard is computed by adding allowances for rent, food, clothing, heat, etc. The methodology is laid out in the State Plan.

[9] Medically Needy recipients get a subset of the Medicaid benefits, but they do get nursing home coverage.

[10] The income standards are regionalized. The maximum is reported.

[11] This amount is adjusted annually by COLA.

Table 1.1(cont): Medicaid Eligibility Rules by State – 2001

	209(b)		SSP	Poverty Expansion	Medically Needy		Special Income Rule	PNA	Community Spouse Protection	
NC			Y	100% FPL	242	2,000		30	Max	Min
ND	530	3,000			475	3,000		40	Max	Max
OH	460	1,500	Y					40	Max	Min
OK	584	2,000		100% FPL	259	2,000	300% SSI	50	Max	Min
OR			Y		413	2,000	300% SSI	30	Max	Min
PA			Y	100% FPL	425	2,400	300% SSI	30	Max	Min
RI			Y	100% FPL	625	4,000	300% SSI	50	Max	Min
SC			Y	100% FPL			300% SSI	30	75%Max	66,480
SD			Y				300% SSI	30	Max	20,000
TN					241	2,000	300% SSI	30	Max	Min
TX			Y				300% SSI	60	Max	Min
UT			Y	100% FPL	382	2,000	300% SSI	45	Max	Min
VT			Y		791[12]	2,000	270% SSI	47.66	Max	Max
VA	531	2,000	Y	80% FPL	336.37[5]	2,000	300% SSI	30	Max	Max
WA			Y		557	2,000	300% SSI	41.62	Max	Max
WV					200	2,000	300% SSI	50	Max	Max
WI			Y		591.67	2,000	300% SSI	45	Max	50,000
WY							300% SSI	50	Max	Max

Source: National Association of Medicaid Directors

[12] This income standard is for Chittenden county. $733 is the standard for the rest of the state.

Table 1.2a: Distribution of Dependent Variables

	Married Households			Single Households		
	Net Worth	Non-housing Wealth	Housing Wealth	Net Worth	Non-housing Wealth	Housing Wealth
5 percent	11,167	1,675	16,500	634	317	10,000
20 percent	59,161	15,634	40,000	13,300	2,600	30,000
35 percent	111,673	40,145	60,000	42,100	9,297	45,468
Median	179,595	88,780	80,000	77,054	25,685	65,000
65 percent	275,833	176,444	100,000	127,829	58,104	85,000
80 percent	459,552	333,903	140,000	222,909	131,500	120,000
95 percent	1,079,000	873,677	250,000	632,070	515,000	200,000
Mean	333,190	237,319	104,673	172,883	119,046	83,284
obs	2,717	2,293	2,716	3,964	2,944	2,975

Table 1.2b: Distribution of Dependent Variables

High Probability	Married Households			Single Households		
	Networth	Non-housing Wealth	Housing Wealth	Networth	Non-housing Wealth	Housing Wealth
5 percent	12,368	1,787	20,000	543	317	5,000
20 percent	57,065	15,076	39,600	8,000	3,350	24,000
35 percent	117,291	42,436	50,000	30,000	10,000	40,000
Median	195,327	100,506	80,000	55,868	26,802	64,500
65 percent	283,091	198,611	98,000	111,000	58,104	85,000
80 percent	424,237	361,000	140,000	212,737	134,566	115,000
95 percent	1,306,216	1,137,949	200,000	632,070	534,914	200,000
Low Probability						
5 percent	11,167	1,675	16,500	634	317	10,000
20 percent	59,161	15,634	24,000	13,736	2,569	30,000
35 percent	111,653	39,867	40,000	43,000	9,085	46,000
Median	178,119	88,050	80,000	78,000	25,685	65,000
65 percent	273,618	173,468	100,000	129,000	58,104	85,000
80 percent	465,000	331,223	140,000	223,346	130,658	120,00
95 percent	1,040,000	832,476	250,000	631,752	508,357	200,000

Table 1.3a: Summary Statistics

	Married Households		Single Households	
	High Probability	Low Probability	High Probability	Low Probability
Long-term care insurance	.19	.13	.07	.08
Have kids	.91	.92	.85	.86
Child live within 10 miles	.21	.28	.22	.28
Own home	.88	.87	.49	.61
Have a mortgage	.11	.14	.06	.09
Education: <HS	.26	.21	.44	.44
Education: HS	.34	.34	.32	.32
Education: Some College	.21	.22	.14	.15
Education: College +	.19	.23	.09	.09
Age	80.40	79.72	81.67	81.11
Own stocks in 1993	.28	.26	.13	.14
Probability of entering nursing home	53.	6.9	81.67	12.91
Median Own 5-year OOP	.29	.27	.29	.31
Median Own 1-year OOP	.91	.80	.64	.62
Median Own Days	969.09	923.63	341.35	455.03
5-year OOP	.34	.41	.42	.41
1-year OOP	.65	.77	.80	.78
Days	672	659	676	658
Housing price index	208.59	223.14	220.73	226.50

Table 1.3b: Summary Statistics: Singles

	Single Households	
	High Probability	Low Probability
Female	77%	78%
Divorced	8%	9%
Widowed	87%	86%
Never Married	5%	5%
Male	23%	22%
Divorced	21%	16%
Widowed	71%	75%
Never Married	6%	7%

Table 1.4: Effect of Medicaid Generosity on Net Worth
Median Regression

Ln (Net Worth)	Single Households			Married Households		
	Days	1-year OOP	5-Year OOP	Days	1-year OOP	5-Year OOP
Days * Hi	-0.002***			0.000		
	(0.001)			(0.001)		
Days	-0.000			-0.001**		
	(0.000)			(0.000)		
1-year OOP * Hi		-0.754**			-0.414	
		(0.320)			(0.382)	
1-year OOP		-0.209**			-0.248**	
		(0.082)			(0.104)	
5-year OOP *Hi			-1.198***			-0.610
			(0.448)			(0.711)
5-year OOP			-0.058			-0.129
			(0.117)			(0.214)
Education: HS degree	0.254**	0.220**	0.249***	0.505***	0.486***	0.501***
	(0.103)	(0.111)	(0.093)	(0.152)	(0.132)	(0.163)
Education: Some College	0.397***	0.369***	0.412***	0.780***	0.827***	0.813***
	(0.129)	(0.139)	(0.116)	(0.170)	(0.147)	(0.182)
Education: College+	0.342**	0.346**	0.320**	0.768***	0.686***	0.746***
	(0.142)	(0.151)	(0.129)	(0.168)	(0.145)	(0.180)
Education: HS degree * Hi	1.874***	1.896***	1.965***	-0.838	0.031	-0.063
	(0.286)	(0.303)	(0.248)	(0.827)	(0.764)	(0.940)
Education: Some College * Hi	1.313***	-1.831***	-2.134***	0.366	1.225	1.118
	(0.368)	(0.424)	(0.367)	(0.489)	(0.818)	(1.008)
Education: College+ * Hi	-0.357	-0.655*	-0.160	-0.519	0.437	0.360
	(0.409)	(0.354)	(0.303)	(0.900)	(0.492)	(0.609)
Children indicator	-0.112**	-0.107**	-0.111***	0.014	0.031	0.013
	(0.046)	(0.049)	(0.041)	(0.083)	(0.072)	(0.089)
Children indicator * Hi	-0.467***	-0.368**	-0.451***	0.109	0.119	0.197
	(0.167)	(0.178)	(0.146)	(0.237)	(0.210)	(0.255)
Separated/Divorced	1.114***	1.077***	1.106***			
	(0.284)	(0.304)	(0.256)			
Widowed	1.417***	1.417***	1.426***			
	(0.282)	(0.302)	(0.255)			
Never Married	1.632***	1.607***	1.642***			
	(0.290)	(0.311)	(0.262)			
Separated/Divorced *Hi	0.373	-0.211	0.007			
	(0.529)	(0.576)	(0.483)			
Female	-0.012	-0.054	-0.030			
	(0.098)	(0.107)	(0.089)			
Female * Hi	0.523	-0.621**	0.209			
	(0.338)	(0.284)	(0.314)			
Constant	7.327***	7.267***	7.131***	9.253***	8.902***	8.803***
	(0.345)	(0.341)	(0.286)	(0.335)	(0.215)	(0.264)
Observations	3,964	3,964	3,964	2,717	2,717	2,717

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.5: Distortions in the Distribution of Net Worth

Quantile Regressions

	Married Households			Single Households		
	Days	1-Year OOP	5-Year OOP	Days	1-Year OOP	5-Year OOP
5 percent	-.0020	.8160	1.4559 **	-.0047 ***	-.3405	-2.3548 **
	(.0017)	(.5166)	(.6742)	(.0014)	(.6001)	(.9304)
20 percent	.0009	.0918	-.8941	-.0019 **	-.9356 ***	-3.1584 ***
	(.0008)	(.3050)	(.6580)	(.0009)	(.3310)	(.6552)
35 percent	.0009	-.4898	-1.0215	-.0024 ***	-1.0484 ***	-2.480 ***
	(.0014)	(.5176)	(.8968)	(.0008)	(.2493)	(.5600)
Median	.0002	-.4137	-.6098	-.0023 ***	-.7539 **	-1.1975 ***
	(.0011)	(.3823)	(.7105)	(.0007)	(.3201)	(.4479)
65 percent	.0003	-.1442	.3641	-.0014 ***	-.3938	-.2422
	(.0007)	(.3552)	(.3955)	(.0005)	(.3094)	(.5907)
80 percent	.0002	.1931	.8780	.0002	-.4952	-.6262
	(.0008)	(.3197)	(.6243)	(.0008)	(.3426)	(.6874)
95 percent	.0003	.5448	.2964	-.0003	-.5086	-.6379
	(.0009)	(.4048)	(.5226)	(.0010)	(.4951)	(.6924)
Obs		2717			3964	

Robust standard errors in parentheses

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

Table 1.6: Distortions in the Distribution of Financial Wealth

Quantile Regressions

	Married Households			Single Households		
	Days	1-Year OOP	5-Year OOP	Days	1-Year OOP	5-Year OOP
5 percent	-.0047	-2.1475 ***	-3.3978 *	.0011	1.5665	2.0014
	(.0034)	(1.0108)	(1.7762)	(.0045)	(2.8023)	(3.4459)
20 percent	-.0034 **	-1.0628	-1.5640 *	-.0035 ***	.1186	1.580
	(.0015)	(.6966)	(.8680)	(.0006)	(.4701)	(1.0542)
35 percent	-.0002	-1.1574	-.4850	-.0026 ***	-.1313	1.0651
	(.0015)	(.9280)	(.8192)	(.0007)	(.5354)	(.9369)
Median	-.0002	-1.0990 ***	-1.3982 **	-.0036 ***	-1.207 ***	-.1891
	(.0016)	(.4114)	(.6120)	(.0001)	(.2896)	(.6709)
65 percent	.0013	-.9206 **	-1.2906 **	-.0022 ***	-.9179 ***	-.6584 *
	(.0010)	(.3647)	(.5381)	(.0006)	(.1396)	(.3936)
80 percent	.0002	-.1552	-.0732	.0001	-.6948 ***	-.6780
	(.0011)	(.4669)	(.8125)	(.0006)	(.2480)	(.8563)
95 percent	.0013	.4618	-.7124	-.0014	-.2015	.6301
	(.0013)	(.5607)	(.7716)	(.0015)	(.4062)	(1.129)
Obs		2293			2944	

Robust standard errors in parentheses

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

Table 1.7a: Distortions in the Distribution of Housing Wealth for Single Households
Quantile Regressions

	Days			1-Year OOP			5-Year OOP		
	W/o Liens	W/ Liens	F-Test	W/o Liens	W/ Liens	F-Test	W/o Liens	W/ Liens	F-Test
5 percent	-.0029 ***	-.0108 ***	16.61 ***	-.6258	-1.6257 ***	5.75 **	-2.401 *	-12.2091 ***	27.93 ***
	(.0010)	(.0021)		(.8323)	(.5472)		(1.4181)	(2.0356)	
20 percent	-.0006	-.0128 ***	84.87	1.6472 ***	1.0032 ***	20.87 ***	-1.4326 ***	-7.4083 ***	130.99 ***
	(.0007)	(.0013)		(.3768)	(.2664)		(.4545)	(.4858)	
35 percent	-.0002	.0012	3.06 *	.4751	.2531	1.52	.7692	-3.0553 ***	13.11 ***
	(.0004)	(.0008)		(.3992)	(.2655)		(.7362)	(.9815)	
Median	-.0007	.0017	2.37	-.3587	-.6865 ***	4.37 **	-1.990 ***	-1.5434 **	.34
	(.0007)	(.0016)		(.3353)	(.2230)		(.5524)	(.7832)	
65 percent	-.0008 ***	.0008	28.64 ***	-.0766	-.3782 ***	13.61 ***	-1.9954 ***	-.8540	1.87
	(.0001)	(.0003)		(.1795)	(.1238)		(.5647)	(.7944)	
80 percent	-.0004	-.0010	.55	-.7373 ***	-.8594 ***	2.58			
	(.0004)	(.0008)		(.1623)	(.1139)		-3.0382 ***	1.4575	2.28
							(.7884)	(.9447)	
95 percent	-.0006	-.0013	.14	-2.0259 ***	-1.4914 ***	3.90 **			
	(.0009)	(.0016)		(.5718)	(.3780)		-2.0235	-2.6069 **	.17
							(1.3177)	(1.1145)	
Obs		2975			2975			2975	

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.7b: Distortions in the Distribution of Housing Wealth for Married Households

Quantile Regressions

	Days			1-Year OOP			5-Year OOP		
	W/o Liens	W/ Liens	F-Test	W/o Liens	W/ Liens	F-Test	W/o Liens	W/ Liens	F-Test
5 percent	-.0019 (.0024)	.0003 (.0025)	1.62	-.9369 (2.0105)	-.4012 (2.2884)	.39	-3.080 (3.1486)	1.6630 (1.7654)	3.79 *
20 percent	.0001 (.0005)	.0011 (.0006)	2.04	.9137 (.6253)	.5556 (.3982)	1.70	-.6256 (1.2701)	1.3211 (.8572)	1.95
35 percent	-.0013 (.0006)	.0012 (.0011)	1.49	.2729 (.7497)	.1890 (.4784)	.06	-1.5425 * (.8969)	1.4561 * (.8131)	8.24 ***
Median	.00001 (.0006)	.0035 (.0009)	15.17 ***	.2306 (.4189)	.2754 (.2790)	.06	.0033 (.8187)	3.4073 *** (.6558)	14.71 ***
65 percent	-.0005 (.0006)	.0025 *** (.0008)	13.54 ***	.7101 (.4589)	.3781 (.3021)	2.62	-.6170 (1.3406)	2.4276 ** (1.1920)	4.37 **
80 percent	.0002 (.0005)	.0022 *** (.0007)	9.32 ***	1.0387 ** (.5204)	.5856 * (.3533)	3.97 **	-.4594 (1.3238)	1.3618 (1.116)	1.59
95 percent	.0005 (.0007)	.0003 (.0011)	.05	-2.0259 *** (.5718)	-1.4914 *** (.3780)	3.90 **	.6304 (.9895)	.0221 (.8289)	.48
Obs		2716			2716			2716	

Robust standard errors in parentheses

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

Table 1.8: IV Quantile Results
Single Households

	Quantile IV	State-Level Measures
DAYS	-.0095	-.0023
95% Confidence Interval	(-.0243 .0485)	(-.0037 -.0010)
5- YR OOP	-1.419	-1.1975
95% Confidence Interval	(-1.419 -.037)	(-2.0757 -.3193)

Table 1.9: Counterfactual Distributions of Net Worth: 5-year Measure

	Single Households					
		High-probability			Low-Probability	
	Base Case	Most Generous	Least Generous	Base Case	Most Generous	Least Generous
5 percentile	4,061	7,109	1,906	3,402	2,916	4,194
20 percentile	14,458	37,066	4,051	11,541	11,343	11,815
35 percentile	25,051	52,673	9,176	23,109	22,887	23,403
Median	42,360	62,017	25,306	38,890	39,583	37,972
65 percentile	68,141	71,958	63,302	64,809	63,587	66,497
80 percentile	108,792	130,000	85,520	113,395	101,933	130,959
95 percentile	248,111	252,097	242,825	230,521	192,988	293,097
	Married Households					
5 percentile	43,005	30,733	67,666	31,552	35,095	27,332
20 percentile	81,057	114,470	50,882	77,562	77,017	64,809
35 percentile	115,643	177,584	64,834	109,761	123,573	93,541
Median	162,178	202,975	119,819	159,604	165,966	151,406
65 percentile	249,124	226,906	282,585	227,954	231,913	222,720
80 percentile	375,293	273,497	575,117	323,096	303,462	351,612
95 percentile	596,940	509,944	738,276	684,123	639,496	749,304

Figure 1.1a: Medicaid Marginal Tax Rates Single Households

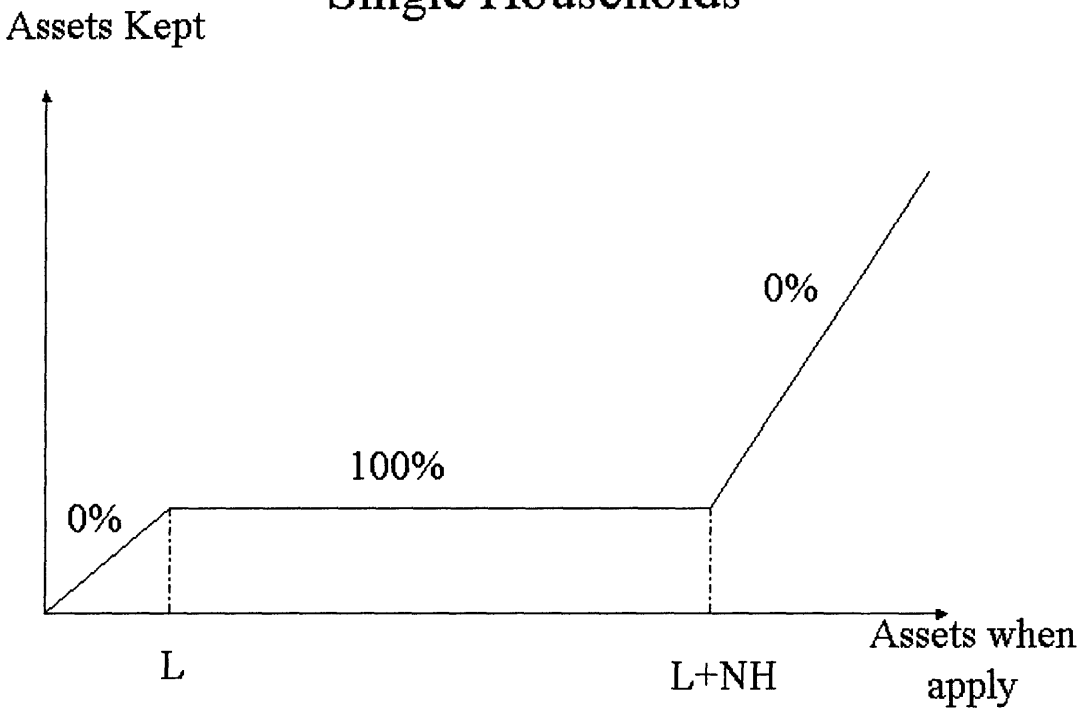


Figure 1.1b:Medicaid Marginal Tax Rates Married Households

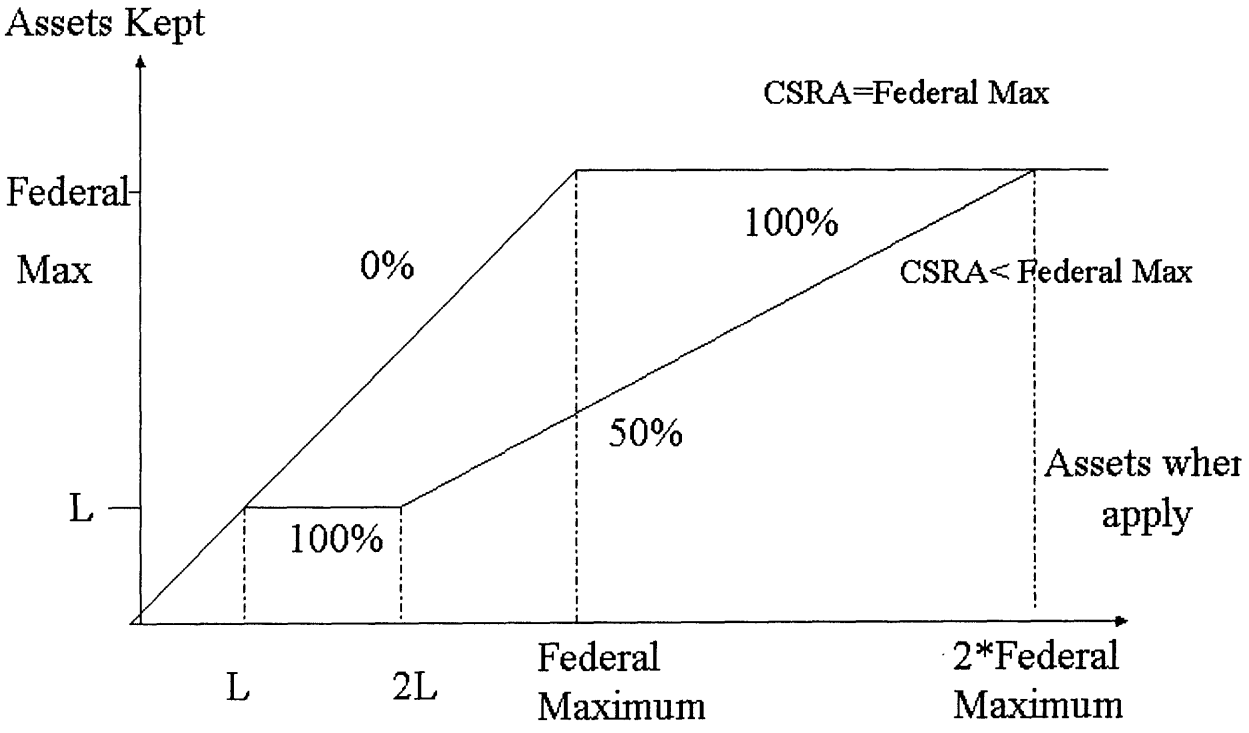


Figure 1.2:Budget Constraints

Increasing Medicaid Generosity

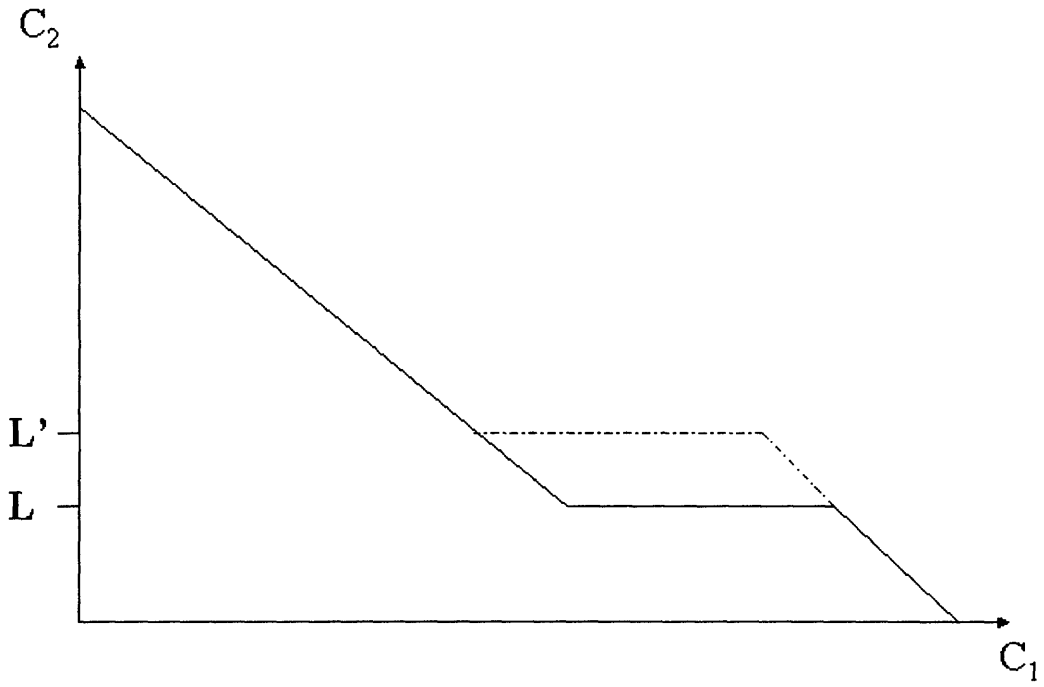
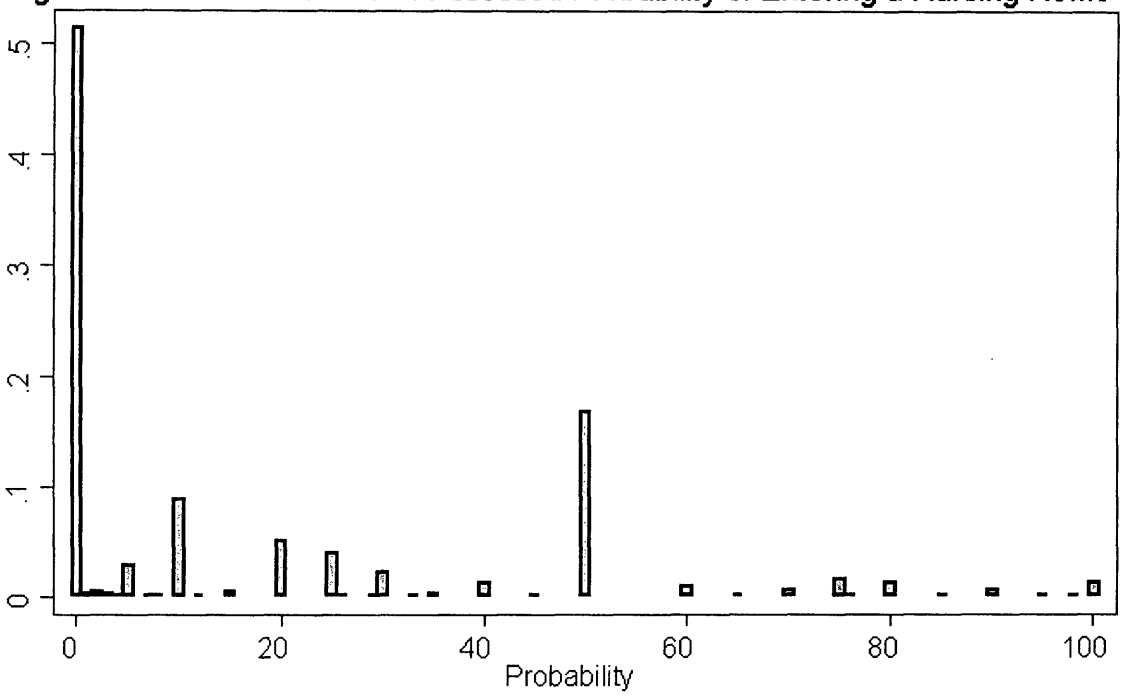


Figure 1.3: Distribution of Self-Assessed Probability of Entering a Nursing Home



2000 wave of the AHEAD

Figure 1.4: Days vs. Fraction OOP

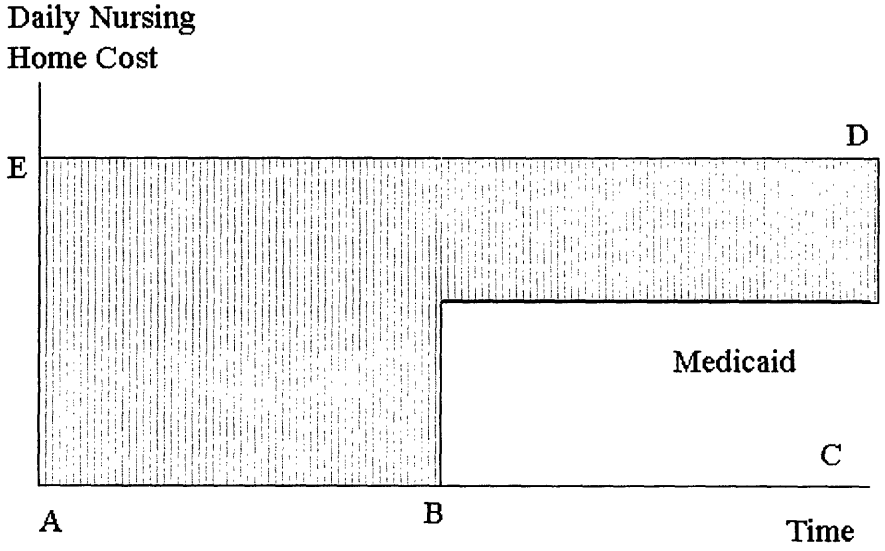


Figure 1.5: Variation in DAYS in 2000

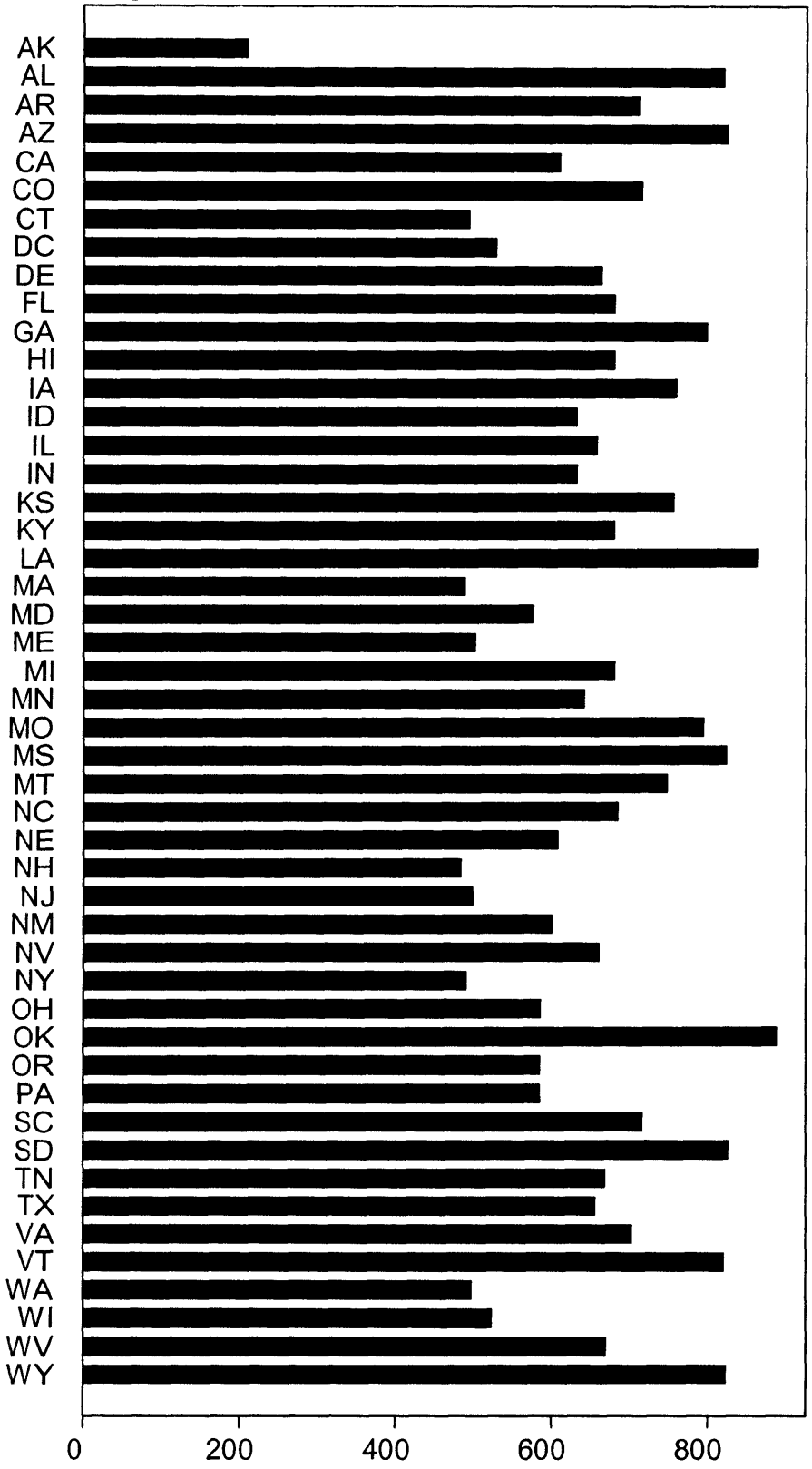
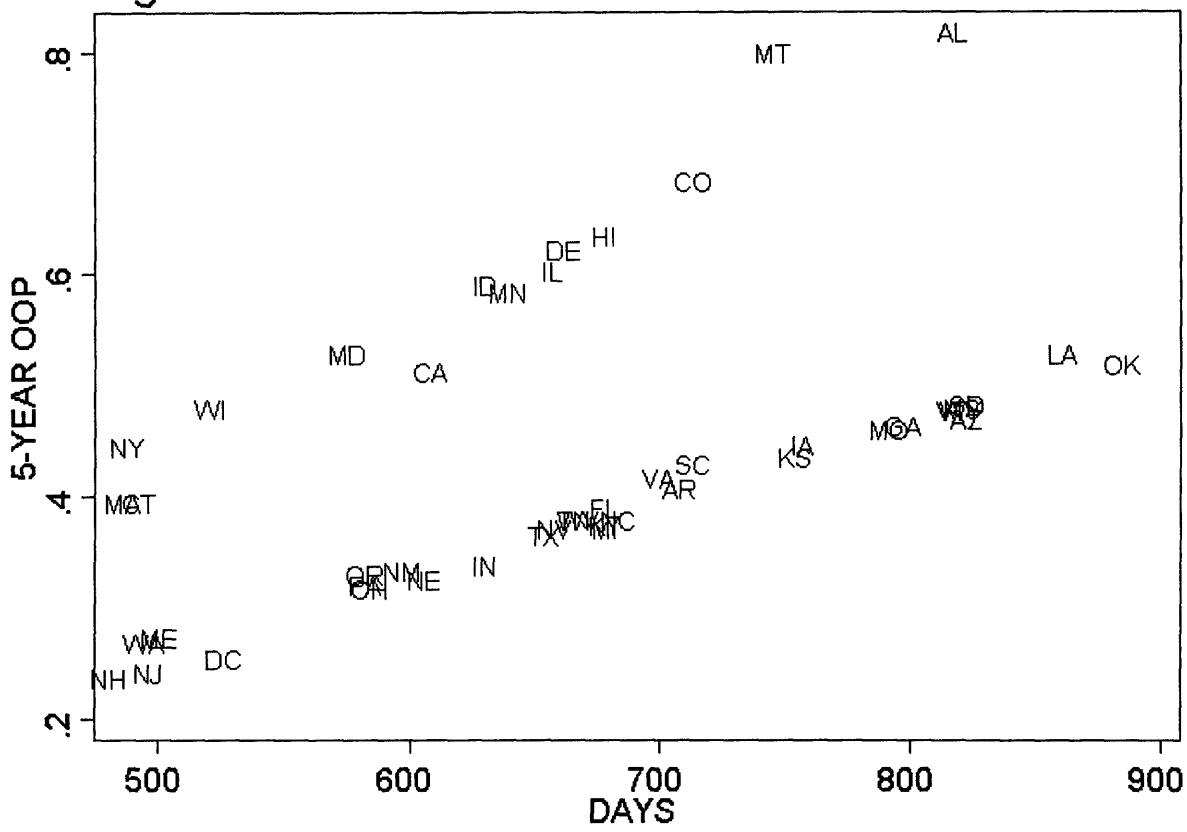


Figure 1.6: DAYS vs. 5-YEAR OOP



Chapter Two

Marginal vs. Fundamental Reform: the Impact of the Medicaid on Private Long-Term Care Insurance Demand

(with Jeffrey R. Brown, University of Illinois and NBER
and Amy Finkelstein, Harvard University and NBER)

2.1 Introduction

Expenditures on long-term care, such as home health care and nursing homes, accounted for 8.5 percent of all health care spending in the United States in 2004 (CBO 2004). Thanks in large part to the aging of the population, this $135 billion of expenditures is expected to grow much faster than inflation, with real expenditures projected to triple over the next few decades (CBO 1999). Because the publicly financed Medicaid program currently pays for approximately 35 percent of total long term care costs, there is rising concern among policy makers about the fiscal pressure that this growth will place on federal and state budgets in the years to come.[13]

In response to these budgetary concerns, there is growing interest among policymakers in stimulating the market for private long-term care insurance. If demand for private long-term care insurance could be substantially increased, then it might remove some of the fiscal pressure on Medicaid budgets by reducing Medicaid's share of expenditures. Today, the market for private long-term care insurance is poorly developed. Indeed, only 4 percent of total long-term care expenditures are paid for by private insurance (CBO, 2004), which is sharply lower than the 35 percent of expenditures that are covered by private insurance in the health care sector as a whole.

[13] For example, in a much-publicized press release issued in October 2004, the National Governors Association announced that states spent nearly as much money on Medicaid in fiscal year 2003 as they did on K-12 education, and expressed concern that Medicaid is putting a "squeeze" on state budgets going forward (NGA 2004).

Aside from budgetary implications, the lack of private insurance also has important implications for individual welfare. Approximately one-third of long-term care expenditures are paid for out of pocket, which is nearly double the fraction of total health care expenditures paid out of pocket. While long-term care needs are common among the elderly (approximately 40 percent of 65-year olds will enter a nursing home during their lifetime), the duration of care is highly variable (one-third of entrants will spend less than 3 months in a nursing home, while 12 percent will stay more than 5 years). Thus, long-term care represents an important source of uncertainty that, left uninsured, exposes consumers to substantial financial risk.

While there are many potential explanations for the small size of the private long term care insurance market in the U.S., recent research has suggested that the means-tested Medicaid program may itself be an important reason why so few individuals purchase private insurance. Using a dynamic programming model of fully rational consumers, Brown and Finkelstein (2004b) estimate that Medicaid could explain the lack of private insurance for at least two-thirds of the wealth distribution, even if there were no other factors limiting the market. Medicaid's large crowd out effect stems from the fact that Medicaid imposes a very large implicit tax (on the order of 60 to 75 percent for a median wealth individual) on the benefits paid from a private insurance policy. An implication of these findings is that public policies designed to stimulate private insurance demand will be of limited efficacy as long as Medicaid continues to impose this large implicit tax.

Thus, according to the simulation results, fundamental Medicaid reform may be a necessary precursor to substantially increasing the size of the private long-term care insurance market. In contrast, marginal changes to Medicaid that fail to substantially reduce the implicit tax are unlikely to be very effective at increasing the size of the private market. This includes changes to the key parameters of the existing Medicaid program, namely, the asset and income disregards that are used for determining Medicaid eligibility. In short, while fundamental reform of Medicaid might stimulate demand, marginal Medicaid reform may not.

Unfortunately, there is very little empirical evidence available with which to confirm or refute the prediction that marginal changes in Medicaid eligibility rules will have little effect on demand. In this paper, we use the Health and Retirement Survey to provide direct empirical evidence about whether altering key Medicaid means-test parameters has a meaningful effect on the demand for private long-term care insurance. Drawing on the substantial variation in the

level of assets that an individual can protect from Medicaid due to interactions between the individual's state of residence, marital status and asset holdings, we estimate the impact of key Medicaid eligibility parameters on private long-term care insurance demand. Our empirical strategy addresses the shortcomings of previous empirical studies by controlling for numerous omitted variables as well as accounting directly for the potential endogeneity of assets.

Our findings indicate that even large changes in the parameters of the existing Medicaid program do little to stimulate substantial private long-term care insurance demand. For example, even if the rules for the entire population were shifted from their current Medicaid regime to the least generous (a maximum difference in asset disregards of $67,000 for couples), our estimates suggest that only an additional 1.9 percent of the population would buy private insurance. While a 1.9 percentage point increase in insurance coverage is large relative to the current 9 percent insurance rate, it is a very small change in the proportion of uninsured individuals. Thus, while such a large change in Medicaid eligibility parameters would significantly grow the size of the market for private insurers (by about 20 percent), such a change would do very little to change the situation in which the vast majority of the elderly do not own private long-term care insurance.

The rest of the paper proceeds as follows. Section 2.2 provides background information on long-term care expenditure risk and the nature of existing public and private insurance coverage for this risk. We also briefly review the existing crowd-out literature. Section 2.3 presents the data and empirical framework. Section 2.4 presents our results. Section 2.5 concludes.

2.2. Background

2.2.1 Background on long-term care and long-term care insurance

Long-term care represents a significant source of financial uncertainty for elderly households. For example, a 65 year-old man has a 27 percent chance of entering a nursing home at some point in the future. The risk is even higher for women; a 65 year-old woman has a 44 percent chance of ever entering a nursing home. Women who use care also tend to spend a longer time in care than men who use care; for example, men who enter a nursing home spend on average 1.3 years there, while women spend on average 2 years. (Dick et al. 1994)

These averages mask the considerable variation in the use of long-term care. Although most 65 year olds will never enter a nursing home, of those who do enter a nursing home, 12 percent of men and 22 percent of women will spend more than 3 years there; one-in-eight women who enter a nursing home will spend more than 5 years there. While substantial uncertainty about potential care utilization would seem to lead to a demand for insurance against long-term care expenditures, rates of private insurance coverage are low. According to the 2000 Health and Retirement Survey, among those individuals aged 60 and over, only 10.5 percent own private long-term care insurance. Coverage rates are similar for men and women (10.7 percent and 10.1 percent) and slightly higher for married than single individuals (11.8 percent vs. 8.4 percent). Coverage rates increase substantially with wealth, from 2.8 percent in the bottom wealth quartile to 19.6 percent in the top quartile. The wealth profile likely reflects the fact that the means-tested eligibility requirements of Medicaid make it a better substitute for private insurance for lower wealth individuals.

In contrast to the market for health insurance for acute medical expenditures, the vast majority (about 80 percent) of private long-term care insurance contracts are sold through the individual, non-group market (HIAA 2000b).[14] Regulation of the market is minimal compared to other insurance markets such as health insurance; in particular, there are no restrictions on the characteristics that may be used in pricing, the level of pricing, or who must be offered insurance. (NAIC 2002a, 2002b, Lewis et al., 2003).

A survey of buyers in 2000 suggests that over three-fourths of purchased private policies are designed to cover all forms of long-term care, including expenditures on home care and nursing homes. Most policies have a deductible that specifies the number of days, typically from 30 to 100, that the individual must be receiving care before benefit payments can begin. Policies also specify a maximum "benefit period" which limits the total number of days the individual may receive benefits for expenditures during the lifetime of the policy. Limits of 1-5 years are often specified, although almost one-third of all policies have unlimited "lifetime" benefit durations. A feature of long-term care insurance contracts that distinguishes them from other health insurance contracts is the use of a maximum daily benefit that the policy will pay per day in covered care. The average maximum daily benefit purchased for nursing home care in 2000

[14] All of the statistics in this paper are based on the non-group market, with the exception of the statistics from the HRS (which does not distinguish the source of the insurance) and national estimates from the CBO (2004).

was $109; the modal benefit was $100. About 60 percent of policies specify a constant nominal maximum daily benefit, while the remainder specify that it will escalate at a pre-set nominal rate such as 3 or 5 percent.[15]

Policies sold in this market are written for single individuals; "joint" policies that jointly insure both members of a couple are not sold in this market. The characteristics of purchased policies are very similar by gender, although policies purchased by women are slightly less comprehensive on several dimensions – including the maximum daily benefit and the benefit period – while indistinguishable from the policies purchased by men on most others.[16]

2.2.2 Theories and evidence on why market is so small.

An extensive theoretical literature has proposed a host of potential explanations for the limited size of the private long-term care insurance market (Sloan and Norton 1997; Norton 2000; Brown and Finkelstein 2004b). Potential explanations include both factors that constrain supply and factors that limit demand. On the supply side, market function may be impaired by such problems as high transactions costs, imperfect competition, asymmetric information, or dynamic problems with long-term contracting.

On the demand side, limited consumer rationality – such as difficulty understanding low-probability high-loss events (Kunreuther, 1978) or misconceptions about the extent of public health insurance coverage for long-term care – may play a role. Demand may also be limited by the availability of imperfect but cheaper substitutes, such as financial transfers from children, unpaid care provided directly by family members in lieu of formal paid care, or the public insurance provided by the means-tested Medicaid program (Pauly 1990; Brown and Finkelstein 2004b).

Brown and Finkelstein (2004a) provide evidence of supply side market imperfections, namely, that the typical policy purchased exhibits premiums marked up substantially above expected benefits and provides very limited coverage of total expenditure risk. However, they also provide evidence that these supply-side imperfections are not sufficient to explain the very

[15] Such escalation is termed "inflation protection" by the industry, although the nomenclature is misleading. Almost none are actually linked to the CPI (Weiss, 2002).

[16] Statistics on purchased policies by gender are presented in Brown and Finkelstein (2004a). They are from a custom tabulation of the 2000 buyer survey conducted by LifePlans Inc.

small size of the private market, which suggests an important role for demand side factors such as Medicaid.

2.2.3 Crowd out literature

A sizeable empirical literature has investigated the extent of Medicaid's crowd out of acute private health insurance among working families. It is interesting to note that this literature has focused almost exclusively on the non-elderly, non-disabled population, despite the fact that total Medicaid expenditures on long-term care are roughly equal to the program's expenditures on the non-elderly, non-disabled. The combined evidence of this literature suggests that Medicaid does crowd-out acute private health insurance. However, the magnitude of the crowd out effect varies considerably across studies, with estimates ranging from approximately 10 to 50 percent of the increases in Medicaid expenditures. (See Gruber forthcoming for a review of this literature).

Even if the magnitude of the crowd out effect were precise in the context of acute health insurance, it is unclear whether Medicaid's effect on long-term care insurance demand for the elderly will be similar. For one thing, the populations are quite different, with most of the existing studies focusing on expanding Medicaid eligibility for groups such as children or women of child-bearing age, whereas the average age of long-term care insurance purchase is 67. In addition, providers of acute medical care (i.e. hospitals and doctors) cannot receive both Medicaid reimbursement and additional private payment for their services (Newhouse 2002). By contrast, nursing homes can and do receive payment for a given patient's care from both private insurance and Medicaid; the private insurance pays first, with Medicaid covering any additional costs not covered by the private insurance (such as the deductible). Finally, Medicaid provides substantially less comprehensive insurance for long-term care expenditures for the elderly than for acute medical expenses, for which Medicaid provides full insurance for eligible individuals (if they can get a provider to accept it).[17]

The potential for Medicaid to crowd out private long-term care insurance arises because Medicaid will cover all long-term care expenditures once an individual qualifies. However, this

[17] The much more incomplete nature of Medicaid's insurance coverage for long-term care than for acute care is not due to any formal differences in coverage for these two types of expenditures. Rather, it stems from differences in the nature of the expenditure risk for long-term care, which is substantially larger than acute medical care. Therefore, in practice people don't spend down to Medicaid eligibility for acute care whereas one-third of nursing home residents who are admitted as private payers eventually spend down to Medicaid (Weiner et al., 1996). For these individuals, the asset spend-down requirements thus make Medicaid very incomplete insurance. See Brown and Finkelstein (2004b) for a complete discussion of the issues.

occurs only after an individual has exhausted a substantial portion of his financial resources, as explained in more detail below. Also, Medicaid is a secondary payer relative to any private insurance policy. Thus, if an individual with private long-term care insurance spends down to sufficiently low income and assets that he is eligible for Medicaid, the private policy must pay whatever benefits it owes before Medicaid makes any payments. Therefore, while Medicaid is clearly a substitute for private insurance, it is by no means a perfect one. Despite these limitations, Pauly (1989, 1990) provides a stylized theoretical model that shows how an incomplete but publicly funded source of long-term care insurance has the potential to substantially reduce demand for private insurance coverage. Brown and Finkelstein (2004b) show this potential for Medicaid to crowd out private insurance may be quantitatively important; even in the absence of other market imperfections that limit demand, at least two-thirds of the wealth distribution would find it optimal not to purchase long-term care insurance due to the presence of Medicaid.

Just because Medicaid crowds out private insurance, however, does not mean that marginal changes to Medicaid rules will have a substantial impact on private insurance demand. Indeed, the simulation model used by Brown and Finkelstein (2004b) suggests that parametric changes to asset and income limits, for example, are unlikely to substantially stimulate demand. The reason for this failure is that such changes do little to reduce the large implicit tax that Medicaid imposes on the benefits paid from a private policy.

Whether marginal changes to the existing Medicaid program can, in practice, lead to substantial changes in private long-term care insurance coverage is an open question. To our knowledge there are only two papers that have examined this issue directly. Sloan and Norton (1997) find that having retirement income below the Medicaid eligibility limits reduces the probability of owning private long-term care insurance in the AHEAD data set of those age 70+, but do not find any evidence of an effect in the HRS sample of those age 51-54. These authors did not estimate the effect of asset limits. In addition, as discussed extensively by Finkelstein and McGarry (2003), the long-term care insurance data in the 1992 and 1994 waves of the HRS is of questionable quality.

More recently, Kang et al (2005) use the 1992 – 1998 waves of the HRS to examine the effect of Medicaid asset and income tests on the purchase of private insurance, using variation in individual financial resources and state Medicaid eligibility limits. They find evidence

consistent with expected Medicaid eligibility reducing the likelihood of purchasing private long-term care insurance. There are several reasons, however, to be cautious about the interpretation of these results. A major source of their variation is cross-state differences in Medicaid rules. In addition to concerns about the rules themselves being endogenous, there are numerous other potentially important determinants of the demand for long-term care and insurance against it that vary by state, such as the price and quality of nursing homes. We believe our empirical approach addresses these issues. Like the earlier studies, these authors also use the 1992 and 1994 waves of the HRS (in addition to two later waves), for which the quality of the long-term care insurance data is questionable. Given the importance and policy relevance of whether changes in Medicaid rules are likely to stimulate substantial demand for private insurance, further empirical investigations are warranted.

3. Data and Empirical Approach

2.3.1 Data and Summary Statistics on Long-Term Care Insurance Coverage

We use the Health and Retirement Survey, a nationally representative sample of the elderly. We use information from the 1996, 1998 and 2000 waves for individuals aged 55 to 70. We choose the age range because this is the prime buying age for long-term care insurance (HIAA 2000a). Because state Medicaid rules have changed over time, we want to examine people who are considering buying under the current Medicaid rules. We therefore in particular exclude the very elderly since the entire structure of eligibility for Medicaid long-term care reimbursement changed with the Medicare Catastrophic Coverage Act of 1988 (Stone 2002). Before 1988, single and married households faced the same asset tests; there were no extra asset allowances to protect a community spouse from poverty. However, assets were not divided evenly between the two spouses; instead, they were divided based on the name on the asset. Therefore married individuals who were of buying age (55 – 70) in the late 1980's would have been buying under dramatically different rules. In sensitivity analysis below, we show results for alternative age cuts.

Unlike the previous two studies of Medicaid crowd out (Sloan and Norton 1997; Kang et al 2005), we limit our analysis to 1996 and later waves because the long-term care insurance

question was only properly posed starting in 1995 (Finkelstein and McGarry 2003).[18] The 1995 wave is excluded because individuals in this wave are outside our age range. We further limit the sample to individuals who responded to the long-term care insurance question and the marital status question. Because of the panel nature of the data, we observe many individuals multiple times over the waves.

This results in a sample of 28,100 individuals. The average age is 61.6, and 70 percent of the sample is married. (Statistics are based on using household weights). Table 2.1, column 1 shows mean long-term care insurance holdings in our full sample, overall and by various covariates. 9.6 percent of the sample has long-term care insurance. This insurance coverage rate for the elderly is comparable to rates found in other surveys (HIAA 2000). Coverage rates are similar by gender, and higher for married individuals than single individuals (10.3 percent vs 7.8 percent). Coverage rates are higher among 65 to 70 year olds than younger ages. There is a positive relationship between wealth and insurance coverage. Only 4 percent of the sample in the bottom quartile owns long-term care insurance, compared to 15 percent in the highest quartile of net worth owns.

For reasons discussed below, we also use a restricted sample for our main specification. This sample is limited to those who did not change marital status between 1996 and 2000 and also live in states that have not had real Medicaid asset changes since 1991. While this reduces sample size dramatically, it is the cleanest sub-sample since we are assured that we know what Medicaid rules are applicable now, and have been applicable to the household during the sample period. Column 2 of table 2.1 shows the average long-term care insurance holdings for this sub-sample. Overall, the percentage holding long-term care insurance is slightly lower, at 9.1 percent. The means of the sub-sample are slightly lower by characteristic as well. One notable difference is that men on average are slightly more likely to be insured than women in the full sample, but are less likely to be insured in the sub-sample.

2.3.2 Overview of empirical approach

Our goal is to examine the impact of Medicaid on long-term care insurance coverage empirically. We focus our analysis on what is arguably the most important Medicaid parameter:

[18] As discussed in detail in Appendix A of Finkelstein and McGarry (2003), the long-term care insurance measure in this wave does not accurately reflect long-term care insurance holdings.

the amount of protected financial assets that an individual can keep while still receiving Medicaid reimbursement for long-term care utilization. Below, we show that the empirical results are similar if we also incorporate additional Medicaid rules such as income disregards and rules concerning an individual's house.

Medicaid asset disregards exhibit substantial variation across individuals based on an individual's marital status, state of residence, and asset holdings. Our empirical strategy, broadly speaking, is to control for any direct effects of marital status, state, and assets holdings on long-term care insurance demand, and then to identify the impact of Medicaid on long-term care insurance demand using the variation in Medicaid generosity that exists across higher interactions of these three variables (i.e. assets by marital status, state by marital status, and assets by state, as well as assets by state by marital status). We use predicted assets to deal with the potential endogeneity of assets to Medicaid spend down rules (Coe 2005).

This empirical approach has three important advantages over empirical work that uses only the cross-state differences in Medicaid programs to estimate the impact of Medicaid on long-term care insurance demand (Kang et al. 2005, Norton and Sloan 1997). First, since we identify the effects of Medicaid using both cross-state and cross-household differences, this alleviates concerns about omitted variable bias that affects both the state rules and the demand for long-term care insurance within a state. States with more generous Medicaid programs may differ systematically in other ways from states with less generous rules that may also affect the demand for long-term care insurance. Indeed, state Medicaid generosity may respond endogenously to the level of long-term care insurance coverage in the state. Even absent such endogenous policy response, analysis of cross-state differences alone may be plagued by omitted variable bias; states that differ in their Medicaid generosity may also differ on other state characteristics such as the cost of long-term care, state regulations of nursing homes, or characteristics of the state population – that also affect the demand for long-term care insurance.

Second, our approach allows us to condition out any other differences across states in their Medicaid program that may influence insurance coverage, as they are the same for married and single individuals within a state or individuals of different asset levels within a state. These include, for example, the Medicaid rules regarding coverage of home health care, and the Medicaid reimbursement rates relative to private payer rates in the state. Our estimates therefore focus precisely on the impact of Medicaid eligibility rules for nursing home coverage on long-

term care insurance demand. Finally, our approach allows us to control for any differences in insurance demand by marital status or by asset holdings that are constant across states.

2.3.3 Econometric Framework

To understand out econometric approach, it is important to first recognize that Medicaid asset rules for single individuals are relatively simple and uniform across states. Single individuals can keep no more financial wealth than the Medicaid-specified asset limit. In 2000, all states had an asset limit in the range of $1,500 to $6,500, with the modal state (representing 34 states and 61 percent of the sample) requiring $2,000. In contrast, the amount of assets a married household is allowed to keep when one spouse goes into a nursing home exhibits substantial variation across states, from a minimum of $16,824 to a maximum of $84,120 in 2000. The different degree of variation between married and single individuals across states forms the core of our empirical analysis.

An additional source of variation arises from the fact that, within states, there is a highly non-linear relation between the level of household assets and the amount of assets protected by the Medicaid asset disregard. For married individuals with assets below or above the minimum amount that federal law allows to be kept when one spouse is in a nursing home, there is no difference across states in Medicaid asset disregards; however for married individuals within this range – which corresponds to roughly the 20^{th} to 60^{th} percentile of the asset distribution for married households in the relevant age range– the maximum amount of assets that a household at a given asset level may keep varies across states by -over $67,000 in 2000. The exact rules are complicated, and understanding them is not essential for understanding the empirical analysis. For interested readers, Appendix A provides detailed information on how the asset disregards are determined for married individuals in different states and at different asset levels. The key conceptual point is that the asset disregards are strongly non-linear in household assets in the affected range. For example, in 2000, some states have a 100 percent tax on assets if the household's assets fall between $16,824 and $33,648. If the household's assets are above $33,648 and below $168,240, the household faces a 50 percent marginal tax rate. Other states set their marginal tax schedule exactly opposite, and have a 50 percent marginal tax rate between the $16,824 and $84,120, and a 100 percent tax rate above $84,120. Still other states set a 100

percent tax when the household's assets are above $16,824. We can use this non-linear relation to gain additional identification, even while controlling for state fixed effects.

Our key variable of interest is the amount of financial assets that a household is allowed to keep and still qualify for Medicaid reimbursement. We label this measure as *Protected* and we calculate it for each person in our sample based on the detailed information in Appendix A. *Protected* is thus a function of the state in which the household lives, their marital status, and their assets.

Because we are using multiple waves of the HRS, we calculate *Protected* using the state rules in effect in the year in which the interview takes place. As we discuss in more detail below, 13 states, affecting 25 percent of the sample, experience real changes in the asset disregards over our four-year sample period (1996 – 2000). In principle, the changes in state rules over time provide us with a fourth source of variation. We do not, however, believe this is a particularly clean or useful source of variation. Long-term care insurance is purchased on a "lifetime" basis (rather than annually as is acute health insurance), and it is not entirely clear exactly when this decision is made, nor is it the same for everyone. Therefore, it is hard to know whether the variation across time in Medicaid rules is really useful for identifying the effect of Medicaid on insurance demand, or whether it is simply adding noise, or possibly inducing spurious correlation. To be conservative, we limit the sample to states that have had no real changes to their asset limits since 1991. Our estimates of crowd-out become larger and more precise when we limit the sample to the approximately two-thirds of individuals in states whose Medicaid rules have not changed since 1991.

Temporarily ignoring several econometric concerns (that we will address below), a natural starting point is to straightforwardly estimate the following equation:

$$LTCI_{ist} = \beta_1 Protected_{is} + \beta_2 Married_{it} + S_i + \beta_4 X_{it} + \varepsilon_{i,st} \qquad (1)$$

LTCI is a dummy variable for whether the individual owns long-term care insurance. The main covariate of interest is *Protected*, which is increasing in the generosity of the Medicaid program. By including a dummy for whether the individual is married and state fixed effects (S_i), we capture any differences across individuals in long-term care insurance holding that is correlated with their state or their marital status. With no other covariates in the regression, *Protected* is therefore identified off of interactions between state and marital status, the impact of wealth on insurance holdings, and two- or three-way interactions of wealth with state or with

marital status. We can also include a basic set of covariates (X) to control for direct effects of wealth on insurance demand, as well as other demographics. Specifically we will include indicator variables for the household wealth decile, education categorized by highest degree achieved (less than high school, high school, some college, college degree or more), gender, occupation, industry, number of children up to 5, Hispanic heritage, race, retired, age, wave, and cohort. In addition, we interact the education variable with all the control variables (other than wealth deciles) to further control for possible information set differences. In estimating equation (1), we will calculate heteroscedasticity-robust standard errors that are clustered on state to allow for an arbitrary variance-covariance matrix within each state. All regressions are weighted using the household weights.

There are two related problems with the estimating equation (1). First, protected assets are a function of savings decisions, which are themselves affected by Medicaid rules (Coe 2005). Thus assets may be endogenous to insurance purchase decisions. Second, and more generally, using variation in asset levels across households to identify the impact of Medicaid on long-term care insurance demand requires the exclusion restriction that assets – or the characteristics of individuals that are correlated with assets such as their education and occupation – have no direct effect on insurance demand and therefore affect insurance demand only through their impact on Medicaid generosity. This seems implausible, as the demand for long-term care insurance stems at least in large part from a desire to protect one's assets from being exhausted on long-term care.

Including controls for plausibly exogenous characteristics that predict assets (such as education, gender, industry and occupation) helps deal with the latter concern that assets – and their predictors – may have a direct effect on long-term care insurance demand. To deal with the more challenging issue that assets may themselves be endogenous to Medicaid rules, we calculate predicted assets for each household using education, age, gender, occupation, industry, race, number of children, marital status, retirement status, wave of interview, and birth cohort. We fully-interact these controls with education. We generate this prediction, which we call *Asset_Hat,* using the national data and then use *Asset_Hat* to predict the amount of assets protected by the Medicaid program for each household, which we call *Protected_Hat.* In other words we first estimate:

$$\text{LogAsset}_{i,t} = \beta_1 X_{it} + \varepsilon_{i,t} \qquad (2)$$

We estimate the asset equation in logs because the highly skewed nature of the asset distribution results in a much better fit in predicting log assets than assets. As covariates we include the same set of covariates used in X in equation (1) above, except that we do not include indicator variables for wealth decile and state dummies in the prediction equation. It is estimated using household weights.

We use the results of equation (2) to predict assets. We then combine the predicted asset measure with the Medicaid asset protection rules for the individual's state and marital status to generate *Protected_Hat*. Thus, *Protected_Hat represents* the amount of assets the Medicaid program would disregard if the household's actual assets were as predicted by their characteristics, thus purging the estimation of endogeneity concerns. We then estimate:

$$LTCI_{i,} = \beta_1 ProtectedHAT_{i,s} + \beta_2 Married_{it} + S_i + \beta_4 X_{it} + \varepsilon_{i,st} \qquad (3)$$

Of course, we now include all of the factors used to generate *Asset_hat* in the asset prediction equation (2) as controls in equation (3). We also include state fixed effects. Thus, the only variation in *Protected_Hat* that is being used to identify the impact of Medicaid on long-term care insurance comes from two- or three-way interactions of state, marital status, and *Asset_Hat*, as well as any higher-order impacts of the covariates used to predict assets on insurance demand that are not captured in the prediction equation.[19] This is estimated using household weights, and clustered on state.

Because *Protected_Hat* is a predicted value, we must adjust the standard errors to account for the sampling variation in this right hand side variable (Murphy and Topel 1985). We do this using the non-parametric bootstrap. Specifically, we bootstrap the prediction equation (equation 2) and for each sample and iteration of the bootstrap, estimate not only equation (2) but then use the results to generate *Asset_Hat* and *Protected_Hat* and then estimate the second stage (equation 3) on the drawn sample.[20] In practice, the standard errors are not affected much by this procedure; we report both sets of standard errors in the results below.

Equation (3) is our preferred specification. While this identification strategy has many advantages over the existing literature, one remaining potential limitation is that we are using current predicted assets, while what matters for the Medicaid asset tax is the assets an individual

[19] Although we do not control for Asset_Hat directly in equation (3), we verified that the results are unchanged if we do so. This is to be expected since we control for the variables used to predict Asset_Hat.

[20] An alternative approach would be the parametric bootstrap in which we use the known distribution of Asset_Hat to draw values of it to use in the second stage.

has at the time of nursing home entry. This will bias against finding an effect of Medicaid. In practice, however, the elderly do not spend down much so this is not likely to be too great a problem.

Table 2.2 provides summary statistics on the *Protected* and *Protected_Hat* variables. Mean and median protected assets for single individuals in our sample – calculated using state rules and an individual's actual assets – are $2,000, with a standard deviation of $1,000. As expected based on the nature of state rules (described above), married households, on the other hand, have a much greater variation in protected assets, with a mean and median of $51,600 and $66,200 respectively and a standard deviation of $33,500. On average, Medicaid allows single households to keep 16 percent of their net worth, while allowing married households to keep 27 percent. These are both highly skewed, though. For example, the median percent of net worth that single households can keep is only 3 percent. We noted earlier that differences in the amount of assets couples are allowed to keep across states only affect couples with combined assets in a certain range; married households in the 2000 HRS between the 20th and the 58th percentile of financial assets for married households would be allowed to keep different amount of assets depending on which state they lived in. Married households in this "affected range" have average financial assets of $74,266.

Of course, all of these statistics concerning protected assets are a function of assets themselves. As discussed above, to deal with this issue, we predict assets – using the prediction equation (2), and calculate *Protected_Hat* based on predicted assets. Estimation of the prediction equation (2) yields an R-squared of 0.24. As expected, the summary statistics are quite similar to those of *Protected.*

2.4 Results

2.4.1 Basic results

We begin in table 2.3 by reporting the results of a linear probability model in which, as described in equation (1), *Protected* is put directly on the right hand side.[21] The first column includes only state indicators and a marital dummy. The relationship between more generous Medicaid (i.e. more protected assets) and long-term care insurance is positive. This

[21] The marginal effects from Probit specifications evaluated at the mean yield nearly identical results.

counterintuitive result simply arises because of omitted variable bias, including the fact that the measure of *Protected* is an increasing function of assets, which are positively correlated with long-term care insurance holdings. To correct for this omitted variable bias, column two shows the results adding the flexible set of covariates to the right hand side.[22] The coefficient attenuates somewhat (from 0.0091 to 0.0054) but is still positive and statistically significant. Column 3 shows the results adding controls for net worth deciles to the specification in column 2; the coefficient attenuates even more and is now negative but small and statistically insignificant. These initial results underscore the importance of controlling for assets (and predictors of assets) that may have a direct effect on insurance demand rather than using these to help identify the impact of Medicaid.

Recognizing that *Protected* is an endogenous variable, we now replace it with the variable *Protected_Hat*. Column (4) is otherwise analogous to column (2) in that it includes the same set of controls, as well as all of the individual characteristics that were used to predict assets in equation 2. The results are now negative and statistically significant. The point estimates suggest that a $10,000 increase in the amount of assets a household can hold and still be eligible for Medicaid is associated with a 0.31 percentage point decline in the probability of holding long-term care insurance. While statistically significant, the effects are substantively quite small. The maximum difference across states by marital status in the amount of assets that can be kept and still qualify for Medicaid is $67,000. Our results imply that if every state changed from their current Medicaid rules to those of the most restrictive state, it would increase the proportion of the elderly holding long-term care insurance by 0.9 percentage points. Even among the most generous states, switching to the least generous Medicaid policies would only increase the proportion of long-term care insurance holdings by 1.2 percentage points. Of course, a 1.2 percentage point change is relatively large compared to the average 9.6 percent insurance coverage rate in our sample; it would represent an increase in the market size by one-eighth. Our results therefore suggest that substantial changes in Medicaid asset disregards could have a substantial increase in the percent of the elderly with long-term care insurance. But this result is driven by the small rate of current holdings, not the large impact of variation in Medicaid rules.

[22] The controls include indicator variables for male, occupation, industry, number of children up to 5, marital status, age, retired, race, ethnicity, and HRS wave. All of these variables are interacted with categorical education variables.

Put another way, the proportion of the elderly that would be uninsured would decrease by less than 2 percent; the vast majority of the elderly would still not purchase insurance.

A comparison of columns 1 through 4 provides a sense of what is driving our results. In particular, recall that the simple *Protected* regression in column 1 suffered from two potential problems: (i) asset levels may have a direct effect on insurance demand, and (ii) asset levels may be endogenous to Medicaid rules. The results in columns 2 and 3 suggest that controlling for the direct effect of assets substantially attenuates the positive estimates in column 1 (from 0.0091 to -0.0002). The results in column 4 – which substitute *Protected_hat* for *Protected* in column 2 – suggest that addressing the endogeneity of assets is also critical; it is only once this is also addressed that we recover a negative and statistically significant impact of Medicaid on long-term care insurance demand.

Of course, a potential concern with the estimates in column (4) is that our asset prediction equation is far from perfect (the R-squared is 0.24) and that failing to control for the direct effect of assets may therefore be biasing our results. Indeed, a comparison of columns (2) and (3) indicates that only controlling for the characteristics used to predict assets (column 2) does not do nearly as much as also including controls for the net worth decile (column 3). On the other hand, controlling for net worth deciles directly is not necessarily desirable, given the endogeneity issues of net worth. Nonetheless, to verify that our estimates using *Protected_hat* in column 4 are not inadvertently picking up some direct effects of assets (due to limitations in our prediction equation), we show the same results in column 5 except with net worth deciles also added as additional right hand side controls. The coefficient barely changes relative to column 4, and remains statistically significant, which helps to alleviate these concerns.

As mentioned earlier, we are concerned that current Medicaid rules might differ from the Medicaid regime in which the decision to purchase (or not purchase) long-term care insurance was made. During our sample period 13 states, affecting 25 percent of the population, made changes to their Medicaid rules. To address potential concerns about such changes, we make a conservative cut, and limit the sample to the 30 states that had no real changes in their Medicaid asset rules from 1991-2000.[23] This cuts the sample by 36 percent. We are also concerned about changes in household marital status that would also affect which Medicaid rules would apply to

[23] The states that had no change in the assets are: AK, AR, CA, DC, FL, GA, HI, ID, IL, KS, KY, LA, MN, MS, MO, MT, NJ, NC, ND, OH, OR, PA, RI, TN, TX, UT, VT, WA, WI, WY.

the family. Therefore we also limit the sample to those households who have no marital status change through our sample period (1996-2000). This cuts an additional 4.6 percent of the sample. While we lose a combined total of 39 percent of our observations due to these data cuts, we believe this is the cleanest sub-sample in which to find a Medicaid effect.

The second panel in Table 2.3 (columns 6-10) repeats the regressions in the first panel (columns 1-5), but with this limited sample. The results in columns 1and 2 using *Protected* are remarkably similar to the full sample results. The marginal effects become slightly smaller, but are still statistically significant and positive. In column 8, when we add controls for net worth, the sign becomes negative as before, and estimated marginal effect is much larger (-0.0023 compared to –0.0002), but remains insignificant.

Column 9 is our preferred specification. This regression uses *Protected_Hat*, and includes the flexible controls. This point estimate suggests that a $10,000 increase in the amount of assets a household can hold and still be eligible for Medicaid is associated with a 0.52 percentage point decline in the probability of holding long-term care insurance. While this point estimate is larger than using the full sample, and statistically significant at the 5 percent level, the effects remain substantively quite small. Our results imply that if all states switched from the current Medicaid regime to that of the least generous state, it would increase the proportion of the elderly holding long-term care insurance by 1.6 percentage points. Among the most generous states, adopting the Medicaid policies of the least generous states would only increase the proportion by 1.9 percent. A 1.9 percentage point change is non-trivial to the average 9.1 percent insurance coverage rate in this sub-sample; in fact, it would represent increasing the demand by up to 20 percent of the current market. Our results therefore suggest that substantial changes in Medicaid asset disregards could have a substantial increase in the percent of the elderly with long-term care insurance. But this remains a small increase in the proportion of the elderly with private insurance, and is thus not likely to be a meaningful way of reducing dependence on the Medicaid program.

In Table 2.4 we explore in more detail the variation that is driving these results in our preferred specification (from table 2.3 column 9). As discussed above, variation in *Protected_hat* in equation 3 comes from interactions of predicted assets with marital status, predicted assets with state, marital status with state, and three way interactions of marital status, predicted assets, and state. To investigate whether each of these sources of variation yields

similar results, Table 2.4 shows the results in which we control one by one for various sources of variation, and therefore identify only off of the others. Column 1 replicates the baseline OLS finding (column 9 from Table 2.3). We compare it to column 2 which controls for predicted assets interacted with marital status, column 3 which controls for predicted assets interacted with state, column 4 which controls for both of these, and column 5 which controls for marital status interacted with state. Finally, column 6 controls for all two-way interactions (predicted assets by marital status, predicted assets by state, and married by state) so that the only variation used to identify *Protected_hat* is the three-way interaction of state by marital status by predicted assets. Although the analysis often loses power when various sources of identifying variation are eliminated, the results indicate that the coefficient on *Protected_hat* always remains negative and roughly of the same magnitude as the -0.0052 in the baseline specification; it various from -0.0032 to -0.0071 depending on the specification. The fact that all the sources of variation yield similar estimates increases our confidence in the empirical strategy and our baseline estimates.

2.4.2 Robustness

We analyzed the sensitivity of the baseline finding to a number of alternative specifications. Tables 2.5 and 2.6 report the results for a number of cuts of the sample. The sample specification suggests the effect is stronger on younger ages – which may be because these individuals are more likely to be buying during the time of the analysis and thus the state rules in effect at that time are more likely to be the relevant one. The point estimates are negative in all three waves of analysis, although only significant in the first, a result we do not have an explanation for. Results are quite similar for retired and non-retired individuals, although again we lose precision due to sample size. Finally, in table 2.6, the estimated negative effects of Medicaid generosity on insurance coverage are concentrated at the lower education levels (less than high school and high school graduate). This seems reasonable given their likely place in the asset distribution. As discussed earlier, the variation in *Protected* that we are using to identify the impact of Medicaid generosity on insurance demand occurs only for individuals in the 20^{th} to 58^{th} percentiles of the asset distribution; above and below this asset level *Protected* is the same for married individuals regardless of what state they are in. We are therefore only identifying the impact of Medicaid rules on a segment of the asset distribution. This is a particularly interesting part to look at, as it is a portion of the asset distribution in which absent Medicaid, insurance should be quite valuable

since it is quite difficult to self insure in this part of the distribution (Brown and Finkelstein 2004b).

Finally, Table 2.6 reports the results of a variety of other alternative specifications. Column 1 again replicates the baseline specification from the estimating equation (3) (Table 2.3 column 9). Column 6 adds controls for two other aspects of Medicaid which vary across state based on marital status and which may also affect insurance demand: the treatment of income and of housing wealth. These rules may be of independent interest, as they provide additional ways in which state Medicaid programs may influence insurance demand. Perhaps more importantly for our interest, we are also concerned about whether multi-collinearity in various Medicaid program rules' generosity could produce misleading estimates of the impact of Medicaid asset rules. Therefore we add controls for "inckeep" – which is the amount of income the household is allowed to keep and still qualify for Medicaid. This varies across states and marital status. We also control for estate recovery practices; Liens is an indicator variable for whether a state will put a lien on a house while a patient is still in the nursing home in order to recoup expenses upon the death of the community spouse. This practice means that the house is no longer a bequeathable asset for married couples and the house is only a temporarily protected asset; there is no change for single households since the house is not a protected asset for them in any state. Unlike the asset and income tests, a higher value makes Medicaid less generous. Appendix 2A describes the state income and housing ("liens") rules in more detail. The results in column 2 of Table 2.6 suggest no significant effects of either rule; inckeep has the right sign but is statistically insignificant, liens has the wrong sign and is statistically insignificant. F-tests of these two variables suggest that they are also not jointly significant. Perhaps most importantly, inclusion of these variables does little to change the parameter of interest – *Protected_hat.*

Since the variation in our variable of interest occurs only in the range of 20^{th} to 58^{th} percentile of the asset distribution, column 7 shows the results limiting the sample to this (albeit endogenous) range; the point estimate increases in absolute value as expected, from –0.0052 to –0.0070. If everyone in this asset range were to go from their current Medicaid policies to those of the least generous state, there would be a 2-percentage point increase in long-term care insurance demand. Again, while the point estimate is significant and large, this would be a very small decrease in the number of uninsured elderly.

2.5: Conclusion

Long-term care is a large, and largely uninsured, potential expense facing the elderly. Medicaid is the insurance of last resort for many, which causes pressure on state budgets. Thus and increasing amount of attention has been paid to how public policy can stimulate the private long-term care insurance market.

Recent simulation research (Brown and Finkelstein 2004b) suggests that changes in the current Medicaid program would do little to change the private long-term care insurance market. Instead, the existence of the Medicaid program, which is in essence a "free" but incomplete insurance product, is what is stifling the private market. Until now, there has been very little empirical research to support the simulation results.

This paper looks empirically at the effects of the Medicaid program on private long-term care insurance purchases. We use the variation in the current Medicaid program between states and individuals of different marital status to measure the effects of the Medicaid program. We find that if every state were to change from their current rules to that of the least generous states, it would only increase the percent of the elderly holding private long-term care insurance between 0.9 to 1.6 percentage points. This suggests that incremental changes within the current Medicaid framework would do little to change individual welfare or state budget forecasts. To fundamentally change the private long-term care market, our results are consistent with the simulation results, suggesting that marginal changes will only have small impacts on the private market, and fundamental Medicaid reform may be necessary.

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Table 2.1: Long-Term Care Insurance Ownership Rates in HRS Sample

Sample	(1) Percent of Full Sample	(2) Percent of Sub-sample with no Medicaid or Marital Changes
total sample	9.6	9.1
Males	9.7	9.0
Females	9.4	9.3
Singles	7.8	7.1
marrieds	10.3	10.0
age 55-60	9	8.2
age 60-65	9	8.5
age 65-70	11.4	11.6
wave = 1996	10.5	9.9
wave = 1998	9.3	9.0
wave = 2000	9.1	8.6
Net Worth, Bottom Quartile	4.1	3.4
Net Worth, 2nd Quartile	7.7	7.1
Net Worth, 3rd Quartile	10.2	10.0
Net Worth, Top Quartile	15.1	14.8

Note: Full Sample consists of individuals aged 55-70 in the 1996, 1998 or 2000 HRS who report their marital status and long-term care insurance coverage. The limited sample is restricted to those in states that did not have real Medicaid asset rule changes between 1991-2000 (30 states) and those who did not experience marital status changes during the panel (1996-2000). All means are calculated using household weights.

Table 2.2: Sample Variation in *Protected* and *Protected_Hat*

Singles	(1) *Protected*	(2) *Protected_Hat*
mean	0.20	0.24
median	0.20	0.20
sd	0.12	0.10
Married		
mean	5.16	5.94
median	6.62	7.25
sd	3.35	2.69

Note: All means are calculated using household weights.

Table 2.3: Basic Regression Results

	Full Sample					Non-Changing States, No Marital Status Changing Households				
LTCI	Protected			Protected Hat		Protected			Protected Hat	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	With full controls	With Net Worth	OLS, with full controls	With Net Worth	OLS	With full controls	With Net Worth	OLS, with full controls	With Net Worth
Protected	0.0091***	0.0054***	-0.0002			0.0090***	0.0050***	-0.0023		
	(0.0010)	(0.0008)	(0.0011)			(0.0013)	(0.0010)	(0.0016)		
Protected HAT				-0.0031*	-0.0032*				-0.0052**	-0.0055**
				(0.0016)	(0.0017)				(0.0023)	(0.0023)
				[0.0018]	[0.0018]				[0.0023]	[0.0023]
Observations	28100	24841	24841	24841	24841	17623	15576	15576	15576	15576
R-squared	0.02	0.04	0.05	0.04	0.05	0.02	0.06	0.06	0.05	0.06

Robust standard errors in parentheses, bootstrapped standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
Notes:
The regression in column 1 contains a married indicator and state fixed effects.
The "with full controls" specification includes all controls from column 1 and adds: education categorical dummies interacted with: male indicator, occupation and industry dummies, dummies for number of children up to 5, married indicator, age dummies, retired, cohort, race Hispanic, wave dummies.
The "with net worth" regression contains all the controls from column 2, and adds net worth decile indicator variables.
All regressions are weighted w/ HH weight, cluster on state.

Table 2.4: Controlling for Different Sources of Variation

	(1) Baseline	(2) Asset HAT * married	(3) Asset HAT * state	(4) Asset HAT * married, Asset HAT * state	(5) Married * State
Protected HAT	-0.0052**	-0.0041	-0.0047*	-0.0032	-0.0071**
	(0.0023)	(0.0026)	(0.0023)	(0.0028)	(0.0028)
	[0.0023]	[0.0025]	[0.0024]	[0.0027]	[0.0023]
Observations	15576	15576	15576	15576	15576
R-squared	0.05	0.05	0.06	0.06	0.06

Robust standard errors in parentheses, bootstrapped standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
Notes:
The baseline regression specification is the same as table 2.3, column 9. The controls are: state fixed effects and education categorical dummies interacted with: male indicator, occupation and industry dummies, dummies for number of children up to 5, married indicator, age dummies, retired, cohort, race Hispanic, wave dummies.
The second column includes all the controls in column 1 plus an interaction term between predicted assets and marital status.
The third column includes all the controls in column 1 plus an interaction term between predicted assets and state.
The fourth column includes all the controls in column 1 plus both of these interaction terms.
The fifth column includes all the controls in column 1 plus an interaction term with married and state.
All regressions are weighted w/ HH weight, cluster on state.

Table 2.5: Robustness Check: Sample Selection

	(1) Baseline	(2) age 55-62	(3) Age 62-70	(4) 1996 wave	(5) 1998 wave	(6) 2000 wave	(7) Retired	(8) Not Retired
Protected HAT	-0.0052**	-0.0065**	-0.0020	-0.0080*	-0.0066	-0.0045	-0.0071	-0.0050**
	(0.0023)	(0.0024)	(0.0041)	(0.0041)	(0.0040)	(0.0028)	(0.0047)	(0.0022)
	[0.0023]	[0.0033]	[0.0034]	[0.0040]	[0.0039]	[0.0041]	[0.0041]	[0.0032]
Observations	15576	8552	7024	4911	5339	5326	5699	9877
R-squared	0.05	0.07	0.08	0.08	0.09	0.09	0.10	0.06

Robust standard errors in parentheses, bootstrapped standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
The baseline regression specification is the same as table 2.3, column 9. The controls are: state fixed effects and education categorical dummies interacted with: male indicator, occupation and industry dummies, dummies for number of children up to 5, married indicator, age dummies, retired, cohort, race Hispanic, wave dummies.
All regressions contain the same controls.

Table 2.6: Robustness Check: Education and Medicaid Parameters

	(1) Baseline	(2) Educ < HS	(3) Educ = HS	(4) Some College	(5) College +	(6) Other Medicaid Parameters	(7) In Affected Range
Protected HAT	-0.0052**	-0.0002	-0.0069*	-0.0004	-0.0121	-0.0054**	-0.0070*
	(0.0023)	(0.0062)	(0.0038)	(0.0046)	(0.0080)	(0.0025)	(0.0037)
	[0.0023]	[0.0047]	[0.0037]	[0.0059]	[0.0085]	[0.0023]	[0.0034]
INCKEEP						-0.0137	
						(0.3885)	
Liens						-0.0045	
						(0.0171)	
Observations	15576	4135	5317	3059	3065	15576	6029
R-squared	0.05	0.05	0.04	0.07	0.07	0.05	0.09
Prob > F (2)						0.9620	
Prob > F (3)						0.1407	

Robust standard errors in parentheses, bootstrapped standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
The baseline regression specification is the same as table 2.3, column 9. The controls are: state fixed effects and education categorical dummies interacted with: male indicator, occupation and industry dummies, dummies for number of children up to 5, married indicator, age dummies, retired, cohort, race Hispanic, wave dummies.
All regressions contain the same controls.

Appendix 2A: Overview of Medicaid Rules

This appendix discusses the three relevant sets of rules that govern financial eligibility for Medicaid. These are: (1) the amount of financial assets that an individual is permitted to keep and still receive Medicaid reimbursement for nursing homes (which we label as *Protected* in the text), (2) the Medicaid income disregards and (3) Medicaid rules concerning one's house. The Medicaid program exhibits substantial variation in these three features across states. In order to not identify the effect of Medicaid solely off of cross state variation as prior studies have done, our empirical strategy is to compare long-term care insurance coverage of married individuals in states with different Medicaid spend down rules to long-term care insurance coverage among single individuals in these same states. The advantages of this empirical approach are discussed in the text.

2A.1 Rules for single people: protected assets, income limits, and housing

Medicaid rules for single individuals are relatively simple and uniform across states. Single individuals can keep no more financial wealth than the Medicaid-specified asset limit and no more income than the Medicaid-specified income limit. Anything above these must go toward paying for the care. Between 1991 and 2000, the modal asset limit was $2,000 (which nearly 70 percent of states used), which is the same as the Federal asset limit for SSI. The remaining states have an asset limit that ranges from $1,500 to $6,500 (see Table A2.1). Personal needs allowances, (PNA), or the amount of income one can keep while in an institution, are in the range of $30 to $77 per month (see Table A2.1). Single people must also sell their house if they are receiving institutional care (and use the proceeds to pay for that care), unless there is a chance of recovery or a dependent child living in the house.

2A.2 Rules for Institutionalized Married Couples

When both spouses need nursing home care, they are essentially treated as two single individuals for Medicaid purposes. Some states set a lower threshold ($3,000 combined instead of 2*$2,000) for the amount of assets the couple can keep. Each is allowed to keep his/her own PNA. Housing is treated the same as for singles: it must be sold to pay for care unless there is a chance of recovery or a dependent child living in the home.

2A.3 Rules for married individuals with one spouse in a nursing home and the other in the community

Protected financial assets: the rules

When one spouse enters a nursing home, total household assets (A) are divided (i.e. attributed) evenly between the two spouses. The house (unlimited value) is left out of the calculation, and is completely protected for the community spouse during his/her lifetime. From this even attribution, the spouse that goes into a nursing home is allowed to keep only the Medicaid-specified asset limit for single individuals (i.e. approximately $2,000).

The amount that the community spouse is allowed to keep is determined by the amount of assets the household owns and state rules for the minimum and maximum assets that the community spouse is allowed to keep (STATEMIN and STATEMAX). These state rules are in turn constrained by the Federal government, which sets a federal minimum (FEDMIN) and a federal maximum (FEDMAX). States must set their STATEMIN at least as high as the

FEDMIN, and their STATEMAX no higher than the FEDMAX. In 2000, FEDMIN and FEDMAX were, respectively $16,824 and $84,120 (Stone 2002); they are indexed to the CPI but have otherwise not experienced any changes over the 1991 – 2000 period.

With combined assets above 2*FEDMAX ($168,240), married couples face a 100% marginal tax rate on all additional assets. With combined assets below FEDMIN ($16,824), couples face no tax on their assets, and are allowed to keep all assets they own. This is true for *all* states.

For married couples with assets between FEDMIN ($16,824) and 2*FEDMAX ($168,240), however, there is variation across states that arises due to the fact that the STATEMIN and/or STATEMAX may differ from the federal rules. For these individuals, it is useful to distinguish between two broad categories of state rules. Case 1 is when STATEMIN=STATEMAX. Case 2 is when STATEMIN < STATEMAX. Table A2.2 shows which states fall under each category.

Figure A1 graphs the assets that a community spouse can keep as a function of household assets for the two most common Medicaid rule cases. In case 1A (used in 26 states) the state sets STATEMIN=STATEMAX=FEDMAX. This is shown by the dark line in Figure 1. In this case, the community spouse is allowed to keep min(A-$2,000, STATEMAX), where A denotes the total household assets. The community spouse is allowed to keep all of the household assets A up to the STATEMAX (equivalently, the FEDMAX), at which point she faces a 100% marginal tax rate on any further assets.

In Case 2A (used in 15 states) the state sets FEDMIN=STATEMIN<STATEMAX= FEDMAX. This is shown by the dashed line in Figure A1. In this case, a community spouse whose share of the assets exceeds STATEMAX (i.e. A exceeds 2*STATEMAX) faces a tax rate of 100% of assets above 2*STATEMAX (which in practice is the same as 2*FEDMAX). However, if the couples' assets (A) are below 2*STATEMAX but above 2*STATEMIN (which in practice is the same as 2*FEDMIN), the community spouse in Case 2A is allowed to keep (½)*A; the couple thus faces a marginal tax rate on assets of 50 percent. If the couple has combined assets above STATEMIN but below 2*STATEMIN, the community spouse gets to keep STATEMIN and the couple face a marginal tax rate on assets of 100%. If the couple has assets below STATEMIN, the community spouse gets to keep all of the combined assets (A). No matter where the couples' assets fall, the spouse in the nursing home is only allowed to keep assets up to the asset limit for single individuals ($2,000).

Thus, figure A1 reinforces that there is no cross state variation in the treatment of married couples with combined assets above 2*FEDMAX or below FEDMIN. Moreover, the figure illustrates that the variation across states in the amount of financial assets the couple can keep if it is within this range is non-monotonic in the couples' assets. This is further illustrated in Figure A2 which shows the difference in the amount of assets a couple could keep if it were in a Case 1A state relative to a Case 2A state as a function of the couples' assets.

While we have focused on the two major types of state rules, there are 10 other states whose rules we have not covered (see Table A2.1). Five of these states, are like Case 1A in that STATEMIN =STATEMAX but they differ from Case 1A in that they set their STATEMIN below the FEDMAX; three set STATEMIN at FEDMIN (Case 1C) and two set STATEMIN in between FEDMIN and FEDMAX (Case 1B). Figure A3 graphs the differential treatment of assets across threes three cases. It shows that the states differ in the level of household assets at which the tax on household assets goes from 0% to 100%.

The final five states, denoted Case 2B, are like those in Case 2A in that they set the STATEMIN below the STATEMAX but they differ from Case 2A in that they set the STATEMIN above the FEDMIN. Figure 4 compares the treatment of assets across these states. It shows that the cut-points for where the 100% marginal tax rate starts and ends, and where the 50% marginal tax rate starts, varies based on where STATEMIN is set.

Protected financial assets: how much variation is there in the data?

There is substantial variation in the amount of assets that individuals are allowed to keep across states with different rules. As noted, differences will only occur for couples with combined assets of between the FEDMIN and 2*FEDMAX; in 2000, this would mean that there is cross state variation only among married couples with combined financial assets between $16,824 to $168,240. Thus married households in the 2000 HRS between the 20th and the 58th percentile of financial assets for married households would be allowed to keep different amount of assets depending on which state they lived in. Married households in this "affected range" have average assets of $74,266. [24] If all people were to move from Case 1A states to Case 2A states, the average difference in the amount a household is allowed to keep is $8,277 in the whole sample, which is approximately 2 percent of average assets. For those in the affected range, the difference in the amount of financial assets one can keep between these two regimes is quite substantial. On average, those in the affected region would be able to keep $21,715 more in assets by moving from a Case 1A state to a Case 2A state, which represents 29 percent of average financial assets in this range. The maximum change is $67,296.

2A.4 Income disregards

Thus far, we have only discussed Medicaid's treatment of financial assets. Two other aspects of Medicaid's treatment are important to mention as they also differ between married and single couples. The first concerns the amount of income that Medicaid disregards. For single people, the amount of income allowed to be kept varies across states from about $30 to $77 per month, with most states permitting $30 (see Table A2.1).

For married households, income is split based on the "name on the check" rule, rather than evenly between the two spouses like assets. The institutionalized individual is allowed to keep the same amount of income as a single household ($30- $77 a month). The community spouse gets to keep an unlimited amount of income if it is in her name. There are safeguards in place to try to prevent poverty of the community spouse. If the community spouse's income is below a minimum amount, specified in the state's community spouse income limit (CSIL), then she is eligible to keep enough of her institutionalized spouse's income to bring her total income up to that limit. This minimum income amount varies across states from approximately $1,407 to $2,133 per month as shown in Table A2.1.

2A.6 Housing

States vary in their treatment of the house, which is a large component of financial wealth for the elderly. In all states, single individuals are required to sell their house to pay for their own care if there is no possibility of recovery, no dependent child living in the home, or no relative

[24] These are summary stats on the 2000 HRS, using financial assets. The sample is limited to married households aged 60-70. The cut points in the distribution are identical for the age 75+ sample (20th-58th percentile).

living in the home that has cared for the institutionalized individual for more than three years preventing earlier institutionalization.

For married individuals, the house (uncapped value) is protected for the community spouse. However, in about one-quarter of states, the states will put a lien on the house, which allows the state to collect money from the sale of the house to reimburse them for their Medicaid outlays upon the sale of the house or the death of the community spouse. We refer to such states as LIEN states, and Table A2.1 indicates which states are LIEN states. Enforcement of estate recovery practices varies across states (Sabatino and Wood, 1996).

2A.7 Changes in Rules

We have described the rules in detail as of 2000. However, we must be aware that individuals might have purchased or considered purchasing long-term care insurance under a different set of rules. There was a radical change in rules in 1988 under the Medicare Catastrophic Coverage Act. Prior to this legislation, states applied the same asset and income tests to institutionalized recipients regardless of their marital status. Another change, though, was that assets of a married couple were not divided evenly between them; instead, they were divided by a "name on the deed" rule. Therefore we will want to limit the sample to look at individuals who are of an age where they would have considered buying in the 1990s (i.e. not too old). It is also the case, however, that 21 states changed their asset protection rules between 1991 and 2000.

There were other changes in Medicaid rules between 1991 and 2000, which we have not addressed in the paper. 26 states and the District of Columbia changed their PNA (income limit for single individuals and the institutionalized partner of a married couple). These were generally substantively small changes (generally increases on the order of $5-$10 a month), and changed for both married and singles, so should be absorbed in the state and wave fixed effects.

OBRA93 mandated that states start employing estate recovery plans in order to recoup Medicaid expenses from deceased individuals. States have been slowly implementing these plans, and they vary greatly in their scope and bite. The LIENS variable we use is one of the more aggressive estate recovery instruments used by states, and thus our measure of the effect of estate recovery practices is limited. 13 states introduced estate recovery plans between 1993-1998, and 4 states were still noncompliant and had not introduced a plan by 1998.

Table A2.1: Medicaid Eligibility Parameters by State, 2000

State	Single Asset Limit [25]	PNA	STATEMIN	Case	CSIL	No change in Asset Rules 1991-2000	Lien
AK	2,000	75	84,120	1A	2,103	1	0
AL	2,000	30	25,000	2B	1,407	0	1
AR	2,000	40	16,824[26]	1B	1,407	1	0
AZ	2,000	76.80	84,120	1A	2,103	1	0
CA	2,000	35	84,120	1A	2,103	1	1
CO	2,000	50	84,120	1A	1,407	0	1
CT	1,600	52	16,824	2A	1,407	1	1
DC	2,600	42	16,824[3]	1B	2,103	1	0
DE	2,000	70	25,000	2B	1,407	0	1
FL	2,000	35	84,120	1A	2,103	1	0
GA	3,000	30	84,120	1A	2,103	1	0
HI	2,000	30	84,120	1A	2,103	1	1
IA	2,000	30	24,000	2B	2,103	0	0
ID	2,000	30	16,824	2A	1,407	1	1
IL	2,000	30	84,120	1A	2,103	1	1
IN	1,500	50	16,824	2A	1,407	1	0
KS	2,000	30	16,824	2A	1,407	1	0
KY	2,000	40	84,120	1A	2,103	1	0
LA	2,000	38	84,120	1A	2,103	1	0
MA	6,500	60	84,120	1A	1,407	0	1
MD	2,500	40	84,120	1A	2,049	0	1
ME	3,000	40	84,120	1A	2,103	0	0
MI	2,000	60	84,120	1A	2,103	0	0
MN	3,000	67	23,774	2B	1,407	1	1
MO	2,000	30	16,824	2A	1,407	1	0
MS	2,000	44	84,120	1A	2,103	1	0
MT	2,000	40	16,824	2A	2,103	1	1
NC	2,000	30	16,824	2A	2,103	1	0
ND	3,000	40	84,120	1A	2,103	1	0
NE	4,000	50	84,120	1A	1,407	0	0
NH	2,500	50	16,824	2A	2,103	1	0
NJ	4,000	35	16,824	2A	1,407	1	0
NM	2,000	45	31,290	2B	1,407	1	0
NV	2,000	35	84,120	1A	2,103	0	0
NY	3,600	50	74,820[3]	1C	2,103	0	1

[25] This is the highest asset limit that can apply, whether through the regular Medicaid program, or through the Medically Needy channel, if the state extends Medically Needy eligibility to institutionalized individuals.
[26] STATEMAX=STATEMIN, not FEDMAX

Table A2.1 (cont) : Medicaid Eligibility Parameters by State, 2000

State	Single Asset Limit[2]	PNA	STATEMIN	Case	CSIL	No change in Asset Rules 1991-2000	Lien
OH	1,500	40	16,824	2A	1,407	1	0
OK	2,000	50	84,120	1A	2,103	0	0
OR	2,000	30	16,824[3]	1B	1,407	1	0
PA	2,400	30	16,824	2A	1,407	1	0
RI	4,000	50	16,824	2A	1,407	1	
SC	2,000	30	66,480[3]	1C	1,662	0	0
SD	2,000	30	84,120	1A	1,407	0	0
TN	2,000	30	16,824	2A	1,407	1	0
TX	2,000	45	16,824	2A	2,103	1	0
UT	2,000	45	16,824	2A	1,407	1	0
VA	2,000	30	16,824	2A	1,407	1	0
VT	2,000	47.66	84,120	1A	1,407	1	0
WA	2,000	41.62	84,120	1A	1,407	1	0
WI	2,000	45	84,120	1A	1,875	1	1
WV	2,000	50	84,120	1A	1,407	0	0
WY	2,000	30	84,120	1A	2,103	1	0

Source: Stone 2002, authors' corrections, Sabatino and Wood 1996.
PNA: Personal Needs Allowance (the amount of income an institutionalized individual can keep)
STATEMIN: Minimum amount of assets that the Community Spouse is allowed to keep
STATEMAX: Maximum amount of assets that the Community Spouse is allowed to keep
CSIL: Minimum amount of income the Community Spouse is allowed to keep
LIEN: Indicator for if the state employs TEFRA-Liens in their estate recovery practices
Estate Recovery pre-1993: Indicator for if the state had estate recovery plans in place before it was Federally mandated in 1993.
CASE: See Table A2.2

Table A2.2: States Divided into Categories of State Rules, 2000

Case 1: STATEMIN=STATEMAX			Case 2: STATEMIN<STATEMAX (for all, STATEMAX=FEDMAX)	
STATEMIN= STATEMAX= FEDMAX	STATEMIN= STATEMAX= FEDMIN	FEDMIN <STATEMIN =STATEMAX <FEDMAX	STATEMIN =FEDMIN	STATEMIN >FEDMIN
(Case 1A)	(Case 1B)	(Case 1C)	(Case 2A)	(Case 2B)
26	3	2	15	5
AK	AR	NY	CT	AL
AZ	DC	SC	ID	DE
CA	OR		IN	IA
CO			KS	MN
FL			MT	NM
GA			NC	
HI			NH	
IL			NJ	
KY			OH	
LA			PA	
MA			RI	
MD			TN	
ME			TX	
MI			UT	
MS			VA	
MO				
ND				
NE				
NV				
OK				
SD				
VT				
WA				
WI				
WV				
WY				

Source: Stone 2002, authors' corrections

Figure A1:Medicaid Marginal Tax
Married Households

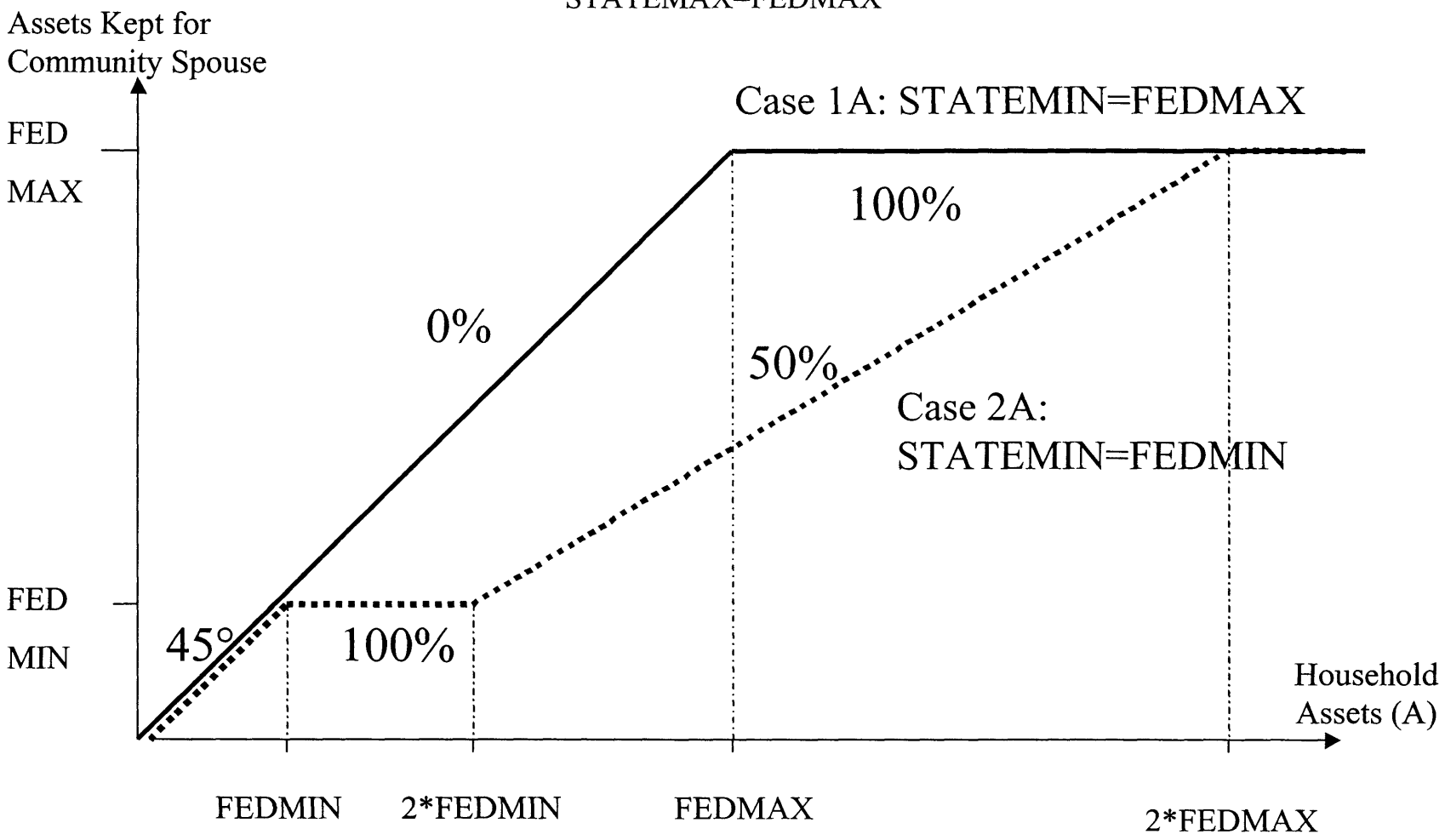


Figure A2:Difference in Assets for Community Spouse

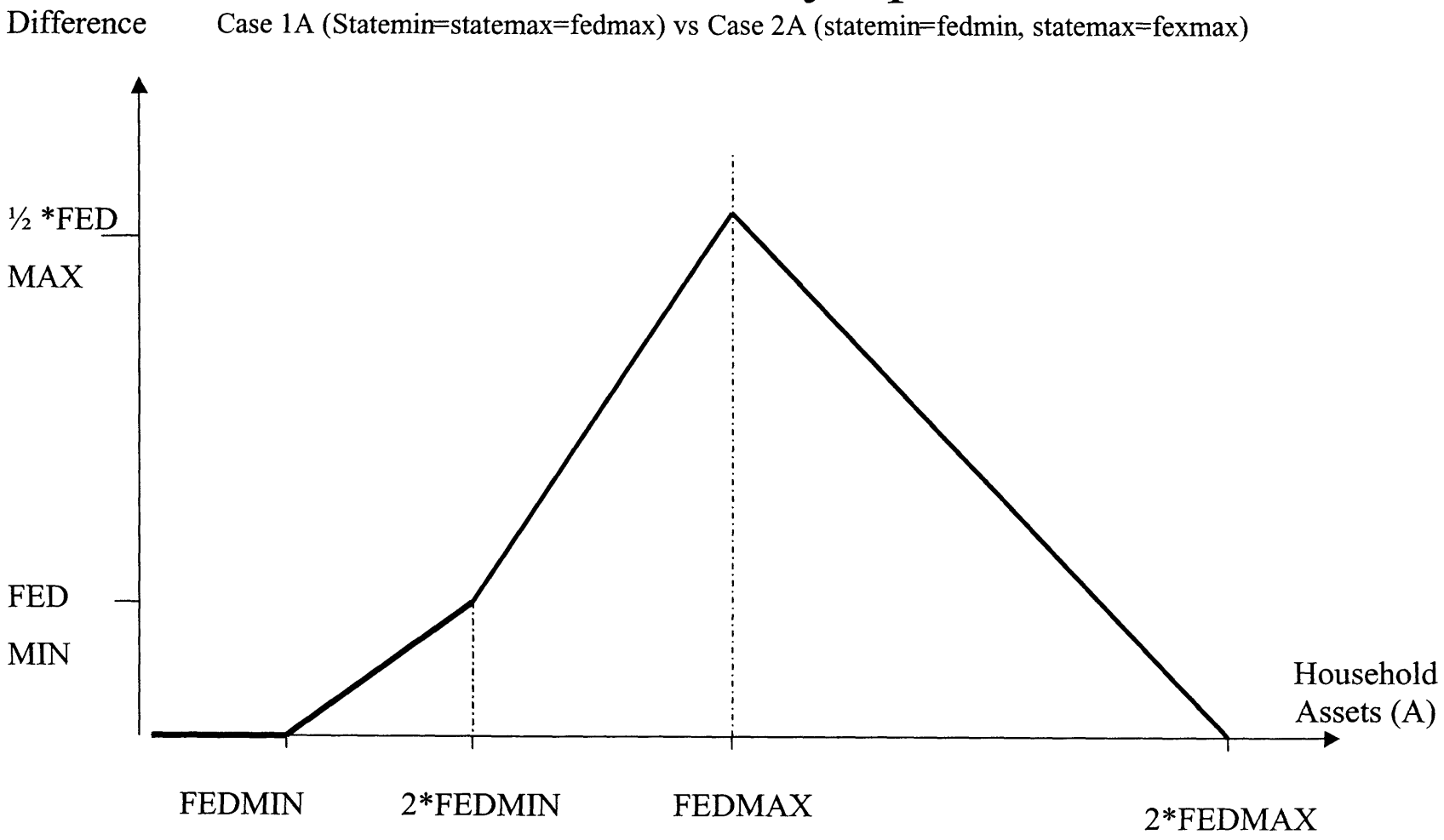


Figure A3:Medicaid Marginal Tax
Comparing Case 1A, 1B, and 1C

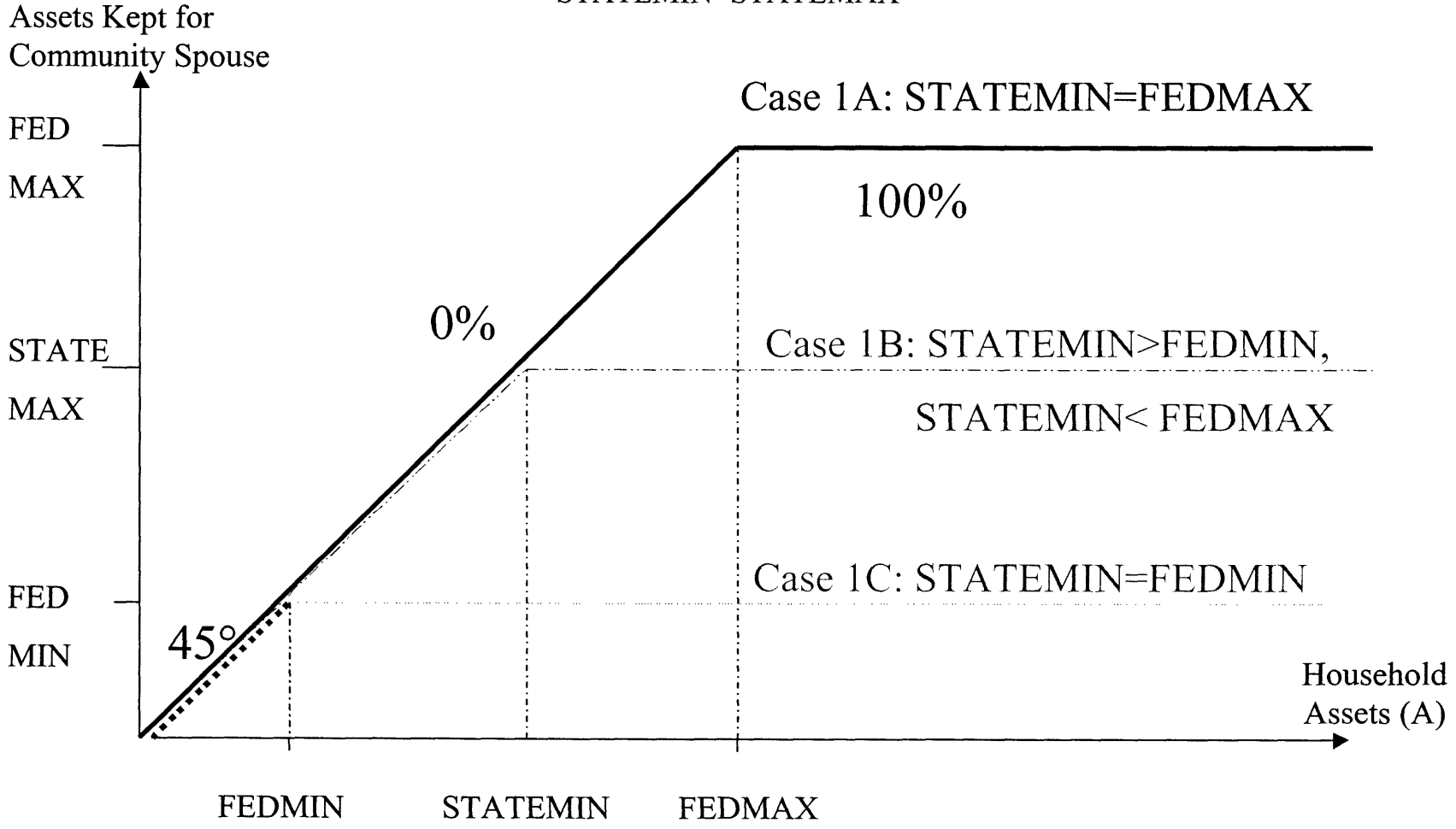
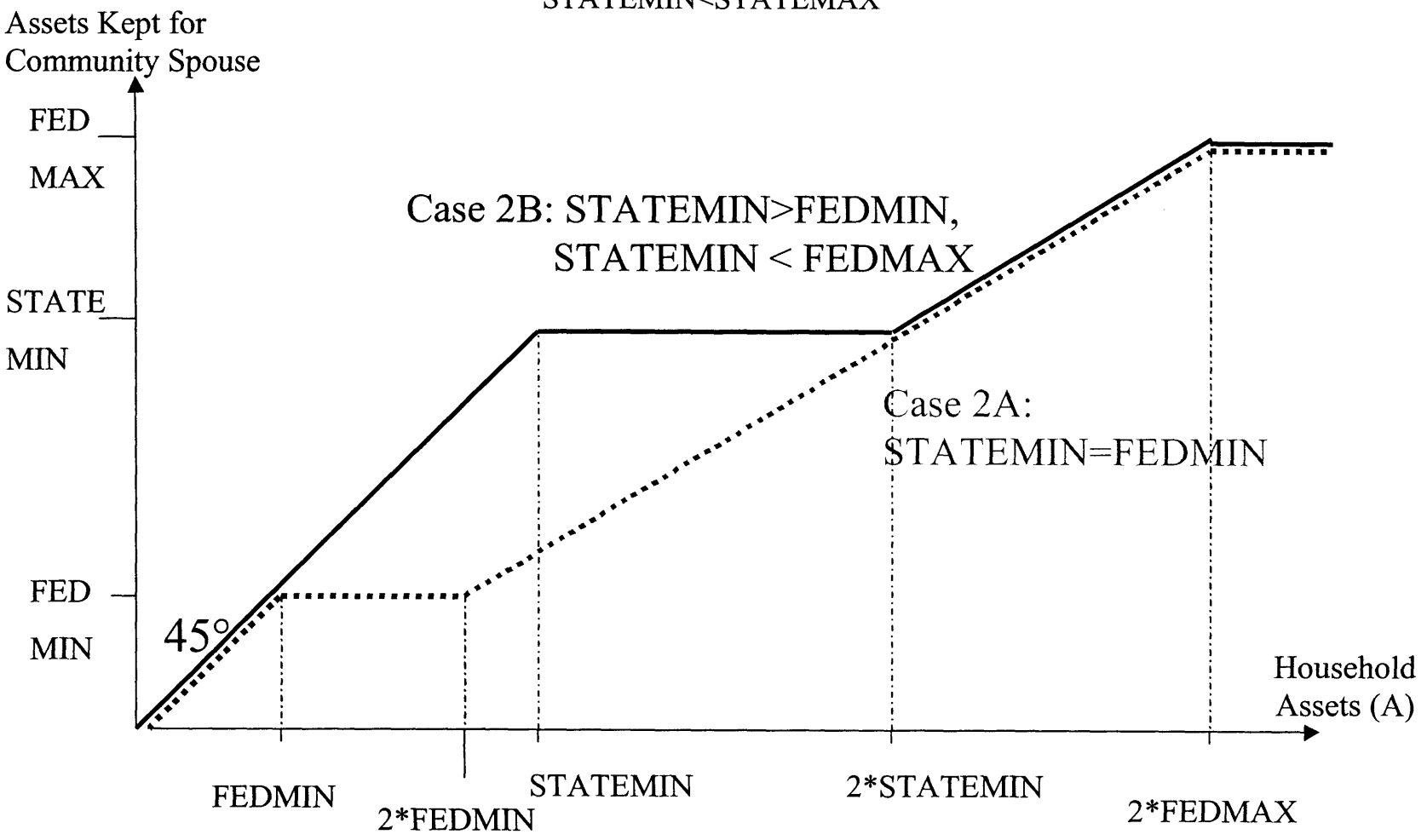


Figure A4:Medicaid Marginal Tax
Comparing Case 2A to 2B

STATEMIN<STATEMAX



Chapter Three

The Determinants of Expectations of Future Nursing Home Use

3.1 Introduction

Economic theory relies heavily on individuals' expectations. The underlying assumptions used in economic models about expectation formation and updating are important for the accuracy of the models, since an individual's behavior will be determined by their actual beliefs. Thus it is important to know how subjective expectations are formed and how they change with new information, so that these empirical realities can be incorporated into our economic models.

There is a growing literature concerning people's subjective expectations about life expectancy (Hammermesh 1985, Hurd and McGarry 1997, Schoenbaum 1997, Hurd et al 1999, Smith et al 2001) and retirement (McGarry 2002). In general, these studies find that people overestimate rare probabilities and underestimate likely probabilities. In addition, they find that subjective measures may be even more important than traditional, objective measures. For example, McGarry (2002) finds that subjective health measures are a stronger determinant of retirement expectations than financial considerations, and remain important even when objective health measures are added.

The current literature has also begun to examine the evolution of expectations, and the determinants of changes over time. McGarry (2002) finds that changes in retirement expectations are driven more by changes in self-reported health than changes in either income or wealth. Hurd et al (1999) finds that subjective life expectations in the HRS change with the onset of health conditions, while Hurd and McGarry (1997) find that subjective survival probabilities in the AHEAD decline with the death of a parent, but cancer is the only new disease diagnoses that appear to affect the survival probabilities.

There has also been recent work looking at how expectations compare with realized outcomes. Smith et al (2001) compare self-reported life expectancies to realized outcomes. They find that the evolution of subjective beliefs show a consistent decline over time for those who actually do die; survivors expectations are higher and relatively stable. But they also find that models based on the subjective probability do *not* reflect all of the private information people have about their survival prospects.

This paper extends the literature on expectations to a new topic, health care expectations for the elderly. I examine people's expectations, and changes to their expectations about nursing home use in the next five years. The patterns of expectation development and evolution may differ from those examined in previous studies since nursing home use is not universal (like death) or something people generally look forward to (like retirement). Finkelstein and McGarry (2003) find that on average, people's expectations are close to realized outcomes. While the average reported probability of using a nursing home in the 1995 wave of the AHEAD was 18%, 16% of the sample does stay in a nursing home by the year 2000.

I use the 1993-2000 panel of the AHEAD data set to examine how people's expectations compare with their statistical probabilities, how they compare with their actual outcomes, and how they change with new information. I find that expectations about nursing home use conform to the findings in the earlier literature. Expectations, on average, are very accurate. Respondents who enter a nursing home have higher expectations in the base-year, and their expectations increase more over time than their counterparts who do not enter a nursing home. Finally, while I find that expectations take into account private information that is not captured in the statistical probability or by observable characteristics, I find that they do not take into account all information that is available to the individual. In particular, I find that the respondents do not take into account their demographic characteristics when forming their expectations, but do adequately take into account their health status.

The structure of the rest of the paper is as follows: section 1 describes both the objective and subjective data. Section 2 explores how the subjective and objective measures compare in the cross-section. Section 3 examines how the subjective and objective measures evolve over time with new information. Section 4 explores how the subjective and objective measures compare with actual outcomes. Section 5 concludes.

3.2 Data

To examine the issue of expectations of nursing home use, one requires two pieces of data. The first is a panel data set where expectations are ascertained and the sample is followed over time so that realized outcomes can be observed. The Asset and Health Dynamics of the Oldest Old (AHEAD) data set is ideally suited for this study. The AHEAD is a nationally representative sample panel survey of households with heads at least age 70 in 1993. This aged population is exactly those that are facing nursing home use in the near future. (The average age of first entry into a nursing home is 83). In addition, the AHEAD is a panel data set that follows households regardless of institutionalization, divorce, or remarriage. Therefore I observe people's actual nursing home use over time.

During the questionnaire, the AHEAD asks of those un-institutionalized over age 65: "Of course nobody wants to go into a nursing home, but sometimes it becomes necessary. What do you think are the chances that you will move into a nursing home in the next five years?" Individuals respond with a ranking between 0 and 100.

As discussed in Finkelstein and McGarry (2003) and Coe (2005), there is the problem of focal answers in the answers to this question (See figure 1). Prima facie, it is unclear what to do with those who answer zero percent chance of entering a nursing home. The zero response could be indicating a true zero chance of nursing home entry, a negligible chance, or that the respondent has not thought about nursing home needs. The same is true of the large proportion of people who answer a 50 percent chance. Thus I will focus on both of these groups separately throughout the paper.

In addition to the expectations question, the AHEAD also includes detailed information about health status (both objective and subjective measures), changes in health, wealth, and family structure. This will allow me to examine many potential determinants of expectations of nursing home use.

The second piece of data that one requires is an objective measure of future nursing home use. For this I use a "state of the art" model of transitions across different states of care (including home health care and assisted living facilities) developed by Jim Robinson, a former member of the Society of Actuaries' long-term care insurance valuation methods task force (Society of Actuaries, 1996). The Robinson model has a strong pedigree (see Robinson 1996 or

Brown and Finkelstein 2004). I will use the Robinson model as a base-line measure of nursing home risk to compare to the subjective measures reported in the AHEAD.

The statistical probability of entering a nursing home in the Robinson model varies based on gender, health status, and age, all of which are observable in the AHEAD dataset. Health status is defined as a categorical variable as: no limitations on the activities of daily living (ADL[27]) or to instrumental activities of daily living (IADL[28]); no ADLs and at least one IADL; one ADL; two ADLs; three or more ADLs; cognitive impairment[29] and less than two ADLs, cognitive impairment and two or more ADLs. I will limit the sample to those respondents who have answered the self-reported probability of entering a nursing home question and whom I can assign a statistical probability of entering a nursing home. This leaves a total sample of X observations, or Y households.

3.3 Cross-Section Comparisons

3.3.1 Means

Table 3.1 compares the statistical probability with the self-reported probability along gender, health status[30], and age parameters. The first number in the table is the number of observations between 1993-2000 in each age, gender, and health status cell. The second is the average self-reported probability while directly below it is the statistical probability. The last 2 rows in table 3.1 indicate the number of people reporting that they have a zero percent chance and a 50 percent chance of entering a nursing home respectively.

The statistical probability of entering a nursing home varies as you would expect based on the nursing home utilization patterns. For every health status/age, women have a higher statistical probability of entering a nursing home than men. Within every gender/health status,

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[27] ADL's include difficulty with: walking, dressing, bathing, eating, getting in or out of bed, using the toilet.
[28] IADL's include difficulty with: preparing a hot meal, grocery shopping, making telephone calls, taking medication, managing money.
[29] I define cognitive impairment as scoring less than eight on the TICS score as Mehta (2002) and Finkelstein and McGarry (2003). The TICS score tests ability to subtract numbers in your head, ability to recall a word list immediately, ability to recall the same word list later, and ability to answer questions about current events (president), the date, and definitions of common words.
[30] While the AHEAD follows respondents regardless of cognitive impairment, once the impairment is severe enough they find a proxy respondent to fill in the questionnaire (often a spouse or child). For obvious reasons, proxy respondents are not asked about the nursing home use expectations. This makes the sample sizes small for the latter two health statuses as defined above, thus I do not present the means.

the probability of entering a nursing home increases with age. Within every age/gender, the probability of entering a nursing home increases with a worsening of health status.

The first thing to note is that the patterns in the self-reported probabilities appears reasonable when compared to the patterns in the statistical probabilities. The self-reported probabilities for women are larger than for men in almost all age/health status cells. The exceptions tend to occur at later ages, and with more functional limitations.
The average self-reported probability tends to increase with health status within a given age/gender, with the exception of those who have a cognitive impairment. This decreased average probability could be a function of their impairment itself, or the fact that they are currently living outside a nursing home with their impairment, so they might have better-than-average assistance networks available.

Another pattern to note is that the self-reported probabilities tend to be "flatter" over health status than the statistical probabilities. For example, women ages 65-70 have a 5.3% to 53.4% statistical probability of entering a nursing home, while the self-reported means only vary from 13.1% to 37.6%. There is a similar pattern with age within a health status. For example, healthy women have a 5.3%-37.8% statistical probability of entering a nursing home, but the average self-reported probability varies from 13.1% to 25.7%. This table supports previous work finding that people overestimate unlikely probabilities (13.1% instead of 5.3%) and underestimate likely probabilities (25.7% versus 37.8%). This is also consistent with Hammermesh (1985) who finds self-reported survival probabilities are flatter than the life tables.

Another interesting pattern apparent in table 3.1 concerns the percent of the sample that is responding zero. If a zero response represents a true zero or a negligible probability, then one would expect a lower percentage of the respondents answering zero as health status worsens or age increases. For younger women (age 65-70 and 70-75), a declining percentage answer zero as health status declines. Men have the reverse pattern, with a higher percentage of people answering zero as health status worsens in the first two age categories, but then this switches back to the predicted pattern at older age groups. Again, this might be a function of having healthier wives at younger ages, thus better-than-average outside care options. It is surprising to see how little impact aging seems to have on the percent answering zero; both men and women are remarkably stable across age groups. Finally, the percentage answering 50 percent does follow the expected pattern; for both men and women, there is a positive age and health status

gradient for the percentage of the sample answering they have a 50 percent chance of needing a nursing home in the future.

In table 3.2, the average statistical probability of needing a nursing home in the next five years is presented by categories of self-reported probabilities. As mentioned above, there is concern about focal answers with self-reported probabilities, especially at zero and fifty in this particular case. On average, there is a 25 percent statistical probability of needing a nursing home for this dataset. When broken down by the self-reported probabilities, the statistical probability increases with the self-reported probability for all except the zero-respondent group.

3.3.2 Regression Analysis

While the statistical probability uses health status, gender, and age, there are a lot of other potential determinants of one's future nursing home use, and potentially also their expectations of such care. While the characteristics of nursing home residents are well known (see Norton 2000), the characteristics that influence expectations are not.

Table 3.3 explores the determinants of nursing home expectations. The estimating equation is:

$$P_t = \alpha + \beta_1 R_t + \beta_2 X_t + \varepsilon \qquad (1)$$

P is the self-reported probability of entering a nursing home in the next five years. R is the statistical probability of a person with the same gender, age, and health status. X are individual controls, such as demographics, wealth, and heath status. All regressions use the 1993-2000 waves of the AHEAD, and are weighted using individual weights. I calculate robust standard errors to take into account the fact that I observe the same individual multiple times.

There are two different ways to control for the statistical probability of entering a nursing home. First, is to use the probability directly as a control variable in the regression. This is done in panel 1 of table 3.3. Second, is to control for the determinants of the statistical probability individually. This allows the expectation formation process to have different weights on age, health status, gender, and their interactions than computed by the statistical model. This is a more flexible specification, and is presented in panel 2 of table 3.3.

Column 1 uses the statistical probability as the only control variable in the regression. In column 2, I add additional demographic control variables that are common characteristics of current nursing home populations. For example, nursing home residents are much more likely to

be single and female that the un-institutionalized population. Column 2 indicates, though, that while marital status is an important factor in expectations (being married decreases your self-reported probability of entry by 3.5 percentage points), this effect does not have a differential effect on men and women. Indeed, as one looks across the columns when more controls are added to the regression, the effect of marital status disappears once wealth is controlled for.

As expected, the number of children people have lowers the self-reported probability of nursing home entry. If your mother is still alive you also report a lower nursing home entry probability. (In results not shown, whether your father, mother-in-law, or father-in-law is alive are not important determinants.) It is somewhat surprising that the more educated one is, the higher the self-reported probability of entering a home. This could be due to an awareness of the need, or the correlation between socio-economic status and longevity.

Earlier studies have found that race, even after controlling for education, wealth, and family characteristics, is a statistically significant factor in nursing home use. They hypothesize that there are cultural differences in the African-American and Latino-American communities that lead them to use nursing homes less frequently than Caucasians. This does not seem to enter into the expectation formation, though. Combined with the result for marital status, this suggests that people weigh their personal characteristics (such as their health, wealth, family structure) more heavily than their demographic group characteristics (marital status, race).

The third column of table 3.3 includes wealth and bequest motive controls. Norton (2000) shows that current nursing home residents have lower asset levels than the non-institutionalized population. This fact could be attributable to the out-of-pocket nursing home costs and Medicaid asset limits, or that wealthier people have more outside care options. Column 3 shows that each wealth is an important determent of the expectation of nursing home use, even after controlling for education. While not monotonic, there seems to be a positive relationship between wealth and expectation of nursing home use. Again, this could be due to an increased awareness or the correlation between socio-economic status and longevity. In addition to a wealth effect, Garber and MaCurdy (1990) found that individuals who own their own homes are less likely to use a nursing home. This fact also weighs in the expectations, where homeowners report a 4.5 percentage point lower probability of needing a nursing home.

Norton (2000) also indicates that those with a strong bequest motive might be less likely to use a nursing home, due to the high costs and the Medicaid asset tests. As table 3.3 shows, this also weighs into the expectations of nursing home use, albeit with a small effect.

In column 4 of table 3.3, controls for health status (other than the IADL, ADL, and cognition that is captured in the statistical probability) and diseases are added. As McGarry (2002) found concerning retirement expectations, I find that self-reported health status is an important determinant for nursing home expectations even after controlling disease and objective measures for health status.

Some health conditions are chronic, and tend to lead to nursing home use. These include incontinence, diabetes, high blood pressure, arthritis, and depression (Norton 2000). I find that that all of these conditions, except diabetes, increase one's expectations of a nursing home by one-three percentage points. I find no measurable effect of diabetes. In addition, some diseases (cancer) and health outcomes (fractures, strokes) tend to produce short-term stays in a nursing home, which are more likely to be unanticipated. (Liu et al. 1994). I find no evidence that these conditions affect nursing home expectations.

The second panel of table 3.3 uses the health status, gender, and age directly as control variables instead of the statistical probability. It has very little difference in measured effects of most of the determinants of nursing home use expectations. The exception is the weight placed on whether ones mother is still alive. This is no longer significant with this more flexible specification.

3.4: Consistency

3.4.1 Means

One way to test if individuals are reporting realistic expectations is to look at the consistency of answers over time. Of course, health shocks, the aging process, and other factors may validly change someone's expectations about future nursing home use, but it is hard to imagine a scenario where there are large, repeated oscillations over the course of the decade of interviews.

Table 3.4 compares the changes in the self-reported probabilities with the changes in the statistical probabilities between waves. The first panel uses the entire sample. The difference between the changes in the self-reported probability and the statistical probability of entering a

nursing home is virtually identical between 1993 and 1995. There is a divergence between 1995 and 1998, where the self-reported probability actually decreases by 1.4 percentage points, but the statistical probability increases by 5.5 percentage points. The average change is again close between 1998 and 2000, with an increase of 3.6 and 5.1 in the expectation and the statistical probability, respectively.

Panel 2 of table 3.4 compares the changes in the self-reported and statistical probabilities of those who answered zero in the base year, while the sample for panel 3 are those respondents who answered 50 in the base year. Comparing the changes in the statistical probabilities, the self-reported zero sub-sample does not appear to be very different from the entire sample. Their expectations set them apart. They have much larger changes on average, and yet their answer is the most stable of any sub-sample; more respondents who answer zero in one wave answer the same response in the next compared to any other initial answer.

Panel 3 of table 3.4 examines the sub-sample that initially reports having a 50 percent chance of entering a nursing home in the base year. Based on the changes in the statistical probability, this group appears to experience a worsening of health more than that of the full sample or the zero-response sub-sample. Their self-reported probability, though, declines on average.

Table 3.5 shows how the self-reported probability changes between waves. The rows are categories of responses in the base-year; the columns are categories of responses in the next wave. The zero-probability respondents are the most consistent, with almost 67 percent responding zero in the next wave as well. It is interesting to note that for each categorical response in period 1, the sample categorical response is the most likely in the second period, except the highest category (51-100). The highest category's most likely response in the second period is 50, and is the least consistent, with only a 20 percent chance of responding in the highest category again in the next wave. While simple frequencies do not tell us if there are reasons for the changes over time, at least the pattern does not indicate large oscillations in reponses.

3.4.2 Regression Analysis

Table 3.6 examines what factors change the expectations of nursing home use. The estimating equation is:

$$P_{t+1} = \alpha + \beta_1 R_t + \beta_2 X_t + \beta_3 (X_{t+1} - X_t) + \varepsilon \qquad (2)$$

Where P is the self-reported probability of entering a nursing home, R is the statistical probability, and X are demographic, health and wealth variables. An individual must answer the expectations question in at least two consecutive waves; since I am using four waves, at most one individual can be in the dataset three times. All regressions are weighted with the respondent weight, and clustered on the individual to take into account that I observe more than one change for some individuals.

The first column in table 3.6 includes only the statistical probability in the base year, and changes in age and health status as controls. This is the "baseline" specification since the statistical probability in period 2 is solely determined by these controls. If anything else is statistically significant, then these factors influence expectations above and beyond the statistical probability.

Column 1 shows that the base year statistical probability is significant in determining the next wave's expectations. Worsening of health conditions is also important and statistically significant, but while improving health is of the expected sign, it is not statistically significant.

In column 2, self-reported improvements or declines in health are added to the regression. As McGarry (2002) finds, self-reported health is an important factor in expectations, even after controlling for changes in objective measures of health status. In column 3, other self-reported health conditions are added to the regression. For those reporting health conditions in the base year (such as arthritis and lung problems), the questionnaire in the next wave ascertains how the individual rates their condition compared to the base year. Unlike self-reported health status, reporting that your arthritis and high blood pressure are better than the base year lowers your expectations of nursing home use. The only condition worsening that seems to directly affect expectations are psychological problems.

I also compare objective measures of health between waves, such as the number of ADLs and IADLs. In column 4, changes in the number of IADLs affects expectations, but changes in the number of ADLs does not affect expectations directly, but is picked up through changes in health status as defined by the statistical model. Additionally, changes in your cognition score have a large effect (-0.28) on expectations. This suggests that expectations respond to much finer changes in cognition, not just the blunt cut (scoring less than 8 vs 8 or more on the TICS cognition test) that determines the statistical probability.

Spousal health, since it is an indicator of outside care possibilities, may also effect nursing home expectations. In column 5 I add the changes in objective health measures for your spouse. Somewhat surprisingly, none of these seem to have an effect on nursing home expectations.

Finally, in column 6 all base-year characteristics that are in the earlier regressions in table 3.3 are added to the model, as well as base-year expectations. These change the coefficients on the factors already discussed very little, and add predictive power themselves. Expectations of Caucasians increase over time more than non-Caucasian respondents. Homeowners, on the other hand, decrease. The higher the net worth (over the 50^{th} decile) the respondent had in the base year, the higher the expectations in the next wave. While none of the base conditions affect the next year's expectations, it is important to note that the base expectation is an important determinant of the next expectation, even after controlling for the baseline statistical probability and all of the determinants of the statistical probability in the second interview.

3.5: Expectations versus Ex-Post Outcomes

3.5.1 Means

Another way to test if expectations are reasonable is to compare the stated probabilities with ex-post outcomes. Since the AHEAD is a panel data set that has been running for seven years, I can compare expectations in 2 waves with the actual outcomes.

As Finkelstein and McGarry (2003) found, expectations on average match the ex-post outcomes quite well. They use the 1995 wave, and note that while the average expectation of nursing home use is 18 percent, 16 percent of the sample does in fact use a nursing home within 5 years. This pattern is also apparent for the 1993 wave, as shown in table 3.7. While the average expectation in 1993 is 14 percent, 11 percent use a nursing home within 5 years, and 15 percent use it within 7 years. So while the mean expectation is slightly higher than the actual realization within 5 years, this seems to reverse within 7 years.

Smith et. al.(2001) highlight that the expectations may evolve differently for those who experience the outcome versus those who do not. Table 3.8 examines this phenomenon for nursing home expectations. There are three important trends to note in this table. First, for all groups except those who enter between 1995-1998, there is a negative dip in expectations in the

year 1998. This could be an overall "good mood" for the year due to generous stock market returns, or a direct wealth effect. Either way, this indicates how important it will be to include wave variables in regressions. Second, that the starting average expectation is higher for each category of individuals. For example, those who are interviewed in 1995 and actually enter a nursing home by 1998, the average reported expectation is higher (23.8) than for those who enter between 1998-2000 (20.4), and is even higher than for those who do not enter a nursing home during the sample period (17.4). This correlation between expectations and actual outcomes is important for the validity of the self-reported expectations. The only exceptions are the 1993 respondents who enter by 1995 and those who enter for the first time between 1995-1998, where the means are close, but slightly larger for the latter group. Finally, it is interesting to note that this trend, where those who use a nursing home sooner have a higher average than those who use it later, is also apparent over time. Those who never enter a nursing home report very little change in their expectations on average, while those who do enter a nursing home report increasing expectations over time.

These trends are also apparent in the frequency of people who answer zero and fifty percent chance of entering a nursing home, as illustrated in table 3.9. It appears that the number of people who answered zero may drive the 1998-wave dip in average expectations found in table 3.8. Obviously people underestimating their probability of using a nursing home, as evidenced by the fact that fifty percent of the 1993 respondents who enter a nursing home in just 2 years answered a zero percent chance in 1993. However, the trends in the number of people answering zero suggest that people are aware of their chances for adverse health shocks that can lead to institutionalization.

3.5.2 Regression Analysis

Another method to test the validity of expectations of future nursing home use is to use regressions techniques to test if, even once controlling for all observables, that the self-reported expectation is a significant predictor of outcomes. Finkelstein and McGarry (2003) do precisely this, and find that base-line expectations remain significant. They do not, however, report if other factors in the regression are significant, thus leaving the question of which factors are not correctly weighted in the expectation formation process unanswered. In table 3.10, I also find that base-line expectations are significant even after controlling for all observables, and highlight

what other factors are important, which indicates they are not reflected properly in the individual's expectation formation process.

In table 3.10, I estimate the following equation:

$$NH_{t+5} = \alpha + \beta_1 R_t + \beta_2 P_t + \beta_3 X_t + \varepsilon \qquad (3)$$

where NH is an indicator variable indicating if the person has been in a nursing home for at least one night in the subsequent 5 years. R is the statistical probability of entering a nursing home, as calculated in the base year. P is the self-reported probability of entering a nursing home, while X are base year characteristics. I use the same progression of controls as used in estimating equation 1 (table 3.3). All regressions are weighted with the respondent weight, and the standard errors are robust to correlations in the error term due to repeated observations of the same individuals.

It is not surprising, considering the earlier results in this paper, that the respondents are generally weighing their personal health conditions and wealth conditions adequately. Out of all of the base-line health conditions in the regression, only 4 seem to add any additional information. Cancer and stroke diagnoses increase the nursing home entry rate, while the number of falls leading to injury and high blood pressure lower the entry rate. The individual also seems to under weigh increased probability of entry associated with more ADL limitations, as was true in the averages in expectations compared to the statistical probabilities. Individuals are not, however, taking their general demographic characteristics, such as marital status, gender, number of children, and race, into account correctly when forming their expectations. Married men are underestimating their likelihood of institutionalization, as are Caucasians. Married women, homeowners, and respondents with a larger number of children are overestimating their likelihood.

In column 1 of table 3.1, the statistical probability, self-reported probability, and wave dummies are the only controls. All are statistically significant. Each column adds more control variables. As is evident, regardless of the controls included, these variables are statistically significant, and have a very stable marginal effect on the nursing home outcome. Even after controlling for the statistical probability and full demographics, the expectation is an important determinant in future nursing home use. Thus individuals have private information that is not captured in the statistical probability.

Further, it is important to note which factors are significant, even after controlling for the expectation and statistical probability. Not surprisingly given previous results in this paper, demographic characteristics do not appear to be factored into expectations in the same way as personal health conditions. Only the presence of psychological problems and a broken hip are independently significant out of all of the health factors included in the regression. Yet most of the demographic characteristics are independently significant, such as marital status, whether your father is alive, educational attainment, the number of children, and home ownership status. So while individuals have private information, they do not use all available information to form their expectations.

3.6: Conclusion

This paper adds to the growing literature concerning people's subjective expectations and how they change over time. In general, I find that people's expectations about future nursing home use are formed, and then change, in ways similar to their expectations of retirement and life expectancy, despite the fact that nursing home use is not desired (such as retirement) or universal (as death). I find that people overestimate rare probabilities and underestimate likely probabilities. Respondents who enter a nursing home have higher expectations in the base-year, and their expectations increase more over time than their counterparts who do not enter a nursing home. Finally, while I find that expectations take into account private information that is not captured in the statistical probability or by observable characteristics, I find that they do not take into account all information that is available to the individual. In particular, I find that the respondents do not take into account their demographic characteristics when forming their expectations, but do adequately take into account their health status.

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Table 3.1: Probability of Entering a Nursing Home, by Gender, Age, and Health Status

	Women					Men				
Age	Well	IADL	1 ADL	2 ADL	3+ ADL	Well	IADL	1 ADL	2 ADL	3+ ADL
Age 65-70										
N	1,844	209	270	129	68	1,195	136	142	45	23
Self-reported	13.1	17.9	16.6	20.3	30.1	12.3	15.5	13.6	14.2	22.1
Statistical	5.3	21.9	30.8	50.9	53.4	4.6	17.2	23.0	41.0	39.7
% answer 0	59.5	54.5	56.7	51.9	48.5	55.3	58.8	59.2	64.4	60.9
% answer 50	10.1	18.7	14.8	16.3	17.6	9.6	13.2	12.7	11.1	21.7
Age 70-75										
N	2,129	300	484	210	119	1,340	208	222	103	52
Self-reported	15.8	18.5	17.1	21.5	28.6	15.4	17.8	21.2	19.6	19.0
Statistical	9.6	29.3	41.0	59.6	59.2	8.5	23.2	32.4	50.3	46.2
% answer 0	54.7	55.7	51.9	48.1	45.4	50.7	52.9	49.1	56.3	55.8
% answer 50	13.9	17.0	15.9	17.6	20.2	13.4	13.0	15.8	13.6	19.2
Age 75-80										
N	1,133	312	450	220	128	722	177	208	93	44
Self-reported	17.1	23.1	22.4	20.9	20.0	16.8	18.5	19.0	19.2	26.3
Statistical	16.3	37.2	49.2	71.0	65.3	15.1	31.3	41.4	60.3	55.0
% answer 0	55.2	52.6	49.3	47.3	53.9	52.2	50.8	53.4	44.1	36.4
% answer 50	16.0	21.2	20.0	22.3	21.9	15.2	14.1	21.6	12.9	31.8
Age 80-85										
N	396	170	269	157	97	269	98	140	60	35
Self-reported	18.8	23.1	21.3	22.0	19.0	17.7	23.6	19.0	31.2	23.8
Statistical	25.6	44.9	57.2	77.0	69.1	24.2	39.0	49.3	69.6	59.4
% answer 0	53.8	55.3	52.4	51.0	57.7	53.5	48.0	48.6	38.3	40.0
% answer 50	15.9	16.5	19.3	15.3	19.6	19.0	23.5	20.0	25.0	22.9
Age 90-95										
N	90	60	105	60	52	57	38	47	17	10
Self-reported	25.7	22.1	24.5	23.0	24.7	21.0	25.3	19.0	33.0	45.2
Statistical	37.8	52.3	64.4	79.9	71.7	34.4	43.7	55.0	73.7	63.7
% answer 0	47.8	55.0	51.4	56.7	44.2	54.4	44.7	53.2	47.1	50.0
% answer 50	22.2	20.0	13.3	23.3	21.2	22.8	28.9	8.5	35.3	30.0

Notes: The statistics are calculated from the 1993-2000 waves of the AHEAD. All means are calculated using individual weights.

Table 3.2: Average Statistical Probability of Nursing Home Entry by Self-Reported Sub-Samples

Self-Reported Probability	Average Statistical Probability
Full Sample	25.5
Answered Zero	21.6
Answered 1-49	20.1
Answered 50	26.7
Answered 51-100	31.0

Note: Author's calculations of the 1993-2000 waves of the AHEAD

Table 3.3: Determinants of Expectations of Future Nursing Home Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	+ Demographics	with wealth	with health	+ Demographics	+ wealth	+ health
Stat. Probability	0.1635***	0.1576***	0.1507***	0.0878***			
	(0.0126)	(0.0131)	(0.0153)	(0.0167)			
Married		-3.6086**	-2.3466	-2.6058	-3.4431**	-2.8236*	-2.8798*
		(1.5221)	(1.6141)	(1.6199)	(1.5700)	(1.6793)	(1.6768)
Married man		0.4327	0.1539	0.7488	-0.9512	0.2257	0.4750
		(0.6571)	(0.7553)	(0.7559)	(1.1350)	(1.3403)	(1.3285)
Children		-0.7450***	-0.8440***	-0.9612***	-0.6653***	-0.8121***	-0.8897***
		(0.1605)	(0.1819)	(0.1802)	(0.1630)	(0.1855)	(0.1834)
White		1.7467**	-0.1865	-0.0344	1.6481**	-0.1260	0.0352
		(0.7799)	(0.9264)	(0.9314)	(0.7943)	(0.9476)	(0.9513)
Mom alive		-3.0195**	-3.8567**	-3.9175**	-1.4661	-2.3574	-2.1939
		(1.3092)	(1.6169)	(1.6563)	(1.3296)	(1.7061)	(1.6806)
HS Educ		2.6121***	1.6413**	2.0066***	2.7638***	1.6746**	2.1226***
		(0.6315)	(0.7341)	(0.7259)	(0.6329)	(0.7374)	(0.7331)
Some College		3.0342***	1.1863	1.6780*	3.0911***	1.2953	1.8224**
		(0.7367)	(0.8734)	(0.8724)	(0.7436)	(0.8820)	(0.8826)
College +		5.3138***	2.8654***	3.7943***	5.3709***	3.0061***	3.9400***
		(0.8208)	(0.9886)	(0.9991)	(0.8241)	(0.9964)	(1.0039)
Own home			-4.2260***	-4.5459***		-4.3867***	-4.4637***
			(0.9720)	(0.9667)		(0.9843)	(0.9820)
Net Worth:							
1st Decile			3.6587***	4.3680***		3.7401***	4.2253***
			(1.1739)	(1.1515)		(1.1896)	(1.1733)
2nd Decile			7.0792***	7.8169***		7.1388***	7.5669***
			(1.3838)	(1.3670)		(1.3992)	(1.3861)
3rd Decile			5.3998***	6.8112***		5.6532***	6.7266***
			(1.3927)	(1.3723)		(1.4029)	(1.3938)
4th Decile			7.1634***	8.7820***		7.1889***	8.4350***
			(1.4280)	(1.4137)		(1.4326)	(1.4271)
5th Decile			8.2926***	9.8690***		8.1305***	9.2852***
			(1.4891)	(1.4735)		(1.4950)	(1.4893)
6th Decile			8.3114***	10.0796***		8.1258***	9.4578***
			(1.5235)	(1.5077)		(1.5352)	(1.5298)
7th Decile			8.1818***	10.0075***		8.1479***	9.5416***
			(1.4987)	(1.4813)		(1.5140)	(1.5061)
8th Decile			8.8407***	10.6006***		8.8655***	10.2242***
			(1.5282)	(1.5130)		(1.5535)	(1.5490)

Table 3.3 (cont): Determinants of Expectations of Future Nursing Home Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	+ Demographics	with wealth	with health	+ Demographics	+ wealth	+ health
9th Decile			8.3621***	10.4788***		8.2492***	9.8708***
			(1.5951)	(1.5912)		(1.6181)	(1.6211)
Probability of Bequest			-0.0036*	-0.0041**		-0.0033*	-0.0040**
			(0.0019)	(0.0019)		(0.0019)	(0.0019)
Self-Reported Health							
Fair				2.2699***			2.4932***
				(0.8098)			(0.8190)
Average				3.9981***			4.0613***
				(0.8285)			(0.8373)
Good				6.1914***			6.5144***
				(0.9567)			(0.9661)
Excellent				7.7764***			8.1110***
				(1.3669)			(1.3643)
Arthritis				1.3804**			1.5054***
				(0.5607)			(0.5639)
High Blood Pressure				1.1445**			1.0901*
				(0.5605)			(0.5636)
Incontinence				2.9979***			3.0391***
				(0.7445)			(0.7503)
Psych				1.5229*			1.6500*
				(0.8985)			(0.9025)
Depressed				1.3472*			1.2314*
				(0.7152)			(0.7213)
Obs	16795	16418	10829	10792	16418	10829	10792
R-squared	0.02	0.03	0.03	0.05	0.05	0.07	0.08

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.4: Changes in the Probabilities of Nursing Home Use Between Waves

	Full Sample			Answered Zero in base year			Answered 50 in base year		
	Self-reported		Statistical	Self-reported		Statistical	Self-reported		Statistical
Waves	Mean	% unchanged	mean	Mean	% unchanged	mean	Mean	% unchanged	mean
1993-1995	3.76	43.71	3.78	11.45	62.7	3.70	-18.83	28.0	4.27
1995-1998	-1.44	40.71	5.77	10.03	71.5	5.70	-22.42	34.0	5.39
1998-2000	3.60	48.14	5.27	10.44	67.5	5.00	-17.02	24.9	5.88

Notes: author's calculations using the 1993-2000 waves of the AHEAD

Table 3.5: Categorical Changes in the Probability of Nursing Home Use Between Waves

	Wave t+1 Response				
Wave t response	0	1-49	50	51-100	Total
0	66.8	20.55	9.23	3.44	100
1-49	35.81	41.25	16.62	6.32	100
50	29.20	26.01	34.44	10.34	100
51-100	29.23	23.08	27.15	20.54	100

Notes: author's calculations using the 1993-2000 waves of the AHEAD

Table 3.6: Determinants of Future Expectations of Nursing Home Use

$Expectations_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Self-reported Health	All self-reported measures	Spousal Health	Parental Health	All base-year characteristics	All age dummies
Stat. Probability	0.1551***	0.1545***	0.1555***	0.2083***	0.2055***	0.2386***	0.1083
	(0.0238)	(0.0311)	(0.0312)	(0.0479)	(0.0481)	(0.0643)	(0.0900)
Changes in Health Status							
Better by 5	-8.2566	-25.1801***	-27.0234***	-11.8876	-11.8370	0.0000	0.0000
	(5.6547)	(1.4476)	(1.8104)	(9.6615)	(9.6483)	(0.0000)	(0.0000)
Better by 4	-6.0838	0.7729	-0.5912	-15.9589***	-15.9065***	-3.4715	0.6743
	(4.0712)	(9.0071)	(9.2825)	(4.2734)	(4.2773)	(9.6968)	(8.2795)
Better by 3	-1.8638	-1.8458	-1.7818	-5.1488	-4.8900	6.4485	7.6397
	(2.6635)	(3.4140)	(3.3794)	(4.8510)	(4.8731)	(9.0668)	(9.2351)
Better by 2	-0.9559	0.4520	0.4148	-1.1202	-1.0834	15.0148*	14.7766*
	(1.6206)	(2.1400)	(2.1315)	(2.6902)	(2.6961)	(7.7475)	(7.8692)
Better by 1	-0.7739	-0.4446	-0.4590	-1.3834	-1.3488	1.6868	3.0203
	(1.3497)	(2.1294)	(2.1383)	(2.0275)	(2.0319)	(6.7090)	(6.9537)
Worse by 1	1.9945*	2.4343	2.3588	0.6900	0.6337	-0.5674	-1.2059
	(1.1914)	(1.5961)	(1.5946)	(2.2426)	(2.2386)	(4.2104)	(4.2020)
Worse by 2	3.5350***	3.0464**	2.9808**	1.8607	1.5282	1.6635	-1.8487
	(1.1049)	(1.3635)	(1.3617)	(2.7926)	(2.7975)	(5.6326)	(5.7448)
Worse by 3	6.4250***	5.8905***	5.7659**	-0.1622	-0.8229	8.7456	2.2453
	(1.9566)	(2.2765)	(2.2918)	(3.9982)	(4.0009)	(7.9129)	(8.3381)
Worse by 4	6.3565*	6.3729	6.5504	4.5067	4.0992	25.9717	23.1977
	(3.4128)	(4.3825)	(4.4017)	(9.8183)	(9.8436)	(24.8778)	(22.6814)
Self-Reported Health: worse		3.4568***	3.3792***			2.6052*	2.6096
		(0.9295)	(0.9307)			(1.5801)	(1.6123)
Changes in Spousal health							
6 Fewer ADLs				-17.3191***	-17.5602***	0.0000	0.0000
				(2.5578)	(2.5735)	(0.0000)	(0.0000)
5 Fewer ADLs				-0.2410	-0.2463	0.0000	0.0000
				(7.9118)	(7.9250)	(0.0000)	(0.0000)
5 More ADLs				9.5599	9.5547	-9.0457	-8.1881
				(11.7342)	(11.7353)	(6.4266)	(6.8900)
6 More ADLs				-19.4127***	-19.2876***	-5.9954	-6.3303
				(4.9788)	(5.0017)	(7.5106)	(7.7363)

Table 3.6 (cont): Determinants of Future Expectations of Nursing Home Use

$Expectations_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Self-reported Health	All self-reported measures	Spousal Health	Parental Health	All base-year characteristics	All age dummies
Mom Died					-1.7267	-8.8253*	-11.3811*
					(3.3892)	(4.8929)	(6.0898)
Dad died					-8.3286*	-13.7391***	-6.5957
					(4.5760)	(4.0398)	(5.3315)
Arthritis better			-2.9306*			-4.4454	-4.7604*
			(1.6495)			(2.8824)	(2.8912)
HBP better			2.1540*			1.5234	1.7916
			(1.1844)			(2.0754)	(2.0365)
Diabetes worse			-5.5782			-14.0370***	-14.6332***
			(4.8304)			(3.9931)	(4.1843)
Own home						-6.9015***	-6.8069***
						(1.9909)	(1.9628)
Expectation						0.2467***	0.2517***
						(0.0270)	(0.0266)
Observations	8971	5165	5165	4291	4250	1849	1849
R-squared	0.02	0.03	0.03	0.02	0.02	0.17	0.19

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.7: Average Expectations and Realized Outcomes

	Mean Expectation	Used Nursing Home care in 5 years	Used Nursing Home care in 7 years
1993 interview	14.3	10.5	15.2
1995 interview	18.2	14.6	--

Notes: Author's calculations of the 1993-2000 waves of the AHEAD. Weighted with respondent weights.

Table 3.8: Average Self-Reported Expectations by Ex-Post Outcomes

	1993	1995	1998	2000
1993 interview				
entered by 1995	19.5	27.8	--	--
entered between 1995-1998	20.2	23.9	31.2	--
entered between 1998-2000	15.7	20.4	19.2	24.0
non-entrants	13.5	17.4	15.2	18.5
1995 interview				
Entered by 1998	--	23.8	31.8	--
Entered between 1998-2000	--	20.4	18.9	25.5
Non-entrants	--	17.4	15.4	18.7

Notes: Author's calculations of the 1993-2000 AHEAD. Weighted with respondent-weights

Table 3.9: Frequency of Zero and 50 Percent Chance of Nursing Home Entry Answers by Ex-Post Outcomes

	Percent answering Zero				Percent Answering 50			
	1993	1995	1998	2000	1993	1995	1998	2000
1993 interview								
entered by 1995	50.9	28.5	--	--	18.6	19.4	30.9	--
entered between 1995-1998	52.0	42.0	46.4	--	15.1	16.5	20.6	--
entered between 1998-2000	58.8	48.9	54.9	46.1	16.8	22.8	16.5	18.8
non-entrants	59.5	49.5	57.3	50.4	12.0	13.5	15.9	17.9
1995 interview								
Entered by 1998	--	42.1	45.3	--	--	16.1	21.5	--
Entered between 1998-2000	--	49.2	55.2	42.3	--	22.9	16.0	19.7
Non-entrants	--	49.5	57.1	49.7	--	13.7	16.0	18.2

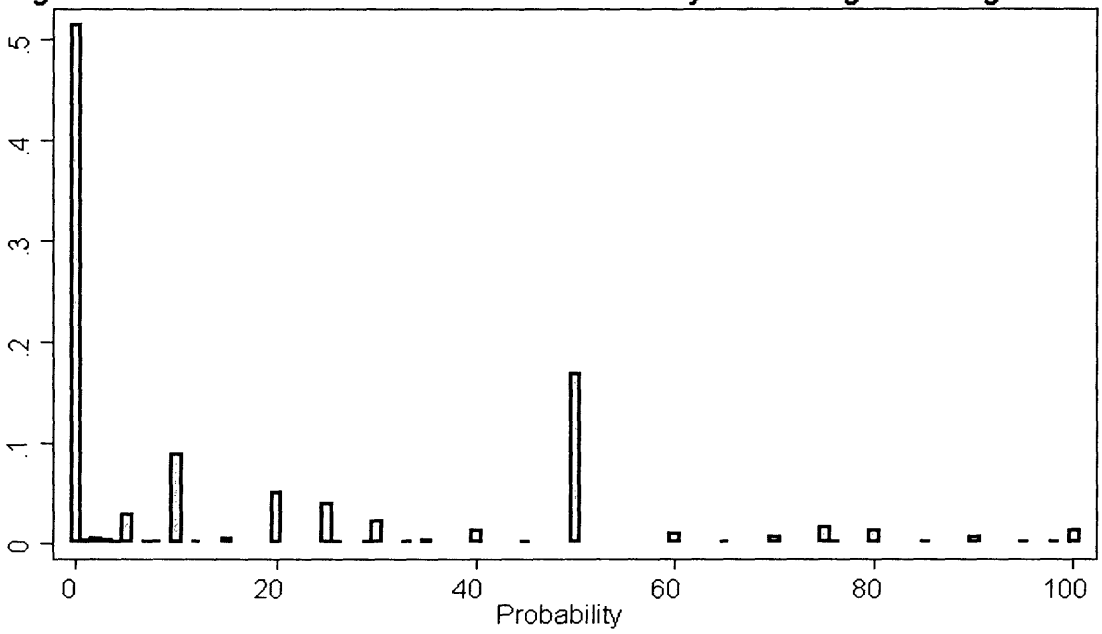
Notes: Author's calculations using the 1993-2000 waves of the AHEAD. Respondent weights used.

Table 3.10: Determinants of Actual Nursing Home Use

NH_{t+5}	(1)	(2)	(3)	(4)
	Baseline	with demographics	with wealth	with health
Expectation	0.0006***	0.0005***	0.0005***	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Stat. Probability	0.0040***	0.0038***	0.0038***	0.0035***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
1995 wave	0.0263***	0.0267***	0.0275***	0.0288***
	(0.0048)	(0.0048)	(0.0051)	(0.0057)
married		-0.0743**	-0.0511*	-0.0538*
		(0.0297)	(0.0290)	(0.0288)
Number of kids		-0.0059**	-0.0062**	-0.0071***
		(0.0027)	(0.0028)	(0.0027)
White		0.0210*	0.0183	0.0166
		(0.0125)	(0.0129)	(0.0131)
Mom alive		-0.0032	-0.0023	-0.0046
		(0.0171)	(0.0174)	(0.0174)
Father alive		-0.0386**	-0.0417**	-0.0619***
		(0.0172)	(0.0180)	(0.0202)
HS Diploma		0.0079	0.0095	0.0107
		(0.0098)	(0.0102)	(0.0102)
Some College		0.0206*	0.0238*	0.0251**
		(0.0118)	(0.0123)	(0.0123)
College +		0.0155	0.0215	0.0226*
		(0.0128)	(0.0135)	(0.0135)
Own home			-0.0361**	-0.0363**
			(0.0156)	(0.0154)
hip				0.0549**
				(0.0248)
psych				0.0394***
				(0.0140)
depressed				0.0169
				(0.0107)
Observations	9982	9781	9478	9446
R-squared	0.07	0.08	0.09	0.09

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
Notes: see text for included variables that are not specified here.

Figure 3.1: Distribution of Self-Assessed Probability of Entering a Nursing Home



2000 wave of the AHEAD