ADVERSE SELECTION AND CONSUMER BEHAVIOR IN THE VIATICAL SETTLEMENT MARKET

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ABSTRACT

The similarities between the viatical settlement market and the standard market for insurance evoke the question of what effect asymmetric information, an oft discussed topic surrounding standard markets, might have in the viatical settlement market. In order to examine the possibility of the existence of adverse selection in this market, as well as to gain a better understanding of the dynamics of the market in general, I analyze a model describing consumer behavior in this market. Applying the results of my analysis to the logic of a classic adverse selection model, I develop and implement a test of adverse selection in the viatical settlement market using nationally representative data on viatical transactions. Additionally, I extract a new prediction from the consumer behavior model relating the probability of selling life insurance to both the policy’s face value and the policyholder’s mortality risk, and I test this prediction against data on HIV+ individuals. In the end I find that there is no empirical evidence for adverse selection in the viatical settlement market, and that the consumer behavior model is largely consistent with the data.

Keywords: life insurance, mortality risk, Rothschild Stiglitz model, asymmetric information

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1. Introduction

Since developing in the late eighties, the viatical settlement industry has had its fair share of bad press and bad associations. The market for viatical transactions arose in 1989 in response to the spread of HIV and AIDS in the United States. AIDS patients faced considerable expenses and had to find a way to fund medical treatment and the cost of care, often after losing the ability to work because of their illness. Without a source of income and often without health insurance, many patients found themselves in desperate need of financial resources, particularly immediate cash. Prior to the development of the viatical settlement market, people in this situation faced few options outside of borrowing against their non-liquid assets. The emerging viatical settlement market allowed them to exploit their life insurance policy and turn it into liquid cash which they could put toward their immediate financial needs (Alpert, Bhattacharya, Sood 2005).

Essentially, the viatical settlement industry created a secondary market for life insurance. Viatical settlement companies are third-parties who purchase a terminally ill policyholder’s life insurance policy for an amount that is less than the policy’s face value and generally greater than the surrender value offered by the insurance company. In return, the buyer of the policy becomes its sole beneficiary when the original policyholder (or the “viator”) dies and is responsible for paying all subsequent premiums on the policy. Representatives of the viatical settlement industry, as well as many investors, often describe viatical transactions as win-win situations. They allow investors to help someone in need by providing them with money, and in exchange they get a return on their investment. Nonetheless, it is undeniable that there is a morbid aspect to these settlements. Like any insurance market, the returns are uncertain and dependent on
the policyholder, yet here the occurrence that lenders and viatical settlement companies
are betting on is death. The earlier the policyholder dies before expected, the higher the
return.

Even aside from this morbid quality, the viatical settlement industry has stood out
among other insurance related markets for its unethical behavior. The market has been
rife with fraud, largely on the part of the viatical settlement companies. There have been
many examples of companies fabricating insurance policies or skimming off large
amounts of money as they transfer the funds from investors to viators. In the wake of all
these cases of fraud many state governments began regulating the formerly unregulated
viatical settlement industry, but potential investors and viators are still advised to remain
wary. All parties involved continue to face the problem of how complete their own
information is, and what information the other parties might not be sharing.

The issue of asymmetric information is one that has been explored countless times
in the context of traditional insurance markets, particularly with regard to adverse
selection. The viatical settlement market is in a sense a mirror image of the standard
market for life insurance—the payout depends on the policyholder’s actions (voluntary or
not), yet here unobservably healthy people are considered high-risk while unobservably
unhealthy people are low-risk. Despite the similarity between the two types of markets,
little research has been done analyzing adverse selection in the viatical settlement market.
In fact, relatively little economic research has been done on this market at all.

The purpose of this study is to develop a better understanding of the viatical
settlement market by examining it in the context of adverse selection and by looking at
consumer behavior in the market. There are two main analytical parts to the paper. In the
first part (sections 3-5) my goal is to determine whether there is empirical evidence for the presence of adverse selection in the viatical settlement market. To do so, I first outline a model developed by Bhattacharya, Goldman, and Sood (2005) describing the consumer’s decision to sell their life insurance. From this model I use a comparative statics prediction relating the amount of policy the consumer chooses to sell with his mortality risk. I apply this prediction to the classic model of adverse selection in order to determine what adverse selection would look like in this market, and then test for evidence of its presence using nationally representative data on viatical transactions involving HIV+ policyholders. In the second part of my paper (section 6) I take a closer look at the consumer decision model and extract from it a new comparative statics prediction. I then test this prediction against data from the HIV Costs and Services Utilization Study (HCSUS) in order to get a better sense of the applicability of this model to the market.

2. Literature Review

To outline the background research for my paper, I first review past literature on adverse selection and then move on to discuss the literature on viatical settlement markets.

2.1 Adverse Selection

Rothschild and Stiglitz’s (1976) paper on adverse selection is a seminal article for numerous studies that have augmented or tested their theoretical predictions. Their model represents a competitive market for insurance, focusing on health insurance, in which
there are two types of individuals: those who are at high risk of being sick and those who are at low risk, the identity of which remains unknown to insurance companies. When consumers are healthy, they pay out premiums to the insurance company and when they are sick, they receive payments from the insurance company. Regardless of health status, every consumer’s optimal state of the world would be to have their expected incomes to be equal when they are healthy and when they are sick.

In this basic model the only sustainable equilibrium is a separating equilibrium between the two risk types. Because the insurance market is competitive, all firms make zero expected profits and must therefore charge higher premiums to high-risk individuals in order to compensate for the greater expected insurance payout. A pooling equilibrium, in which both types of individuals pick the same contract and pay the same amount, is impossible because low-risk individuals prefer not to subsidize their high-risk counterparts by paying higher premiums. Another firm could break the equilibrium by entering the market and making positive profits, offering lower premiums for smaller insurance payouts and attracting only low-risk individuals because high-risk would be unwilling to buy so little insurance coverage. Likewise, a separating equilibrium between the two types of individuals in which the insurance company offers consumers their ideal outcome—full insurance—is also impossible. Assuming asymmetric information, high-risk individuals could successfully pretend to be low-risk in order to enjoy the lower premiums, ultimately making the firm earn negative profits.

In order to achieve a separating equilibrium, insurance companies must restrict low-risk consumers from enjoying their optimal state of the world, offering full insurance at a high price for high-risk individuals, and offering only partial insurance at a lower
price to low-risk individuals. In this way, high-risk individuals who want more insurance because they know they will frequently be sick self-select into the high-risk category and are willing to pay a higher price for it. On the other hand, low-risk individuals know that they will be sick less often and will not be willing to pay the high premiums of a bigger insurance package; they will self-select into the partial insurance at a lower price.

This leads us to one of the key predictions of the Rothschild Stiglitz model of asymmetric information: in order for equilibrium to be reached in a competitive insurance market, firms will have to charge more premium per amount of insurance they pay out as the insurance packages get larger. Simply put, the per-unit marginal cost of insurance is increasing with the quantity of insurance. This prediction contradicts the more typical “bulk discounting” price structure that is frequently found in competitive markets, in which marginal per-unit cost decreases with the quantity of product.

A second key prediction of Rothschild and Stiglitz’s adverse selection model is a straightforward corollary of the self-selection that occurs in the model. Essentially, if the high-risk individuals separate out from the low-risk individuals and the high-risk select a greater amount of insurance, then those with more insurance ought to display a greater hazard of needing to use this insurance. In the case of health insurance, those with more insurance ought to be sick more often or with greater severity; in the case of life insurance, those with more insurance ought to have a greater mortality rate.

While the logic behind the theory of this model is clear, it is unclear whether such predictions can be observed in actual markets that we assume to have asymmetric information. Economists have written numerous papers testing the model’s implications in an attempt to see whether there is empirical evidence for asymmetric information and
if so, how big a role it plays in the insurance market. Cawley and Philipson (1999) studied the U.S. life insurance market, Cardon and Hendel (2001) studied the U.S. health insurance market, and Finkelstein and Poterba (2004) studied the U.K. annuity market. Chiappori and Salanie (2000) studied the French auto insurance market, and Puelz and Snow (1994) analyzed the U.S. auto insurance market. Cutler and Zeckhauser (2000) cite nearly thirty studies that have been done since Rothschild and Stiglitz developed their model, analyzing various markets and their evidence for adverse selection. With respect to finding a verdict on the empirical importance of asymmetric information and the presence of adverse selection, the papers have been inconsistent.

Cawley and Philipson’s study (1999) examines the U.S. market for life insurance by drawing considerably from the Rothschild and Stiglitz model. To test both key predictions of the model, they use data from the Teachers Insurance and Annuity Association (TIAA), as well as the Health and Retirement Study (HRS), the Asset and Healthy Dynamics Among the Oldest Old (AHEAD), CompuLife price data, and LIMRA price data. To examine the price structure prediction of the model, Cawley and Philipson analyze the TIAA price data and find that within subgroups of consumers defined by age and whether they smoke, the per-unit price of insurance actually decreases with the quantity of insurance bought. Further evidence that marginal per-unit prices do not increase with quantity is that, for this price structure to be feasible, there would have to be something preventing consumers from buying multiple insurance policies with which they could get the same total coverage as a large policy for a lower price. The high empirical prevalence of consumers purchasing multiple policies, however, suggests that the increasing per-unit prices do not occur.
Additionally, Cawley and Philipson examine the covariance between contract size and risk and find that, unlike Rothschild and Stiglitz would indicate, the two are not positively correlated (for the most part, the ratio of the mortality risk of insured males to the overall population of males is less than 1). Using data from HRS and AHEAD, they find that the covariance between actual risk and quantity of insurance is neutral or negative rather than positive. The same is true of the covariance between self-perceived risk and insurance demand. In fact, asymmetric information may not even be a factor in this market. Correlation tests run between actual risk and self-perceived risk show that the two are not highly correlated; life insurance policyholders may not have significantly greater information about their own risk than the insurance companies do.

Finkelstein and Poterba (2004) and Finkelstein and McGarry (2006) take different approaches by studying the U.K. annuity market and the U.S. long-term care insurance markets. Both papers discuss the prediction regarding a correlation between insurance coverage and risk occurrence, the subject of the second part of Cawley and Philipson’s study. In Finkelstein and McGarry (2006), the authors argue that the uni-dimensional model of adverse selection used in Cawley and Philipson (1999) and other similar studies, focusing on only risk type and risk occurrence, may not adequately reveal the information asymmetries in these markets. Both Finkelstein and Poterba (2004) and Finkelstein and McGarry (2006) examine other dimensions in their respective markets in which asymmetric information might occur.

The annuities market offers a form of insurance that insures consumers against running out of resources in the later part of their life by paying out annual streams of income in return for a given premium. In this market, a high-risk individual would be one
who lives longer, and therefore receives a greater number of annuity payments. The three elements of annuities contracts that Finkelstein and Poterba (2004) analyze for evidence of adverse selection are the initial annual annuity payment (comparable to the quantity of insurance in a life insurance contract), whether the annuity may make payments to the annuitant’s estate in the event of an early death, and the annuity’s degree of back-loading. Assuming that adverse selection holds true, the model of the paper predicts that: 1) consumers who buy annuities with larger initial annual payments should be longer-lived, 2) consumers who buy annuities that make payments to the estate should be shorter-lived, and 3) consumers buying back-loaded annuities should be longer-lived. With respect to pricing, the model predicts that back-loaded annuities should be priced higher because annuitants who purchase them tend to be longer-lived, whereas annuities making payments to the estate should be priced lower to account for the higher concentration of short-lived annuitants who select to buy this feature.

To test these predictions, Finkelstein and Poterba model the hazard for annuitant deaths as a function of all the known characteristics of the annuitants and of their annuity policies. In this model, the null hypothesis is that the covariations between hazard of death and the degree of back loading, the presence of payments to the estate, and the initial annual annuity payment, will all be zero. After applying the data to their model, the resulting coefficients suggest that there is significant self-selection based on back-loading, moderate selection based on payments to the estate, and little to no selection based on the quantity.

Although the market analyzed in Finkelstein and McGarry (2006) is more closely related to the typical insurance markets applied to uni-dimensional models than the
annuities market, the authors introduce the factors of wealth and cautiousness to show that there may be evidence for asymmetric information even when there is no correlation between insurance coverage and risk occurrence. The authors use survey data on people’s subjective assessments of the likelihood that they will enter a nursing home and apply it to a probit model to estimate their actual probability of entering long-term care. They then estimate a similar probit model using the actual risk classification system that insurance companies use. Although they find that the insurance company’s classification is more indicative of whether an individual will actually enter a nursing home than is the subjective assessment, another model controlling for the company’s risk classification shows that individuals’ beliefs are in fact a positive and significant predictor of future nursing home enrollment. This indicates that there is private information unknown to the insurance companies that affects whether or not consumers will use the long-term care. Further analysis shows that usage of long-term care insurance is positively correlated with both wealth and several indications of cautiousness (e.g. seat belt use, pap smears, prostate screening), which the authors suggest may serve as proxies for characteristics unknown to insurance companies that affect the individual’s hazard. Lastly, Finkelstein and McGarry test their data with the uni-dimensional model—correlating insurance coverage and risk occurrence—and fail to reject the null hypothesis that there is zero correlation, indicating that their evidence for asymmetric information is not specific to their data but rather to their multi-dimensional analysis.

One possible way to explain the inconsistency between the results of Cawley and Philipson (1999) and those of Finkelstein and Poterba (2004) and Finkelstein and McGarry (2006) is that more risk-averse individuals are more likely to buy mortality or
health-related insurance, and are also likely to live longer (Finkelstein and Poterba, 2004). However, while a long-lived, risk averse individual is low-risk in the long-term care or life insurance market, she is high-risk in the annuities market, and therefore her actions may be consistent with one market’s model for adverse selection and not with another. Another example of an insurance-related market that views a consumer’s risk in a way that differs from the standard insurance market is that of viatical settlements, the focus of this study.

2.2 Literature Review: Viatical Settlements

Although the viatical settlement industry is fairly new and as a whole there has been relatively little economic research done in this subject area, a series of studies in recent years have examined it in greater depth. Bhattacharya, Goldman, and Sood (2005) use an analysis of the viatical settlement market to find whether or not people accurately predict their mortality risk. Some psychological and health studies have already shown systematic errors in people’s perceptions of their mortality risk. For example, Lichtenstein et al. (2000) have shown that people overestimate their likelihood to die of improbable causes of death, while underestimating their mortality risk from likely causes of death. Similarly, Schoenbaum (1997) and Hurd et al. (1999) have both shown that people with high mortality risk, such as smokers, tend to be overly optimistic about their longevity. By revealing consumers’ perceptions of a fair price that they are willing to accept for their life insurance policy, viatical settlements provide another instrument with which to demonstrate individuals’ perceptions of their own mortality risks.

Studies have also tracked the evolution of the industry, which has seen
considerable change in less than twenty years. In 1996 viatical settlement companies faced a significant technological shock with the unexpected introduction and distribution of Highly Active Anti-Retroviral Therapy (HAART), a highly effective set of drugs that, “delay the onset of terminal AIDS symptoms and mortality in HIV infected patients…. In the wake of their widespread diffusion in the U.S., annual mortality rates among HIV patients declined by 60% between 1996 and 2001 (CDC, 2001; CDC, 2002),” Alpert, Bhattacharya, Sood (2005, p. 3). In response the viatical settlement industry showed a marked decline in both the number of viatical transactions and the total value of all the settlements. Alpert, Bhattacharya, and Sood (2005) analyze this market response and build a model to explain what drove the decline.

Price regulations, typically showing up in the form of price floors, have also had a significant effect on the viatical settlement market. Proponents of such regulation argue that the market is non-competitive and that the partial monopsony on insurance policies exploits people at a particularly vulnerable time. Others, including the viatical settlement industry, argue that the price floors distort the market and restrict the number of trades that occur, lowering the welfare of those left out of the market and eliminating a valuable way to liquidate a formerly illiquid asset when resources are depleted. Bhattacharya, Goldman, and Sood (2004) tests the effects of price regulations and finds that a significant number of potential transactions are left out of the market. The paper goes on to estimate the welfare effects of the market distortion and finds that the welfare loss is also considerable.

The authors of these three studies have developed some basic models with which to analyze the dynamics of the viatical settlement market. In their 2005 paper on
misperceived mortality risk, Bhattacharya, Goldman, and Sood construct two models that represent a consumer’s decision to sell his life insurance. The first is a standard model that assumes that consumers accurately predict their mortality risk and decide to viaticate based on their expected utility stemming from current and future consumption and from the bequests they will leave when they die. I use this standard model as a foundation for my own analysis in this paper. The second model assumes that consumers similarly maximize their expected utility, but that they misperceive their mortality risk—relatively healthy consumers overestimate their risk and more unhealthy consumers underestimate it—which changes their expectation of their utility. The two models come up with separate comparative static predictions, which Bhattacharya, Goldman, and Sood test against data from the HIV Costs and Service Utility Survey (HCSUS), which collected information HIV+ patients such as demographics, income and assets, health status, life insurance, and participation in the viatical settlement market.

There are three testable comparative statics predictions: 1) Health status is negatively correlated with the decision to sell life insurance, 2) In the standard model the decision to sell life insurance is positively correlated with non-liquid assets, while in the alternate model this decision is negatively correlated with non-liquid assets for healthy consumers and positively correlated for sicker consumers, 3) In the standard model an increase in liquid assets or current income will increase the incentive to sell life insurance, while in the alternate model such an increase will either reduce or leave unchanged the incentive to sell life insurance. The authors use a logit model to derive the decision to sell life insurance and compare the results with the above predictions. In the end, the results are more consistent with the misperceived mortality risk model than the
standard model.

Bhattacharya, Goldman, and Sood (2004) adapts the standard version of this model of consumer decision to show how price regulations will alter the market. The paper reasons that when the price floor is above the actuarially fair price of certain settlements, it removes these settlements from the market and reduces the likelihood of trades. If the price floor is below the actuarially fair price, it can either have no effect if the market is competitive (settlements continue to sell at actuarially fair pricing) or can increase the likelihood of trades and increase the price if the market is monopsonistic or imperfectly competitive. The authors then develop a model to estimate actuarially fair prices based on life expectancy, derived values for premiums paid, and cost of capital. They find that for patients with 4.5 years of life expectancy or more, the price floor in regulated states exceeds the actuarially fair price, indicating that the likelihood of trades for these patients should be significantly less when in regulated states. The irony of this outcome is that healthier patients are restricted from obtaining the financial means with which they can keep themselves healthy. The authors compare this theoretical outcome with data from the HCSUS survey, which confirms this prediction and also shows that price regulation seems to have no effect on the likelihood to sell for relatively unhealthy patients.

The paper goes on to model the monetary and welfare effects of these regulations. It estimates that if price regulation were implemented in all states, its binding effects would rule out approximately $119 million worth of transactions. Despite variations in the estimates for welfare loss based on the wealth of the consumer, his bequest motives and his mortality risk, a simulation to model welfare effects shows that welfare loss as a
whole is significant.

The sentiment that price regulations ultimately harm the consumer is also reflected in Alpert, Bhattacharya, and Sood (2005), despite the fact that settlement prices have been decreasing over the past decade. Contrary to industry literature, this paper provides evidence that the viatical settlement industry has declined and the supply of transactions (i.e. insurance policy buyers) has shrunk. It also finds that the Hirschman-Herfindahl Index (HHI), which describes market concentration, is increasing for the industry and is above the value considered to be the threshold for a competitive market. Within each category of life expectancy returns faced by the consumers have gone down and have decreased more dramatically for those with longer life expectancies. Although these market developments are not favorable toward consumers, the authors argue that reducing the supply further with price floors would simply prevent more policyholders from enjoying the benefits of viatical transactions.

Although Alpert, Bhattacharya, and Sood (2005) focuses on the technology shock of the introduction of HAART, the paper also considers the increase of market power on the side of the viatical settlement firms as a driver in the industry’s decline. HAART not only significantly increased HIV patients’ life expectancies but also raised the general optimism that more life-extending drugs would be developed in the future. In the paper’s model this second effect can be shown by an increase in risk premium charged to the viatical settlement firms by the lenders of their funds. An increase in market power, on the other hand, shows up as an increase in the price cost margin for the viatical settlements firms.

This model predicts that a change in market power will affect all viatical
settlement transactions and prices equally, whereas changes in the risk premium charged to the viatical settlement companies will have a greater effect on transactions with patients with longer life expectancies, because there is a greater possibility that new technology will be developed in their lifetime. To test these predictions the authors regress settlement prices on consumers’ life expectancies for three separate time periods representing benchmarks in the adoption and distribution of HAART—1995, 1996-98, and 1999-2001. The results suggest that an increasing risk premium was the main driver in the change in prices between 1995 and 1996-98, the pre- and post-HAART eras, whereas an increase in market power is a strong factor in the price change in the most recent period (likely caused by market exit). Although decreasing prices reduce consumer welfare regardless of its cause, market inefficiency only occurs when the price drop is a result of increased market power, whereas increased risk premiums still leave policyholders facing actuarially fair prices.

As these three papers show, economists are gaining a better understanding of the factors that have shaped the viatical settlement market and will continue to in the future in the form of medical, regulatory, and competitive developments. However, little work has been done analyzing this market within the context of adverse selection, the frequently debated characteristic of standard insurance markets. My thesis focuses on the intersection of the two, outlining a model to show how adverse selection plays out in this market and using empirical data to determine whether there is evidence for the model’s predictions. I also delve deeper into the model describing the policyholder’s decision to sell by deriving a new comparative statics prediction and using it to test the applicability of the model to empirical data.
3. Modeling Consumer Decision in the Viatical Settlement Market

For my analysis of the viatical settlement market, I begin with the standard model developed in Bhattacharya, Goldman, and Sood (2005) describing consumers’ decision to sell their life insurance. From this model I draw a comparative statics prediction relating the amount of insurance that a consumer chooses to viaticate with his mortality risk. This prediction shapes the viatical settlement market from the perspective of both the consumers and the viatical settlement firms, who need to be aware of consumer incentives in order to price their settlements correctly and remain profitable.

The standard model of the decision to sell life insurance supposes that consumers are endowed with life insurance policies that were purchased before they became ill or before unforeseen events occurred that increased their mortality risk. Because policy premiums are determined before these events occur, they are lower than actuarially fair premiums would be had the events already occurred. For a consumer, the increase in mortality risk essentially creates for him equity in his insurance and when he sells all or part of his life insurance, we can consider him to be selling this equity.

The model itself is a two period utility maximization model. All consumers live through the first period and nature decides for them at the end of this period whether they will survive through the second; those that do survive the second period inevitably die at the end of it. Each consumer’s utility is a net present value function of his consumption in the first and second period (if he survives) and the bequests he leaves to dependents when he dies in either state of the world. Both consumption and bequests are assumed to be normal goods. Because the model applies to terminally ill patients, it is reasonable to assume that they are in need of liquid assets, which they can finance either from the sale
of their life insurance or by selling or borrowing against their non-liquid assets in the capital market, which reduces bequests. Although not separately detailed in this model, selling or borrowing against non-liquid assets is implicit in consumers’ level of consumption and level of face value viaticated. Both the market for capital and the viatical settlement market are assumed to be competitive.

The consumer’s problem in this model is to choose the value of consumption and the means to finance this consumption that will maximize his expected utility streams from consumption and bequests. More specifically, he will maximize expected utility with respect to consumption in period one, consumption in period two, and the amount he chooses to viaticate. This maximization is subject to his policy’s face value, the per-unit price offered by viatical settlement firms, and his mortality risk. The expected utility function can be described as:

$$EU = U(C_1) + \pi \beta V(B_D) + (1 - \pi)\beta U(C_2) + (1 - \pi)\beta V(B_S)$$  \hspace{1cm} (1)$$

Where \(\pi\) is the probability of dying before period two, \(\beta\) is the intertemporal discount factor, \(B_D\) is the level of bequests if the consumer dies after period one, and \(B_S\) is the level of bequests if he survives to period two. \(C\) represents his consumption, and \(U\) and \(V\) are the utility functions for consumption and bequests, respectively. The model assumes that the consumer will know for certain at the end of the first period whether he will survive through the second and that he leaves his assets as bequests \(B_D\) at the beginning of this second period. For simplicity sake, the model also assumes that since the consumer already knows at the beginning of the second period that he will die by the
end of it, he leaves his bequests $B_S$ at the beginning of the period as well. If this assumption were to be relaxed, the ultimate predictions of the model would not change.

The level of bequests left if the consumer dies after one period is represented as:

$$B_D = (L_1 + P(\pi) * F - C_1) * (1 + r) + NL + \bar{F} - F$$  \hspace{1cm} (2)$$

Here, $L$ is the consumer’s income and $NL$ is his non-liquid assets. The market interest rate— at which viatical settlement companies can borrow funds— is indicated by $r$, and $P(\pi)$ is the perfectly competitive market price that a viatical settlement firm pays per unit of insurance (i.e. per dollar of face value) as a function of the policyholder’s mortality risk, $\pi$. The first term in (2) makes up the consumer’s net lending or borrowing from period one and the following terms show his non-liquid assets and the total amount of his insurance policy ($\bar{F}$) minus the insurance he viaticated ($F$).

The level of bequests left if the consumer survives to the second period is made up of the savings left over from the first period, the remaining unsold life insurance and non-liquid assets discounted to the beginning of the period, as well as net earnings in the second period:

$$B_S = (L_1 + P(\pi) * F - C_1) * (1 + r) + (NL + \bar{F} - F) * \left(\frac{1}{1 + r}\right) + L_2 - C_2$$  \hspace{1cm} (3)$$

Additionally, the viatical settlement firm’s expected profit on a viatical transaction is:
The equation shows that their profits consist of the expected revenue they get once the policyholder dies, minus the price paid for the policy. Because this market is assumed to be perfectly competitive, firms make zero profits, which implies:

\[
P(\pi) = \left( \frac{\pi}{1 + r} + \frac{1 - \pi}{(1 + r)^2} \right)
\]

(5)

The viatical settlement market is assumed to be in equilibrium, so all the prices are actuarially fair and the supply of insurance policies equals demand.

To solve the consumer’s problem, one can substitute in the equations for price, \(B_D\), and \(B_S\) into the consumer’s expected utility equation and then maximize expected utility by differentiating it with respect to \(C_1\), \(C_2\), and \(F\) to find its first order conditions:

\[
\frac{U'(C_1)}{[(\pi)V'(B_D) + (1 - \pi)V'(B_S)]} = \beta(1 + r)
\]

(6)

\[
U'(C_2) = V'(B_S)
\]

(7)

\[
V'(B_D) = V'(B_S)
\]

(8)

Finding the first order conditions with respect to all choice variables yields important information on consumer behavior. The consumer will pick his choice variables so that the marginal utility of consumption is equal to his expected marginal net present value of utility from bequests. Also, the expected marginal utility of future consumption equals that of future bequests.

With the first order conditions I can use comparative statics to derive the key prediction that allows this model of viatical settlement markets to be applied to the
Rothschild Stiglitz model of adverse selection. In order to determine the relationship between the amount of insurance that a consumer chooses to viaticate and his mortality risk, I find the derivative of the amount to viaticate with respect to the probability that he will survive into the second period:

\[
\frac{dF}{d\pi}
\]

To find this relationship, one can rearrange and simplify the first order conditions to find:

\[
U'(C_1) = \beta(1 + r)V'(B_D) \tag{9}
\]

\[
U'(C_2) = V'(B_D) \tag{10}
\]

\[
C_2 = L_2 - (NL + F - F)
\left(\frac{r}{1 + r}\right) \text{ as } [V'(B_D) = V'(B_S) \Rightarrow B_D = B_S] \tag{11}
\]

Substituting in the equation for \( B_D \) and differentiating (9) with respect to \( C_1, F, \) and \( \pi \) (i.e. totally differentiating and setting constant all exogenous parameters except the mortality risk) yields:

\[
\left[U''(C_1) + \beta(1 + r)^2V''(B_D) \right]dC_1 + \left[\beta r (1 - \pi)V''(B_D) \right]dF = \left[\beta Fr V''(B_D) \right]d\pi \tag{12}
\]

Likewise, substituting equation (11) into (10) and doing the same yields:

\[
[(1 + r)V''(B_D)]dC_1 + \left[\left(\frac{r}{1 + r}\right)U''(C_2) + \left(\frac{r}{1 + r}\right)(1 - \pi)V''(B_D) \right]dF = \left[\left(\frac{r}{1 + r}\right)F V''(B_D) \right]d\pi \tag{13}
\]

Solving (12) and (13) for the derivative of the amount viaticated with respect to the mortality risk then leaves:
\[
\frac{dF}{d\pi} = \frac{\left(\frac{r}{1+r}\right)F U''(C_i)V''(B_D)}{D}
\]

(14)

Where D is defined as follows:

\[
D = \left(\frac{r}{1+r}\right)U''(C_2)U''(C_1) + \beta r(1 + r)U''(C_2)V''(B_D) + \left(\frac{r}{1+r}\right)(1 - \pi)V''(B_D)U''(C_i)
\]

Assuming that both utility functions for consumption and for bequests are standard Cobb-Douglas functions with negative second derivatives, one can see that both D and the numerator are positive terms.

\[
\frac{dF}{d\pi} > 0
\]

Intuitively, this relationship makes sense. When a consumer’s mortality risk increases, his equity in his life insurance policy also increases. This can be interpreted as an increase in his wealth. In response to this increase, there is a classic income effect—the consumer demands more of both consumption and bequests, both assumed to be normal goods. Because all his increased wealth has gone toward bequests, the consumer will sell some or all of his life insurance in order to increase funding for consumption and also increase investment for future consumption or bequests. Thus, the face value he chooses to viaticate increases with mortality rate.

4. Adverse Selection in the Viatical Settlement Market

The above prediction relating a consumer’s decision to sell his life insurance and his mortality rate can be applied to the classic Rothschild Stiglitz model of adverse selection in order to determine how adverse selection would appear in a viatical settlement market. In its most simplified characterization, the viatical settlement market
is simply the reverse of the standard insurance market. In the standard market, individuals who are sicker than they appear to the insurance company are considered high-risk, while those who are truly healthy are low-risk. In the viatical settlement market these roles are switched; individuals who are unobservably healthy are high-risk because they live longer and those who are unobservably sick are low-risk because they will not live as long. Subsequently, the model used to describe the consumer’s decision in the viatical settlement market predicts that high-risk healthy people viaticate less of their life insurance policy. This prediction is comparable to the standard insurance model’s prediction that high-risk unhealthy people are likely to demand more insurance than their low-risk counterparts.

To determine a possible equilibrium in the viatical settlement market with adverse selection, one can mirror the Rothschild Stiglitz methodology and examine the theoretical outcomes of both a pooling and a separating equilibrium. In this model, there are only two types of individuals: high-risk unobservably healthy individuals and low-risk unobservably sick individuals. If a viatical settlement company were to try to establish a pooling equilibrium between the two types, it would essentially offer the same price per unit of life insurance sold to all individuals, regardless of their health status.

This basic pooling scenario is illustrated in Diagram 1, in which the axes represent consumers’ wealth when they are in two different states of the world—living and dead. As the diagram indicates, all consumers are assumed to begin at an endowment point, E. Branching out from this endowment point are the viatical settlement firm’s zero profit lines, representing transactions in which the price the firm pays to policyholders is equal to the expected return on its purchase. A firm offering contracts to the right of a
zero profit line would make negative profits, and to the left would make positive profits. The zero profit line for low-risk consumers is steep because low-risk people will die sooner and therefore the firm can pay them more money when they are living per dollar amount that it receives from the consumers when they die. Similarly, the zero profit line for healthy consumers who live longer is relatively flat: to make zero profits, the firm only pays a small amount when they are alive in exchange for the return when the consumers die. The diagram also shows the indifference curves of the two types of individuals. Healthy people who live longer value their wealth when they are alive highly compared to after their death, and therefore their indifference curves are flatter. On the other hand, sicker people who will die sooner value highly their wealth after death; to remain indifferent they must be compensated a lot when living per dollar they give up when dead, so their indifference curve is steep.

Because Diagram 1 represents a pooling equilibrium, both types of individuals are combined into one contract. As a result, the viatical firm’s zero profit line is simply the average of the low-risk and high-risk line. Both types of individuals accept the contract (indicated by the dot) because it will put them on a higher indifference curve than their endowment point, E.

However, this equilibrium would be unsustainable. In order to compensate for the presence of high-risk individuals, the viatical settlement company would have to offer an average price that would be below the actuarially fair price for low-risk individuals. In this situation, a second viatical settlement firm could enter the market, offering to buy large viatical packages at a higher per-unit price (see Diagram 2). These transactions would be preferable to the initial transaction for low-risk individuals because the price
offered would be closer to their own actuarially fair price. Because the model predicts that low-risk individuals are more likely to sell large viatical packages than high-risk individuals, the firm could still make non-negative profits because only low-risks would self-select into its group and high-risk healthy people would be unwilling to sell such a large amount of their life insurance. Simply put, this new contract would put low-risk individuals on a higher indifference curve, and high-risk individuals on a lower one. The entrance of this successful firm would violate the equilibrium conditions for the pooling equilibrium.

A separating equilibrium is possible; however the transactions available must be limited for the equilibrium to be sustainable. Suppose first that a viatical settlement firm were to offer two types of transactions: one specific to relatively unhealthy individuals and one specific to relatively healthy individuals. This scenario is represented in Diagram 3. Regardless of the size of the insurance policy sold, the viatical settlement firm offers the actuarially fair per-unit price to both the healthy and the unhealthy individuals; in other words, the firm offers high prices to the low-risk unhealthy, and low prices to the high-risk healthy. If one assumes that information in this market is asymmetric, high-risk individuals can successfully masquerade as low-risk, getting high prices for their insurance policies and forcing the viatical settlement firms to make negative profits. This is shown in Diagram 4. All consumers will sign up for the contract intended for low-risks. This contract is to the right of the average zero profit line, indicating that the firm is making negative profits. The conditions for equilibrium are thus violated.

On the other hand, if the viatical settlement firm were to offer two separate types of transactions so that the two types of individuals would self-select into either group, the
market would reach a sustainable equilibrium. To do so, the viatical settlement firm would offer to purchase large viatical packages at a high price, and small viatical packages at a low price (see Diagram 5). Essentially, it would be doing the job of the two separate firms in the pooling equilibrium scenario. Unhealthy individuals would be able to sell large amounts of insurance at high prices and would therefore self-select into the high per-unit price transaction group. On the other hand, healthy individuals would be unwilling to sell so much of their insurance and would self-select into the low per-unit pricing group. The individuals would have successfully separated themselves into a sustainable equilibrium. Even the entrance of another firm, Gamma (shown in Diagram 6), would not break the equilibrium because this firm would make negative profits.

The empirical result that this adverse selection model predicts is that viatical settlement firms offer higher per-unit prices for larger insurance sales, and lower per-unit prices for smaller insurance sales. From the point of view of the policyholders, this can be seen as bulk discounting: better prices for transactions of greater magnitude. This would only be the case if asymmetric information were an issue; if there were perfect information, viatical settlement companies could simply pay each individual the actuarially fair per-unit price for their insurance policy regardless of its magnitude.

In reality, the viatical settlement market is not perfectly asymmetric as this simplified model describes. Viatical settlement firms invest significant resources into researching viators’ health status, examining past medical records and even requiring records from a doctor’s visit prior to agreeing on a settlement. To empirically test this model’s predictions, it is more appropriate to control for the life expectancy based on these assessments. Within each life expectancy category, an increasing per-unit price
structure would suggest that in the presence of adverse selection, viatical settlement firms use individuals’ behavior to infer a mortality risk that is more accurate than what their own information can indicate.

5. The Empirical Test of the Viatical Settlement Market Model with Adverse Selection

The logic of my empirical test follows that of Cawley and Philipson’s per-unit pricing test on standard insurance pricing, developed using the classic adverse selection model. The increasing per-unit pricing scheme predicted from their model is essentially the reverse of that predicted from my viatical settlement model, in which the consumers become the sellers in the market and the firm becomes the buyer. Cawley and Philipson’s increasing per-unit pricing is the opposite of bulk discounting, while viatical firm’s per-unit pricing in my model is comparable to bulk discounting from the point of view of the consumer.

To test the predictions of the viatical settlement market model with adverse selection, I use data collected as a result of the Freedom of Information Act (FOIA) requests to state insurance regulatory agencies. The dataset is made up of over twelve thousand viatical transactions that took place between 1995 and 2001 from firms licensed in states that regulate viatical settlement markets. The data compiled includes information on the face value of policies sold, the settlement amount received, the life expectancy of the seller at the time of the sale, the date of transaction, the premium paid, and the type of policy.
The per-unit price used to test for adverse selection in this market is essentially the ratio of the settlement amount of the transaction to the face value of the insurance sold. In its simplest form, running an OLS regression of face value on this ratio would yield a relationship between per-unit price and face value in the market.

\[
\frac{S}{F} = \alpha + \beta_1 F + \gamma_1 \text{Expectancy} + \gamma_2 X + \epsilon
\]

Here, \( S \) is the settlement value, \( F \) is the face value of the policy, \( \text{Expectancy} \) is the stated life expectancy in months, and \( X \) is a vector of control variables such as the year and state of the transaction. However, regressing this ratio on the face value of the policy would cause the coefficients to be biased because \( F \) appears on both sides of the equation. Instead, it is necessary to have only \( S \) as the dependent variable and see what quadratic relationship there is between the face value and the settlement price.

\[
S = \alpha + \beta_1 F + \beta_2 F^2 + \gamma_1 \text{Exp} + \gamma_2 X + \epsilon
\]

In this case, an increasing per-unit price would cause the settlement value to curve upward with the face value, which would be reflected in a positive \( \beta_2 \) (see Diagram 7).

Additionally, while the consumer decision to sell model simplified the transactions by assuming that the policyholder continued to pay any ongoing premium payments even after selling his insurance, in reality the viatical settlement company assumes responsibility for these payments. The expected net present value of all future premium payments over the course of the policyholder’s lifetime can be considered to be
an add-on to the viatical price paid by the firm. This value can be calculated using the market interest rate for the company’s funds, the monthly premium payments on the policy, and the hazard rate $\lambda$ (the probability of dying in period $t$ assuming that one has survived to time $t-1$), which is assumed to be constant. $\lambda$ is calculated as the inverse of the life expectancy:

$$\lambda = \frac{1}{\text{Expectancy}}$$

With this definition of $\lambda$, one can see that the probability of surviving up to time $t$ is $(1 - \lambda)^t$. Therefore, the expected net present value of premiums, if premium payments were to equal 1, is:

$$ENPV = 1 + \frac{1}{1 + r} (1 - \lambda) + \frac{1}{(1 + r)^2} (1 - \lambda)^2 + \frac{1}{(1 + r)^3} (1 - \lambda)^3 + ...$$

Multiplying both sides by $\frac{1 - \lambda}{1 + r}$ and then subtracting this new equation from the first then gives:

$$ENPV - \frac{ENPV(1 - \lambda)}{1 + r} = 1 \Rightarrow ENPV = \frac{1 + r}{r + \lambda}$$

Therefore, to apply this formula to the data, one can multiply the expression for expected net present value by the actual value of the policy premium:

$$\left(\frac{1 + r}{r + \lambda}\right) \times \text{Premium}$$

Because this term—the expected net present value of premiums—is calculated using the life expectancy, keeping it on the left hand side of the regression as an element of the settlement price would lead to a bias in the coefficient on $\text{Expectancy}$. To regress
the settlement value without the bias, this term is moved to the right hand side of the equation and the coefficients are then estimated with the constraint that $\gamma_3$ is equal to $-1$:

$$S = \alpha + \beta_1 F + \beta_2 F^2 + \gamma_1 \text{Exp} + \gamma_2 X + \gamma_3 \left(\frac{1 + r}{r + \lambda}\right) \text{Prem} + \varepsilon \quad (15)$$

where $\gamma_3 = -1$

5.1 A Closer Look at the Data

With more than twelve thousand transactions over the course of six years, the range in settlement and face values of the observations in the dataset is considerable. The settlement amounts range from zero dollars to $4,100,050 and the face values go from a mere $100 to $8,200,000. Even the life expectancies range from less than one month to a rare case of over forty years. Although all three of these variables are significantly skewed to the right, no observations are thrown out on account of being extremely high or low. This paper seeks to find pricing trends reflected in the market as a whole and the whole range of observations has been kept to avoid eliminating evidence for or against adverse selection in the market.

Incomplete observations, for example those without a purchase date or life expectancy listed, have been weeded out. Additionally, those observations with a life expectancy of zero months were thrown out because they prevented the calculation of $\lambda$. The resulting dataset is made up of 11,863 observations. See Table 1 for the summary statistics of these transactions.

5.2 Extra Control Variables and Variations on the Standard Regression

With equation (15), a standard regression can be run without $X$, the control variables. This would reflect the most important factors in the pricing of viatical
settlements, namely the face value of the insurance policy and the policyholder’s life expectancy. However, date and location of the transaction are both variables that potentially have a significant effect on pricing. The dataset includes information on viatical transactions that occurred between 1995 and 2001. Despite this relatively short timeframe, it is likely that technological shocks and market trends within the industry may have affected the prices offered by viatical settlement firms. Alpert, Bhattacharya, and Sood (2005) show that the 1996 introduction of HAART had a significant effect on the viatical settlement market. The new set of drugs extended the life expectancy of HIV patients, increasing the risk premium that firms faced from their investors and decreasing the prices offered on settlements. Additionally, the technological shock induced many viatical settlement firms to exit the market, thus increasing the remaining firms’ market power and again decreasing prices. To control for these date-specific variations, I add a purchase date variable into the regression.

With regard to the location of the transaction, the dataset is only made up of viatical transactions that occurred in the U.S.; however, there may be intrastate pricing differences. For instance, prices offered for viatical settlements may be higher in states with a higher cost of living. Alternatively, in states with less viatical settlement companies and therefore a less competitive market, prices may be lower. To control for these variations, I include the state of purchase in the regression as fixed effect dummy variables.
5.3 Results and Discussion

The results of the three regressions described above—standard (1), with the purchase date (2), and with state dummies (3)—are shown in Table 2. As one can see from the results, all coefficients are significant at the 1% level (except for the state fixed effects, which are not significant). The coefficients on the purchase date in regressions (2) and (3) are consistent with the results from Alpert, Bhattacharya, and Sood (2005), indicating that the price of viatical settlements has gone down over time in the years represented.

A look at the most relevant factors in the settlement pricing shows that, as expected, the life expectancy has a negative effect on the price offered and that the face value of the policy and the viatical amount are positively related. The coefficient on the squared face value variable is negative at a 1% significance level; however, its value is extremely small, practically zero. Diagram 8, which graphs the fitted values of the amount viaticated on the face value of the policy, shows a slight negative parabola, reflecting this small but negative coefficient. This is not consistent with the viatical Rothschild Stiglitz model with adverse selection, which predicts that per-unit prices increase with face value and that therefore, the coefficient on the squared face value should be positive. In short, these results suggest that adverse selection does not exist in the viatical settlement market.

In some respects, this result is not surprising. As discussed earlier in the literature review, the results of this study join a long list of previous studies that find no evidence for adverse selection in certain insurance markets. Yet these outcomes have certainly not eliminated the issue of adverse selection from discussions either among economic
theorists or among insurance companies. These companies continue to seek new cost
effective ways to determine more information about potential policyholders to reduce the
risk of adverse selection. In terms of health care, private insurance providers dedicate
large portions of their revenue to underwriting costs, uncovering as much information as
they can.

Studies that show no evidence of adverse selection do not necessarily suggest that
such efforts are a waste of time and money. There are multiple reasons that the
predictions of adverse selection models may not be consistent with the empirical data.
One potential cause is a problem in the model’s applicability to real markets. In its
simplest form, the adverse selection model argues against the sustainability of an
insurance company offering a single contract to all policyholders. While this may be true,
no insurance company actually behaves in this oversimplified way. Similarly, viatical
settlement firms do not have a singular contract that they offer to all viators, or even a
singular contract offered to all viators of certain life expectancies. The inconsistency
between the model’s predictions and actual firm behavior may in part be a result of the
incomplete picture that the model paints of the firm’s actions and the contracts it offers to
consumers.

Furthermore, the data used in this study is not always directly applicable to the
model of consumer decision in the viatical settlement market. The data collected from the
FOIA include information on the face value of the insurance that the policyholder sold in
each transaction; however, it does not include information as to whether this amount
equaled the full amount of the viator’s life insurance policy, and if not, what the full
amount was. To use the language of the model, the data provides $F$ but not $\tilde{F}$. Although
for simplicity sake, one can assume that viators generally sell all of their life insurance
when they choose to viurate, there is a likely possibility that this is not the case for all
viatical transactions.

The comparative statics analysis of the same consumer decision model in Alpert,
Bhattacharya, and Sood (2005) shows that $F$ increases with $\overline{F}$:

$$\frac{dF}{d\overline{F}} > 0$$

In other words, consumers with higher face valued insurance policies tend to sell a higher
face value amount when they viurate. When I apply the predictions of this model to the
model of adverse selection, I assume that viatical firms would view a higher $F$ as an
indication of a higher $\pi$. However, this is an incomplete picture, as the above relationship
indicates that a high $F$ could just be related to a high $\overline{F}$.

A different but related possibility is that the assumption that $F$ tends to equal $\overline{F}$ in
real transactions is in fact the case. In a viatical settlement market where most all
individuals choose their $F$ separately from $\overline{F}$ to maximize their utility, then the
predictions of the model may hold true. However, if empirically viators tend to just sell
their entire insurance policy regardless of the other variables that factor into their utility,
then viatical settlement firms may view $F$ as independent from the mortality rate.
Consequently, they would not use $F$ as an indication of true life expectancy and therefore
would not price their purchases to reflect this relationship.

Another source of inconsistency between the model and the data may stem from
the oversimplification of the information itself. Adverse selection comes as the result of
asymmetric information; however, in neither standard insurance markets nor in viatical
settlement markets is information perfectly asymmetric. Just as standard insurance
companies use underwriting processes and actuarial analysis to reduce risk and try to
determine more information, viatical settlement companies require information on
potential viators. Most require records from a physician’s visit as well as knowledge of
medications that the patient is taking. Some firms research medications that are not even
on the market yet because of the possibility that they will become available in the
patient’s lifetime.

Asymmetric information may also be more complicated than the model represents
it as. Regardless of whether viatical settlement companies are capable of discerning a
patient’s true life expectancy based on their symptoms and health records, the
information may still be asymmetric because patients know something about themselves
that the firm does not. For example, this model does not incorporate risk aversion into the
likelihood that someone will viaticate or not. A more risk-averse person may be less
willing to liquidate a large portion of their life insurance but also more likely to be
diligent with medications and doctor’s visits, which may extend their life. On the other
hand, a more risk-averse person may be more likely to sell a lot or all of their life
insurance, in order to fund the numerous medications and doctor’s visits they know they
will be using. To examine these possibilities and the effects they may have on the market,
the consumer decision model would have to be expanded to include these less concrete
characteristics.

Nonetheless, even without such modifications the consumer decision model can
offer more testable predictions that can be used to examine other aspects of its real life
applicability. In the next section, I analyze this model further and come up with a
different and less obvious prediction about the dynamics of the viatical settlement market, and then examine how it holds up to the actual data.

6. More on the Consumer Decision Model: The Relationship Between $F, \overline{F}$, and $\pi$

In section 2, the comparative statics analysis was outlined leading up to the relationship $\frac{dF}{d\pi}$, which is positive. A similar technique can be used to derive the relationship $\frac{dF}{d\overline{F}}$, or in other words, how the amount of insurance that the consumer viaticates changes with the total face value of his policy. This literal interpretation of the derivative is somewhat difficult to apply to real life, however, because in reality, policyholders tend to sell all or none of their insurance policy when they viaticate. A more realistic interpretation of $\frac{dF}{d\overline{F}}$ is that it represents how the likelihood of viaticating changes with the total face value of the policy; I use this interpretation in the following analysis of the model.

To solve for $\frac{dF}{d\overline{F}}$, the first order conditions (equations (9), (10), and (11)) are again used. As in section 2, the equation for $B_D$ is again substituted in and (9) is differentiated, now with respect to $C_1, F$, and $\overline{F}$ (i.e. totally differentiating and setting constant all exogenous parameters except the total face value of the policy). Doing so yields:

$$\left[ U''(C_1) + \beta(1 + r)^2 V''(B_D) \right] dC_1 + \left[ \beta r (1 - \pi) V''(B_D) \right] dF = \left[ \beta(1 + r) V''(B_D) \right] d\overline{F}$$

(15)
Likewise, substituting equation (11) into (10) and doing the same yields:

\[
\left[(1 + r)V''(B_D)\right]dC_1 + \left[\left(\frac{r}{1 + r}\right)U''(C_2) + \left(\frac{r}{1 + r}\right)(1 - \pi)V''(B_D)\right]dF = \\
\left[\left(\frac{r}{1 + r}\right)U''(C_2) + V''(B_D)\right]dF
\]

Solving (15) and (16) for the derivative of the likelihood of viaticating with respect to the total face value of the policy then leaves:

\[
\frac{dF}{dF} = \frac{A}{D}
\]

Where A and D are defined as follows:

\[
A = U''(C_1)\left[V''(B_D) + U''(C_2)\left(\frac{r}{1 + r}\right)\right] + \beta r(1 + r)V''(B_D)U''(C_2)
\]

\[
D = \left(\frac{r}{1 + r}\right)U''(C_2)U''(C_1) + \beta r(1 + r)U''(C_2)V''(B_D) + \left(\frac{r}{1 + r}\right)(1 - \pi)V''(B_D)U''(C_1)
\]

Assuming that both utility functions for consumption and for bequests are standard Cobb-Douglas functions with negative second derivatives, one can see that both A and D are positive terms.

\[
\frac{dF}{dF} = \frac{A}{D} > 0
\]

From here one can find the cross derivative relationship between \(F, \bar{F},\) and \(\pi\) by differentiating (17) with respect to the mortality risk.

Let X be defined as follows:

\[
X = \left\{\left(\frac{1}{1 + r} - \frac{1}{(1 + r)^2}\right)\frac{dF}{d\pi} - \frac{dC_1}{d\pi}\right\}(1 + r) - \frac{dF}{d\pi}
\]
Differentiating (17) with respect to \( \pi \) yields:

\[
\frac{d^2 F}{dF d\pi} = U''(C_1) U''(C_2) V''(B_d) X \left( \frac{r (\pi r + 1)}{(1 + r)^2} \right) + V''(B_d) U''(C_2) U''(C_1) \frac{dC_1}{d\pi} \beta r (\pi r + 1)
\]

\[
- U''(C_1) V''(B_d) U''(C_2) \frac{dF}{d\pi} \left( \frac{r^2 (\pi r + 1)}{(1 + r)^3} \right) - V''(B_d) U''(C_1) U''(C_2) \frac{dF}{d\pi} \beta r^2 \frac{\pi r + 1}{1 + r}
\]

\[
+ U''(C_1) V''(B_d) \left( \frac{r}{1 + r} \right) + U''(C_1) U''(C_2) V''(B_d) \left( \frac{r}{1 + r} \right)^2 + V''(B_d) U''(C_1) U''(C_2) \beta r^2
\]

(18)

Maintaining the standard assumptions about the utility functions, the first term in this equation is positive, as are the last three. The second, third, and fourth terms are negative. As a result, the sign of the equation appears to be ambiguous. However, by specifying the utility functions and substituting the previously derived equations for \( C_1, C_2 \) and \( B_d \) into (18), the above cross derivative can be numerically estimated.

6.1 Signing the Cross Derivative

Suppose the consumer’s utility functions for consumption and bequests are as follows:

\[
U(C_i) = C_i^{\gamma_1} \text{ where } 0 < \gamma_1 < 1
\]

\[
V(B_i) = B_i^{\gamma_2} \text{ where } 0 < \gamma_2 < 1
\]

Here, \( \gamma_1 \) does not necessarily equal \( \gamma_2 \), allowing for the likely possibility that a consumer gains utility from consumption in a different way than he gains utility from his bequests.
Substituting the second and third derivatives of these functions into (18) and substituting
\( C_1, C_2 \) and \( B_D \) leaves the following unknown parameters:

\[
\begin{align*}
  r, \beta, \pi, L, NL, \bar{F}, F, C_j, \text{ as well as } \gamma_1 \text{ and } \gamma_2
\end{align*}
\]

It is assumed that \( L_1 \) is equal to \( L_2 \), or in other words, individuals’ incomes do not
change over the course of the two time periods in the model. Furthermore, the market
interest rate, \( r \), is assumed to be .05 and the intertemporal discount rate, \( \beta \), is assumed to
be .9. The rest of the unknown parameters are somewhat more complicated. In order to
estimate the value of the cross derivative \( \frac{d^2 F}{d\bar{F}d\pi} \), one can use data from the HCSUS
dataset to estimate the values for \( \pi, L, NL, \bar{F}, F, \) and \( C_j \).

The HIV Costs and Services Utilization Study (HCSUS) followed a random
sample of HIV patients over three periods (from 1996-1998) and asked various questions
including inquiries on patients’ health care and physical and emotional wellbeing. The
data provides information on whether the patients ever had life insurance, and if so,
whether they ever sold or cashed out on their policy. In order to fill in the missing values
in equation (18), I found the average values for income, assets (i.e. non-liquid income)
and face value among those patients that did have life insurance at some point in time (a
total of 1,225 respondents). As mentioned earlier, patients who choose to viaticate their
insurance policies typically sell the entire policy rather than just a portion of it, so for the
sake of this calculation \( \bar{F} \) and \( F \) are assumed to be equal. Relaxing this assumption by
making \( \bar{F} \) greater does not change the final result. Additionally, these average values are
all calculated from the most recent observations (the last of the three periods) of the
survey, except for the average value of \( NL \), which was only recorded in the first period.
The summary statistics are shown in Table 3.
Although the status of the patients in the survey (responded, deceased, or unaccounted for) could be used to calculate the actual mortality rate of the respondents, a more relevant measure of $\pi$ would be the perceived ex-ante mortality risk of the patients, because this is what actually helps inform the consumer’s decision. This can be calculated by running a probit model on the variable died, which records whether the respondent passed away in the twelve months following the interview, based on relevant indicators of the patient’s medical health. In my analysis, I use the following variables as determinants of the likelihood of died:

- CD4 count (number of CD4, or T-helper, cells per ml of blood)
- Symptomatic status (asymptomatic, symptomatic, AIDS)
- Viral load (number of HIV RNA copies per ml of the patient’s blood)
- Months since diagnosis
- Gender
- Age category

The results of the probit analysis are used to predict the ex-ante mortality risk for each respondent. The average of these 931 individual mortality risks is then substituted in for $\pi$ in (18). These probit results and more detail on $\pi$ can be found in Table 4.

Lastly, the HCSUS survey does not contain data on patients’ consumption, so to estimate this value I used the 1985-2005 average US savings rate of 16.1% to calculate average consumption as a function of income (Business Week Online, July 11, 2005).

Once the values for $\pi, L, NL, \bar{F}, F,$ and $C,$ are obtained from HCSUS, $\gamma_1$ and $\gamma_2$ still remain unknown. Because these values cannot be estimated based on empirical data, I estimate the value of $\frac{d^2F}{dF d\pi}$ for all combinations of $\gamma_1$ and $\gamma_2$ with each value ranging from .05 to .95 with intervals of .05. The results can be seen in Appendix A. All combinations of $\gamma_1$ and $\gamma_2$ yielded a positive value for $\frac{d^2F}{dF d\pi}.$ Additionally, adjusting the
values of the assumed parameters $r$ and $\beta$ still consistently yielded a positive result for

$$\frac{d^2F}{dF d\pi}.$$

### 6.2 Interpreting the Cross Derivative

A positive value for $\frac{d^2F}{dF d\pi}$ effectively means that consumers with larger insurance policies are more likely to sell their policy, and that this likelihood increases the greater a consumer’s mortality rate.

The intuitive explanation for this outcome is similar to that of $\frac{dF}{d\pi}$ in section 2. First, one can consider the positive value of $\frac{dF}{dF}$. When the total face value of a consumer’s life insurance policy increases, this is comparable to an increase in wealth that will only contribute to his utility once he dies. In response to this wealth increase, there is a classic income effect—the consumer demands more of both consumption and bequests, both assumed to be normal goods. Because all his increased wealth has gone toward bequests, the consumer is more likely to sell some or all of his life insurance in order to increase funding for consumption and also increase investment for future consumption or bequests.

The addition of the effects of mortality risk affects the likelihood of viaticating in much the same way. When a consumer’s mortality risk increases, his equity in his life insurance policy effectively increases. This can also be interpreted as an increase in his wealth. The greater his mortality risk, the greater the income effect which increases his likelihood of viaticating; consequently, the probability of selling which already increases
with total face value increases even further with \( \pi \). In other words, when one considers the cross derivative one is examining the combination of effects that the two variables, face value and \( \pi \), have on the probability, and it is seen that the effect of changes in the first variable increases with changes in the second. (See Diagram 9.)

6.3 The Empirical Test of the Cross Derivative

To test this less obvious prediction of the consumer decision model, I again refer to the HCSUS dataset to analyze how respondents’ likelihood of viaticating changed in response to the face value of their policy and their mortality risk. To look at the cross derivative relationship, I run the following probit model on the data, shown in its simplest form below:

\[
\Pr(\text{Sell} = 1 | F, \pi) = \Phi(\alpha + \beta_1 \pi + \beta_2 F + \beta_3 (\pi \times F))
\]  \hspace{1cm} (19)

Given this empirical function, the interaction term complicates the marginal effect, and so the actual value of the cross derivative can be found as follows:

\[
\frac{d^2 \Pr(\text{Sell})}{dFd\pi} = \phi(x) \left[ \beta_3 - (x)(\beta_2 + \beta_3 \pi)(\beta_1 + \beta_3 F) \right]
\]

where \( x = \alpha + \beta_1 \pi + \beta_2 F + \beta_3 (\pi \times F) \) \hspace{1cm} (20)

and \( \phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \)

Because there are other determinants of \( \Pr(\text{Sell}=1) \), other control variables are also included:

\[
\Pr(\text{Sell} = 1 | F, \pi, Y) = \Phi(\alpha + \beta_1 \pi + \beta_2 F + \beta_3 (\pi \times F) + \delta Y)
\]

where \( Y \) is a vector of control variables.
Two different versions of this model are run: one in which \( Y \) includes a dummy for whether the respondent is working at the time and also an income variable, and a second time in which \( Y \) additionally includes dummies denoting marital status (divorced, separated, widowed, never married) and whether the respondent lives alone. In all of these probit models, the variable for \( F \) is measured in thousands of dollars.

The logic behind these particular controls is that the consumer’s financial stability, represented by his employment status and income, may affect his need for liquidity and therefore affect his likelihood of selling his insurance. On the other hand, his marital status may suggest varying possibilities. While the presence of a spouse may indicate an additional source of income, their presence may also mean that the consumer has dependents to support. Similarly, if the consumer lives alone, he is less likely to have other sources of income outside of himself, although he is also less likely to have dependents. These personal factors may change the consumer’s probability of selling his insurance.

6.4 Results and Discussion

The results for the above three probit models—the simple model without controls (1), with financial factors added (2), and with financial and marital/living situations added (3)—are shown in Tables 5 and 6. To find the values for the cross derivative, the beta results from the probit are entered into (20). This gives a cross derivative value for each observation; I use the mean of these values as an estimate for the cross derivative across the data. The values for the simple derivatives \( \frac{d Pr(Sell)}{dF} \) and \( \frac{d Pr(Sell)}{d \pi} \) are calculated in the same way, and are also shown in Table 5.
The results show that the data is in fact consistent with the predictions of the model, both the cross derivative prediction and the first derivative predictions. For all three of the probit models, the mean cross derivative value is positive as the consumer decision model predicts, all at around 0.01. Additionally, the values for the simple derivatives are also consistently positive, as predicted. The results from the third probit model (including all control variables) indicate that a $1,000 increase in the face value of a policy increases the consumer’s probability of viaticating by only .0002 percentage points, a .2% increase in the probability itself. The effect of a change in mortality risk is significantly greater—a one point increase in mortality risk increases the probability of viaticating by nearly .69 percentage points. While this may seem high, an increase in mortality risk this large would represent a considerable decrease in health, considering the average mortality risk of all respondents who have had life insurance is only .013 (after all, increasing mortality risk from 0 to 1 signifies going from no chance of death to certain death).

It is somewhat more difficult to interpret the value of the cross derivative—the main subject of this test—in direct relation to the change in the probability of viaticating because this value stems from an interaction term. Although the t statistics suggest that the cross derivative is statistically significant, it is hard to discern the economic significance of the relationship from the number alone. The value shares units with both $\bar{F}$ and $\pi$; because the scale of $\pi$ is extremely sensitive, the result for the cross derivative is actually very small. While its positive sign certainly supports the mathematical predictions of the model, it is likely that this aspect of consumer behavior plays a very small role in the dynamics of the market and may not even be readily observable. Further
tests that outline in detail the effects of face value on the probability of viaticating for individuals of various mortality risks would be helpful in determining the economic significance of these results.

Regarding the control variables, the results from the second and third probit models shed some light on the influence of other factors that contribute to a consumer’s decision to viaticate. Table 6 shows that the marginal effects of the financial stability controls included in this model are fairly small, significantly smaller than the effects of the marital and living situation of the respondents. Compared to a married respondent, one who is divorced is 60% more likely to sell his life insurance according to this model, while one who is widowed is over 70% less likely and one who has never been married is only about 35% more likely to sell. Additionally, someone who lives alone is about 25% more likely to viaticate than someone who does not. Clearly, this model does not include every control variable that could affect a consumer’s probability of selling. A more complete model (with additional data) might also include information on the respondent’s children, other dependents, or other surviving relatives, as well as their financial situations, so that one can get a better sense of the other people who are affected by the viator’s decision.

In general, however, the results from the analysis of this model are encouraging. The results suggest not only that the simple, more intuitively obvious predictions of the consumer decision model are consistent with the data but also that the complex and less easily observable predictions extracted from it are consistent as well. This provides evidence that the model is an effective one that holds weight beyond just its surface predictions, and can be used for future analysis with continued research on the dynamics
of the viatical settlement market. This said, the result for the cross derivative value suggests that although such predictions may be supported by the data, this does not mean that they in fact have a significant role in consumer behavior or the market as a whole and should therefore be viewed cautiously in terms of economic effects.

7. Conclusion

The goal of this paper has been twofold: to outline a model describing how adverse selection would play out in the viatical settlement market and then determining whether there is empirical evidence for its existence, and to take a closer look at the applicability of the consumer decision model by analyzing whether the model’s less obvious predictions are consistent with the empirical data. The first part concluded that the data on viatical transactions was not consistent with the adverse selection model’s pricing predictions; however, in the end of section 5, I describe other considerations that indicate that this study alone is insufficient to conclude that adverse selection does not exist in this market. The second part of my paper shows consistency between the data on HIV patients’ behavior and the comparative statics of the consumer decision model, which extends from realistically observable behavioral trends to the less obvious ones. I also indicate in section 6 that even if there is evidence that these predictions are true, their economic significance may be in question.

Despite the potential limitations to this paper’s models and its characterizations of the viatical settlement market, this study’s results still yield important information regarding the dynamics of this market. The second part of the study shows that the consumer decision model, one of the few such models developed for this market, is in
fact effective and would be valuable to future research in this area. The first, and perhaps more pertinent part of the study, shows no evidence to support the existence of adverse selection, raising the important question of how much information firms—both standard insurance and viatical settlement firms—should be allowed to extract about consumers. In the standard health and life insurance industries, scientific developments regarding the human genome have raised the issue of whether insurance companies deserve to know whether potential policyholders have certain genetic mutations, for example those that increase the risk of different types of cancer. If there were evidence for adverse selection in these markets, insurance companies’ arguments for the use of genetic testing would likely gain some support. Without this evidence, however, some people may find it morally grating to use such information as a basis for the pricing or the offering of a contract—a sort of discrimination based on information that should best be kept private or even unknown.

The viatical settlement industry is a newer and smaller industry than standard insurance, and has spent less time in the spotlight in terms of adverse selection and its related policies. Regardless, the problem of asymmetric or incomplete information has equal significance in this market and raises the same question of how much information disclosure is appropriate. Despite the various methods used to estimate life expectancy, industry experts acknowledge that there remains considerable uncertainty. Patients’ health statuses may change and their response to future medications can only be conjectured, leaving considerable room for inaccuracy in these predictions. Even worse, there are instances of fraud involving fabricated medical records suggesting lower life expectancies (or even a disease where there is none), although the percentage of such
cases is relatively low (Wolk 1998). Yet despite such uncertainty, there is a limit to the amount of examination and prodding that terminally ill viators deserve to go through.

What behavior is appropriate for the firms is a question that carries an increased significance because it addresses issues that are ethically charged. For many of us, both funding for health care and financial stability when it is most needed are necessary and deserved. To deny vulnerable people these resources, or only offer them at a higher price, requires some legitimate form of justification. Like all the adverse selection studies that have come before it, this study has not found the answer to how this market works and what subsequent actions should or should not be taken. Instead, this study has provided a piece of evidence that, along with further research and additional theoretical and empirical approaches, can contribute to this understanding.
Appendix A

Signing the Cross Derivative

To calculate the sign of the cross derivative, the average values of the variables outlined in section 6, the calculated value of $\pi$, and the assumed values for $r$ and $b$ were all plugged into (18), the equation for $\frac{d^2F}{dF\,d\pi}$. The following table shows the sign on the results for all tested values of $\gamma_1$ and $\gamma_2$ (the x and y axes), all of which are positive.

<table>
<thead>
<tr>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\frac{d^2F}{dF,d\pi}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.95</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.9</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.85</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.8</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.75</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.7</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.65</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.6</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.55</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.5</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.45</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.4</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.35</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.3</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.25</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.2</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.15</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.1</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>0.05</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Below is a sampling of the calculated values of the cross derivative.

- $\gamma_1 = 0.3$, $\gamma_2 = 0.3$, $\frac{d^2F}{dF\,d\pi} = 8.88062E-37$
- $\gamma_1 = 0.5$, $\gamma_2 = 0.5$, $\frac{d^2F}{dF\,d\pi} = 1.0333E-32$
- $\gamma_1 = 0.9$, $\gamma_2 = 0.9$, $\frac{d^2F}{dF\,d\pi} = 5.8651E-27$
- $\gamma_1 = 0.3$, $\gamma_2 = 0.9$, $\frac{d^2F}{dF\,d\pi} = 8.92004E-32$
- $\gamma_1 = 0.9$, $\gamma_2 = 0.3$, $\frac{d^2F}{dF\,d\pi} = 1.56765E-30$
### Table 1 - Viatical Transaction Data Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Face Amount</td>
<td>11863</td>
<td>116.7729</td>
<td>262.0852</td>
<td>1</td>
<td>8200</td>
</tr>
<tr>
<td>Viatical Amount</td>
<td>11863</td>
<td>58.54574</td>
<td>113.3515</td>
<td>0</td>
<td>4100.05</td>
</tr>
<tr>
<td>Expectancy</td>
<td>11863</td>
<td>28.17702</td>
<td>16.6648</td>
<td>0.5</td>
<td>500</td>
</tr>
</tbody>
</table>

*Face Amounts and Viatical Amounts given in 1,000s of dollars*
### Table 2- Viatical Transaction Data: OLS Regression Results

<table>
<thead>
<tr>
<th></th>
<th>Model (1) Viatical Amount</th>
<th>Model (2) Viatical Amount</th>
<th>Model (3) Viatical Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>34,287.003</td>
<td>182,914.727</td>
<td>185,847.734</td>
</tr>
<tr>
<td></td>
<td>(31.02)**</td>
<td>(14.03)**</td>
<td>(5.78)**</td>
</tr>
<tr>
<td>ENPVprems</td>
<td>-1.000</td>
<td>-1.000</td>
<td>-1.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>Expectancy</td>
<td>-999.212</td>
<td>-917.478</td>
<td>-914.073</td>
</tr>
<tr>
<td></td>
<td>(30.54)**</td>
<td>(27.54)**</td>
<td>(27.38)**</td>
</tr>
<tr>
<td>Face Amount</td>
<td>0.483</td>
<td>0.489</td>
<td>0.489</td>
</tr>
<tr>
<td></td>
<td>(131.53)**</td>
<td>(132.56)**</td>
<td>(131.58)**</td>
</tr>
<tr>
<td>Face Amount Sqd</td>
<td>-3.16e-08</td>
<td>-3.24e-08</td>
<td>-3.26e-08</td>
</tr>
<tr>
<td></td>
<td>(36.14)**</td>
<td>(37.14)**</td>
<td>(37.33)**</td>
</tr>
<tr>
<td>Purchase Date</td>
<td>-11.039</td>
<td>-10.994</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.44)**</td>
<td>(11.33)**</td>
<td></td>
</tr>
<tr>
<td>State FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>11,863</td>
<td>11,863</td>
<td>11,863</td>
</tr>
</tbody>
</table>

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Interested readers can request to see results for state fixed effects variables
Table 3- HCSUS Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>1175</td>
<td>31.70929</td>
<td>115.7779</td>
<td>0</td>
<td>2400</td>
</tr>
<tr>
<td>Assets</td>
<td>1049</td>
<td>48.80082</td>
<td>349.3788</td>
<td>-95</td>
<td>10500</td>
</tr>
<tr>
<td>Fbar</td>
<td>699</td>
<td>81.27685</td>
<td>137.6483</td>
<td>0</td>
<td>2000</td>
</tr>
</tbody>
</table>

All variables given in 1000s of dollars

All statistics only include those respondents who have ever had life insurance
Table 4 - Mortality Risk: Summary Statistics and Probit Results

<table>
<thead>
<tr>
<th>π</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>931</td>
<td>.0131699</td>
<td>.0257211</td>
<td>0</td>
<td>.2605992</td>
</tr>
</tbody>
</table>

**Reporting marginal effects**

<table>
<thead>
<tr>
<th></th>
<th>Pr(died)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD4</td>
<td>-0.000</td>
</tr>
<tr>
<td>Symptomatic</td>
<td>0.081</td>
</tr>
<tr>
<td>AIDS</td>
<td>0.257</td>
</tr>
<tr>
<td>Viral Load (C/ML)</td>
<td>0.000</td>
</tr>
<tr>
<td>Months since diagnosis: 13-24</td>
<td>0.001</td>
</tr>
<tr>
<td>Months since diagnosis: 25-48</td>
<td>0.000</td>
</tr>
<tr>
<td>Months since diagnosis: 49-84</td>
<td>0.001</td>
</tr>
<tr>
<td>Months since diagnosis: 85-120</td>
<td>0.000</td>
</tr>
<tr>
<td>Female</td>
<td>0.000</td>
</tr>
<tr>
<td>Age 30-34</td>
<td>-0.001</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>-0.001</td>
</tr>
<tr>
<td>Age 45-49</td>
<td>-0.001</td>
</tr>
<tr>
<td>Age 50+</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

Robust z statistics in parentheses
* significant at 5%; ** significant at 1%
Table 5- Probit Model Results for Likelihood to Sell Insurance

**Probit model (1)**

\[ \text{Mean } Pr(Sell) = .080827 \]

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
<th>t statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{d^2 Pr(Sell)}{dF d\pi} )</td>
<td>533</td>
<td>.010547</td>
<td>.00408</td>
<td>59.67936</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{dF} )</td>
<td>533</td>
<td>.000140</td>
<td>.000422</td>
<td>7.62816</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{d\pi} )</td>
<td>533</td>
<td>.500241</td>
<td>1.13832</td>
<td>10.14559</td>
</tr>
</tbody>
</table>

**Probit model (2)**

\[ \text{Mean } Pr(Sell) = .078695 \]

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
<th>t statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{d^2 Pr(Sell)}{dF d\pi} )</td>
<td>522</td>
<td>.010563</td>
<td>.004543</td>
<td>53.11698</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{dF} )</td>
<td>522</td>
<td>.000153</td>
<td>.000452</td>
<td>7.75565</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{d\pi} )</td>
<td>522</td>
<td>.586076</td>
<td>1.17094</td>
<td>11.43547</td>
</tr>
</tbody>
</table>

**Probit model (3)**

\[ \text{Mean } Pr(Sell) = .081349 \]

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
<th>t statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{d^2 Pr(Sell)}{dF d\pi} )</td>
<td>505</td>
<td>.013242</td>
<td>.007772</td>
<td>38.28837</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{dF} )</td>
<td>505</td>
<td>.000175</td>
<td>.000594</td>
<td>6.63238</td>
</tr>
<tr>
<td>( \frac{dPr(Sell)}{d\pi} )</td>
<td>505</td>
<td>.689785</td>
<td>1.4276</td>
<td>10.85808</td>
</tr>
</tbody>
</table>
Table 6- Probit Model Results for Control Variables

*Marginal effects reported*

<table>
<thead>
<tr>
<th></th>
<th>Model (2) Pr(Sell)</th>
<th>Model (3) Pr(Sell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of Sell</td>
<td>.0786948</td>
<td>.0813492</td>
</tr>
<tr>
<td>Work now</td>
<td>0.006 (0.27)</td>
<td>0.002 (0.09)</td>
</tr>
<tr>
<td>Income (in 1000s)</td>
<td>-9.28e-05 (1.06)</td>
<td>-1.21e-04 (1.09)</td>
</tr>
<tr>
<td>Divorced</td>
<td>0.050 (0.97)</td>
<td></td>
</tr>
<tr>
<td>Widowed</td>
<td>-0.059 (2.04)*</td>
<td></td>
</tr>
<tr>
<td>Never married</td>
<td>0.029 (0.85)</td>
<td></td>
</tr>
<tr>
<td>Live alone</td>
<td>0.020 (0.83)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>521</td>
<td>504</td>
</tr>
</tbody>
</table>

Robust z statistics in parentheses

* * significant at 5%; ** significant at 1%
Diagram 7

Viatical amount

Face amount
Diagram 8

Estimate Viatical Amount on Face Amount Quadratic

Face Amount
Fitted values viatamt
Estimate Viatical Amount on Face Amount Quadratic
References


