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Asymmetric information in insurance markets: evidence and explanations from the long-term care insurance market

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Asymmetric information has often been viewed as a key factor hindering the efficient operation of insurance markets. Yet several recent empirical analyses have concluded that asymmetric information may not exist in insurance markets as diverse as the automobile and life insurance markets. The conclusions of these studies are based on a widely used test of asymmetric information, specifically that its presence would imply a positive relationship between insurance coverage and risk occurrence. In this paper, we show empirically that despite the lack of this positive relationship, asymmetric information may still impair market functioning. We analyze the market for long term care insurance and find no evidence that individuals with more long-term care insurance are more likely to use nursing home care. However, we also find direct evidence of asymmetric information: controlling for the information set of the insurance company, individuals have residual private information about their risk type and this private information is positively correlated with insurance coverage. Further, we show that the lack of a positive relationship between insurance coverage and care utilization in equilibrium – *despite* asymmetric information about risk type – is attributable to other unobserved characteristics of the individual that are positively related to coverage and negatively related to care utilization. For example, we find that more cautious individuals are both more likely to have insurance and less likely to enter a nursing home. Such preference-based selection can offset the positive correlation between insurance coverage and care utilization that asymmetric information about risk type would otherwise produce. It cannot, however, offset the negative efficiency consequences of this asymmetric information for insurance coverage.

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Theoretical research has long emphasized the potential importance of asymmetric information in impairing the functioning of insurance markets. Its empirical relevance, however, remains the subject of considerable debate. Several recent studies of the automobile, health, and life insurance markets have concluded that asymmetric information may not exist in these insurance markets (e.g. Chiappori and Salanie, 2000; Cardon and Hendel, 2001; and Cawley and Philipson, 1999). Specifically, contrary to the predictions of many moral hazard and adverse selection models, there appears to be no evidence that individuals with more of these types of insurance are more likely to experience the insured risk. These findings appear to challenge the conventional wisdom among economists and policymakers that asymmetric information is likely to create problems in insurance markets.¹

These findings also raise an important but, as yet largely unanswered, question: *why* do we fail to find evidence in some insurance markets that those with more insurance are higher risk? Alternative explanations for the same observed equilibrium relationship between insurance coverage and risk occurrence can have very different implications for the structure of information, for market efficiency, and potentially for public policy. Understanding the underlying structure of the insurance market that produces this equilibrium is therefore critical. However, to our knowledge, there exists no systematic empirical investigation of this issue.

We investigate this issue in the context of the private long-term care insurance market in the United States. In addition to providing an interesting setting for studying asymmetric information, the long-term care insurance market is of substantial interest in its own right. Long-term care expenditures represent one of the largest uninsured financial risks faced by the elderly in the United States. As the baby boomers age and medical costs continue to rise, the implications of the lack of long-term care insurance for the welfare of both the elderly and their children, will only become more pronounced. One potential explanation for the private market's limited size is the presence of adverse selection or moral hazard. To date, however,

¹ Indeed, even when awarding the 2001 Nobel prize for the pioneering theoretical work on asymmetric information, the Nobel committee noted in its extended citation that empirical evidence of asymmetric information in insurance markets was “ambiguous” (Bank of Sweden, 2001).

there exists very little empirical evidence on the presence of asymmetric information in this market, let alone whether it is an important factor in limiting the market's size.

We begin by following the existing literature and examine whether there is positive correlation between the quantity of insurance purchased and the occurrence of the risk (in this case, the individual's ex-post use of a nursing home). We analyze data from three different sources: aggregate actuarial tables produced by the Society of Actuaries, proprietary micro data from a large private long-term care insurance company, and individual-level panel data from the Asset and Health Dynamics Among the Oldest Old (AHEAD) survey. In none of the data sets do we find evidence that those with more long-term care insurance end up using more nursing home care—in anything, we find suggestive evidence of the reverse.

Similar evidence of a lack of a positive correlation between insurance and risk occurrence in other insurance markets has been interpreted as evidence against the presence of adverse selection and moral hazard in these markets (see e.g. the papers cited in the opening paragraph). Indeed, one potential explanation for these findings is that individuals do not have private information about their risk type. If this were true and information were indeed symmetric, the market equilibrium for insurance against the risky event could be first best. However, recent theoretical work by de Meza and Webb (2001), Jullien et al. (2002) and Chiappori et al. (2002) suggests an alternative explanation: the insurance company may lack information not only about the individual's risk type, but also about preference-related characteristics which have the *opposite* correlation with insurance coverage and with risk occurrence (e.g. risk aversion). These other “unobserved factors” may offset the positive correlation between insurance coverage and risk occurrence that asymmetric information about risk type would otherwise produce. But, as we explain in more detail below, this offsetting effect does not correct the market inefficiencies produced by asymmetric information. In equilibrium, even if the insured are not above-average in their risk type, coverage levels will not be optimal.

To explore which of these competing explanations is responsible for the equilibrium in the private long-term care insurance market, we directly examine whether individuals have private information about

their risk type. We are fortunate to have a direct measure of individuals' beliefs about their risk type; the AHEAD asks each individual what he believes are his chances of entering a nursing home over the next five years, and then provides information on his subsequent, five-year nursing home utilization. We supplement these data with measures of the insurance companies' information set and risk classification practices; these measures are based on insurance company application forms which reveal the set of individual characteristics observed by the insurance companies, and on the industry's actuarial model of nursing home utilization as a function of these observed characteristics. Our results indicate that, after controlling for the risk-classification of the individual done by the insurance company, the individual's beliefs about his subsequent nursing home use remain positively and statistically significantly correlated with this subsequent use. This provides direct evidence of asymmetric information in the private long-term care insurance market: the individual *does* have residual private information about his risk type. Moreover, we find that this private information is positively correlated with whether the individual has insurance coverage.

We then demonstrate that the existence of unobserved heterogeneity not only in risk type but also in preferences can reconcile the evidence that individuals have private information about their risk type with the evidence that, in equilibrium, there is no positive relationship between insurance coverage and care utilization. We also provide direct evidence of the existence and nature of these other unobserved, preference-related characteristics. For example, consistent with the theoretical models of de Meza and Webb (2001) and Jullien et al. (2002), we find that more cautious individuals (a characteristic not observed by the insurance companies) are both more likely to own long-term care insurance and less likely to end up using long-term care. We discuss below why insurance companies may not collect such information.

Thus in the case of the long-term care insurance market, there appears to be asymmetric information about risk type *despite* the lack of a positive correlation between insurance coverage and care utilization. Asymmetric information may therefore be an important contributor to the limited size of the private long-term care insurance market. However, the lack of a positive correlation between insurance coverage and

care utilization does suggest that asymmetric information about risk type should not raise the *price* of long-term care insurance above the population-average actuarially fair price; from the viewpoint of the insurance company, the insured do not have above-average risk characteristics.

The rest of the paper is structured as follows. Section one provides some brief background on long-term care and the private long-term care insurance market. Section two provides the conceptual framework for the paper and outlines the empirical approach. The next three sections present, respectively, the three main empirical findings. Section three documents the lack of a positive correlation between long-term care insurance coverage and nursing home care utilization. Section four provides evidence that individuals have private information about their risk type. Section five investigates the relationship between characteristics of the individual unobserved by the insurance company and the individual's insurance coverage and care utilization. Section six presents suggestive evidence of the existence of insurance rationing in the private long-term care insurance market. The final section summarizes our findings and discusses their implications for other insurance markets.

1. Background on long-term care and long-term care insurance

At almost \$100 billion in the year 2000, long-term care expenditures in the United States represent 7.5% of total health expenditures *for all ages*, and about 1% of GDP. There is substantial variation among the elderly in their long-term care utilization (see e.g. Dick et al. (1994) and Kemper and Murtaugh (1991)), suggesting potentially large welfare gains from insurance coverage. For example, Dick et al. (1994) estimate that while two-thirds of individuals who reach age 65 will never enter a nursing home, one-quarter of women who do enter a nursing home will spend at least three years there.

Most of this risk is uninsured, making long-term care expenditures one of the largest uninsured financial risks facing the elderly (and potentially their children). Only about 10 percent of those aged 60 and over had private long-term care insurance coverage in 2000.² Moreover, most private insurance policies provide limited insurance benefits. As a result, less than 5 percent of long-term care expenditures

² Authors' calculation based on 2000 Health and Retirement Survey. This is consistent with other estimates (e.g. Cohen, forthcoming).

for the elderly are paid by private insurance, compared to 35 percent in the health sector as a whole. Public insurance is also quite limited. Medicare, the public health insurance program for the elderly, covers only a very restricted set of long-term care services. And Medicaid, the public health insurance program for the indigent, requires a deductible of almost one's entire wealth before it will cover long-term care expenses. As a result, 40 percent of long-term care expenditures for the elderly are paid for out of pocket, compared to only 17 percent of expenditures in the health sector as a whole (US Congress, 2000, National Center for Health Statistics, 2002).

Currently most buyers of long-term care insurance are of retirement age or older. In 2000, the average age of buyers in the individual market was 67, and over one-fifth of the buyers were 75 or older at the time of purchase (HIAA 2000a). Premiums, which tend to be a constant nominal amount paid on a monthly or annual basis, increase linearly with the maximum benefit the policy allows the individual to receive per day in covered care.³ Coverage rates are roughly comparable for men and women but increase substantially with asset levels, probably due to the means-tested nature of the public Medicaid insurance (HIAA, 2000a). About 80% of private insurance is provided by the individual (non-group) market, with the remaining share sold through employer-sponsored plans or life insurance (HIAA 2000b). Presumably to reduce moral hazard, insurance policies specify a set of standard health-related criteria ("benefit triggers") that must be satisfied before an individual is eligible to receive benefits for covered care (Wiener et al., 2000).

Despite the absence of regulatory restrictions, firms use relatively little information in pricing policies. Policies are not experience-rated, and premiums tend to vary only with age and several broad health categories (ACLI, 2001; Weiss 2002). Most notably, they do not vary with gender, despite known long-term care utilization differences by gender (Society of Actuaries, 1992). One potential explanation for this ostensibly puzzling practice is that – even though a given policy covers only a single life – policy ownership is highly correlated among couples; for example, although only 10% of the elderly in the 1995

³ Pricing data are from Weiss Ratings Inc and from the insurance company whose proprietary data we analyze in Section 3.2.

AHEAD data have private long-term care insurance coverage, over 60% of the spouses of individuals in these data with long-term care insurance also have this insurance.

A variety of theoretical explanations have been proposed for the limited size of the private long-term care insurance market (see e.g. Norton, 2000 for a review). Asymmetric information is one potential explanation, yet there exists very little empirical evidence on its presence in this market. Consistent with moral hazard, Garber and MaCurdy (1993) present evidence of an increase in nursing home discharges when the Medicare nursing home benefit is exhausted. The widespread use of deductibles in long-term care insurance policies (Brown and Finkelstein, 2003) is also suggestive of asymmetric information in this market.⁴

2. Theoretical background

2.1 The “positive correlation” prediction

The standard empirical test for asymmetric information is to test for a correlation between the amount of insurance coverage and the ex-post occurrence of the (potentially) insured risk. A wide variety of asymmetric information models predict that – in markets in which observationally identical individuals are offered a choice from a menu of insurance contracts – coverage and the probability of the risky event being realized will be positively correlated (Chiappori and Salanie, 2000; Chiappori et al., 2002).

Throughout, the paper we will refer to this test as the “positive correlation” prediction.

Of course, this prediction – and hence a valid empirical test – applies only among individuals who would be treated symmetrically by the insurance company (i.e. placed in the same risk category and offered the same menu of insurance contracts, defined over price and benefit characteristics).⁵ Therefore, any discussion of the “positive correlation” (or lack thereof) in the paper always refers to the correlation conditional on the risk classification of the individual done by the insurance company. In the empirical work below, we will take great care to appropriately condition on this risk classification.

⁴ Sloan and Norton (1997) examine the relationship between insurance coverage and individuals’ beliefs about their nursing home risk using an early wave of the HRS. However, this early wave does not provide a reliable measure of long-term care insurance coverage (see Appendix A).

⁵ See Dionne et al. (2001) for a more detailed discussion of this point.

The “positive correlation” can arise from either adverse selection or moral hazard, both of which result in a market that is inefficient relative to the first best. The two types of market failures do, however, imply different mechanisms through which this positive correlation arises. In the case of adverse selection, the insured is assumed to have superior information to the insurance company about his risk type. Because individuals who appear to the insurance company to be observationally equivalent face the same menu of insurance options, and because the marginal utility of insurance at a given price is increasing in risk type, those with private information that they are high risk will select contracts with more insurance than those with private information that they are low risk (Rothschild and Stiglitz, 1976). In the case of moral hazard, the causality is reversed: coverage by insurance lowers the cost of an adverse outcome and thus increases the probability or magnitude of the risk occurrence. The classic explanation is that insurance reduces the individual’s incentive to invest in (costly) risk-reducing effort (see e.g. Arnott and Stiglitz, 1988). In the health insurance context, another form of moral hazard may be quantitatively more important: insurance lowers the marginal cost of consuming the insured good (medical care), and may therefore induce additional consumption.

Empirically, the positive correlation property appears to exist in some insurance markets but not others. In health insurance, Cutler (2002) reviews an extensive empirical literature that finds evidence in support of this prediction, although he notes the existence of exceptions, such as Cardon and Hendel (2001). There is also evidence from annuity markets that the insured are higher risk (Finkelstein and Poterba 2000, 2002), but no such evidence in life insurance markets (Cawley and Philipson, 1999). In the automobile insurance market, the empirical evidence is mixed. Chiappori and Salanie (2000) and Dionne et al. (2001) fail to reject the null hypothesis of no correlation; but Pueltz and Snow (1994) and Cohen (2001) find support for the positive correlation prediction.

2.2 What does a lack of positive correlation imply for the information structure and for market efficiency?

There are two broad classes of explanations for a lack of a positive correlation between insurance coverage and risk occurrence. These have different implications for the underlying structure of information and for market efficiency. The first class of explanations challenges the central assumption of

adverse selection models that the individual has information about his risk type (i.e. expected loss experience) that is unknown to the insurance company. Given the vast amount of information that insurance companies can, and do, collect about potential customers, information about the individual's risk type may be symmetric.⁶

Under symmetric information, insurance coverage among individuals placed in the same risk class by the insurance companies should not vary systematically with expected loss experience.⁷ Therefore, the equilibrium insurance coverage against the underlying financial risk can be first best.⁸ However, a market with symmetric information about risk type will not provide insurance against the *classification* risk of being classified as a high-risk individual and thus facing correspondingly higher insurance premiums (Hirshliefer, 1971, Crocker and Snow, 2000).

A symmetric information story, however, is not enough to explain the apparent lack of moral hazard that may also be implied by the failure to find the positive correlation property. It may be that moral hazard does not exist in particular insurance markets. For example, in the case of long-term care insurance, the unappealing nature of nursing homes, and the use of health-related criteria that must be satisfied before care will be reimbursed, may be sufficient to dampen any potential moral hazard effects.

The second class of explanations for a lack of a positive correlation between insurance coverage and risk occurrence offers an explanation in a market in which both asymmetric information about risk type and moral hazard may be present. This class of explanations argues that risk type is not the only source of unobserved heterogeneity. Individuals may also differ on unobserved preferences – such as risk aversion – that are correlated with the demand for insurance coverage and risk occurrence. We refer to this as “preference-based” selection to distinguish it from traditional adverse (or “risk based”) selection based directly on the individual's private information about his risk type. If unobserved preferences are

⁶ It is also possible that the insurance company, with its access to sophisticated actuarial methods, may have *superior* information about the individual's risk type. In this case, the equilibrium may involve a *negative* correlation between risk type and amount of insurance coverage. (Villeneuve 2000, Villeneuve forthcoming).

⁷ This of course assumes a competitive insurance market with no marginal load (or production cost) on the policy. See Chiappori et al. (2002) for a formal exposition.

⁸ An important caveat, is that if the information is costly for the insurance company to collect, the private market may collect *too much* information relative to what is socially efficient (Crocker and Snow (1987)).

positively correlated with insurance demand and negatively correlated with risk occurrence, then there may be no positive correlation between insurance coverage and risk occurrence in equilibrium, even in the presence of asymmetric information about risk type. For example, if more risk averse individuals – who value insurance more – are also lower risk, the correlation between insurance coverage and risk occurrence may be zero or even negative.⁹

The exact nature of the equilibrium with multiple unobserved characteristics can be complex, in part because the single crossing property may no longer hold. The equilibrium will, however, be inefficient relative to the first best, and will generally result in underinsurance¹⁰. In equilibria that pool different risk types (see e.g. Smart (2000) and Wambach (2000)), no risk type faces his actuarially fair price on the margin and all individuals receive less than full insurance; it would therefore be Pareto improving if each type could buy additional insurance at his risk-type-specific actuarially fair price. However, additional insurance is not offered in equilibrium because it would disproportionately attract those with private information that they are high risk.¹¹ Equilibria that separate different risk types involve the standard inefficiency that at least one type is constrained from receiving his optimal insurance coverage. However, these equilibria need not yield a positive correlation between insurance coverage and risk occurrence since, in the presence of multiple unobservables, it may be optimal for an insurance company with market power to offer contracts that in equilibrium constrain the less risk averse (but higher risk) to receive less coverage than the higher risk averse (but lower risk); the intuition is most clearly seen in the case with heterogeneity of risk aversion is substantially greater than heterogeneity of (unobserved) risk type

⁹ The more risk averse may be exogenously assumed to be of lower risk, or their lower risk may be determined endogenously in models of both adverse selection and moral hazard in which the more risk averse investment more in risk-reducing effort (Jullien et al. (2002), or de Meza and Webb (2001)).

¹⁰ An exception is de Meza and Webb (2001) in which the equilibrium may involve overinsurance.

¹¹ Of course, a single pooling equilibrium – and the resultant lack of a correlation between insurance coverage and risk occurrence – may also exist in asymmetric information models with only unobserved risk type (see e.g. Wilson, 1977). However, the positive correlation prediction applies to market in which observationally equivalent individuals choose *different* contracts. For the positive correlation property not to exist in a model with asymmetric information on multiple characteristics *and* multiple contracts requires a wedge between price and expected loss. Jullien et al. (2002) and Chiappori et al. (2002) develop monopoly models with these features; de Meza and Webb (2001) develop a competitive model with administrative costs (i.e. loading) that also exhibits these features. The equilibria in these models may exhibit a positive, negative, or zero correlation between insurance coverage and risk occurrence (see e.g. Jullien et al, 2002).

(Chiappori et al. 2002). Although the equilibrium in these models will therefore not be first best, it is less clear whether Pareto improvements through public policy are feasible given the information structure, or whether the equilibrium are second best (or constrained) Pareto efficient.¹²

A failure to find a positive correlation is thus not sufficient to reject the presence of asymmetric information. It should also be noted that the finding of a positive correlation is not sufficient to reject the null of symmetric information; a positive correlation between insurance coverage and risk occurrence could instead reflect an (efficient) symmetric information equilibrium in a competitive insurance market with a marginal load on insurance, in which the lower risk are also less risk averse and therefore choose (optimally) to buy less insurance in equilibrium. Indeed, Chiappori et al. (2002) show formally that the test for a positive correlation only serves as a test for the presence of asymmetric information about risk type in two special cases: if insurance is priced at marginal cost (with no loading), or if insurance is priced above marginal cost but risk type is the only source of unobserved heterogeneity.

2.3 Overview of empirical approach

Here, we briefly sketch the set of empirical tests that we use to distinguish among these alternative models of the insurance market. We assume throughout that individuals differ on a set of characteristics (X) that insurance companies use to classify individuals into risk categories, and that these characteristics are all observable to the econometrician. Imagine first that, conditional on X , the unobserved characteristics of the individual (which we denote by T for the individual's unobserved type) relate only to his probability of risk occurrence; any (unobserved) preferences are identical across individuals.

If T were observable to the econometrician, we could estimate:

$$(1) \text{ CARE} = Xb_1 + b_2\text{LTCINS} + b_3T + \varepsilon$$

$$(2) \text{ LTCINS} = Xd_1 + d_3T + \eta$$

CARE is a dependent variable that measures the amount of long-term care used by the individual (i.e. the

¹² The scope for Pareto improvement through public policy depends critically on the specific modeling assumptions. For an example of a model of asymmetric information in which the positive correlation property need not apply and government policy may be Pareto improving, see de Meza and Webb (2001).

occurrence of the risk). LTCINS is a measure of the individual's long-term care insurance coverage. By definition, $b_3 > 0$ (higher risk individuals use more care). If moral hazard is present, we expect $b_2 > 0$.

Now assume that T is unobserved by the econometrician and thus omitted from estimation of equation (1). We therefore can only estimate:

$$(1a) \quad \text{CARE} = X\beta_1 + \beta_2\text{LTCINS} + \varepsilon'$$

Equation (1a) suffers from the classic omitted variables bias problem, with the sign of the bias on $\hat{\beta}_2$ equal to the sign of $b_3 * d_3$. If the only unobserved characteristic of the individual is his risk type, adverse selection models predict $d_3 > 0$ (those with private information that they are high risk will select more insurance in equilibrium), hence $\hat{\beta}_2$ will be an upward biased estimate of the moral hazard parameter b_2 in equation (1). The "positive correlation" prediction examined in the existing empirical literature is therefore that if *either* adverse selection *or* moral hazard (or both) is present in the market, we should find $\hat{\beta}_2 > 0$ in equation (1a). In Section 3 we estimate various versions of equation (1a) but find no evidence that $\hat{\beta}_2$ is positive.

As discussed, there are two potential explanations for this finding: 1) individuals do not have private information about their risk type and there is no moral hazard in this market, or 2) individuals do have private information about their risk type but there are also unobserved preferences for insurance that are correlated with risk occurrence. In the latter case, it will not necessarily be true that those with higher risk buy more insurance *even in the presence of private information about risk probabilities*. In other words, d_3 in equation (2) is not necessarily positive, and can be negative or zero. As a result the sign of the bias on $\hat{\beta}_2$ as an estimator of b_2 is ambiguous and, consequently, $\hat{\beta}_2$ need not be positive.

To distinguish between these two alternative hypotheses, in Section 4 we investigate directly whether individuals, conditional on the classification done by the insurance company (X), have any residual ability to predict their risk type. To do so, we take advantage of an innovative question in the AHEAD that asks

each individual his beliefs (B) about his chance of entering a nursing home in the next five years.

We therefore estimate:

$$(3) \text{ CARE} = X\beta_1 + \beta_3\text{B} + \varepsilon''$$

We find direct evidence of asymmetric information: $\beta_3 > 0$.¹³ In Section 5, we show empirically that the existence of preference-based selection can reconcile the direct evidence of asymmetric information with the lack of a positive correlation between insurance coverage and long-term care utilization

3. Is there a positive correlation between LTC insurance and LTC utilization?

Long-term care encompasses both institutional care (i.e. care in a nursing home) as well as home health care. Institutional care accounts for three-quarters of total long term care expenditures (US Congress, 2000). Until quite recently, policies tended to cover exclusively nursing home care.¹⁴ As a result of this, and data limitations discussed below, we focus our empirical tests on the relationship between insurance coverage and nursing home utilization. We comment briefly on the limited evidence of the relationship between insurance coverage and home health care utilization.

Our measure of care utilization is usually a binary measure of whether the individual consumes *any* nursing home care; where data permit, we also test for a positive correlation between insurance coverage and the *intensity* of care utilization (i.e. length of stay). We make two basic types of comparisons. First, we compare care utilization *among* insured individuals with different amounts of insurance using a proprietary database on insurance purchases and subsequent claims experiences of a large, private long-term care insurance company. Second, we compare care utilization for the insured population with that of the general population using individual-level panel survey data from the ADEAD.

Before embarking on this formal analysis, however, we begin by presenting some simple, but illustrative, comparisons using actuarial data from the Society of Actuaries (SOA).

¹³ We do not control for LTCINS in estimating equation (3) – as might be suggested by equation (1) – because to the extent that private information about risk type is correlated with insurance coverage due to adverse selection, we would be controlling away part of the individual's information.

¹⁴ The long-term care insurance market began in the early 1980s with policies that tended to cover nursing home care only. Even in 1990, two-thirds of policies sold covered only nursing homes. By 2000, however, over three-quarters of new policies covered both home care and nursing home care (AARP 2002, SOA 2002, HIAA 2000a).

3.1 Actuarial Data from the Society of Actuaries (SOA)

The SOA publishes tables of nursing home admission rates for the general population and for about 60% of the privately-insured population (SOA, 2000, 2002). Figure 1 plots the ratio of nursing home admission rates for insured individuals whose policies have no deductible to admission rates for the general population, by age and by sex.¹⁵ The positive correlation property predicts that the insured-to-population ratio of admission rates should be larger than one. Figure 1 is not consistent with this prediction. We observe similar admission rates at younger ages and much *lower* nursing home admission rates for the insured relative to the population at older ages.

Figures 2 and 3 compare nursing home admission rates (by age) among insured individuals with different benefit periods and different maximum daily benefits, respectively.¹⁶ The benefit period denotes the total number of days that benefits can be received during the lifetime of the policy; the maximum daily benefit denotes the maximum amount of incurred care expenditures that the policy will reimburse per day in care. Increases in either aspect of the policy increase the total amount of insurance in the contract. However, the figures do not indicate a positive correlation between the amount of insurance in the contract and nursing home admissions; nursing home admission rates are non-monotonic in the daily benefit amount (Figure 3) and are in fact *decreasing* in the benefit period (Figure 2).

Although suggestive, the results in Figures 1 through 3 do not represent a formal test of the positive correlation prediction. Most importantly, they do not condition on the risk classification of the individuals done by the insurance companies. In addition, the comparison of utilization rates between the insured and the general population further suffers from the fact that many “uninsured” individuals may in fact be able to collect public Medicaid insurance should they end up in a nursing home. Our formal analysis of micro

¹⁵ We limit the insured data to the approximately 12% of the exposure that reflects the experience of policies with no deductible because the insurance company data only record an admission that results in a claim; admissions that do not stay longer than the policy’s deductible period will therefore be missed in the insurance company data. Of course, admissions that do not result in a claim because of failure to meet the health-related benefit triggers will also be missed. The omission of these “uncovered” admissions” will tend to understate the nursing home utilization of the insured relative to the population, although the impact is likely to be small; only about 6 to 10 percent of nursing home admissions in the population are for individuals who fail to meet these benefit triggers (Brown and Finkelstein, 2003).

¹⁶ Both figures show results for the most common deductible (20 days), which represents about one-third of the exposure in the data; results for other common deductibles are similar (not shown).

data in the next two sub sections is designed to address these issues.

3.2 Proprietary policyholder data from a large private insurance company

3.2.1 Data and empirical framework

We have data on the complete set of individual (non-group) private long-term care insurance policies sold by a large U.S. private long-term care insurance company from January 1, 1997 through December 31, 2001. The company is among the top-five companies in this market (which combined account for almost two-thirds of premiums (LIMRA ,2001)) and sold about 150,000 policies during the period covered by the data. We observe a complete description of the features of each policy. Crucially, we also observe the risk classification of the individual done by the insurance company. As is typical of the industry as a whole, this company assigns premiums based on the individual's age at the time of issue, when the policy is issued, and whether the individual is rated preferred, standard, or substandard based on detailed health information; we observe all three of these features (issue age, rating category, and issue date) although we do not observe the underlying health information on which the rating category is determined. We also observe a complete description of all claims incurred through December 31, 2001.

Although these data come from a single company, they appear comparable to the broader market on a variety of dimensions. These include the average age at purchase, the gender-mix of the purchasers, the average daily benefit, and the average length of the benefit period.¹⁷ In addition, this particular company has experienced similar growth rates in policy sales to the industry as a whole over the last five years (LIMRA 2001). However, there are a few dimensions along which the company differs from industry averages. Almost all of the policies sold cover both home care and nursing home care, whereas in the industry as a whole only about three-quarters of recent policies do (HIAA 2000a). In addition, the policies tend to have larger deductibles than industry averages.

To test the positive correlation prediction, we examine the relationship between the characteristics of the policy that affect the quantity of insurance provided and nursing home utilization, conditional on the individual's risk classification. Since we only observe care utilization if it results in a claim, we will miss

¹⁷ Table 1 provides the statistics for the company data. HIAA (2000a) provides comparable industry-wide statistics.

stays that do not use up the deductible (which must be used up anew for each care episode). Therefore, we define a “failure” in our hazard model as having at least 100 continuous days of nursing home care and we restrict the sample to the 94% of policies that have a deductible of 100 days or less (and were issued at least 100 days before the end of the sample period). The average failure rate (0.3 percent) is quite low, but is consistent with market-wide and population statistics on nursing home care utilization (SOA 1992, 2002).¹⁸ Conditional on entering a nursing home, stays of more than 100 days are quite common (Dick et al, 1994, Kemper and Murtaugh, 1991, and Murtaugh et al. 1997).

We let $\lambda(t, x_i, \beta, \lambda_0)$ denote the hazard function, the probability that a policyholder with personal and policy characteristics x_i enters their 100th day of continuous nursing home care t periods after purchasing the policy, conditional on not having done so prior to t . We use the standard proportional hazard model which assumes that $\lambda(t, x_i, \beta, \lambda_0)$ can be decomposed into a baseline hazard $\lambda_0(t)$ and a proportional “shift factor” $\exp(x_i'\beta)$ as follows:

$$(4) \quad \lambda(t, x_i, \beta, \lambda_0) = \exp(x_i'\beta)\lambda_0(t).$$

We estimate a semi-parametric Cox proportional hazard model to avoid making any parametric assumptions about the baseline hazard $\lambda_0(t)$.

The hazard model framework is particularly well-suited to handling the extensive right-censoring in the data. Censoring (exiting the sample for reasons other than failure) occurs either because the sample period ends or because the policy terminates due to death or to failure to pay premiums. Slightly less than 10 percent of our policies terminate; this is comparable to industry-wide termination rates (SOA 2002).¹⁹

Because the positive correlation prediction is conditional on the individual’s risk classification, we include a set of covariates designed to capture this risk classification. These consist of indicator variables

¹⁸ Due to this low failure rate, the sample size appears insufficient to analyze the relationship between policy characteristics and length of stay beyond 100 days, or the occurrence of multiple stays of at least 100 days in length.
¹⁹ Treating terminated policies as censored at the date of termination is equivalent to a competing risks framework in which the two risks (termination and failure) are assumed independent. This may not be an appropriate assumption. We ascertained that our results were not sensitive to instead keeping terminated policies in the “at risk” sample through the end of the observed sample period (or even beyond).

for issue year, rating category (standard, preferred or substandard), and issue age (which we divide into five roughly equal size bins that are less than 60, 60-64, 65-69, 70-74, and 75+).²⁰

The primary covariates of interest measure the four main aspects of the policy that affect the quantity of insurance in the policy.²¹ These are: (1) the deductible, (2) the maximum daily benefit, (3) the total number of days for which benefits may be received in the lifetime of the policy (“benefit period”), and (4) how the nominal maximum benefit increases over time (“benefit escalation”). The positive correlation property predicts that the hazard rate should be increasing in the benefit amount, the benefit period and the amount of benefit escalation, all of which increase the amount of insurance in the contract; similarly, the hazard should be decreasing in the size of the deductible, which reduces the amount of insurance in the contract.

We measure the deductible with indicator variables for 20-day, 60-day and 100-day deductibles. We measure the daily benefit amount using three roughly-equal sized indicator variables for less than \$100, \$100, and more than \$100 per day.²² In measuring the benefit period, we create a series of indicator variables that take account of two factors. First, we distinguish among policies with benefit periods of 1-4 years, 5+ years (but finite), and unlimited. Second, among policies with finite benefit periods, we further distinguish policies that reset the allowable benefit period to the original benefit period if the individual has had 180 continuous days since the last day of receiving covered care; this reset option effectively extends the benefit period. Finally, we use indicator variables for the four possible benefit escalation options: constant nominal benefits, benefits escalate at 5 percent of the original benefit per year (“simple” escalation), benefits escalate at 5 per year (“compound” escalation), and benefits are increased by the greater of 5% compounded annually over 3 years or CPI-growth over the last 3 years at the option of the

²⁰ In practice, price varies with issue age on a yearly basis. Including separate indicator variables for each age rather than five-year intervals does not affect the coefficients of interest. We adopt the coarser set of controls as our main specification simply for ease of presentation.

²¹ For completeness, we also control for the remaining policy features. These are described in the notes to Table 2.

²² We do not include the daily benefit for home health care separately because the correlation between the two daily benefit is very high (0.92). We do include an indicator for whether the policy pays lower home health care benefits than nursing home benefits. Twenty percent of policies pay the same amount for both types of care, while the remainder cap home health care costs at either 50 or 80 percent of the nursing home limit.

policy holder (“indexed”).

Table 1 provides summary statistics on the main individual and policy characteristics examined in the analysis. We do not control for the premium because we have controlled for all of the characteristics of the individual and the policy that determine it. We also do not control for gender because it is not used in determining the pricing of contracts.

3.2.2 Results

Table 2 reports the results from estimating equation (4). The first column shows results for the entire sample. Since some of these policies have been in effect for only a short time, in the second column we also report results for the subset of policies issued in 1997 or 1998, all of which have had at least three years of exposure. The results are substantially unchanged.²³

The results in the top half of the table show the estimated coefficients on several covariates that reflect the insurance company’s risk-categorization of the individual. As expected, the hazard rate increases monotonically with the individual’s issue age and assessed risk category.

The lower portion of the table reports the coefficients on covariates for which the positive correlation property makes predictions; these predictions are summarized in the left-most column. There is little evidence in support of these predictions. The coefficients on the benefit escalation and benefit period variables all have the *opposite* sign from what is predicted by the positive correlation property. The coefficients on the deductible and daily benefit variables are positive as predicted (those with shorter deductible periods and higher daily benefits are more likely to use services) but are not statistically different from zero. More importantly, their magnitudes suggest that any effect is quantitatively unimportant. For example, the change in hazard rate associated with a 20-day deductible compared to a 100-day deductible (which is the largest right-signed coefficient) is not only statistically insignificant but only about half the magnitude of the change in the hazard rate associated with being rated standard risk instead of high risk; it is considerably smaller in magnitude than the change in hazard associated with any

²³ The results are similarly unchanged if we limited the sample to individuals who are 75 and older at the time of purchasing the policy, and for whom we therefore observe a greater fraction of the policies’ actual lifetime.

5-year increase in issue age. This lack of evidence of a positive correlation between the amount of insurance and nursing home utilization is consistent with the pricing of these contracts; Brown and Finkelstein (2003) conclude that the price differential between more and less comprehensive policies is smaller than would be predicted were purchasers of the more comprehensive policies of systematically higher risk.

A potential concern with these findings is that our inclusion of a series of additive controls for the individual's age, year of purchase, and rating category may produce misleading estimates of the relationship between features of the contract and nursing home utilization if there are important interaction effects among these various determinants of the individual's risk classification and nursing home utilization. We therefore estimated a more flexibly specified version of equation (4) in which we included fixed effects for each risk class, defined by the interactions of the individual's issue age category, rating category and issue year. We also re-estimated the hazard model restricting our sample to an increasingly homogenous population with respect to the insurance company's risk categories.²⁴ We found (in results not shown) that the coefficients on the policy characteristic variables in these alternative specifications were, if anything, less consistent with the predictions of the positive correlation property than those shown in Table 2.

3.3 Evidence from the individual panel data in the AHEAD

The proprietary insurance company data provide detailed information on the relationship between the amount of insurance and subsequent claims. However, they contain no comparative information on the experience of those without private insurance. The remainder of the paper thus draws primarily on micro-data from a representative sample of the elderly population.

3.3.1 Data and empirical framework

Our data are from the Asset and Health Dynamics (AHEAD) cohort of the Health and Retirement Study (HRS). This sample, first interviewed in 1993, was designed to be representative of the non-

²⁴ For example, we limited the sample to the approximately 70 percent who are rated standard risk, or to the approximately one-fifth who are rated standard risk *and* purchased the policy between ages 65 and 69.

institutionalized individuals born in 1923 or earlier and their spouses. Because the first wave of the survey does not provide a reliable measure of long-term care insurance coverage, our analyses begin with the second interview in 1995. We use the panel nature of the data to track nursing home utilization for the 1995 respondents through the latest currently available interview in 2000. Appendix A provides more detail on the sample and variable definitions used.

The basic estimating equation is exactly that shown in equation (1a). We regress a measure of the individual's long-term care utilization from 1995 through 2000 (CARE) on whether he has long-term care insurance coverage in 1995 (LTCINS); 10% of the sample has long-term care insurance coverage. We include as controls a series of covariates (X) designed to control for any categorization of the individual done by the insurance company.

We use two different measures for the dependent variable CARE. The first is a binary measure of whether the individual spent any time in a nursing home in the five years between 1995 and 2000 (mean is 0.19). The second measure is the total number of nights that the individual spent in a nursing home in this period (mean is 33 nights)²⁵.

As discussed, the correct empirical test requires controlling for the risk classification of the individual done by the insurance companies. We therefore collected insurance applications from five leading long-term care insurance companies to determine what characteristics of the individual the insurance companies observe. All companies collect a limited set of demographic information: age, gender, marital status, and age of spouse. They also all collect very similar and extremely detailed information on current health and on health history. However, we found only one company that asked applicants to report any financial information (specifically, whether they had less than \$30,000 in financial assets).

The very rich information in the AHEAD about the individual's current health and medical history allows us to measure essentially all of the information observed by the insurance companies. However, we do not observe the individual's risk classification directly, as we do in the proprietary data. We know that companies for the last fifteen years have offered age-specific prices with only two or three broad rate

²⁵ For those who spent any time in a nursing home over this period, the average amount of time was 187 nights.

classifications within each age based on the individual's health information (ACLI 2001, Weiss 2002, Kemper et al. 1995).²⁶ We do not, however, know the algorithm mapping the detailed health information to the rate classifications.

Given the importance of controlling for the individual's risk classification in the analysis, we therefore experiment with four alternative approaches. First, we do not include any covariates (X) in estimating equation (1a) ("no controls" specification). Second, we control for the individual's age by including a separate indicator variable for each age ("age dummies" specification).²⁷ Both of these approaches are likely to underestimate the amount of categorization done by insurance companies.

Therefore, our third approach ("all observables" specification) tries to control for everything the insurance companies observe about the individual. This specification therefore includes not only the age dummies, but also all of the demographic information that insurance companies observe, (gender, marital status and age of spouse, which we enter linearly), and indicator variables for each of the detailed current health and health history characteristics collected by any insurance companies that we can measure in the data. To be conservative, we also include indicator variables for the household's income quartile and asset quartile, even though it appears that most companies do not collect this information. This complete set of controls is summarized in Table 3 and described in more detail in Appendix A.²⁸

By including a separate indicator variable for each health characteristic, the "all observables" specification invokes a much more finely defined categorization of risk than insurance companies actually use. We therefore believe that this specification is likely to overestimate the amount of risk classification done by the insurance company. However, a potential issue with this approach is that, by merely including each observed characteristic as an additive control we may misestimate the true relationship

²⁶ According to industry actuaries, insurance companies collect more detailed information than they currently use in risk classification in order to build a detailed claims database for future improvements in actuarial modeling.

²⁷ At the tails of the age distribution we use catch-all indicators for "younger than 70" and "older than 90".

²⁸ There are a few characteristics that the insurance companies observe that we cannot measure in the AHEAD. Most are rare health conditions – such as double amputation or unoperated aneurysm. To try to compensate for this, we added all of the additional health measures observed in the AHEAD and not by the insurance company to the analysis (e.g. self-reported health status and cataract surgery) and did not find any substantive changes in our results. In addition, since many of the characteristics we cannot measure (e.g. handwriting samples) are only collected by insurance companies for observably high risk individuals, we verified that the results were not sensitive to restricting the sample to the observably most healthy individuals.

between insurance coverage and care utilization if there are substantial interaction effects among these controls.

Our final alternative specification therefore substitutes these linear controls with a single summary measure of the insurance companies' prediction about each individual in the AHEAD's chance of entering a nursing home in the next five years. We generated these predictions using the same actuarial model that is employed by much of the long-term care insurance industry. We use a version of the model that predicts care utilization for typical individuals in the *population* and makes no adjustment for potential moral hazard effects of the insurance.²⁹ The predictions depend non-parametrically on the individual's age, gender and membership in one of seven different health states (defined by the number of limitations with respect to instrumental activities of daily living (IADLs), the number of limitations to activities of daily livings (ADLs), and the presence or absence of cognitive impairment); all of this information is available in the AHEAD. This measure provides a parsimonious way of controlling for non-linear (and non-parametric) interactions between the observed characteristics of the individual and nursing home utilization.³⁰

3.3.2 Results

Table 4 describes the results of estimating equation (1a) for these four alternative definitions of the control variables (X). When the dependent variable is the binary measure of any nursing home use, we report results from OLS estimation of equation (1a); probit estimation produces similar results. When the dependent variable is the cumulative number of nights spent in a nursing home since 1995, we report estimates from a Tobit model; a linear model produces similar results, as does a linear estimate of the number of nights spent in a nursing home among those who report any nursing home stays.

The results are not supportive of a positive correlation between long-term care insurance coverage

²⁹ For more details on the model and its pedigree, see Brown and Finkelstein (2003), Robinson (1996), or Robinson (2002).

³⁰ As an alternative way of dealing with non-linearities in the relationship between observable characteristics and long-term care utilization, we also estimated equation (1a) on increasingly homogenous sub samples of individuals from the perspective of the insurance company (e.g. by age and health conditions). The results (not reported) were not affected by this alternative approach.

and long-term care utilization. Instead, in all but one specification, long-term care insurance coverage is *negatively* associated with long-term care utilization; in the one case in which the relationship is positive, it is substantively and statistically indistinguishable from zero. Across all specifications, we can reject a higher probability of nursing home utilization for the insured relative to the uninsured of more than 3 percentage points with 95 percent confidence.³¹

One potential concern with this analysis is that a substantial fraction of the seemingly uninsured may in fact rely on the public insurance provided by Medicaid, which pays for 40% of all nursing home expenditures (US Congress, 2000). Since Medicaid coverage requires a deductible of almost all of one's assets (AARP 2000), Medicaid is a more attractive substitute for private insurance for lower-wealth individuals, and may therefore induce selection based on wealth levels. Moreover, some of those without private insurance may experience moral hazard effects from public insurance, which could bias downward our estimate of any moral hazard effects of private insurance. To account for these possibilities, we repeat the regressions shown in Table 4, restricting the sample to individuals who are in the top quartile of the household income or wealth distribution in 1995, and who are therefore least likely to find Medicaid an attractive substitute for private insurance. The top panel of Table 5 indicates that the relationship between insurance coverage and care utilization appears *more negative* when the sample is restricted to these individuals. Indeed, across all specifications, we can now reject a higher probability of nursing home utilization for the insured relative to the uninsured of more than 0.7 percentage points with 95 percent confidence.

Another concern with the sample definition is that many individuals in our sample would have been denied insurance coverage because of a health condition, had they applied. The application forms from long-term care insurance companies explicitly discourage individuals with certain health conditions from applying; Figure 4 provides illustration using the application forms of two of the top-10 long-term care

³¹ To address the possibility of attenuation bias due to measurement error in long-term care insurance coverage, we ascertained that the results were not affected by instrumenting for long-term care insurance coverage reported in 1995 with long-term care insurance coverage reported in 1998, the next survey year for which data are available.

insurance companies.³² We therefore repeat the regressions from Table 4 for a restricted sample of individuals who are unlikely to be classified as ineligible; Appendix A describes the criteria for constructing this sample. The middle panel of Table 5 shows the results based on restricting the sample to the eligible population. The bottom panel shows the results when the sample is restricted to those who are *both eligible and unlikely* to view Medicaid as a good substitute for private insurance. The coefficients on long-term care insurance remain consistently negative across specifications.

Finally, because we do not observe care consumption over the lifetime of the policy, it is possible that the positive correlation property would appear if the data were analyzed over a longer time horizon. We experimented with several approaches to try to gauge the sensitivity of our findings to this possibility. For example, we used information on how long the individual has had his policy to restrict the insured individuals in the sample to the two-thirds who had had their policy since at least 1992 and we defined the dependent variable based on care utilization from 1992 through 2000 (thus observing 8 years of information rather than only 5).³³ We also tried limiting the sample to the one-third of individuals who died between 1995 and 2000, and for whom utilization subsequent to 2000 is not possible. None of these alternative specifications affected the qualitative nature of the results.

3.4 Insurance coverage and home health care utilization

The analysis thus far has focused exclusively on the relationship between long-term care insurance coverage and nursing home care utilization. However, increasingly, long-term care insurance policies also cover home health care. We therefore examine – where the data permit – the relationship between insurance coverage and other measures of care utilization (results not shown).

Only two of our data sets allow some measure of long-term care utilization other than nursing home utilization. In the AHEAD, we can measure whether the individual consumed any nursing home *or* any home health care between 1995 and 2000 (40% of the sample did, compared to 19% for nursing home use

³² In Section 6, we discuss how this denial practice may reflect that unraveling of the asymmetric information equilibrium for (observably) high risk individuals, and how preference-based selection may increase the likelihood of such unraveling.

³³ 1992 is the furthest back that nursing home care utilization is available since the first interview wave, in 1993, asked about nursing home use in the preceding 12 months.

alone). We cannot measure home health care use separately since, in follow-up interviews, individuals who are currently in a nursing home are not asked if they had used home health care since the previous interview.

We re-estimate equation (1a) using as the dependent variable whether the individual used *any long-term care*. The relationship between insurance coverage and *any care utilization* is slightly more negative than the relationship between insurance coverage and *any nursing home utilization*. This finding persists if we restrict the insured sample to the two-thirds whose policies provide some home health care benefits. This suggests that the relationship between insurance coverage and home care is also likely to be negative. Indeed, when we restrict our sample to the approximately 80% of individuals who do not use nursing home care – and for whom we therefore observe an accurate measure of home health care utilization – the relationship between insurance coverage and home care utilization appears more negative than the relationship between insurance coverage and nursing home care shown in Tables 4 and 5.

In the proprietary data, we directly observe home health care utilization. We therefore re-estimate equation (4) with the failure defined as the 100th consecutive day of home health care; this failure rate is 0.2%. Here, the coefficients on the deductible and maximum daily benefit amount variables are of the sign predicted by the positive correlation property and are statistically significant. There is also some (weaker) evidence of the positive correlation property on the benefit period variables. The coefficients on the benefit escalation variables, however, tend to be wrong signed.

The evidence from the AHEAD and the proprietary data therefore point to opposite conclusions, and together are inconclusive about the relationship between insurance coverage and home health care utilization. We suspect that if there is a positive relationship between insurance coverage and home health care utilization, this most likely reflects a larger role of moral hazard for care that is not in a nursing home; home care may provide some net consumption value and therefore be more susceptible to moral hazard than the less desirable nursing home care. Because policies that cover both types of care offer similar benefits for each type of care, we do not think a differential selection explanation is compelling.

We do not think that a plausible explanation for the lack of a positive correlation between insurance

coverage and nursing home care is that private insurance induces increased use of home health services, which in turn substitute for the (less desirable) nursing home care. For we find that the negative relationship between the quantity of insurance coverage and nursing home care in each data set persists when we restrict the insured sample to those with no home health care coverage. This is consistent with studies based on quasi-experimental evidence that conclude that home health care does not serve as a substantial substitute for nursing home care. (Kemper, 1988; McKnight, 2002).

4. The structure of information in the private long-term care insurance market

The results in the previous section provide no empirical support for a positive correlation between insurance coverage and nursing home utilization, suggesting that asymmetric information may not exist in the private long-term care insurance market. In this section, we test directly for asymmetric information by examining whether individuals have any private information about their risk type, conditional on the risk classification done by the insurance company.

4.1 Data

Information on individual beliefs about their risk of nursing home utilization comes from responses to the following question asked in the 1995 AHEAD:

“Of course nobody wants to go to a nursing home, but sometimes it becomes necessary. What do you think are the chances that you will move to a nursing home in the next five years?”

Individuals are asked to give a response on a scale from zero to 100, which we rescale to be between 0 and 1. The question was not asked of the approximately 13 percent of the 1995 respondents for whom the interview was completed by a proxy respondent; this excludes, among others, the most cognitively impaired.³⁴ The results in Tables 4 and 5 are robust to this sample restriction.

An important consideration is whether individuals’ reporting of their beliefs contains any meaningful information about their actual beliefs. Several factors are encouraging on this dimension. First, individuals’ predictions appear right on average: the average self-reported probability was 18 percent, and

³⁴ The response rate among those asked is high (95%).

16 percent of the responders enter a nursing home over the next five years.³⁵ Second, we find that self-reported nursing home entry probabilities co-vary in consistent ways with known risk factors; they are higher for women than for men, and increase monotonically with age and with deteriorating health status. These results are consistent with other work that has found sensible covariance patterns for self-reported *mortality* probabilities and characteristics such as the individual's age or health status (Hamermesh, 1985, Hurd and McGarry, 2002, Smith et al., 2001).

However, one well-known issue with self-reported probabilities is quite evident in our data. This is the problem of “focal” or “categorical” responses wherein respondents give round figures such as 0, 50 or 100 percent. Figure 5 shows a histogram of the responses; almost 50% of respondents report a five-year nursing home entry probability of zero; 14 percent report a 50 percent probability, and about 1 percent report a probability of 100 percent.³⁶ Hurd and McGarry (1995) and Gan et al. (2003) report a similar preponderance of such categorical responses for self-reported mortality probabilities.

It is somewhat unclear how to treat the issue of categorical responses – or other forms of reporting error more generally – in individual responses. Our goal is to measure individual beliefs. To the extent that the categorical responses represent the “true” subjective probability of the individual, no adjustment to individuals' statement of their beliefs seems warranted. However, the preponderance of categorical responses raises the possibility that individual responses convey information about their beliefs of the general nature of their risk (e.g. low, medium, or high) but not about the *scale* of the risk.³⁷ In this case, grouping the individual predictions into several categories, rather than including them as a continuous variable, might be more appropriate.

Given these issues, we report results from two alternative approaches to measuring the individual's

³⁵ The accuracy of the average prediction holds for both men and women. We find some evidence that those with insurance and those in better health tend to overestimate their risk. It is unclear, however, to what extent the apparent underestimation of risk by those in poor health is driven by the tendency of individuals to give focal responses, particularly 0 or 50.

³⁶ Given that there is some individual discretion involved in the decision to enter a nursing home, individuals who report a zero probability of five-year nursing home entry may be partially expressing intent or desire.

³⁷ For example, although individuals who report a zero probability of 5-year nursing home entry are about 20 percent less likely than individuals who report a positive probability to hold long-term care insurance, nevertheless 8.2% of them have insurance. This suggests that an answer of zero may be intended to convey that the individual believes the probability to be quite low, not that it is literally zero.

beliefs. First, we use the (continuous) response of the individual for the individual's beliefs. Second, to account for the categorical nature of the responses we use a series of indicator variables for whether the individual reported 0 (49%), 1-49 (30%) or 50-100 (21%). We chose these break points to create categories of roughly equal size; in results not reported, we experimented with other groupings, or the use of additional categories, and found the qualitative results not sensitive to these changes.

Of course, another possibility is that individuals may not be comfortable reporting probabilistic answers, and may not in fact even think in these terms. If they use probabilistic information in making insurance purchase decisions, but are unable to translate these latent probabilities into numbers when faced with a survey question, the resulting measurement error will lead us to underestimate the extent of private information.

4.2 Results

The estimating equation was shown in equation (3). We estimate a linear probability model of whether the individual went into a nursing home in the five years between 1995 and 2000 on his 1995 self-reported beliefs of this probability (B) and controls for the risk classification done by the insurance company (X).³⁸ The results are shown in Table 6 for the two alternative measures of the individual's beliefs (continuous and categorical), and for the four alternative definitions of risk classification used in Tables 4 and 5; probit estimation (not shown) produces similar results. Two basic findings emerge.

First, columns (1) and (2) indicate that using either the continuous or categorical measure of beliefs, individual beliefs about the likelihood of entering a nursing home are a statistically significant (positive) predictor of subsequent nursing home experience. This provides a complement to studies that have found that individuals have some ability to predict their mortality risk (see e.g. Hurd and McGarry, 1995, 2002; Smith et al. 2001). Using the continuous measure of individual beliefs, the results in column 1 indicate that a 10 percentage point increase in self-reported probability is associated with only a 1 percentage point increase in the probability of going into a nursing home (a coefficient of 1 would indicate perfect

³⁸ We find qualitatively similar results if we use as the dependent variable the number of nights spent in a nursing home over the five year period, rather than whether the individual ever used a nursing home over these five years.

predictive ability). Using the categorical measure of beliefs, the results in column 2 indicate that individuals who report a prediction of 50 or higher are 6 percentage points (about 40 percent) more likely to go into a nursing home than individuals who report a prediction of 0. Individuals who report a prediction of 1 to 49 are no more likely to go into a nursing home than individuals who report 0, but are significantly less likely to go into a nursing home than individuals who report a prediction of 50 to 100.

Second, and most importantly, the results in the remaining columns indicate that the individual still has residual private information about his risk type *conditional on the risk class that the insurance company assigns to the individual*. This result holds across all of the specifications. Table 6 thus provides direct evidence of the presence of asymmetric information in the private long-term care insurance market. Specifically, it provides direct evidence of the assumption of adverse selection models that individuals have private information about their risk type. An alternative interpretation might be that individuals and insurance companies initially have symmetric information but that individuals, in reporting their beliefs, anticipate the moral hazard effects of insurance. However, this is not corroborated by the data as the results look similar if we restrict the sample to the 90% of individuals without private insurance.³⁹

In results not reported, we ascertained that these results were not sensitive to a number of alternative specifications. For example, we tried adding the actuarial prediction to the “all observables” specification, and we tried using a categorical measure of the actuarial prediction to control for the insurance company prediction when the measure of individual beliefs is categorical. We also verified that restricting the sample to individuals who are more homogeneous with respect to their risk category (i.e. similar ages and/or similar health status), to individuals likely to be eligible for insurance, or to individuals in the top quartile of the income or asset distribution did not affect the magnitude of the coefficient on individual beliefs, although it was sometimes no longer statistically significant in these smaller samples. Finally,

³⁹ Interestingly, we do not find evidence that the insured are better predictors of their utilization than the uninsured. This suggests that individuals do not appear to update their beliefs about their risk type based on the price offered by the insurance company. We also investigated whether predictive power varies systematically across other observable groups. More educated and older individuals tend to be better predictors; there is weak evidence that women may be better predictors than men. We found no evidence that eligible (i.e. healthier) individuals are better predictors than ineligible (less healthy) individuals, or have greater residual private information.

because of concerns about possible measurement error in individuals' reported beliefs (especially relative to the actuarial prediction which is based on aggregate data and therefore presumably less subject to measurement error) we tried including an additional measure of individual beliefs: their answer to the same question about their beliefs of their five-year entry probability when it was asked in the prior wave (1993). In results not reported, we find that this additional measure of beliefs – when included either continuously or categorically in a regression that already includes the 1995 measure of beliefs – is always statistically significant, suggesting that the results in Table 6 may be an underestimate of individuals' private information.

If individuals have residual private information about their chances of using a nursing home, this raises the interesting question of why insurance companies do not collect additional information about the individual. There is clearly some information about the individual that the insurance company could in principle observe but that in practice it does not. This includes, for example, additional health conditions measured in the AHEAD data but not by the insurance company as well as measures of the individual's race, religion, education, spouse's health, the number, gender, and proximity of the individual's children, and indicator variables for whether the individual engaged in each of a variety of potential preventive health measures (described in more detail in Section 5). We found that when these variables are added to the "all observables" specification in Table 6, they are jointly significant, but their addition does not affect the magnitude or statistical significance of the coefficient on the individual's prediction. This suggests that feasible collection of additional information about the individual would not help the insurance company vis a vis the consumer's information set, but that it would give the insurance company an advantage over competitor companies that do not collect the information. Insurance companies presumably do not collect this information because the costs of doing so are high relative to the benefits; in addition, the use of behavioral information in pricing insurance contracts (such as decisions regarding preventive health care investment) could affect individuals' behavioral choices and thus reduce the informative content of these characteristics.

5. Unobserved characteristics, insurance coverage, and care utilization

The results in Section 4 thus provide direct evidence of asymmetric information, while the evidence in Section 3 suggests that there is no positive correlation between long-term care insurance coverage and nursing home utilization. In this section, we investigate how to reconcile these apparently conflicting findings by investigating separately the role of private information about risk type and the role of other unobserved factors in affecting the purchase of insurance.

5.1 The relationship between individual beliefs and insurance coverage

We begin by investigating the possibility that individual beliefs are not correlated with insurance coverage. In practice, this does not appear to be the case. We find that individuals who believe that they are higher risk are, in fact, more likely to purchase insurance. Specifically, we estimate:

$$(5) \text{ LTCINS} = X\delta_1 + \delta_3 B + \mu$$

where B is once again the individual's beliefs about his chances of going into a nursing home and X is a series of controls for the risk classification done by the insurance company. The results are shown in Table 7 for a linear probability model and indicate $\delta_3 > 0$; probit estimation (not shown) produces similar results. Individuals who believe that they are higher risk are, controlling for the risk categorization done by the insurance company, more likely to purchase insurance. We consider the most natural interpretation of this result to be that it is evidence of risk-based selection. However, we cannot rule out the possibility that the causality goes the other way and that the result reflects individuals' rational incorporation of the moral hazard effects of insurance into their perceptions of their chances of using care.

The combined evidence from Tables 6 and 7 indicates that individuals have private information about their risk type *and* that this private information is positively correlated with insurance coverage. Therefore, mechanically, to explain the lack of a positive correlation between insurance coverage and care utilization in Tables 4 and 5, there must be some other unobserved characteristic of the individual (which we denote by P for the individual's unobserved preferences) that has the opposite correlation with insurance coverage and care utilization.

To demonstrate this, we use the results from estimating equation (5) to decompose LTCINS into the

component of long-term care insurance coverage that is explained by the individual's residual private information about his risk type ($\hat{\delta}_3 B$) and the residual ($\hat{\mu}$), which is the portion of long-term care insurance coverage that is unexplained by either the individual's beliefs or by the risk classification done by the insurance company. We refer to these two components of insurance coverage as RISKTYPE_HAT and RESID_HAT respectively. We then estimate:

$$(6) \text{ CARE} = X\beta_1 + \lambda_1 \text{RISKTYPE_HAT} + \lambda_2 \text{RESID_HAT} + \varepsilon$$

The results are shown in Table 8. The coefficient on RISKTYPE_HAT is always positive and is statistically significant in most specifications.⁴⁰ Thus, the portion of insurance coverage that is correlated with individuals' private information about risk type is positively correlated with the probability of using a nursing home. However, the coefficient on RESID_HAT is always negative; the portion of insurance coverage that is not explained either by the individual's private information about risk type or by the categorization done by the insurance company is negatively correlated with nursing home use.⁴¹ In other words, there are characteristics of the individual not controlled for in equation (6) that have the *opposite* correlation with insurance coverage and care utilization.

5.2 Direct evidence of preference-based selection

We exploit the richness of the data to search for these characteristics of the individual that are unobserved by the insurance company and have the opposite correlation with risk occurrence and preferences for insurance. Econometrically, imagine we can measure two aspects of the individual that are unobserved by the insurance company, and related (with noise) to the individual's (unobserved) type T: his beliefs about his type (B) and some aspect of his preferences (P) that the insurance company does not observe. We have seen that B is positively related to insurance coverage and to care utilization and are

⁴⁰ If – to compensate for potential measurement error in individual beliefs – we include measures of individuals' beliefs in 1993 as well as measures of their beliefs in 1995 in estimating the insurance coverage equation (5), the coefficient on RISKTYPE_HAT in equation (6) is now not only always positive but is statistically significant at at least the 5 percent level in all specifications.

⁴¹ We ascertained that these results are not substantively sensitive to restricting the sample to eligible individuals or to individuals in the upper quartile of the income or asset distribution, although the coefficient on RISKTYPE_HAT is often not statistically significant in these smaller samples.

looking for a P that has the opposite correlation with insurance coverage and care utilization.⁴² We therefore estimate:

$$(7) \quad \text{CARE} = Xb_1 + b_2\text{LTCINS} + b_3\text{B} + b_4\text{P} + \varepsilon$$

$$(8) \quad \text{LTCINS} = Xd_1 + d_3\text{B} + d_4\text{P} + \eta$$

and look for variables to measure P that produce the opposite sign on b_4 and d_4 .

It is difficult to measure all (or even most) of the components of P. By definition, they must be unobserved by the insurance company; many of them are therefore likely to be unobserved by the econometrician as well. We therefore focus on a particular type of preference-based selection that has attracted considerable theoretical attention: selection based on risk aversion. The more risk averse (or “cautious”) have a greater preference for insurance; they are also either exogenously assumed to be lower risk (e.g. Smart, 2000), or choose greater preventive effort and through this greater preventive effort, endogenously reduce their probability of risk occurrence (de Meza and Webb, 2001; Jullien et al. 2002).

The AHEAD data provide a nice measure of the individual’s investment in risk-reducing behavior. We observe, in 1995, whether the individual undertook various gender-appropriate potential *preventive health care measures* over the last two years. These are: whether the individual had a flu shot, had a blood test for cholesterol, checked her breasts for lumps monthly, had a mammogram or breast x-ray, had a pap smear, and had a prostate screen. There is substantial variation in the fraction of gender-appropriate potential preventive activity actually undertaken: the median individual does two-thirds of these activities, but 7% report doing nothing and 30% report doing all.⁴³

⁴² The fact that P is correlated with care utilization but not incorporated into the individual’s beliefs about his care utilization (B) indicates that the individual does not use information about P in forming his beliefs. Note that this implies that the individual is inefficient in forming his beliefs; it does not imply that his beliefs must exhibit any systematic biases or mistakes. Consistent with this view, Smith et al. (2001) find that individual’s self-reported *mortality* probability in the HRS does not reflect all of the private information individuals have about their survival prospects, even though it is a good predictor of actual mortality and is updated in sensible ways based on experienced health shocks.

⁴³ We considered whether our preventive health measure was affected by whether the individual has been to a doctor or what his insurance will cover, but concluded that it was not. Over 90% of the sample has had a doctor’s visit over the past two years and our results are not sensitive to limiting the sample to these individuals. In addition, over 99% of the sample is covered by Medicare, which reimburses for all of these preventive health measures.

Table 9 reports the results. To conserve space, we only report results using the continuous measure of individual beliefs; the results look similar if the categorical measure of beliefs is used instead. Each of the four panels reports the results separately for a different set of controls for the insurance company risk classification.⁴⁴ Within each panel, the first column indicates that individuals who undertake a greater fraction of potential preventive health activity (i.e. more cautious individuals) are more likely to own insurance. The second column indicates that those who undertake more preventive health activity are also less likely to subsequently go into a nursing home.

We used the results from estimating the insurance coverage equation (8) to decompose insurance coverage into a component predicted by the preventive health activity (PREVENT_HAT), a component predicted by individuals' private information about risk type (RISKTYPE_HAT) and the residual (RESID_HAT).⁴⁵ The third column of each panel of Table 9 shows the results of estimating the care utilization equation (6) with these three different components of insurance coverage on the right hand side. Not surprisingly, given the previous results in Table 9, PREVENT_HAT is always negative; the variation in insurance coverage that is positively correlated with preventive health activity is negatively correlated with long-term care utilization.

Thus, consistent with the theoretical models of de Meza and Webb (2001) and Jullien et al (2002), more cautious individuals are both more likely to own insurance and less likely to experience the insured risk. The results, however, fall short of demonstrating the *causal* relationship between risk aversion and risk occurrence posited in these models. Although it is possible that the relationship is causal (for example, flu shots reduce the risk of pneumonia which is a nontrivial contributor to the need for a nursing home for the elderly), other interpretations are also plausible. It may be that our measured preventive health activity is positively correlated with greater caution and care more broadly about one's health over

⁴⁴ We also include a control for gender since the fraction of potential preventive activity undertaken may vary with gender simply because the *number* of potential preventive activities is 3 for men and 5 for women. The results reported in Table 9 are not sensitive to whether we include this control.

⁴⁵ For this specification, we include separate indicator variables for each preventive health activity (and gender) in order to more flexibly estimate the relationship between preventive health activity and insurance coverage. The results are similar if we instead use the fraction of gender-appropriate preventive health activity undertaken.

the course of the life cycle, which in turn reduces nursing home utilization. Consistent with this, we find that individuals who invest more in the measured preventive health activities are substantially less likely to have a hip fracture (which is another important contributor to nursing home residence); this is unlikely to reflect a causal effect of any of the preventive health activities that we measure, but may reflect a causal effect of unmeasured preventive health activities (such as perhaps greater exercise and calcium consumption in earlier years).

It is also likely that our preventive health measures are picking up the effects of socio-economic status. Indeed, we find a strong positive correlation between the amount of investment in the gender-appropriate preventive health activities we measure and individuals' wealth. Moreover, we find that higher asset individuals are both substantially more likely to have insurance and substantially less likely to use nursing homes.⁴⁶ Preference-based selection along wealth – which may be driven in large part by the crowd out of private insurance demand by Medicaid for lower-wealth individuals (Pauly 1990, Brown and Finkelstein, 2003) – therefore also appears to contribute to the lack of a positive correlation between insurance coverage and care utilization. The negative relationship between PREVENT_HAT (that portion of long-term care insurance correlated with preventive health activity) and nursing home utilization shown in Table 9 persists if controls for asset quartiles are added to the three specifications that do not already have them. However, we cannot rule out the possibility that these preventive health measures may be proxying for other unmeasured aspects of socio-economic status.

Interestingly, besides preventive health activity and wealth, we found that all of the other characteristics of the individual that we can measure and that the insurance companies do not observe have the *same* correlation with insurance coverage and risk occurrence. For example, individuals with less schooling or more children are both less likely to have insurance and less likely to use nursing home care. Similarly, nonwhites, Hispanics, and Catholics are each less likely to have insurance and less likely to use

⁴⁶ Since we found only one insurance company who collected information on income and assets (and they only inquired whether financial assets were less than \$30,000), it seems reasonable to look for potential preference-based selection along this dimension.

care, while Jews are both more likely to have insurance and more likely to use care.⁴⁷ Relatedly, it is important to note that even if we add all of the factors that we observe and the insurance company does not as additional controls in a regression of care utilization on insurance coverage (i.e. equation 1a) we still do not recover a positive relationship between insurance coverage and care utilization. This indicates that, not surprisingly, we are not able to fully measure all of the unobserved characteristics of the individual that have the opposite correlation with insurance coverage and with risk type.

6. Insurance rationing with risk-based and preference-based selection

The direct evidence of asymmetric information presented in this paper raises the possibility that asymmetric information may contribute to the limited size of the private long-term care insurance market. As discussed above, private information about risk type can produce inefficient restrictions on the amount of insurance purchased by one or more risk types in equilibrium, even if preference-based selection undoes any positive correlation between insurance coverage and risk occurrence. In this section, we therefore briefly discuss how insurance appears to be rationed in this market along two dimensions, both of which may reflect the effects of asymmetric information. Of course, more work is needed to establish the extent to which this rationing is due to asymmetric information, as opposed to other factors, and we regard this as an important direction for further work.

First, policies tend to insure only a very limited fraction of long-term care expenditures. In addition to the use of deductibles and caps on total benefits, which are typical of other health insurance contracts as well, most long-term care insurance contracts also specify a maximum (constant, nominal) daily benefit that tends to be substantially below average *current* daily cost of nursing homes, and is not scheduled to rise with medical cost inflation. As a result, Brown and Finkelstein (2003) find that typical private long-term care insurance contracts tend to pay for less than 50 percent of the expected present discounted value of long-term care costs for a 65 year old. Moreover, they present evidence that individuals who would not find the purchase of the currently-available limited-coverage policies welfare-enhancing might want to

⁴⁷ We also investigated the relationship between spousal health and long-term care insurance holdings and nursing home utilization but were unable to detect any statistically significant and robust patterns.

purchase policies with more comprehensive coverage. The fact that, despite this, such contracts are not offered may reflect the effects of asymmetric information in this market (i.e. if insurance companies offered more comprehensive contracts, they would attract disproportionately (unobservably) higher risk types), although other explanations for the structure of these contracts are possible (Cutler, 1996).

Second, many (observably) high-risk applicants would be denied insurance coverage at any price. This practice is non-trivial, and persists despite the lack of any regulatory restrictions on the level of prices or on actuarially-based pricing differentials. For example, Weiss (2002) estimates that 15% of non-group long-term care insurance *applications* are denied, while Murtaugh et al. (1995) estimate that up to one-quarter of 65 year olds and one-third of 75 year olds would be denied insurance based on their observable health characteristics if they applied. Such denials may reflect an adverse selection equilibrium in which there is no interior pricing solution for certain (observably) high risk groups (i.e. “unraveling”), resulting in no trade in equilibrium (Akerlof, 1970). Of course, other explanations for denials are possible, such as a lack of much residual variation in care utilization – and hence much insurance value – among the very high risk, or binding wealth constraints for the observably high risk.

In this context, it is interesting to note that preference-based selection that tends to offset a positive correlation between insurance coverage and risk occurrence that would otherwise be produced by private information about risk may make it more likely for the market to unravel for a given (observable) risk class. Figure 6 illustrates this phenomenon graphically in a simple model with private information about risk type and linear pricing (e.g. Stiglitz and Weiss, 1981, Cutler 2002). $C(p)$ denotes the expected claims over all those with risk type p or higher. If individuals differ only in terms of their unobserved risk type, the value of insurance at a given price ($V_0(p)$) is rising with risk type (p). The equilibrium shown in Figure 6 exhibits an interior pricing solution in which all those of risk type p^* or higher buy insurance at price $C(p^*)$. Now imagine that we make the higher risk (unobservably) less risk averse. As we decrease the risk aversion of the higher risk individuals, the $V(p)$ curve flattens from $V_0(p)$ to $V_1(p)$, and the market may unravel: as drawn, there is no longer any \hat{p} at which the value of insurance ($V_1(p)$) at all

$p > \hat{p}$ exceeds the expected claims for all insured individuals ($C(\hat{p})$).

7. Conclusion

A growing body of empirical work has begun to question the empirical relevance of theoretical models of asymmetric information to insurance markets. In several different insurance markets, recent papers have found no evidence of a positive correlation between the amount of insurance and the occurrence of the risk, and have concluded that asymmetric information may therefore not exist in these markets. In this paper, we show empirically that asymmetric information may exist *even if* the insured are not above-average in their risk type.

We explore these issues in the context of the private long-term care insurance market in the United States. We do not find a positive correlation between individuals' insurance coverage and their consumption of nursing home care in any of three complementary data sources. However, using information about individuals' assessment of their nursing home risk, we find direct evidence of asymmetric information. Even after conditioning on the information set of the insurance company, the individual's beliefs about his risk type are positively correlated with both insurance coverage and subsequent care utilization.

The lack of a positive correlation between insurance coverage and care utilization – *despite* the presence of private information about risk type – is explained by the existence of another type of private information: individuals have private information not only about their risk type but also about preference-related characteristics that have the opposite correlation with insurance coverage and risk occurrence. For example, we find evidence that more “cautious” individuals – as measured by their investment in preventive health measures, which is not observed by the insurance company – are both more likely to have long-term care insurance and less likely to use nursing home care.

Such preference-based selection can offset the tendency of asymmetric information about risk type only to produce a positive correlation between insurance coverage and risk occurrence. As a result, the insured risk pool is not “adversely-selected”; its risk is not above-average relative to the population. This

suggests that the presence of private information about risk type in the long-term care insurance market does not raise prices above their population-average actuarially fair price. However, as discussed above, preference-based selection cannot offset the negative efficiency consequences of private information about risk type. The quantity of insurance is often restricted relative to the first best (see e.g. Chiappori et al. 2002), although models with overinsurance are also possible (de Meza and Webb, 2001). Further work is needed to try to quantify the insurance rationing that asymmetric information may produce, and its contribution to the extremely limited nature of the private long-term care insurance market.

It is particularly striking that preference-based selection appears to offset the positive correlation that asymmetric information would otherwise produce between insurance coverage and risk occurrence in the long-term care insurance market, given the extensive evidence of such a positive correlation in the market for acute medical care insurance (see Cutler (2002) for a review). It may be that preference-based selection plays more of a role in the long-term care insurance market, and or that moral hazard may play less of a role, than in the market for acute medical care insurance. Additionally, it seems likely that private information about risk type – and hence risk-based selection – may be greater in the market for acute medical care, where the individual may be continually learning more about his risk, than in the market for long-term care where the risk occurs less frequently and later in life.

The results in this paper suggest that preference-based selection may help explain the apparent differences across insurance markets in the presence or absence of a positive correlation between insurance coverage and risk occurrence. For example, there is evidence of such a positive correlation in annuities (Finkelstein and Poterba, 2000) but not in life insurance (Cawley and Philipson, 1999) which insures the (opposite) longevity risk to that insured by annuities. One potential explanation is that there are characteristics of the individual that the insurance company does not observe – such as their level of caution or their wealth – that are positively correlated with preferences for both types of insurance but are *negatively* correlated with the life insurance risk of dying and *positively* correlated with the annuity risk of living. We regard this as an interesting direction for further work.

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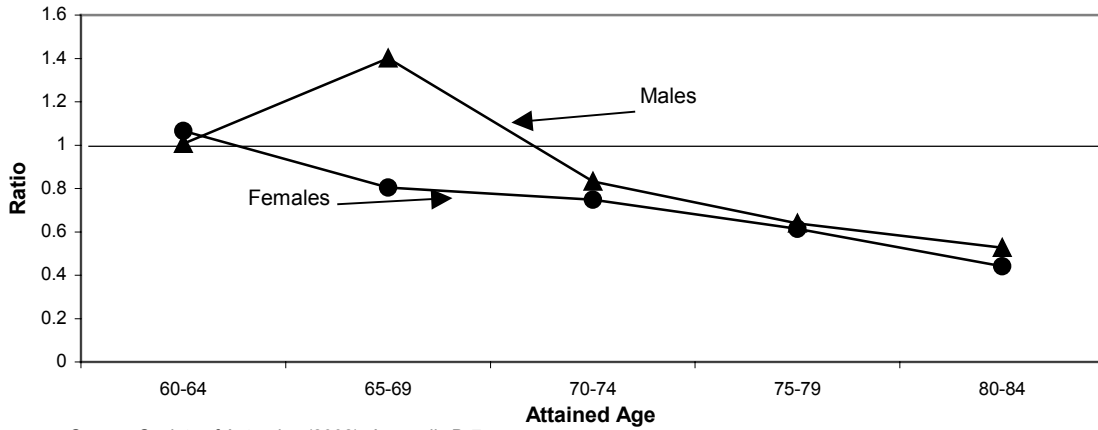
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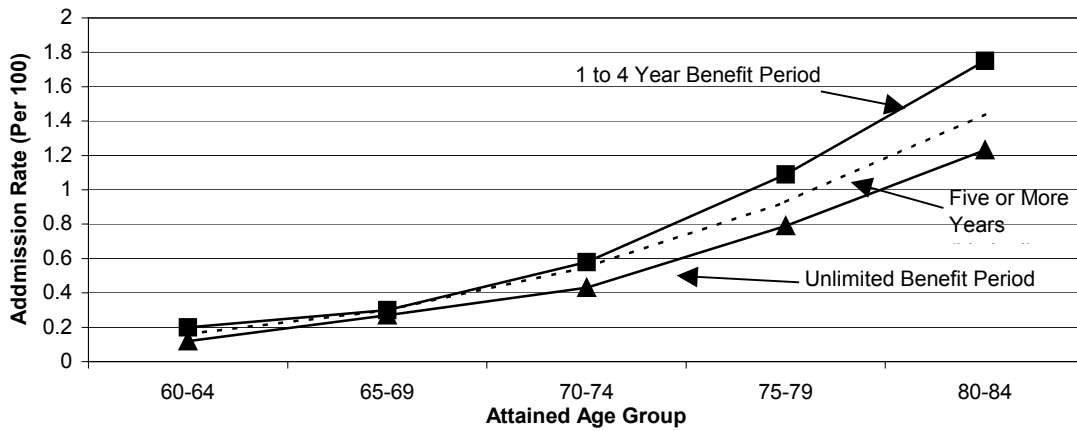
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Figure 1: Ratio of Insured to Population Nursing Home Admission Rate



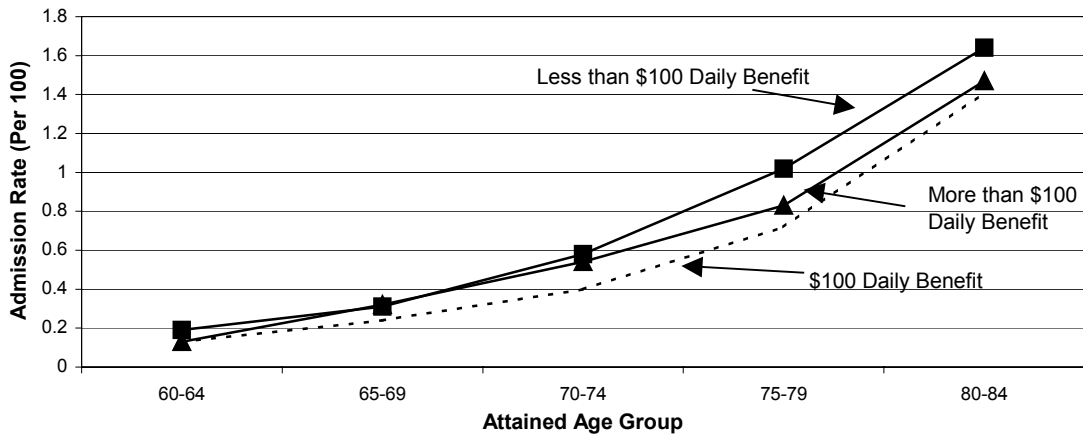
Source: Society of Actuaries (2002), Appendix D-7
 Note: Insured estimates based on policies with no deductible

Figure 2: Variation in Nursing Home Admission Rate by Benefit Period



Source: Society of Actuaries, Table D-5
 Note: Data reported for policies with 20-day deductible

Figure 3: Variation in Nursing Home Admission Rate by Daily Benefit



Source: Society of Actuaries, Table D-6
 Note: Data reported are for policies with 20-day deductible

Table 1: Summary statistics for proprietary insurance company data.

	Policies Issued 1997-2001	Policies Issued 1997 or 1998
FAILURE RATE	0.3%	0.6%
CATEGORIZATION OF INDIVIDUALS		
Median Issue Date	September 1, 1999	February 8, 1998
Average Issue Age	64.4	65.3
% Rated Low Risk	29	16
% Rated Standard Risk	66	79
% Rated High Risk	5	5
CHARACTERISTICS OF POLICY		
Deductible		
% with 20-day deductible	5	5
% with 60-day deductible	8	8
% with 100-day deductible	87	87
Maximum Daily Benefit		
Average nursing home daily benefit (in \$)	119	113
Average home health care daily benefit (in \$)	112	103
% With Home Care Benefit Less than Nursing Home Benefit	19	26
Benefit Period		
% of policies with Unlimited Benefit Period	18	18
Average Benefit Period for Policies w/ limited benefit period	4.3	4.2
% of Policies with Limited Benefit Period that allow extension	10	13
Benefit Escalation		
% with no benefit escalation	2	----
% with 5% “simple” benefit escalation	30	29
% with 5% compound benefit escalation	28	18
% with “indexed” escalation	40	53
N	144,798	49,887

Table reports means. Percentages all rounded to nearest whole number. Dashed line indicates less than 1 percent. 60% of policy sales are to women; we do not report this in the above table since it is not a characteristic used by the insurance company to categorize individuals.

Table 2: Hazard rate of receiving nursing home care for 100th consecutive day

Sign predicted by the “positive correlation” property	Covariates in Regression	Policies Issued 1997 - 2001	Policies Issued 1997 or 1998
	Issue Age Categories (reference category = less than 60)		
	Issue Age 60-64	1.199*** (0.423)	1.039** (0.505)
	Issue Age 65-69	1.729*** (0.423)	1.798*** (0.475)
	Issue Age 70-74	2.944*** (0.400)	2.928*** (0.469)
	Issue Age 75+	4.010*** (0.403)	3.913*** (0.473)
	Price categories (reference category = rated high risk)		
	Rated low risk	-1.100*** (0.259)	-0.964*** (0.322)
	Rated standard risk	-0.535*** (0.175)	-0.562*** (0.200)
	Deductible (Reference category = 100-day deductible)		
Positive	60-day deductible	0.024 (0.208)	-0.030 (0.252)
Positive (and larger than 60- day deductible)	20-day deductible	0.233 (0.238)	0.312 (0.268)
	Daily Benefit (Reference Category = < \$100)		
Positive	Daily Benefit = \$100	0.095 (0.127)	-0.007 (0.141)
Positive (and larger than \$100 category)	Daily Benefit > \$100	0.240* (0.134)	0.143 (0.151)
	Benefit Period (Reference Category = 1-4 years w/ no extension possible)		
Positive	1-4 years w/ ext. possible	-0.306 (0.207)	-0.509** (0.254)
Positive	5+ years w/ no extension	-0.391** (0.162)	-0.543*** (0.193)
Positive (and larger than 5+ years w/ no extension)	5+ years w/ ext. possible	-0.160 (0.343)	-0.257 (0.389)
Positive (and larger than 5+ years with extension)	Unlimited Benefit Period	0.168 (0.153)	0.075 (0.175)
	Escalation of Benefits (Reference Category = 5% compound)		
Negative	No escalation of daily benefit	0.438 (0.399)	-----
Negative (but larger than “no escalation”)	5% “simple” escalation of daily benefit	0.213 (0.244)	0.270 (0.302)
Larger than “no escalation”	“Index option” for escalation of daily benefit	0.102 (0.236)	0.254 (0.288)
	Failure Rate	0.3%	0.6%
	N	144,798	49,888

Note: Table reports exponentiated coefficients from estimation of Cox proportional hazard model. Variables that are included in regression but not shown in table are: indicator variables for issue year, whether the policy is tax qualified, whether the home health care benefits are lower than (rather than equal to) the nursing home benefits, frequency of policy premium payments, and an indicator variable for a “shared care” rider benefit (which makes the spouse eligible for the policy benefits if the individual dies within a specified time period after policy issue).

Table 3: Summary Statistics for care utilization, insurance coverage, and covariates in the AHEAD

	Whole		Top quartile by inc or assets	
	Whole	Eligibles	Whole	Eligibles
Dependent Variables:				
Any NH Utilization (1995 – 2000)	0.187	0.113	0.130	0.089
Total # of nights in NH (1995 – 2000)	32.7	16.23	17.39	11.06
Key Independent Variable:				
Long-term care insurance coverage (1995)	0.104	0.109	0.155	0.155
Control Variables				
<i>Demographics (1995)</i>				
Age	77.5	76.4	76.2	75.5
Female	0.63	0.58	0.55	0.50
Married	0.54	0.60	0.74	0.77
Spousal Age if Married	73.8	73.5	73.6	73.7
Household Assets (median)	138,400	159,000	420,750	422,000
Household Income (median)	18,000	20,000	35,000	35,000
<i>Current health (1995)</i>				
ADL limitation: bathing	0.11	0	0.07	0
ADL limitation: eating	0.05	0	0.03	0
ADL limitation: dressing	0.13	0	0.09	0
ADL limitation: toileting	0.08	0	0.06	0
ADL limitation: walking	0.10	0	0.06	0
Incontinence	0.22	0	0.22	0
Cognitively impaired	0.03	0	0.02	0
Use wheelchair	0.03	0	0.02	0
Use walker	0.07	0	0.04	0
Use crutches	0.003	0	0.0009	0
Use Cane	0.13	0	0.09	0
Use oxygen	0.01	0	0.008	0
Regularly use prescription drugs	0.79	0.73	0.78	0.74
IADL limitation: grocery shopping	0.15	0.03	0.09	0.02
IADL limitation: managing medication	0.05	0.007	0.03	0.003
Low BMI	0.10	0.09	0.09	0.09
High BMI	0.13	0.11	0.10	0.09
Currently smoke	0.08	0.08	0.07	0.07
<i>Health History (1995 and before)</i>				
Home Health Care Use	0.17	0.07	0.11	0.06
Nursing Home Use	0.02	0.008	0.02	0.006
Depression	0.21	0.12	0.15	0.09
Drinking Problem	0.03	0.04	0.03	0.04
Diabetes	0.14	0.12	0.11	0.10
Diabetes treated with insulin	0.05	0.03	0.03	0.02
Kidney Failure Assoc w. Diabetes	0.02	0.005	0.007	0.002
Stroke	0.12	0.07	0.09	0.06
Heart condition	0.34	0.30	0.30	0.27
Medication for heart problem	0.22	0.19	0.19	0.18
Heart Attack	0.09	0.07	0.07	0.07
Congestive Heart Failure	0.04	0.02	0.03	0.02
High Blood Pressure	0.54	0.49	0.49	0.46
Hip fracture	0.05	0.03	0.04	0.02
Lung Disease	0.12	0.9	0.10	0.08
Cancer	0.16	0.14	0.17	0.15
Psychiatric problems	0.15	0.11	0.12	0.09
Arthritis	0.54	0.44	0.47	0.39
Injury from falling	0.15	0.10	0.14	0.10

Note: All means are weighted. See Appendix A for our construction of cognitive impairment, depression, drinking problem, household assets and BMI. All of the listed control variables are used in the “all observables” specification.

UnumProvident Application for Individual Long-Term Care Insurance (p.1)

Part 2: Insurability Profile	
<input type="checkbox"/> Yes <input type="checkbox"/> No	2a. Do you use mechanical devices such as: a wheelchair, walker, quad cane, crutches, hospital bed, dialysis machine, oxygen, or stairlift?
<input type="checkbox"/> Yes <input type="checkbox"/> No	2b. Are you cognitively impaired or do you currently need or receive help in doing any of the following: bathing; eating; dressing; toileting; transferring; or maintaining continence?

If you answered "Yes" to either of these questions in Part 2, DO NOT SUBMIT THIS APPLICATION.

John Hancock Application for Individual Long-Term Care Insurance (p. 2)

Part 3 -- Should You Submit This Application?	
3a. <input type="checkbox"/> Yes <input type="checkbox"/> No	Do you currently use mechanical devices, such as: a wheelchair, walker, crutches, hospital bed, dialysis machine, oxygen, or stairlift?
3b. <input type="checkbox"/> Yes <input type="checkbox"/> No	Do you currently need or receive help in doing any of the following: bathing; eating; dressing; toileting; transferring from bed to chair; maintaining continence?
3c. <input type="checkbox"/> Yes <input type="checkbox"/> No <input type="checkbox"/> Yes <input type="checkbox"/> No	Do you currently have, or have you ever had a diagnosis for or symptoms of: 1. Alzheimer's disease, dementia, or organic brain syndrome? 2. multiple sclerosis, muscular dystrophy, ALS (Lou Gehrig's Disease) or Parkinson's Disease?
3d. <input type="checkbox"/> Yes <input type="checkbox"/> No	Have you been diagnosed or treated by a member of the medical profession for AIDS or AIDS related complex?
STOP HERE!	If you answered "YES" to any questions in part 3, you may not wish to submit this application as it may not be favorably considered. If not, please continue.

Table 4: Long-term care insurance coverage and long-term care utilization in the AHEAD

	No Controls	Controls for Age Dummies	Controls for “all observables”	Controls for insurance company prediction
Dependent Variable	(1)	(2)	(3)	(4)
Any nursing home utilization	-0.045*** (0.016) [N=6,277]	-0.014 (0.015) [N=6,276]	0.0005 (0.015) [N=6,080]	-0.012 (0.015) [N=6,273]
Number of nights spent in nursing home	-71.44*** (25.79) [N=6,186]	-25.32 (25.11) [N=6,185]	-12.19 (25.29) [N=5,995]	-25.82 (24.76) [N=6,182]

Notes: Each cell reports the coefficient on LTCINS from estimating equation (1a) on a specific dependent variable and definition of the set of control variables. The column headings describe the set of control variables used. See text and Appendix for detailed description of these covariates. Coefficients in the first row are from a linear probability model. Coefficients in the second row are from a Tobit model. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denotes statistical significance at the 1 percent, 5 percent, and 10 percent level respectively.

Table 5: LTC insurance coverage and LTC utilization in the AHEAD; RESTRICTED SAMPLES

	No Controls	Controls for Age Dummies	Controls for “all observables”	Controls for insurance company prediction
Dependent Variable	(1)	(2)	(3)	(4)
Panel 1: Restricted to Individuals for whom Medicaid is not a Close Substitute for Private Insurance (top quartile of income or asset distribution)				
Any nursing home utilization	-0.046*** (0.017) [N=2,159]	-0.027* (0.016) [N=2,158]	-0.031* (0.017) [N=2,158]	-0.027 (0.017) [N=2,121]
Number of nights spent in nursing home	-91.18*** (35.39) [N=2,138]	-61.90* (34.27) [N=2,137]	-62.86* (33.12) [N=2,101]	-66.81** (34.18) [N=2,137]
Panel 2: Restricted to Eligible Individuals				
Any nursing home utilization	-0.013 (0.017) [N=3,600]	-0.007 (0.016) [N=3,599]	-0.0004 (0.017) [N=3,526]	-0.004 (0.017) [N=3,599]
Number of nights spent in nursing home	-37.16 (35.83) [N=3,563]	-30.23 (35.66) [N=3,562]	-28.84 (36.64) [N=3,491]	-17.08 (35.35) [N=3,562]
Panel 3: Restricted to Eligible Individuals for whom Medicaid is not a good substitute				
Any nursing home utilization	-0.026 (0.019) [N=1,362]	-0.030 (0.019) [N=1,361]	-0.032* (0.019) [N=1,343]	-0.026 (0.019) [N=1,361]
Number of nights spent in nursing home	-108.75** (50.90) [N=1,354]	-109.69** (50.21) [N=1,353]	-109.69** (48.21) [N=1,336]	-103.08** (50.52) [N=1,353]

Notes: See notes to Table 4.

Table 6: Individuals' predictions of nursing home entry

	No Controls		Controls for Age Dummies		Controls for "All observables"		Controls for Insurance Company Prediction		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Individual Prediction (continuous)	0.097*** (0.024)		0.069*** (0.022)		0.037* (0.022)		0.044** (0.022)		
Individual predicts 1 to 49		-0.019 (0.012)		-0.004 (0.011)		0.003 (0.011)		-0.003 (0.011)	
Individual predicts 50 to 100		0.062*** (0.015)		0.045*** (0.014)		0.029** (0.014)		0.033** (0.015)	
Actuarial Prediction							0.505*** (0.029)	0.503*** (0.029)	0.511*** (0.029)
R ²	0.004	0.006	0.11	0.11	0.17	0.17	0.10	0.10	0.098
N	5,146	5,146	5,146	5,146	5,032	5,032	5,146	5,146	5,146

Note: Reported coefficients are from linear estimation of equation (3). Dependent variable is whether individual enters nursing home over subsequent five years. When individual prediction is entered continuously, it has been rescaled to range from 0 to 1. When categorical measure of beliefs is used instead, the omitted category is "individual predicts 0". The column headings describe the additional covariates included in the regression. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denotes statistical significance at the 1 percent, 5 percent, and 10 percent level respectively.

Table 7: The relationship between insurance coverage and individual beliefs about risk type

	No Controls		Controls for Age Dummies		Controls for "All observables"		Controls for Ins. Co. Prediction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual Prediction (continuous)	0.077*** (0.019)		0.082*** (0.019)		0.084*** (0.019)		0.091*** (0.019)	
Individual predicts 1 to 49		0.056*** (0.013)		0.052*** (0.011)		0.040*** (0.011)		0.052*** (0.011)
Individual predicts 50 to 100		0.059*** (0.013)		0.062*** (0.013)		0.061*** (0.013)		0.066*** (0.013)
Actuarial Prediction							-0.128*** (0.019)	-0.121*** (0.017)
R ²	0.004	0.008	0.01	0.02	0.05	0.05	0.02	
N	5,233	5,233	5,233	5,233	5,118	5,118	5,233	5,233

Note: Coefficients are from linear estimation of equation (5). Dependent variable is whether individual has LTC insurance. See notes to Table 6 for more details.

Table 8: Decomposing the relationship between care utilization and insurance

	No Controls			Controls for Age Dummies			Controls for “All observables”			Controls for Ins. Co Prediction		
	----- (1)	Continuous Beliefs (2)	Categorical Beliefs (3)	----- (4)	Continuous Beliefs (5)	Categorical Beliefs (6)	----- (7)	Continuous Beliefs (8)	Categorical Beliefs (9)	----- (10)	Continuous Beliefs (11)	Categorical Beliefs (12)
LTCINS	-0.046*** (0.015)			-0.021 (0.015)			-0.006 (0.015)			-0.017 (0.015)		
RISKTYPE_HAT		1.274*** (0.307)	0.303 (0.191)		0.863*** (0.276)	0.365** (0.185)		0.454* (0.266)	0.372* (0.207)		0.443*** (0.220)	0.244 (0.160)
RESID_HAT		-0.051*** (0.015)	-0.049*** (0.015)		-0.025* (0.015)	-0.025* (0.015)		-0.008 (0.015)	-0.009 (0.015)		-0.020 (0.015)	-0.020 (0.015)
N	5,070	5,070	5,070	5,070	5,070	5,070	4,958	4,958	4,958	5,070	5,070	5,070

Notes: All estimates are by OLS. The dependent variable is “any nursing home entry”. The column headings describe the additional covariates included in the regression and the measure of individual beliefs used. For comparative purposes, columns (1), (4) and (7) and (10) report the coefficient on LTCINSURANCE from estimating equation (1a). The rest of the columns report the coefficients on RISKTYPE_HAT and RESID_HAT from estimating equation (6). RISKTYPE_HAT and RESID_HAT are predicted based on the results from estimating the insurance coverage equation (5). They reflect, respectively, the portion of insurance coverage that is explained by the individual’s beliefs about his risk type, and the portion of insurance coverage that is unexplained by either these beliefs or by the risk classification done by the insurance company. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denotes statistical significance at the 1 percent, 5 percent, and 10 percent level respectively.

Table 9: Preference-based selection

	No Controls			Controls for Age Dummies			Controls for “All Observables”			Controls for Ins. Co. Prediction		
	LTCINS (1)	NH ENTRY (2)	NH ENTRY (3)	LTCINS (4)	NH ENTRY (5)	NH ENTRY (6)	LTCINS (7)	NH ENTRY (8)	NH ENTRY (9)	LTCINS (10)	NH ENTRY (11)	NH ENTRY (12)
Preventive Activity	0.064*** (0.016)	-0.112*** (0.019)		0.050*** (0.016)	-0.036** (0.018)		0.011 (0.020)	-0.017 (0.019)		0.051*** (0.016)	-0.056*** (0.018)	
Individual Prediction	0.087*** (0.019)	0.104*** (0.024)		0.091*** (0.020)	0.072*** (0.023)		0.094*** (0.020)	0.039* (0.022)		0.099*** (0.020)	0.050** (0.023)	
PREVENT _HAT			-1.383*** (0.222)			-0.662*** (0.244)			-0.400 (0.341)			-0.714*** (0.246)
RISKTYPE _HAT			1.371*** (0.316)			0.923*** (0.286)			0.457* (0.267)			0.559*** (0.259)
RESID _HAT			-0.042*** (0.015)			-0.022 (0.015)			-0.007 (0.015)			-0.016 (0.015)
N	5,070	5,070	5,070	5,070	5,070	5,070	4,958	4,958	4,958	5,070	5,070	5,070

Note: All estimates are by OLS on the binary dependent variable given in the column headings. “Preventive activity” measures the fraction of gender-appropriate preventive health activity undertaken by the individual. All regressions include a control for gender. “Individual prediction” measures the individual’s (continuous) prediction. The “risk classification controls” row describes the additional covariates included in the regression. PREVENT_HAT, RISKTYPE_HAT and RESID_HAT are generated based on the results from estimating the insurance coverage equation (8) and reflect the portion of insurance coverage that is explained, respectively, by “Preventive activity”, the individual’s beliefs about his risk type, and the portion unexplained by either preventive activity, individual beliefs, or the risk classification controls. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denotes statistical significance at the 1 percent, 5 percent, and 10 percent level respectively.

Figure 5: Sample distribution of self-reported probability of entering a nursing home in next five years

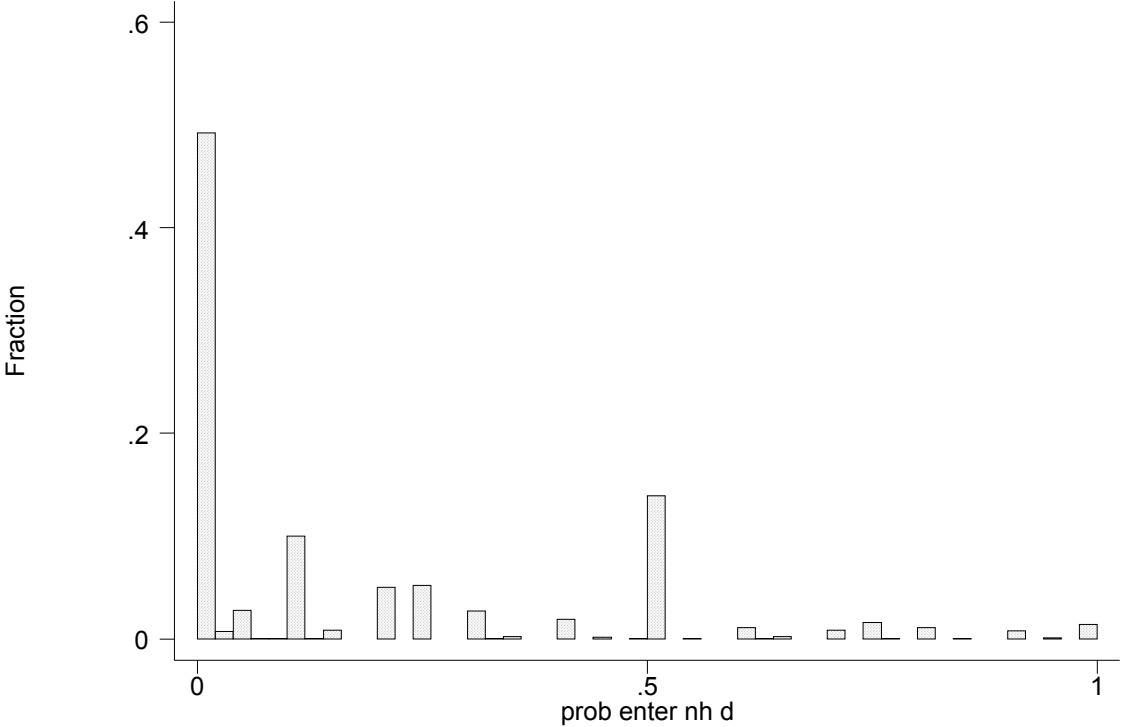
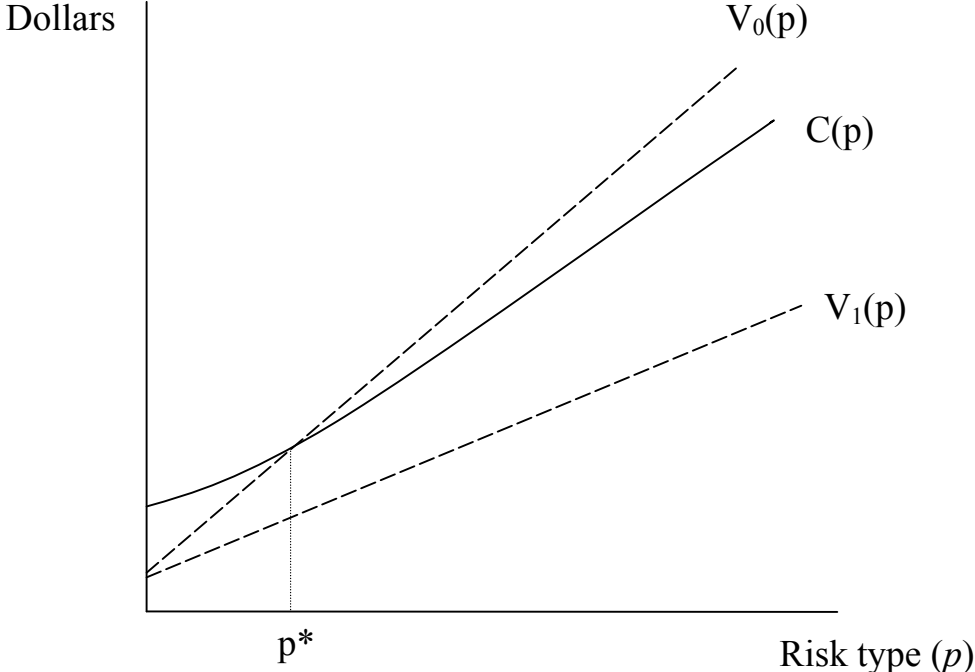


Figure 6: Unraveling



Appendix A: Detailed information on the AHEAD Sample and Variable Definitions.

Sample definition. Our sample is drawn from the original Asset and Health Dynamics (AHEAD) cohort of the Health and Retirement Study. This original AHEAD cohort consists of individuals born in 1923 or earlier and their spouses; when appropriately weighted, it is representative of the non-institutional population of this age group.⁴⁸ To increase sample size, we include observations on the sample members spouses even if they are outside this age range (1.5% of the sample), but we exclude 50 spouses who were younger than 60 at the 1995 interview. We also exclude the 3 percent of original respondents who were in a nursing home in 1995. The results are not sensitive to any of these inclusions or exclusions.

The AHEAD respondents were interviewed in 1993, 1995, 1998 and 2000. We restrict our analysis to data from 1995 to 2000, omitting information in 1993, because the question of long-term care insurance in that year was poorly worded and we do not believe reflects true insurance coverage (see below). Non-death attrition (i.e. “real” attrition) from our sample is just over 4 percent from 1995 and 2000. Those who attrited from the sample have significantly lower income and wealth, on average, and are slightly less likely to have long term care insurance, although the difference is not statistically different from zero.

Measuring care utilization: Our analyses use the panel nature of the data to track individual care utilization through the 2000 interview wave, which is the latest currently available wave of data. We use responses to questions about care utilization since the last interview obtained in the 1998 and 2000 surveys. Specifically, at each interview we know whether the individual is currently in a nursing home or has been in a nursing home since the last interview and if so, for how many nights. If the individual is not in a nursing home, they are also asked whether they are currently receiving home care or have since the last interview.

Sample weights: All of the means and the regression results reported in the paper from the AHEAD data are weighted using the 1995 household weights. The use of household weights rather than respondent weights allows us to include out-of-age-range spouses. The regression results are not sensitive to using respondent-level weights instead or to running un-weighted regressions.

Key independent variable: Long-term care insurance. As we noted above, we measure individuals’ insurance coverage in 1995, the first wave for which reliable information is available. Our indicator variable LTCINS is coded 1 if the individual answers yes to the following question:

R15: Aside from the government programs, do you now have any insurance which specifically pays any part of long-term care, such as, personal or medical care in the home or in a nursing home?

Although a few papers have used answers to questions about long-term care insurance in the 1993 wave (see e.g. Norton and Sloan 1997 or Mellor 2001) we are uncomfortable with relying on this measure. In that year the survey asked specifically about a variety of types of health insurance and then asked if the respondent had any (other) type of insurance:

R6. Do you have any (other) type of health insurance coverage?

R7. What kind of coverage do you have? It is basic health insurance, a supplement to Medicare (MEDIGAP) or to other health insurance, long-term care insurance, or what?

⁴⁸ A younger cohort, born in the years 1931-1941, was interviewed for the companion HRS survey. We use the AHEAD cohort because the HRS cohort was not asked to report their subjective probability of entering a nursing home (the key variable for the analysis in Section 4) until later waves.

The question thus does not specifically target long-term care insurance coverage. It yields an estimated coverage rate of just over 2 percent, substantially below what other analyses have indicated for this time period (see e.g. Cohen, forthcoming and citations therein). Our concern about the accuracy of long-term care insurance coverage measurement in the 1993 AHEAD was corroborated by the staff of the HRS (email correspondence with David Weir, Assistant Director of HRS, April 2002).

With the 1995 question, the reported coverage rate in the 1995 wave was 10 percent. This estimate roughly matches that of Cohen (forthcoming) who estimates – based on industry survey data – that 3.5 to 4.0 million Americans have private long-term care insurance. (Although people of any age may hold long term care insurance, it tends to be held by the elderly (HIAA 2000a)). By means of comparison there are about 35 million individuals aged 65 and over in the United States (U.S. Bureau of the Census, 2000).

The long-term care insurance question was altered again in 1998 to define long-term care insurance as a policy covering *stays of a year or more*, in order to distinguish long-term care policies from policies that cover short stays related to acute care. The mean coverage rate did not change and we have found our results to be robust to the use of the 1998 measure in lieu of the 1995 measure.

A note on other covariates

Cognition: Cognitive functioning is an important factor in considering potential nursing home use, and our understanding is that insurance companies pay a great deal of attention to assessing cognitive limitations. Insurance companies ask directly about cognitive impairment and use other techniques such as interviews to assess cognition. (One company asks for a hand-written statement.) Fortunately AHEAD provides numerous measures of cognition allowing for a rich measure. We follow Mehta et al. (2002) who work specifically with AHEAD and use a modified version of the Telephone Interview for Cognitive Status (TICS) score. A score of 8 or less on a scale of 35 is used as our definition of cognitive impairment. The questions that are used in the TICS include the respondent's ability to report the day and date, count backwards from 20, count backwards from 100 by 7, define a set of commonly used words, and remember a list of words (immediate and delayed recall). For proxy respondents, cognitive ability was based on assessments offered by the proxy.

Depression: Our measure of depression also follows that used in Mehta et al. (2002) and is based on the CES-D8. We use scores of 3 (out of 8) or greater as an indicator of depression. The CES-D8 questions ask if the respondent considers himself depressed, whether he feels that everything he does is an effort, if he has trouble sleeping, feels happy, lonely, sad, and enjoys life. (The scaling of "happy questions" is inverted in summing the responses.) Based on this measures, 20 percent of our sample is categorized as depressed. This measure is not available for proxy respondents. An indicator of a proxy interview is included in the regressions and the depression measure is set to zero.

Alcohol uses: Although many insurance companies query respondents about drinking, we could find no commonly accepted survey measure of a drinking problem. We define 3 or more drinks per day as a drinking problem.

BMI. Insurance companies collect information on individuals' height and weight. We used this to construct a measure of body mass index (BMI) defined as weight in kilograms divided by height in meters squared. We include controls for extreme BMI (above 30 or below 20) as an indicator of poor health. A BMI of 30 or more is considered obese, and a BMI of 18.5 or less is considered underweight according to the Centers for Disease Control and Prevention (<http://www.cdc.gov/nccdphp/dnpa/bmi/bmi-adult.htm>). The results are not sensitive to instead including height and weight linearly in the regression in place of our categorical measure of BMI.

Assets. Household assets are defined as total bequeathable assets (including housing wealth but not Social Security or Defined Benefit pension wealth) less debts.

Missing values: Some of our regressions include a very rich set of covariates, particularly for current health and medical history. A few of these variables are missing for relatively large fractions of the sample. In order to retain observations with missing values in our regression analyses we use dummy variables to indicate a missing value on a variable, and set the variable itself equal to zero. Similarly, some questions were not asked of proxy respondents. We thus include a dummy variable indicating that the interview was conducted by proxy (9% were), and set the value of the unasked variable to zero. The results are not sensitive to dropping any observations with missing values from the sample.

Restriction of sample to individuals who are not likely to view Medicaid as a good substitute

In addition to having low income, Medicaid coverage essentially requires the spend-down of nearly all assets.⁴⁹ We therefore define a restricted sub-sample that consists only of those individuals who are unlikely to qualify for Medicaid. We experimented with several approaches to restricting the sample. In the estimates we report in the paper, we select as Medicaid-ineligible only those respondents who are in the top quartile of either the income or asset distribution. This restriction eliminates two-thirds of the original sample. Our measure is similar in spirit to Cutler and Gruber's (1996) measure of "conditional coverage" by Medicaid among the non-elderly.

Restriction of sample to "eligibles". We identified current insurance company denial practices using information from long-term care insurance applications as well as underwriting guides from the insurance company. This information of course reflects current (2002) denial practices, while we are analyzing insurance coverage in 1995. We therefore investigate the consistency of practices over time. Murtaugh et al. (1995) collected information on long-term care insurance denial and pricing practices in the late 1980s using sources similar to those we employ in 2002. Their description suggests that the basic practice has not changed much of time. This pattern was confirmed in conversations with actuaries and we are therefore comfortable with our definition.

The measure of eligibility used in the paper uses denial criteria that are common across the current applications of several major insurance companies as well as the older applications described in Murtaugh et al. (1995). The three criteria are: limitations with respect to activities of daily livings (bathing, eating, dressing, toileting, walking, and maintaining continence), use of mechanical devices (wheelchair, walker, crutches, quad cane, oxygen) or cognitive impairment. There are a few cases where some companies employ additional tests. We do not use these additional criteria because any item that is limited to a single firm (or to a handful of firms) may be non-binding; an individual who is denied based on this uncommon parameter can simply apply to another company that does not impose the same restrictions. We experimented with stricter definitions of eligibility in which criteria used to deny individuals in several firms were also used to exclude them from the eligible sample; the results were not sensitive to this alternative approach.

Based on this algorithm, we classify 40% of the sample as ineligible for long-term care insurance. Our algorithm is likely to overly restrict the eligible sample because it is based on *current* health conditions and individuals may have applied at a younger age when they would likely have been in better health. Consistent with this strict selection, those ineligible, based on our definition, have only a slighter lower long-term care insurance coverage rate than the general population (9.6 vs. 10.4 percent). However, even in the population, ineligibility is a non-trivial phenomenon. Weiss (2002) reports that approximately 15% of non-group long-term care insurance *applications* are denied. Murtaugh et al. (1995) estimate that between 12 and 23% of 65-year olds would have their applications denied if they applied for insurance and that between 20 and 31% of 75-year olds would be denied. Merlis (2003) estimate that over 20% of individuals aged 60 to 64 and almost 40% of individuals aged 75 – 79 would be denied insurance.

⁴⁹ There is a substantial asset allowance for a non-institutionalized spouse that is excluded from the determination of Medicaid eligibility (AARP, 2000).