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ABSTRACT

This paper provides an empirical estimate of "price" and "risk" elasticities of demand for term life insurance for those who purchase some insurance. It finds that the elasticity with respect to changes in premiums is generally higher than the elasticity with respect to changes in risk. It also finds that the elasticity, in the range of -0.3 to -0.5, is sufficiently low that adverse selection in term life insurance is unlikely to lead to a death spiral and may not even lead to measured effects of adverse selection on total purchases.

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Introduction

To many economic theorists, adverse selection seems a pervasive characteristic of insurance markets. This position seems eminently reasonable. Not only does it seem virtually certain that insurance buyers will have some information on the probability or amount of loss that insurers lack, but real world insurers seem obsessed by the thought that those who agree to buy from them must know something to make that purchase an unusually good deal.

In the face of this theoretical and practitioner consensus, some recent high-quality empirical economic work is finding the opposite: signs that, in both life and health insurance markets, there is no detectable adverse selection (Cawley and Philipson 1999; Cardon and Hendel 2001).

While the authors of both articles interpret their results as evidence that, in some way, insurers must have found out everything insureds know, such a scenario seems implausible on its face. In both settings, the key risk is limited to an individual's health state, and that state is notoriously hard to measure objectively. Witness the skimpy results after enormous effort to measure the quality of medical care by its outcome; external observers have a hard time knowing as much about a person's body as the person does.

However, even if buyers indeed know more than the sellers of insurance, serious adverse selection would not occur if those buyers were sluggish in their willingness to respond to that information. Real consumers, after all, have more on their minds than paying attention to small bargains in insurance markets. In short, low demand responsiveness to risk and premium variation can also cause markets with truly asymmetric information to avoid the instability and bias associated with adverse selection.

This responsiveness depends on two parameters: the response of insurance demanders to changes in risk, given price ("risk elasticity") and the response of insurance demanders to changes in price, given risk ("price elasticity"). In the traditional Von Neumann-Morgenstern theory of choice under risk, the responsiveness (measured by elasticity) to the two influences should be approximately equal and large. The demand for insurance should primarily depend on the relationship of premium to risk, usually summarized by the "loading" ratio. The word "approximately" is included because the income effects of an increase in premium that changes the ratio by a given amount are opposite to those of a reduction in risk that produced the same effect.

In this paper we estimate price and risk demand elasticities for 1year annually renewable term life insurance. We then use these estimates to indicate how a hypothetical (but realistic) information asymmetry would affect this market. Obviously, if information is sufficiently asymmetric, there can always be adverse selection even with very low price elasticity of demand, as long as the elasticity is not zero. We therefore argue that, based on the range of plausible assumptions about variation in risk, information asymmetry would have to be very pronounced indeed for the insurance market to exhibit strong adverse selection effects; the likelihood of a "death spiral" is even lower.

Life Insurance Purchase and Adverse Selection

One difficulty with using observations of existing practices in the life insurance industry to judge the chances of adverse selection is that those practices themselves are probably shaped by the concern buyers and sellers have for selection. That is, both the market equilibrium that prevails and the institutional structures that support it are potentially endogenous.

To be specific: the best-known economic models of insurance markets with adverse selection assume that all insurers have costless and accurate information on the total quantity of insurance each purchaser buys (Rothschild and Stiglitz 1976). Then the instrument insurance firms use to induce lower risks to self-select is a so-called "price-quantity" policy, a combination of premium and the amount of coverage. The institutional feature which permits insurers to have this kind of information is the Coordination of Benefits provision that exists for health insurance and some other types of insurance. These provisions in principle give any insurer the power to determine the total amount of insurance a buyer has and/or to make payments of benefits dependent on truthful prior information about the total amount.

Term life insurance, however, has no such provision. While life insurers will sometimes inquire about how much coverage a prospective buyer already has, there is no mechanism for ensuring truthful revelation and, more to the point, no evidence that the premium for additional coverage is in any way affected by the amount of existing coverage. If insurers thought themselves to be at substantial risk of adverse selection, they might price larger policies at higher unit costs.

However, as Philipson and Cawley point out, the typical-firm-level pricing policy for term life insurance exhibits quantity discounts: unit prices which decline with quantity.

Knowing the total amount of insurance a consumer has bought is important if there is moral hazard as well as adverse selection. The absence of such provisions for term life is consistent with the conclusion that moral hazard is small and that adverse selection is small. However, if observation of the total amount of coverage is itself especially costly, then the main Cawley-Philipson result—that premiums from a given firm fall with quantity from that firm—is not sufficient to indicate there is no adverse selection. As noted below, the decline in premiums with coverage could simply reflect the insurer's administrative cost structure that includes a fixed cost per customer; the approximately constant-over-quantity marginal premium is what one would expect if customers could purchase from multiple sellers (so long as the fixed cost is moderate). No insurer that tried to charge increasing premiums with quantity would be able to sell large policies. Moreover, insurers do increase their medical information requirements for applicants for applicants who apply for policies which are large relative to their "needs;" this may be a defense against adverse selection. In a similar vein, both non-economic and economic (Gokhale and Kotlikoff 2002) planning models for life insurance purchase do not advise potential buyers to adjust their life insurance purchases if they face premiums which vary relative to mortality risk; instead people are advised to buy the insurance their dependents will "need" to replace lost income and maintain a level of consumption, regardless of the level of the premium or the person's risk. That is, buyers are not advised to engage in adverse selection, even when it would be to their private advantage to do so.

An Informal Model of Adverse Selection When Insurance Quantity Is Unknown

We want to model insurance markets with potential adverse selection when insurance firms do not know the total quantity a given individual purchases.

Let us therefore assume that insurers do not know the total (face) amount of life insurance any individual has purchased. Next, let us assume that the annual premium P an insurer would charge for x units of coverage purchased from the firm takes the form

(1) $P=c+bx$

where c is a fixed component of total firm revenue per policy sold, and b is a (constant) marginal price per unit of coverage. There is a fixed component to the premium because there is a fixed component to the administrative cost; the cost of some of the administrative functions (like processing an application for coverage) does not vary with the amount of coverage purchased. The key assumption here is that b (and c, for that matter) depends only on the firm's value of x, not on the total x the person buys from all sources. Of course, once the marginal price is independent of x at any firm, then there is no strong incentive to the buyer to buy from more than one firm.

Assume also that, initially, all buyers have the same level of risk, that they know the level of risk, and that they choose the amount of insurance to buy by maximizing a risk averse utility function, given the premium schedule (1).

What would then be the expected effect of private information for some or all buyers that indicates a change in loss probability from its initial (average) level? If the premium schedule is unchanged, those who discover that they are high risks will optimally buy more coverage, and those who discover that they are lower risks will cut back. How much either type of buyer will change depends on the risk elasticity of demand for insurance.

As a result, the initial premium will no longer cover the firm's benefit costs and administrative expenses. As the insurer raises the marginal premium in the next period to cover the additional benefit costs incurred (now more heavily weighted by the higher risks and less heavily weighted by lower risks), *all* risks will reduce coverage as long as the price elasticity of demand is not zero.

If the price elasticity of demand is uniform, regardless of risk, this reduction in coverage will take the form of an equi-proportional reduction, across all risk classes. Then the process will achieve a new equilibrium at these smaller quantities. There will be no cycle. This result differs from the Rothschild-Stiglitz case. No "death spiral" will have occurred. To produce a death spiral, one would have to assume that the price elasticity of demand is less elastic for higher risks than for lower risks.

However, the net reduction in coverage from the initial no-information-asymmetry case provides a measure of the inefficiency associated with adverse selection. If the reduction in coverage is relatively small in response to a price change, we can say that adverse selection is small.

Toward Empirical Analysis

Somewhat surprisingly, while there have been many studies of the "determinants" of life insurance decisions, there have been few microeconomic studies of the effect of premiums or price on the demand for term life insurance.[3] Such an analysis would be more complex than the typical demand elasticity estimation for several reasons.

First, the total premium for a policy obviously depends on the amount of coverage purchased: it represents total expenditure, or average price multiplied by quantity. However as noted, premiums are not linear in coverage, so that the premium per dollar of coverage is not uniform over the amount of coverage. Because the "fixed price" term c is positive, the average premium usually falls as coverage grows; the marginal premium may or may not be constant.

There is a literature on behavior and empirical analysis of demand in situations where consumers face nonlinear price schedules (Hausman 1985; Hausman and Wise 1980; Nordin 1976). The behavioral models are consistent with our earlier summary; the quantity demanded is determined by responding to the substitution effects from the marginal price and to the income effects associated with the fixed price component.

Second, life insurance is typically sold in national markets, so that there is no obvious or identifiable source of substantial cross-sectional variation in marginal prices. However, premiums do appear to vary across firms for what seems to be similar coverage. Premiums change over time, but much of this change is a response to changes in (perceived) mortality rates. The demand for insurance should depend not on the premium *per se* but on persons' (perceived) mortality rate relative to the premium. The primary source of price variation would then be variation in premiums *not* matched by variations in (perceived) risk. Demand might also change if premiums and mortality rates experience equal proportional changes, because of lifetime income or wealth effects.

Brown and Goolsbee (2002) have argued that the spread of the Internet lowered markups on average term insurance premiums, especially for younger buyers.[4] There may be some eventual hope of finding time series variation in marginal premiums, if either profitability or administrative costs change, but the detailed data on risk-adjusted premiums at the individual level has yet to become available.

The price elasticity of demand for term life insurance is of more than casual interest. Its value determines how total insurer revenues would be expected to respond to price changes. For instance, if demand was greater than unit elastic, the price reduction found by Brown and Goolsbee would be associated with an increase in insurer revenues. But those revenues would fall if demand (in the neighborhood of the current price) was relatively inelastic. More relevant

[3] Babbel (1985) provides a time series study of the relationship between market-level price and the total amount of life insurance demanded in the United States. Eisenhauer and Halek (1999) estimate a model of demand for term life which includes a "loading" variable, but they do not interpret it as the price.

[4] The subsequent increase in rates following insurance regulators' allegations of under-reserving has not been investigated. Presumably under-reserving was most severe for the types of people who use the Internet. It may be good for price but not for quality. If both change, the amount demanded could rise or fall depending on relative magnitudes.

for our purposes, the value of price elasticity determines how much information asymmetry will matter.

A behavioral issue is whether an individual's demand for insurance depends only on the ratio of premiums to expected benefits, the traditional "loading percentage", which in turn implies that the demand elasticity with respect to premium, given risk, should equal the demand elasticity with respect to risk, given premium. This percentage plays the role of price in insurance theory (Ehrlich and Becker 1972), but actual behavior might be different. For example, if doubling premiums (controlling for risk) has an effect on the amounts and types of insurance demanded, would we expect to observe the same or a similar effect if the mortality rate halved, holding the premium constant? Both changes display the same change in the ratio of premiums to benefits.

Another issue, which will be important for our empirical work, deals with consumer information. The premium a person pays is presumably known by that person; the premiums charged by other sellers may, however, only be known imperfectly. An even more serious question concerns consumer perceptions of risk. The right risk measure to use in the behavioral equation is what the consumer perceives to be the risk of death. However, we only have information on the mortality rates calculated ex post, which might or might not be known to the consumer. Take the case of a buyer who is a smoker. The buyer knows that the premium he would have to pay is higher than if he were a non-smoker, but what would he assume about death probability? Would he assume the same death probability as low risks, as the average risk, as the average risk for all smokers (regardless of the volume of smoking), or as the observed death rate for smokers smoking a certain number of cigarettes? Or would he use the difference in premiums as a measure of the difference in risk (Kunreuther and Pauly, 2003). In our analysis we will explore the effect of using a number of measures of relative risk..

Demand Estimation in the Presence of Quantity Discounts

If adverse selection were a serious problem in life insurance markets, if insurers could observe the total quantity of life insurance purchased at the individual level, and if the administrative cost per unit of insurance were constant over units, conventional microeconomic theory would predict that in a competitive equilibrium (if it exists) unit prices would be increasing in the face amount of coverage (Rothschild and Stiglitz 1976). However, empirical evidence from the life insurance market suggests that the unit premium for term insurance declines as the face amount of coverage increases (Cawley and Philipson 1999); these discounts exist both because average administrative and selling costs fall as a buyer purchases a larger policy, and because sellers of insurance are unable to observe the total amount of insurance bought from all sellers. Of course, with average costs falling with quantity, adverse selection would be consistent with unit premiums that decline with quantity as long as the decline is less steep than that of costs.

One key question is whether the alleged failure of life insurers to pay attention to insurance purchased from other sellers is due to a high cost of monitoring insurance quantity or whether it is due to the fact that there is so little information asymmetry about actual risk that knowledge of the total quantity would not be helpful. The answer is probably some of both. Compared to health insurance, say, or even property-casualty insurance, there is no observable benchmark of loss or cost to which life insurance quantities could be compared. Someone who bought health insurance that paid out more than his medical bills, or homeowners insurance that paid more than the damage done by a fire would be an obvious candidate as someone with inside knowledge about risk (not to mention strong incentives for moral hazard before the fact). But there is no objective loss measure associated with premature mortality, and so more difficulty in identifying the high risk by noting "excess" insurance purchases. However, it is also true (according to Cawley and Philipson) that the simple correlation between the amount of insurance purchased and (actual) mortality is inverse, perhaps reflecting other influences on the demand for life insurance that are inversely correlated with mortality (such as income) but also perhaps indicating that buyers do not know more than sellers. Moreover, life insurers do sometimes have stricter underwriting standards for people applying for large amounts of term life insurance; variation in standards with quantity might substitute for variation in unit premiums with quantity.

Due to the presence of quantity discounts, each consumer in the life insurance market faces a downward sloping rather than horizontal supply curve (Cawley and Philipson 1999) at what might be called the "intensive" margin. In this situation, the observed unit or average price and quantity are simultaneously determined by the consumer's demand. This phenomenon adds to the challenge to estimating the price elasticity of demand for term life insurance using consumer-level microeconomic data.

In order to generate an unbiased measure of price elasticity, the price used should be exogenous to the consumer demand framework. There are two reasons why observed prices will not be exogenous. First, estimating the consumer demand equation using an *ex-pos*t unit price paid (calculated from purchase data) will obviously yield a biased price elasticity estimate due to the endogeneity of price in the consumer demand system. However, if the actual price schedules that individuals with a given set of risk characteristics face in the market vary exogenously in a way that can be observed by the econometrician (from offered price schedules), then the marginal price for each risk group can be obtained either directly from the tariff data or by estimating an industry-level pricing equation using firm-level offered premiums as the dependent variable in the regression.[5] But if price schedules do not vary much across observations (because all buyers are purchasing in the same competitive market), or if the prices people find are correlated with demand (for example, because people with stronger demands search more extensively for low prices), elasticity estimates will still be potentially biased. The best solution would be to find exogenous price measures that vary across risk groups. (This is the strategy we follow below.) Alternatively an instrumental variables approach could be used to control for the endogeneity of *ex-post* prices in the consumer demand equation. Good price instruments, however, are hard to find.

The presence of bulk discounts in the life insurance market introduces non-convexities into the consumer's budget constraint. This creates the possibility that there will be multiple tangencies between the consumer's indifference curves and budget constraint set (Taylor 1975; Hausman 1985). In order to uniquely identify parameters in the consumer demand function, two price variables should be included in the demand equation: the marginal price, which captures the price effect on quantity demanded given that a positive quantity of insurance is purchased; and the "fixed cost" to the consumer of the opportunity to purchase insurance beyond the minimum

[5] It is reasonable to assume that term insurance premiums in the United States are set in a national market, and that there is one industry supply curve (Brown and Goolsbee 2002). The group specific marginal price for term insurance is equal to the regression coefficient on the face amount of coverage in a linear pricing equation with a constant term, and is by definition exogenous to the consumer demand system. We ignore possible simultaneity

quantity at a given marginal price (Nordin 1976). The impact of this fixed cost on the size of policy demanded should primarily be that of an income effect, but it may also serve as indicator of self-selection into the sample of buyers. That is, people who buy insurance only at a low fixed price may have lower demands for insurance (on average) than those still willing to buy some insurance even though the fixed price is high. In principle, then, the coefficient on the fixed cost could be positive, suggesting a censoring of observations, or negative, suggesting income effects in quantity demanded.

Price Measure

There are econometric and theoretical justifications for using exogenous measures of marginal price in order to capture how consumers change coverage when the prevailing premiums change. If one wants to recover the parameters in the consumer demand system, it is necessary to control for the two-part pricing of term insurance contracts. We control for the fixed cost to the consumer of being able to purchase life insurance at the offered marginal premium by including the fixed cost in the demand equation (see Taylor 1975; Dubin 1985). As noted above, any effect of the fixed cost will capture the "income effect" on purchasing (for those who demand positive amounts of insurance), while the marginal price measure captures the "price effect" on term insurance demand (Dubin 1985).

Secondly, if a competitive insurer's expected payouts rise because the probability of survival falls, its premiums will also rise. However, almost all of this increase should affect the marginal

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between premium and quantity in the pricing equation, which would arise if insurers set premiums to induce a given level of demand.

price rather than the fixed price, since variations in the mortality rate should not affect the fixed costs of selling insurance. We assume that this property holds both for changes in survival probability, given age, over different years and for changes in survival probability for individuals of different ages at a given point in time. In short, the elasticity parameter that we care about in a life insurance market is the elasticity of demand with respect to the *marginal* premium rather than the total or average premium.

The other characteristic of a price measure is that it should vary to some extent across otherwise identical buyers. The problem here is that term life insurance at any point in time is generally sold in a national market. While posted or quoted prices may vary across firms, there is no obvious reason why buyers with the same set of risk characteristics cannot all have access to the same set of prices, and would therefore all choose the same (lowest) price. If they do not do so, we do not know why.

The absence of a clear source of exogenous variation in prices is an issue in generating unbiased estimates of price elasticity. For example, suppose one plausibly assumes that a demander who would buy more insurance at a given (marginal) price would search more intensively for a low price than a person with a smaller demand. On average, those with stronger demands will then be paying lower prices, but the price measure will be inversely correlated with unobserved terms in the demand equation. More generally, in the empirical estimates which follow, we pay attention to possible exogenous causes for variation in prices. We try to find "market-level" price measures as well as "individual-level" measures.

Data Sources

We do not know exactly which prices consumers were facing and which risk measures they were using to guide their insurance purchasing decisions. Accordingly we experiment with a variety of specifications using different measures of each.

We use two industry data sources to estimate the price elasticity of demand for term insurance. The first is a monthly dataset sold by CompuLife that contains firm-level premium data for term life insurance contracts of 17 different sizes from all major companies in the US market in every state. The CompuLife datasets are used by life insurance agents to compare premium offerings across companies, and are generally thought to contain accurate premium information. In the CompuLife datasets, premium offerings are broken down by the risk characteristics of the insured persons, including their age, sex, smoking status and health status.

The presence of multiple insurers raises the questions of what quantity premium schedule to use. Should it be that of a single "typical" insurer, or should it be a composite of those of all insurers offering contracts to a given risk group? A buyer who selects a firm making the best offer for one quantity of insurance is not obliged to use that firm for other quantities. Also, not all insurers offer contracts of all sizes to a given risk group, so buying from the same firm may not be an option.

We use two alternative estimates of "market" price schedules to test the robustness of our estimates. In one, we use the premium of the median firm in each demographic cell-quality combination. In the other, we use, as data for the premium regression, the premiums posted by all firms weighted by the number of offers in a given policy size category. These weights, which sum to 1 for each policy size, are necessary because the number of offers vary significantly across the 17 different policy sizes in the CompuLife dataset.

We first use the January 1997 CompuLife dataset to estimate term insurance pricing regressions for 1-year level term contracts for the median firm in the market as of January 1997 for each risk class separately. We use two statistical methods to estimate a linear pricing equation for the term insurance industry. Insurance premiums vary across states, but only to a very modest extent. We therefore look at premiums offered by the median firm in the largest state (California) to 30, 40, 50 & 60 year olds for all 48 possible combinations of the sex, smoking and health status categories. We interpolate the estimated marginal prices and fixed costs by single year of age for all the relevant risk groups to reflect the pricing gradient by age controlling for all other risk factors. There are 48 separate pricing regressions, each with 17 different values for the quantity of coverage. We then use the average and marginal prices estimates from these regressions as explanatory variables to explain the variations in the amounts of coverage purchased by consumers in another data set, from LIMRA International. The second specification for the pricing regression makes use of premium offerings from all firms (weighted by the number of policy size offers in a given contract size class) in the California market to estimate a similar pricing equation which is used in a similar way.[6] Using the marginal price and fixed cost estimates from the two general techniques described above, we therefore estimated demand

[6] We considered estimating the pricing equation with firm-level fixed effects. However, that technique would be relevant only if consumers typically chose a firm in advance and considered only its price schedule for different amounts of coverage. However, it is surely possible that a firm with the lowest price for, say, $50,000 of coverage

regressions using (as the "exogenous" premium) the estimated marginal premium per $1000 coverage. This "market" premium varies across risk groups, not individuals, and is independent of the quantity of term insurance purchased, thereby reducing concerns about endogeneity bias.

To explore the effect of possible variation in premiums across persons, we used a second type of measure: a person-specific marginal premium. This measure of premium is constructed from the premium reported in the same LIMRA data used for the total quantity of coverage purchased. We estimate a person-specific marginal premium by subtracting the class-average fixed cost from the CompuLife pricing regressions from the annual premium the person paid for the life insurance contract, and then dividing that number by the quantity of coverage purchased. Exactly why different individuals would pay different premiums for the same coverage is unclear; it might be related to consumer search behavior. If so, the price paid is to some extent endogenous, so these results should be interpreted with caution; we should expect these measured elasticities to be higher in absolute value than in the first case. We also use another person-specific premium: the ratio of annual premium paid (for the quantity purchased) divided by the predicted premium based on the person's fixed cost and marginal price coefficients from the CompuLife pricing regressions.

Consumer-level data on the quantity of new term life insurance purchased is taken from the 1997 US Buyer's Study sold by LIMRA International. The 1997 LIMRA Buyer's study consists of a random sample of policies bought by customers in a given year by over 35 life insurance companies comprising approximately half of the life insurance market in terms of number of

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might not be the lowest price if the person wanted to buy $500,000 of coverage. Thus, the within-firm marginal price would not represent the price schedule a consumer faces.

policies sold (LIMRA 1998). We analyze data from the 1997 LIMRA Buyer's study since it is the most recent dataset available for purchase. The term life insurance market has undergone significant changes in market structure during the 1990s associated with market entry and the introduction of on-line search engines for term insurance (Brown and Goolsbee 2002). Because the increase in market competition in the 1990s may have caused a structural change in the price elasticity parameter, we focus our analysis on the most recent year available.[7]

The LIMRA data also contains information on the attributes of the life insurance contracts sold and the basic demographic characteristics of the buyers. The data include information on the amount of coverage purchased, the annual premiums paid, the amount of existing life insurance coverage in force, the term lengths of the contracts, riders attached to the policies, the annual premium, the month and year of purchase, and basic demographic information on insured persons, including: age, sex, income, occupation, marital status, and receipt of a non-smoking discount. Individual company identifiers were masked. Weights are provided to make the sample representative of the policies sold at the contributing firm level.

Some of the key factors that are known to influence life insurance demand (but usually not premiums)—like self-evaluated current health status, number of children, income and wealth—are either completely missing, or are not available for a large number of observations in the LIMRA data. (For example, even family income data is missing for about a third of the observations.) We report regression results using the large LIMRA sample in which individual observations are augmented by median household income by zip code from the 1990 US Census.

[7] In separate analyses not reported here we estimate the price elasticity of demand for term insurance using the 1993 and 1995 LIMRA Buyer's datasets, and find that there has been an increase in the price elasticity of demand during

Although additional socio-demographic controls are available at the zip code level from the 1990 census, we do not include these controls due to concerns about measurement error.

While using Maximum Likelihood estimation with an error components error structure will enable us to control from biases arising from sample truncation inherent to using purchase data to model consumer demand, we are nevertheless without information on what determines whether someone buys any life insurance, and, specifically, on the effect of price on this choice.

Mortality Risk

The mortality risk measure used in the demand regressions is the national average annual probability of dying during the period of coverage for all individuals with a given set of age, sex, health status, and (in some cases) smoking characteristics. This measure was calculated using mortality data from the 1997 U.S. Life Tables published by the National Center for Health Statistics (see Anderson 1999, and National Center for Health Statistics 1997 & 1998). Sex-age-specific mortality data on the number of survivors at various years of age in 1997 were used to estimate the percent of people that will die during the period of term life insurance coverage based on the age of the insured person at the beginning and end of term insurance coverage. The mortality risk variable included in the regressions is the natural log of this annual mortality risk estimate, which varies across individuals. Using data on the relative risk of dying (over a one-year period) between smokers and non-smokers across various age intervals published in Rogers and Powell-Griner (1991), and data on smoking prevalence by age group from the Centers for

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the decade of the 1990s (LIMRA 1996; LIMRA 1994).

Disease Control and Prevention (1998), we adjust the mortality risk for smoking status.[8] The smoking status adjustments were necessarily imperfect, so we show results with and without this imperfect adjustment.

CompuLife Pricing Regressions

We use the CompuLife dataset to estimate industry-level pricing regressions for 1-year annually renewable level term contracts for the median firm in the market as of January 1997. We first define risk groups based on the age, sex, smoking and health status of the buyers. Companies with all ratings are used in the analyses. In 1997, the CompuLife data require that we view premium and contract offerings by state. Based on conversations with life insurers, we assume that median premiums are unlikely to vary significantly across states (with the exception of New York, where state withholding regulations affect premiums).[9] We also expect variation in the degree of market competition—and hence premiums—to be minimal across states (Brown and Goolsbee 2002).

We limit our sample to 1-year annually renewable term contracts priced for 30, 40, 50, and 60-year old males and females for all possible combinations of the smoking and health status categories. Separate pricing regressions are estimated for each risk group. We priced contracts

[8] The adjustment assumes that the relative death risk between smokers and non-smokers is equal to the 1 year relative death risk published in Rogers and Powell-Griner (1991). In order to obtain the 1 year death risk measure for smokers, we use a weighted average of the light and heavy smoker death rates published in Rogers and Powell-Griner (1991). We assume that for all age groups 83 percent of smokers are light smokers and 17 percent of smokers are heavy smokers (American Lung Association, 2002). The adjustment may introduce measurement error into the smoking-adjusted mortality estimate since the adjustment for smoking requires that we use smoking prevalence estimates that are aggregated by 5-year age intervals and approximations for the distribution of light and heavy smokers in the smoking population. The key question, of course, is what different buyers *perceive* to be their risk.

for 17 different policy sizes among firms offering life insurance contracts in California in 1997.[10] The premium regression equation estimated is then:

(2) Offered Premium=a_j+P_jQ +ε

where Q is the term insurance face amount for individuals in risk group j in January 1997. Then a_j is the estimated fixed cost for each risk class and P_j is the estimated marginal price. As mentioned above, we estimate pricing equation (2) using two different sample—premium offerings from the median firm in the market (Tables 1a and 1b), and premium offerings from all firms in the market pooled and weighted (Tables 2a and 2b). We then interpolate fixed costs and marginal premiums by single year of age to more accurately reflect the age pricing gradient for each risk group.

Separate pricing regressions are estimated for each risk group. Tables 1a and 1b show the estimated marginal premiums from the different pricing specifications we tried using the CompuLife data.[11] The pricing equation approximates the actual tariff schedule that individuals of a given risk class face in the market for the "median" firm in the market. The R^2 for most of these pricing regressions is close to unity, which indicates that a linear pricing schedule above a fixed cost fits the data well. Table 1b shows marginal premium estimates when we include all premium offerings in the market.

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[9] Telephone conversation with Bob Barney, President of CompuLife, March 2002.

[10] We price level term insurance policies for the following face amounts: $50 K, $100 K, $150 K, $200 K, $250 K, $300 K, $350 K, $400 K, $500 K, $750 K, $1 million, $2 million, $3 million, $5 million, $10 million. $15 million & $25 million.

[11] The marginal price estimates are the regression estimates multiplied by 1,000, or the marginal price per $1,000 of coverage.

Estimated marginal prices always decline with improved health status holding other risk factors constant. Marginal prices at any age are higher for males than for females, as well as for smokers than for non-smokers. Marginal prices also increase with age holding all other risk factors constant. There is not a large difference between the "preferred" and "preferred-plus" health categories. We tested whether marginal prices varied over units, and could not reject the hypothesis of constancy.[12]

Tables 2a and 2b show the estimated fixed cost (or the "average premium" component of the premium per policy) for all risk groups using the two different specifications for the CompuLife life insurance pricing equation. These fixed cost estimates are the intercept terms of the estimated Compulife regression equations and are used to calculate the value of the marginal premium that varies across individuals rather than risk groups after interpolating for single year of age. Differences in the estimated intercept term across groups reflects differences in costs (associated with medical underwriting, etc.) inherent to selling any coverage to individuals in a given risk category. These estimates are generally in the range of $40-$70 per contract. (By way of illustration, a fixed component of $70 would amount to 31% of the annual premium for $100 thousand of coverage for a non-smoking 40-year-old male.) The estimates for ages 50 and 60 vary a great deal, but relatively few new term policies are sold at this age. (A negative fixed price would, however, imply the existence of adverse selection).

Estimation of Demand Elasticities

We focus our analysis on the purchase of 1-year annually renewable level term contracts, or the "spot market" for term insurance in 1997.

Econometric Methodology

The LIMRA Buyer's data is not a random sample. Rather sample selection occurs on the basis of whether or not a contract is purchased. Accordingly, a truncated regression model is used to estimate the price elasticity of demand.

The smallest contract size sold in 1997 is \$2,500. We do not observe the purchase of any life insurance contracts with a face amount less than \$2,500 because smaller life insurance policies are not sold by insurers. Data on non-purchasers for whom Q_i=\$0 is not observed. Hence the selection equation for the LIMRA data, which defines the subset of the population included in the sample, is:

(3) $S_i=1[\$2,500 < Q_i < \infty]$

where S_i=1 if individual i is included in the sample, and S_i=0 when individual i is excluded from the sample.

[12] Cawley and Philipson (1999) also report that conversations with life insurers suggest that insurers rely upon a linear rather than non-linear incremental pricing schedule to price term insurance contracts, and their own regression results from this data show insignificant quadratic terms.

The selection rule allows us to characterize the subset of the population excluded from the LIMRA sample. Although we cannot use the price elasticity coefficients based on a sample of life insurance purchasers to infer the price elasticity of non-purchasers, the price elasticity of demand conditional on having decided to purchase a life insurance contract is still of interest because it measures the price sensitivity of purchases on the *intensive* margin.

In order to obtain consistent and efficient estimates of the parameters in the conditional consumer demand equation will need to specify the conditional distribution of Q_i given X_i and S_i and use maximum likelihood estimation. We assume that the conditional distribution is normal with mean $X\beta$ and variance σ^2, where X is a matrix of control variables that enter the consumer demand equation. The relevant estimation technique is the truncated normal regression model that can be carried out in SAS.

Sample Definition

We limit the sample to include adults who bought level term contracts with no rider or a level term rider on their own lives. We exclude contracts that are part of an employee benefit plan, that are not owned by the insured person, or that contain missing data on the smoking status of the insured. We exclude military sales and sales by home service companies.

Price Measures

We report regression results using three price definitions. The first price definition uses the estimated CompuLife *marginal* price for the person's risk group interpolated for single year of age as the exogenous price measure in the consumer demand equation. This price is the fitted coefficient P_j from equation (1) for individuals that belong to risk group j. Implicitly, the assumption is that this "average marginal" price for the person's risk group is independent of the other terms ("tastes") in that individual's demand function. The LIMRA data do not contain information the health characteristics of the buyers even though life insurers are known to condition their premium offerings on health status indicators. We therefore use the mid-point between the CompuLife regular and preferred-plus marginal and average prices for each risk group as the relevant price measure for individuals in the LIMRA sample. We assume that the insurer does know smoking status of the insured.

The regression also controls for the (observed) mortality rate in the person's risk group. Thus, over all observations, it is presumably variation in the relationship between marginal prices and risk across risk cells that generate variation in the net cost of insurance. For example, if two cells have the same mortality rate, but different marginal premiums, we would expect to see different amounts of insurance demanded. The Brown-Goolsbee results on the effect of the Internet would suggest, for example, that this price measure should be lower for Web-using younger people.

The second price definition uses an individual-level marginal premium as the exogenous price measure. We calculate the person specific marginal price by using the average price estimate by risk group (interpolated by single year of age) from the CompuLife pricing regressions, and data on total premium paid and face amount of life insurance coverage purchased from the LIMRA datasets. The relevant equation is:

(4) $[Premium_i - a_j]/Q_i = P^*_i$

where a_j is the estimated constant term in the CompuLife pricing regression for risk group j (see equation 2). Unlike the CompuLife marginal prices, P_i^* varies across individuals.

The third price definition uses a relative premium measure which varies across individuals. This relative premium measure is the ratio of total premium paid divided by predicted CompuLife premium. The predicted Compulife premium for each individual is:

(5) Predicted $Premium_i = a_j + P_j * Q_i$

where a_j and P_j are the estimated coefficients from the CompuLife pricing equation (2) interpolated by single year of age. We include the log of the ratio of the annual premium paid to the predicted premium based on the CompuLife coefficient estimates as exogenous price variable in the relative premium specification.[13]

Regression Specification

[13] A fourth price expression would estimate the marginal price direct from the LIMRA data. The problem here is that the price paid is endogenous in the consumer demand system. Preliminary estimates of demand equations based on such a measure gave implausible positive price elasticities.

We assume that the consumer demand equation for term life insurance has the following general form:

(6) $Q_i = C\ P^{\beta} FC_i^{\psi} R_i^{\gamma} Z_i^{\delta} \exp(\varepsilon_i)$

where Q_i is the face amount of term life insurance purchased, C is a constant term, P is one of the marginal premium measures, FC_i is the estimated fixed cost, R_i is the individual mortality risk variable, and Z_i are demographic controls that affect life insurance demand, including income, age, sex and marital status. The regression equation has a log-linear form, since some of the controls included in the Z_i matrix are binary variables.

Taking logs, we estimate the following empirical demand equation using Maximum Likelihood:

(7) $\ln Q_i = \phi + \beta \ln P + \psi \ln FC_i + \gamma \ln R_i + \delta Z_i + \varepsilon_i$

where the marginal price measure (P) is the CompuLife marginal price (P_j), the person-specific marginal price (P_i^*), or a relative price, which is the annual premium paid divided by the predicted premium given the quantity purchased and using the fixed and marginal price coefficients from the CompuLife regression to predict the premium. The dependent variable is the log of the total coverage purchased.

Results

Tables 3 and 4 show the estimated demand regressions using the marginal premiums calculated from the CompuLife data for the median-premium insurer in each cell. In both cases the estimated price elasticity is approximately -0.5; the estimated risk elasticity has a positive and statistically significant elasticity in the range from 0.16 to 0.29. The fixed cost component of the premium is positive but not statistically significant. Other significant variables include median income by zipcode, with an expected positive sign, female sex with an expected negative sign, and significantly higher demand in New England relative to the Midwest. The quarterly dummies are not statistically significant, which suggests that life insurance demand is not seasonal.

Table 5 shows the price and risk elasticities for several other different specifications of the price variable and of the data set used to estimate the price variable. The estimated values of the price elasticities vary little; price elasticity generally varies between -0.41 and -0.58. The risk elasticities tend to be higher when the all-firm estimate of marginal price is used; in some specifications they are also in the neighborhood of 0.5. When the relative premium is used as a measure of price, the smoking-adjusted risk elasticity is either statistically insignificant or negative in sign. In the majority of cases, however, the risk elasticity has a point estimate which is positive but is lower (in absolute value) than that of the premium "price" elasticity. The elasticities tend to be approximately the same in the market-price and individual-price specification, suggesting no endogeneity bias.

An analysis of the goodness-of-fit statistics suggests that the fit is better when risk is adjusted for smoking for the specifications using the CompuLife or individual marginal premia. When the relative premium is used, the fit is worse with smoking adjusted risk. However, the relative premium measure itself does not provide as good a fit as do the other two price measures. In addition, the relative premium measure is likely to be partly endogenous because it is calculated from the actual premium paid.

To sum up: the price (or marginal) premium elasticity of demand is estimated to be in the range of -0.31 to -0.58; this finding is robust with regard to measures of marginal price in the demand system. The elasticity of coverage with respect to mortality risk is generally positive and statistically significant, but ranges in value from 0.2 to 0.5. The coefficient on mortality risk is usually smaller than the coefficient on marginal premium, suggesting that proportional loading does not entirely determine quantity demanded. These results indicate that people do pay attention to premiums they face and their own risk of needing benefits; the "needs" model favored by insurance advisors is strongly rejected. However, although people do respond to premiums and expected benefits, their response is relatively modest in magnitude.

Conclusion

These results suggest that the elasticity of demand for 1-year level term life insurance contracts is about -0.4 to -0.5. It is more price sensitive than the insurance "needs" models would assume, but is still only moderately responsive. Demand is usually less sensitive to risk than to premiums although the risk term is usually positive and statistically significant.

If there is asymmetric information, the interpretation of this result depends on the extent and importance of that information. If the portion of the population receiving information about large differences in death risk probabilities is substantial, adverse selection can occur even with a low price elasticity. However, these results are consistent with the view that life insurance markets can remain reasonably stable even with information asymmetry on individual mortality risk (when the variation in information is also modest, insurers are unable to observe the total amount of insurance purchased).

Another finding is even more important for the model (but somewhat less reliable in the empirical estimation method). For the process of adverse selection even to begin as a result of information asymmetry, consumers must start the process by choosing substantially different amounts of insurance when their perceived risks are altered by information. The usually lower risk elasticity implies that the first step in the process, a response in terms of desired insurance quantity to changes in risk with premiums held constant, may be small.

Our results suggest that life insurance purchasers engage in behavior (or, more accurately, non-behavior) which greatly mitigates the effect of asymmetric information about individual risk between insured and insurer in term life insurance markets. It would, of course, still be possible for asymmetric information that secretly and substantially changed loss probabilities for a large portion of the population to cause adverse selection. But as long as any substantial information asymmetry is concentrated in a small population share, and as long as any large group's information asymmetry is small, adverse selection will not occur.

Whether these elasticities are "small enough" to avoid symptoms of adverse selection depends on what we assume about the extent of information asymmetry. Chronic conditions generally affect only about 15 percent of persons aged 45 (in the midpoint of the data), but most chronic conditions are detectable. More plausibly, people may have some idea of how they feel physically, but the information content of differences in this information is likely to be low.

For example, suppose 5 percent of buyers have information that suggests that their mortality rate is three times greater than the standard (200% greater). (This is the magnitude of the impact of a positive genetic test for the breast cancer gene on female survival (Subramanian et al, 1999).) If they respond to this information with an elasticity of 0.4 (and other buyers respond to the absence of information that they are high risks), the overall risk level per dollar of purchased coverage will rise by only 8.6 percent. The subsequent reduction in insurance purchases by lower risks would be only 3.4 percent (using the same elasticity). Moreover, as noted above the high risks will also reduce their insurance purchases so that there may be only weak subsequent adjustments. This is not enough of a response to provoke a death spiral or even a large reduction in coverage.

One might suppose that the result that small amounts of special information for many or large amounts of special information concentrated only on a few does not distort the market is close to the Cawley and Philipson conclusion of no adverse selection. Had demand or risk elasticity been substantially greater (even in the "small difference" or "small numbers" cases), the conventional models could lead to a prediction of serious problems. Our results suggest that this case does not arise. Adverse selection behavior may fail to be manifested not because sellers know as much as buyers, but rather because buyers have more important things to care about than reacting to asymmetric information in life insurance markets.

References

American Lung Association Best Practices and Program Services Epidemiology and Statistics Unit, "Trends in Tobacco Use," (June 2002), http://www2.lungusa.org/data/smoke/SMK1.pdf, 12 May 2003.

Anderson RN, "United States Life Tables, 1997," *National Vital Statistics Reports* (December 13, 1999); 47(28).

Anderson RN, "United States Life Tables, 1998," *National Vital Statistics Reports* (February 7, 2001); 48(18).

Babbel DF, "The Price Elasticity of Demand for Whole Life Insurance," *Journal of Finance* (March 1985); 40(1): 225-239.

Barney B, Telephone conversation with Kate H. Withers, March 2002.

Brown J, Goolsbee A, "Does the Internet Make Markets More Competitive?" *Journal of Political Economy* (June 2002); 100(3): 481-507.

Cardon J, Hendel I, "Asymmetric Information in Health Insurance: Evidence From the National Medical Expenditure Survey," *RAND Journal of Economics* (Autumn 2001); 32(3): 408-427.

Cawley J, Philipson T, “An Empirical Examination of Information Barriers to Trade in Insurance,” *American Economic Review* (September 1999); 89(4): 827-846.

Centers for Disease Control and Prevention, Division of Adult and Community Health, National Center for Chronic Disease Prevention and Health Promotion, “Behavioral Risk Factor Surveillance System Online Prevalence Data, 1995-2001,” http://apps.nccd.cdc.gov/brfss/index.asp, May 7, 2003.

Dubin JA, “Rate Structure and Price Specification in the Demand for Electricity,” Chapter 4, Consumer Durable Choice and the Demand for Electricity (Amsterdam, The Netherlands: Elsevier Science Publishers, 1985): 123-153.

Eisenhauer JG, Halek M, “Prudence, Risk Aversion, and the Demand for Life Insurance,” *Applied Economics Letters* (April 1999); 6(4): 239-242

Ehrlich I, Becker GS, “Market Insurance, Self-Insurance, and Self-Protection,” *The Journal of Political Economy* (July/August 1972); 80(4): 623-648

Gokhale J, Kotlikoff LJ, “The Adequacy of Life Insurance,” *TIAA-CREF Institute Research Dialogue* (July 2002); 72.

Hausman JA, “The Econometrics of Nonlinear Budget Sets,” *Econometrica* (November 1985); 53(6): 1255-1282.

Hausman JA, Wise D, "Discontinuous Budget Constraints and Estimation: The Demand for Housing," *Review of Economic Studies* (January 1980); 47(1): 75-96.

Kunreuther H, Pauly MV, "Neglecting Disaster: Why Don't People Insure Against Large Losses?" Forthcoming in *The Journal of Risk and Uncertainty*.

LIMRA International, "The Buyer Study United States: A Market Study of New Insureds and the Ordinary Life Insurance Purchased" (Hartford, CT: LIMRA International, Inc., 1998).

LIMRA International, "The Buyer Study United States: A Market Study of New Insureds and the Ordinary Life Insurance Purchased" (Hartford, CT: LIMRA International, Inc., 1996).

LIMRA International, "The Buyer Study United States: A Market Study of New Insureds and the Ordinary Life Insurance Purchased" (Hartford, CT: LIMRA International, Inc., 1994).

Nordin JA, "A Proposed Modification of Taylor's Demand Analysis: Comment," *The Bell Journal of Economics* (Autumn 1976); 7(2): 719-21.

Rogers R, Powell-Griner E, "Life Expectancies of Cigarette Smokers and Nonsmokers in the United States," *Social Science Medicine* (1991); 32(10): 1151-1159.

Rothschild M, Stiglitz JE, "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," *Quarterly Journal of Economics* (November 1976); 90(4): 630-649.

Subramanian K, et al., "Estimating Adverse Selection Costs from Genetic Testing for Breast and Ovarian Cancer: The Case of Life Insurance," *The Journal of Risk and Insurance* (December 1999); 66(4): 531-550.

Taylor LD, "The Demand for Electricity: A Survey," *The Bell Journal of Economics* (Spring 1975); 6(1): 74-110.

Table 1a.
Marginal Premium Per $1000 Coverage from Median Firm Pricing Regression
1997 CompuLife Data. Linear Pricing Equation. Only Premium Quotations from Median Firm in Market Used in Pricing Regressions

Sex	Age	Smoker	Health Status	Marginal Premium Per $1000 Coverage	StdErr	tValue	Probt		Sex	Age	Smoker	Health Status	Marginal Premium Per $1000 Coverage	StdErr	tValue	Probt
FEMALE	30	NO	Preferred-Plus	0.728	0.000	544.337	0.000		MALE	30	NO	Preferred-Plus	0.816	0.000	659.321	0.000
FEMALE	30	NO	Preferred	0.737	0.000	614.031	0.000		MALE	30	NO	Preferred	0.818	0.000	1558.431	0.000
FEMALE	30	NO	Regular	0.783	0.000	803.484	0.000		MALE	30	NO	Regular	0.903	0.000	1537.827	0.000
FEMALE	30	YES	Preferred-Plus	1.268	0.000	1073.171	0.000		MALE	30	YES	Preferred-Plus	1.548	0.000	3068.536	0.000
FEMALE	30	YES	Preferred	1.268	0.000	1073.171	0.000		MALE	30	YES	Preferred	1.548	0.000	3068.536	0.000
FEMALE	30	YES	Regular	1.381	0.000	1091.681	0.000		MALE	30	YES	Regular	1.655	0.000	2743.886	0.000
FEMALE	40	NO	Preferred-Plus	0.896	0.000	409.410	0.000		MALE	40	NO	Preferred-Plus	1.023	0.000	376.194	0.000
FEMALE	40	NO	Preferred	0.906	0.000	394.382	0.000		MALE	40	NO	Preferred	1.027	0.000	535.878	0.000
FEMALE	40	NO	Regular	1.008	0.000	739.869	0.000		MALE	40	NO	Regular	1.116	0.000	752.636	0.000
FEMALE	40	YES	Preferred-Plus	1.737	0.000	1291.520	0.000		MALE	40	YES	Preferred-Plus	2.240	0.000	916.849	0.000
FEMALE	40	YES	Preferred	1.737	0.000	1291.520	0.000		MALE	40	YES	Preferred	2.240	0.000	916.849	0.000
FEMALE	40	YES	Regular	1.855	0.000	2751.044	0.000		MALE	40	YES	Regular	2.280	0.000	4582.768	0.000
FEMALE	50	NO	Preferred-Plus	1.404	0.000	484.742	0.000		MALE	50	NO	Preferred-Plus	1.878	0.000	219.700	0.000
FEMALE	50	NO	Preferred	1.414	0.000	564.699	0.000		MALE	50	NO	Preferred	1.906	0.000	206.038	0.000
FEMALE	50	NO	Regular	1.577	0.000	494.087	0.000		MALE	50	NO	Regular	2.150	0.000	1250.823	0.000
FEMALE	50	YES	Preferred-Plus	2.959	0.000	1164.831	0.000		MALE	50	YES	Preferred-Plus	4.296	0.000	902.804	0.000
FEMALE	50	YES	Preferred	2.959	0.000	1164.831	0.000		MALE	50	YES	Preferred	4.296	0.000	902.804	0.000
FEMALE	50	YES	Regular	3.212	0.000	441.718	0.000		MALE	50	YES	Regular	4.551	0.000	372.326	0.000
FEMALE	60	NO	Preferred-Plus	3.066	0.000	391.654	0.000		MALE	60	NO	Preferred-Plus	4.584	0.000	925.375	0.000
FEMALE	60	NO	Preferred	3.072	0.000	446.524	0.000		MALE	60	NO	Preferred	4.642	0.000	385.020	0.000
FEMALE	60	NO	Regular	3.382	0.000	504.696	0.000		MALE	60	NO	Regular	5.228	0.000	356.921	0.000
FEMALE	60	YES	Preferred-Plus	6.007	0.000	4295.932	0.000		MALE	60	YES	Preferred-Plus	10.299	0.000	363.650	0.000
FEMALE	60	YES	Preferred	6.007	0.000	4295.932	0.000		MALE	60	YES	Preferred	10.299	0.000	363.650	0.000
FEMALE	60	YES	Regular	6.627	0.000	550.640	0.000		MALE	60	YES	Regular	10.893	0.000	374.038	0.000

Note: Marginal prices are estimated for 1-year level term contracts using the median premium offered in the California market in January 1997. All data are taken from the January 1997 CompuLife dataset. Companies with all ratings are included in the analysis. Contracts are priced without riders. Marginal price estimates shown are the regression estimates multiplied by 1,000 – or the marginal price per $1,000 of term insurance coverage.

Table 1b.
Marginal Premium Per $1000 Coverage.
All Firm Premium Offerings Included in Regression Analyses. Weights Are Used. 1997 CompuLife Regressions.

Sex	Age	Smoker	Health Status	Marginal Price Per $1000 Coverage	StdErr	tValue	Probt		Sex	Age	Smoker	Health Status	Marginal Price Per $1000 Coverage	StdErr	tValue	Probt
FEMALE	30	NO	Preferred-Plus	0.648	0.000	115.185	0.000		MALE	30	NO	Preferred-Plus	0.743	0.000	128.786	0.000
FEMALE	30	NO	Preferred	0.654	0.000	116.291	0.000		MALE	30	NO	Preferred	0.752	0.000	132.623	0.000
FEMALE	30	NO	Regular	0.774	0.000	144.227	0.000		MALE	30	NO	Regular	0.895	0.000	154.943	0.000
FEMALE	30	YES	Preferred-Plus	1.204	0.000	138.737	0.000		MALE	30	YES	Preferred-Plus	1.470	0.000	146.713	0.000
FEMALE	30	YES	Preferred	1.204	0.000	138.737	0.000		MALE	30	YES	Preferred	1.470	0.000	146.713	0.000
FEMALE	30	YES	Regular	1.316	0.000	150.519	0.000		MALE	30	YES	Regular	1.608	0.000	161.180	0.000
FEMALE	40	NO	Preferred-Plus	0.809	0.000	110.958	0.000		MALE	40	NO	Preferred-Plus	0.946	0.000	103.699	0.000
FEMALE	40	NO	Preferred	0.820	0.000	113.914	0.000		MALE	40	NO	Preferred	0.959	0.000	106.735	0.000
FEMALE	40	NO	Regular	0.982	0.000	134.079	0.000		MALE	40	NO	Regular	1.167	0.000	118.930	0.000
FEMALE	40	YES	Preferred-Plus	1.639	0.000	135.600	0.000		MALE	40	YES	Preferred-Plus	2.130	0.000	121.835	0.000
FEMALE	40	YES	Preferred	1.639	0.000	135.600	0.000		MALE	40	YES	Preferred	2.130	0.000	121.835	0.000
FEMALE	40	YES	Regular	1.795	0.000	163.357	0.000		MALE	40	YES	Regular	2.336	0.000	148.955	0.000
FEMALE	50	NO	Preferred-Plus	1.438	0.000	82.191	0.000		MALE	50	NO	Preferred-Plus	1.901	0.000	80.662	0.000
FEMALE	50	NO	Preferred	1.441	0.000	81.581	0.000		MALE	50	NO	Preferred	1.927	0.000	81.195	0.000
FEMALE	50	NO	Regular	1.723	0.000	93.570	0.000		MALE	50	NO	Regular	2.311	0.000	93.503	0.000
FEMALE	50	YES	Preferred-Plus	2.988	0.000	105.600	0.000		MALE	50	YES	Preferred-Plus	4.271	0.000	99.744	0.000
FEMALE	50	YES	Preferred	2.988	0.000	105.631	0.000		MALE	50	YES	Preferred	4.271	0.000	99.744	0.000
FEMALE	50	YES	Regular	3.311	0.000	118.854	0.000		MALE	50	YES	Regular	4.739	0.000	122.325	0.000
FEMALE	60	NO	Preferred-Plus	3.035	0.000	80.137	0.000		MALE	60	NO	Preferred-Plus	4.584	0.000	81.944	0.000
FEMALE	60	NO	Preferred	3.040	0.000	79.153	0.000		MALE	60	NO	Preferred	4.639	0.000	83.207	0.000
FEMALE	60	NO	Regular	3.654	0.000	99.242	0.000		MALE	60	NO	Regular	5.582	0.000	103.248	0.000
FEMALE	60	YES	Preferred-Plus	5.999	0.000	101.441	0.000		MALE	60	YES	Preferred-Plus	9.725	0.000	102.984	0.000
FEMALE	60	YES	Preferred	5.999	0.000	101.441	0.000		MALE	60	YES	Preferred	9.725	0.000	102.984	0.000
FEMALE	60	YES	Regular	6.728	0.000	119.230	0.000		MALE	60	YES	Regular	10.791	0.000	125.393	0.000

Note: Marginal prices are estimated for 1-year level term contracts using all premiums offered in the California market in January 1997. All data are taken from the January 1997 CompuLife dataset. Companies with all ratings are included in the analysis. Contracts are priced without riders. Marginal price estimates shown are the regression estimates multiplied by 1,000 – or the marginal price per $1,000 of term insurance coverage.

Table 2a.
Fixed Cost Per Policy from Median Firm Pricing Regression
1997 CompuLife Data. Linear Pricing Equation. Only Premium Quotations from Median Firm in Market Used in Pricing Regressions (N=17)

Sex	Age	Smoker	Health Status	Fixed Price per Policy	StdErr	tValue	Probt		Sex	Age	Smoker	Health Status	Male Fixed Price per Policy	StdErr	tValue	Probt
FEMALE	30	NO	Preferred-Plus	59.445	10.201	5.827	0.000		MALE	30	NO	Preferred-Plus	54.645	9.442	5.787	0.000
FEMALE	30	NO	Preferred	56.441	9.166	6.158	0.000		MALE	30	NO	Preferred	59.446	4.006	14.841	0.000
FEMALE	30	NO	Regular	58.394	7.436	7.853	0.000		MALE	30	NO	Regular	56.469	4.483	12.596	0.000
FEMALE	30	YES	Preferred-Plus	75.336	9.015	8.357	0.000		MALE	30	YES	Preferred-Plus	59.945	3.850	15.569	0.000
FEMALE	30	YES	Preferred	75.336	9.015	8.357	0.000		MALE	30	YES	Preferred	59.945	3.850	15.569	0.000
FEMALE	30	YES	Regular	71.493	9.654	7.405	0.000		MALE	30	YES	Regular	66.781	4.603	14.510	0.000
FEMALE	40	NO	Preferred-Plus	37.184	16.698	2.227	0.042		MALE	40	NO	Preferred-Plus	36.678	20.750	1.768	0.097
FEMALE	40	NO	Preferred	34.009	17.528	1.940	0.071		MALE	40	NO	Preferred	42.406	14.633	2.898	0.011
FEMALE	40	NO	Regular	39.771	10.395	3.826	0.002		MALE	40	NO	Regular	45.216	11.320	3.994	0.001
FEMALE	40	YES	Preferred-Plus	52.728	10.267	5.136	0.000		MALE	40	YES	Preferred-Plus	34.920	18.649	1.872	0.081
FEMALE	40	YES	Preferred	52.728	10.267	5.136	0.000		MALE	40	YES	Preferred	34.920	18.649	1.872	0.081
FEMALE	40	YES	Regular	61.913	5.148	12.027	0.000		MALE	40	YES	Regular	83.007	3.797	21.860	0.000
FEMALE	50	NO	Preferred-Plus	33.354	22.110	1.509	0.152		MALE	50	NO	Preferred-Plus	-18.384	65.235	-0.282	0.782
FEMALE	50	NO	Preferred	34.291	19.117	1.794	0.093		MALE	50	NO	Preferred	-39.365	72.787	-0.541	0.597
FEMALE	50	NO	Regular	21.190	24.361	0.870	0.398		MALE	50	NO	Regular	48.875	13.118	3.726	0.002
FEMALE	50	YES	Preferred-Plus	59.339	19.386	3.061	0.008		MALE	50	YES	Preferred-Plus	33.361	36.323	0.918	0.373
FEMALE	50	YES	Preferred	59.339	19.386	3.061	0.008		MALE	50	YES	Preferred	33.361	36.323	0.918	0.373
FEMALE	50	YES	Regular	147.334	55.504	2.654	0.018		MALE	50	YES	Regular	78.238	93.283	0.839	0.415
FEMALE	60	NO	Preferred-Plus	-21.129	59.753	-0.354	0.729		MALE	60	NO	Preferred-Plus	37.959	37.806	1.004	0.331
FEMALE	60	NO	Preferred	2.649	52.517	0.050	0.960		MALE	60	NO	Preferred	-17.373	92.028	-0.189	0.853
FEMALE	60	NO	Regular	-7.098	51.139	-0.139	0.891		MALE	60	NO	Regular	-30.279	111.796	-0.271	0.790
FEMALE	60	YES	Preferred-Plus	72.385	10.673	6.782	0.000		MALE	60	YES	Preferred-Plus	-173.217	216.166	-0.801	0.435
FEMALE	60	YES	Preferred	72.385	10.673	6.782	0.000		MALE	60	YES	Preferred	-173.217	216.166	-0.801	0.435
FEMALE	60	YES	Regular	202.545	91.852	2.205	0.043		MALE	60	YES	Regular	-176.688	222.287	-0.795	0.439

Note: Marginal prices are estimated for 1-year level term contracts using the median premium offered in the California market in January 1997. All data are taken from the January 1997 CompuLife dataset. Companies with all ratings are included in the analysis. Contracts are priced without riders.

Table 2b.
Fixed Price Per Policy Estimates.
Weights Included. All Firm Offerings Included. No Firm-Level Fixed Effects Included. CompuLife Linear Pricing Equation.

Sex	Age	Smoker	Health Status	Estimate	StdErr	tValue	Probt		Sex	Age	Smoker	Health Status	Estimate	StdErr	tValue	Probt
FEMALE	30	NO	Preferred-Plus	63.755	42.969	1.484	0.138		MALE	30	NO	Preferred-Plus	62.072	44.012	1.410	0.159
FEMALE	30	NO	Preferred	62.238	42.960	1.449	0.148		MALE	30	NO	Preferred	60.375	43.269	1.395	0.163
FEMALE	30	NO	Regular	60.746	40.976	1.482	0.138		MALE	30	NO	Regular	57.920	44.081	1.314	0.189
FEMALE	30	YES	Preferred-Plus	76.939	66.213	1.162	0.245		MALE	30	YES	Preferred-Plus	59.783	76.473	0.782	0.434
FEMALE	30	YES	Preferred	76.939	66.213	1.162	0.245		MALE	30	YES	Preferred	59.783	76.473	0.782	0.434
FEMALE	30	YES	Regular	78.308	66.758	1.173	0.241		MALE	30	YES	Regular	67.999	76.147	0.893	0.372
FEMALE	40	NO	Preferred-Plus	52.657	55.676	0.946	0.344		MALE	40	NO	Preferred-Plus	54.417	69.603	0.782	0.434
FEMALE	40	NO	Preferred	50.265	54.922	0.915	0.360		MALE	40	NO	Preferred	51.090	68.584	0.745	0.456
FEMALE	40	NO	Regular	46.791	55.909	0.837	0.403		MALE	40	NO	Regular	46.161	74.894	0.616	0.538
FEMALE	40	YES	Preferred-Plus	49.754	92.246	0.539	0.590		MALE	40	YES	Preferred-Plus	46.532	133.460	0.349	0.727
FEMALE	40	YES	Preferred	49.754	92.246	0.539	0.590		MALE	40	YES	Preferred	46.518	133.457	0.349	0.727
FEMALE	40	YES	Regular	62.554	83.892	0.746	0.456		MALE	40	YES	Regular	59.239	119.681	0.495	0.621
FEMALE	50	NO	Preferred-Plus	24.317	133.490	0.182	0.855		MALE	50	NO	Preferred-Plus	14.679	179.917	0.082	0.935
FEMALE	50	NO	Preferred	45.521	134.815	0.338	0.736		MALE	50	NO	Preferred	4.514	186.647	0.024	0.981
FEMALE	50	NO	Regular	23.117	140.588	0.164	0.869		MALE	50	NO	Regular	13.677	188.677	0.072	0.942
FEMALE	50	YES	Preferred-Plus	12.773	215.954	0.059	0.953		MALE	50	YES	Preferred-Plus	-11.087	326.814	-0.034	0.973
FEMALE	50	YES	Preferred	12.709	215.889	0.059	0.953		MALE	50	YES	Preferred	-11.087	326.814	-0.034	0.973
FEMALE	50	YES	Regular	20.279	212.622	0.095	0.924		MALE	50	YES	Regular	22.842	295.680	0.077	0.938
FEMALE	60	NO	Preferred-Plus	6.756	289.024	0.023	0.981		MALE	60	NO	Preferred-Plus	-0.929	426.978	-0.002	0.998
FEMALE	60	NO	Preferred	7.231	293.198	0.025	0.980		MALE	60	NO	Preferred	-13.946	425.558	-0.033	0.974
FEMALE	60	NO	Regular	7.358	281.022	0.026	0.979		MALE	60	NO	Regular	-7.107	412.643	-0.017	0.986
FEMALE	60	YES	Preferred-Plus	13.724	451.357	0.030	0.976		MALE	60	YES	Preferred-Plus	-57.568	720.813	-0.080	0.936
FEMALE	60	YES	Preferred	13.724	451.357	0.030	0.976		MALE	60	YES	Preferred	-57.568	720.813	-0.080	0.936
FEMALE	60	YES	Regular	27.791	430.707	0.065	0.949		MALE	60	YES	Regular	25.201	656.878	0.038	0.969

Note: Marginal prices are estimated for 1-year level term contracts using the all premiums offered in the California market in January 1997. All data are taken from the January 1997 CompuLife dataset. Companies with all ratings are included in the analysis. Contracts are priced without riders.

Table 3. Demand Regressions, Marginal Premium Estimated from Median Firm Data. 1-Year Level Term Contracts in 1997.

	Estimate	StdErr	DF	tValue	Probt
Intercept	7.401	0.753	1429	9.823	0.000
Log of CompuLife Marginal Premium per $1000 Coverage	-0.538	0.085	1429	-6.343	0.000
Log of (Unadjusted) Death Probability	0.287	0.087	1429	3.280	0.001
Log of Fixed Price	0.136	0.079	1429	1.719	0.086
Log of 1990 Median Income by Zip-Code	0.612	0.054	1429	11.310	0.000
Quarter 1	0.033	0.055	1429	0.604	0.546
Quarter 2	0.025	0.057	1429	0.436	0.663
Quarter 3	0.091	0.058	1429	1.572	0.116
Quarter 4	0.000				
Married	0.104	0.063	1429	1.646	0.100
Single	-0.237	0.092	1429	-2.593	0.010
Widowed/Divorced	0.000				
No Previous Coverage	-0.066	0.045	1429	-1.464	0.143
Previous Coverage	0.000				
Female	-0.483	0.045	1429	-10.756	0.000
Male	0.000				
Additional Coverage	0.174	0.240	1429	0.725	0.468
Region: Mid-West	-0.167	0.066	1429	-2.509	0.012
Region: New England	-0.085	0.065	1429	-1.313	0.190
Region: South	-0.117	0.066	1429	-1.783	0.075
Region: West	0.000				

Table 4. Median Premium Regressions. 1-Year Level Term Contracts in 1997.

Variable	Estimate	StdErr	DF	tValue	Probt
Intercept	7.240	0.927	1429	7.811	0.000
Log of CompuLife Marginal Premium per $1000 Coverage	-0.556	0.141	1429	-3.953	0.000
Log of annual probability of dying during period of term coverage adjusted for relative mortality risk due to smoking over a 1 year period (never smokers vs. weighted average of light & heavy smokers)	0.193	0.108	1429	1.795	0.073
Log of Average Premium	-0.004	0.061	1429	-0.065	0.948
Log of 1990 Median Income by Zip-Code	0.619	0.054	1429	11.403	0.000
Quarter 1	0.035	0.055	1429	0.632	0.528
Quarter 2	0.023	0.057	1429	0.403	0.687
Quarter 3	0.089	0.058	1429	1.538	0.124
Quarter 4	0.000				
Married	0.118	0.063	1429	1.872	0.061
Single	-0.220	0.092	1429	-2.404	0.016
Widowed/Divorced	0.000				
No Previous Coverage	-0.075	0.045	1429	-1.678	0.093
Previous Coverage	0.000				
Female	-0.484	0.053	1429	-9.115	0.000
Male	0.000				
Additional Coverage	0.171	0.241	1429	0.710	0.478
Region: Mid-West	-0.173	0.067	1429	-2.595	0.010
Region: New England	-0.085	0.065	1429	-1.317	0.188
Region: South	-0.119	0.066	1429	-1.810	0.070
Region: West	0.000				

Table 5

Marginal Price Variable	**Price Elasticity**	**Risk Elasticity (Unadjusted)**	**Risk Elasticity (Adjusted for Smoking)**
Using Median Firm Data			
Individual Marginal Premium	-0.477	0.328	
	-0.473		0.200
Relative Premium	-0.458	-0.020*	
	-0.434		-0.110
Using Weighted All-Firm Data			
CompuLife Premium	-0.408	0.468	
	-0.578		0.382
Individual Marginal Premium	-0.405	0.495	
	-0.422		0.311
Relative Premium	-0.467	0.334	
	-0.446		0.071

All variables statistically significant unless indicated
**Not statistically significant*