Winner’s Curse and the Competitive Effect:  
Measuring Competition in the Viatical Settlement Market

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May 10, 2010

Abstract

This paper attempts to develop a methodology for measuring competition in markets where the object for sale has a common but unknown monetary value. We do this by conceptualizing transactions in the viatical settlement market as first-price, common value auctions and deriving a parametric model for equilibrium bid functions. Within this model, we then estimate parameters and make observations about bidder behavior. Our analysis finds on average, fewer than five bidders compete for viatical contracts. We believe this is strong evidence of market power. Finally, by simulating comparative statics on the distribution of number of bidders, we conclude that at our estimated levels of competition, any evidence of winner’s curse was completely dominated by the competitive effect.

Keywords: winner’s curse, viatical settlement, competitive effect, common value auction, life insurance

This thesis would not have made it to its current state if not for the direction, patience and amazing encouragement from Professor Jay Bhattacharya. I also express endless gratitude to Professor Han Hong; his vast knowledge has been inspiring. Lastly, thanks go to all my friends who have been so incredibly supportive.
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1 Introduction

Fundamental to economics is the core postulate that increased competition improves social welfare, and that perfect competition is welfare maximizing. Hence, measuring the level of competition is essential for evaluating the functioning of any market. We attempt to add to literature on this topic by conceptualizing a market as a first-price auction. In this framing, the final auction price is determined by the number of bidders and the ability of these bidders to reliably judge the value of the auctioned item. The number of bidders serves as our measure of competition, and using an auction model, we can measure the impact of competition and information on market efficiency.

We conduct this analysis on data between 1995-2001 from the secondary life insurance market, where transactions known as viatical settlements allowed life insurance holders to trade their future death benefits for immediate payouts. Participants in this market were typically those who had previously purchased a life insurance policy but were recently diagnosed with a terminal illness. The insured individual can then agree to gain a lumpsum cash benefit now in exchange for listing the third-party purchaser as the policy's sole beneficiary. This purchaser, a viatical firm, then receives the full face value upon the policieseller's (i.e. viaticator's) death. Though the eventual value to the viatical firm is constant at the policy face value, the firm cannot collect until after the seller's death, so it shoulders risks that the insured outlives the predicted life expectancy or that the death occurs in such a way that voids the policy. The insured individual's predicted life expectancy and judgment of these risks determine the viatical settlement amount that the policy seller receives, and this amount is inversely related to life expectancy and the level of uncertainty.

Even when purchasers price against these risks, the sale of a life insurance policy can be pareto-improving. Sellers benefit from the heightened liquidity, which can finance vital end-of-life medical care or consumption. Viatical settlement payouts also generally greatly exceed the policies' cash surrender values, because the cash surrender value calculation neglects to adjust for the policyholder's altered health status. Hence, the viatical insurance market can be a source of much needed equity for the terminally ill. Despite this potential benefit, the viatical market faces its criticisms, ranging from the benign "macabre" (Goldstein 2007) to the more condemning "ghoul- ish, perverse and vampire" (Quinn 2008). Parts of this backlash stem from moral discomfort about the business of death speculation. Others worry about the moral hazards present when the new life insurance policy owner post-transaction suddenly has economic interest in an early death of the insured. Fears of abuse in this market are also accentuated by the possibly acute vulnerability of the policy seller. Could the terminally ill be exploited into giving up their policies for "below market" rates?

This conflict has drawn scrutiny into the ethics of viatical settlements and also spurred attempts to regulate the market (Trinkaus and Giacalone 2002; Quinn 2008). Gloria Grening-Wolk fears that viatical firms exploit consumers by exercising market power, and four-time Presidential candidate Ralph Nader too has spoken out for regulation (Grenning Wolk 1997). We attempt to evaluate these claims of imperfect competition by comparing settlement values to the actuarially fair prices.

Several other factors make the secondary insurance market between 1995-2001 worthy of study.
First, the market has undergone tremendous change in a small number of years. Though a Supreme Court decision upheld their legality in 1911 (Quinn 2008), viatical transactions remained very rare until the surge in HIV/AIDS in the early 1990s. So the market was still fairly new in 1995. We also hypothesize that the market was deeply altered by the arrival of efficacious treatments for HIV in 1996. The adoption of Highly Active Anti-Retroviral Therapy (HAART) almost overnight removed HIV/AIDS as an immediate death sentence. Because our data spans the adoption of this new treatment, we can assess the impact of HAART on calculations of mortality risk as well as its effect on market competition.

Lastly, though our data supports other reports that the popularity of viatical settlements has fallen dramatically since its peak in the mid-1990s (Belth 2000), the market seems not to have vanished but transitioned from the terminally ill to the elderly. Those transactions between policy purchasers and the elderly known as life settlements reached $3.4 billion in 2005 (LISA 2007) and an estimated $12.2 billion in 2007 (Tergesen 2008). As end of life care becomes more expensive, the importance of this secondary insurance market will only grow. Hence, learnings gained from our investigation into the 1995-2001 viatical settlement market may be insightful for current policy questions about this burgeoning market as well.

2 Bidding for Viatical Settlements

In this section, we note relevant literature and then introduce a model of competitive bidding for viatical settlement contracts. We observe first that the value from purchasing a viatical settlement (i.e. the death benefit) is constant independent of buyer identity. This true value, however, is unknown a priori, because it depends on the policy’s face value, a known, and the achieved lifespan, which is measured with noise. Together these two characteristics motivate the conceptualization of a viatical settlement transaction as a first-price, common value auction.

To further support this framing, we emphasize the similarities between bidding for a viatical settlement and bidding for a oil field lease. Like the true value of the oil field, the payoff from purchasing a policy remains hidden until possibly well after the actual transaction. While oil bidders conduct seismic surveys for oil, viatical firms rely on medical examinations to estimate the contract value, but both these tests only reveal noisy signals of what the true auction item value may be.

Hence, we will investigate the functioning of the viatical market as an auction. Specifically, we compare two potentially opposing forces in common-value auctions – the competitive effect and winner’s curse. The competitive effect arises from the core economics tenet that increased competition indicated by a larger pool of bidders should cause price to approach the item’s true value. This has been formalized for auctions by Wilson (1977) and Milgrom (1979), who show that as long as the signal is a extremal-consistent estimate of the actual value, the final auction price should converge to the “true value” in the case of asymptotic number of bidders. This occurs even with when auction participants only have access to limited sample information.

Although increased competition may elicit more aggressive bids from participants, a higher
number of bidders also raises the spectre of winner’s curse, which occurs when auction winners receive a negative profit because their signal overestimated the contract’s true value. This fear of having an overly-optimistic value estimate encourages more cautious bidding behavior, and the more bidders the more caution. This has led Bulow and Kemperer (2002) to argue that in some scenarios, restricting entry into the auction may actually increase prices, because bidders may shade their bids less. Literature has agreed that that auction participants are aware of the winner’s curse, and in equilibrium, at least the sophisticated bidders do incorporate it into their bidding strategies (Harrison and List 2008). For example, Hendricks, Pinkse and Porter (2003) found evidence of winner’s curse internalized into bidding behavior for wildcat oil leases on the Outer Continental Shelf from 1954 to 1970. We similarly conjecture that firms acting in the viatical settlement market are sophisticated enough to protect against winner’s curse in their equilibrium strategies.

Thus, bidder behavior in common value auctions reacts mainly to these two effects – higher competition and winner’s curse. Paarsch (1992) argues that bids and therefore, prices should initially rise with increased competition as participants reduce their profit padding to increase the probability of winning. However, beyond a certain point, the adverse selection impact of winner’s curse eclipses the competitive effect as potential purchasers increasingly shade their bids to avoid negative profits. The critical point of balancing these two effects remains an open question depending on market attributes (Armantier 2002), though Kagel and Levin (2002) in their survey of experimental common value auctions, claim that at least five bidders are necessary before winner’s curse arises.

Also crucial to the functioning of common value auctions is the reliability of bidders’ signals of the auctioned item’s true value. Poor estimates raise the risk associated with participating in the auction and so may distort bids downward. An auction might also collapse if buyers and sellers do not share the same information set. Specifically, if viaticators know their own mortality risks better than the firms, then Akerlof’s market for lemons problem of adverse selection might arise (1970). The market would also be impacted if policy sellers have biased judgments about their own mortality risk depending on their perceptions of death. But Cawley and Philipson (1999) develop evidence that in life insurance markets, firms and consumers make decisions from the same information set. Similarly, Bhattacharya and Snood (2001) argue that the viatical settlement market better matches the full-information model than adverse selection ones.

Literature on parametrically estimating common auction models has been more limited. Most of the early work including Rothkopf (1969), Smiley (1979), Thiel (1988) and Levin and Smith (1991) have relied on bidding models that produce closed-form solutions, which enable estimation through non-linear least squares or maximum likelihood (Paarsch 1994). The model we propose does not lend itself as easily to a closed form, so we opt instead to emulate the simulated non-linear least squares strategy taken by Hong and Shum (2002).

Lastly, before we develop our model, we describe an important difference between our conceptualization and the more canonical auction model. For a viatical settlement transaction, the policy seller approaches viatical firms to request offers. This is different from the case of an oil field when interested bidders take the initiative to conduct seismic surveys. So the number of offers
for a viatical settlement may be better modeled as a sequential search for an acceptably high bid. Additionally, auction entry may be endogenous to the viaticator’s search costs and health. While this presents a possible extension to our analysis, we will instead argue that the number of bidding firms can be well-modeled by a probability distribution known to all viatical firms.

We develop our model of viatical settlement auctions with the following notation:

- Let $N$ be the number of firms that the seller chooses to contact.
- Let $i$ be an index over the $N$, and let $\Pi_i$ represent firm $i$’s profits.
- Let $b_i$ be firm $i$’s bid, so $b = (b_1, ..., b_N)$ denotes a vector of firm bids.
- Let $r$ be the fixed interest rate.
- Let $v$ be the true value from winning the auction. In the viatical settlements market, this value depends upon the life expectancy of the seller (longer life expectancy implies a smaller $v$) and upon the interest rate (increases in $r$ also imply a smaller $v$). $G(v)$ represents the cumulative distribution function of $v$ over the population of viaticators. For a policy with face value $C$, $g(v)$ has support on $[0, C]$.
- When a seller approaches a firm, the potential bidder receives a noisy signal $x_i$ of the true value of the viatical settlement. $F_v(x_i) = F(x_i | v)$ is the cumulative distribution of $x_i$ given the viatical settlement’s true value. Similarly, $f_v(x_i)$ also has support over $[0, C]$.
- When the firm bids on a contract, it does not know the number of other firms that it competes against. But the firm does the distribution of $N$, which we denote by $p_n = P[N = n]$.
- Let $B_i$ denote the event that $b_i$ is the winning bid, $B_i = \{b_i > b_j | j \neq i\}$. Analogously, $X_i$ represents the event that firm $i$’s signal dominates all others, $X_i = \{x_i; x_i > x_j | j \neq i\}$.

To derive the equilibrium bidding function, we modify a strategy well-documented in literature (Paarsch and Hong 2006, p.34). We assume a market of risk-neutral firms striving to maximize expected profits. Firm $i$’s expected profit if it makes a bid of $b_i$ is the probability that it wins the auction times the expected return it earns after paying that bid.

$$E[\Pi_i|x_i, b_i] = P[B_i|x_i] (E[v|x_i, B_i] - b_i)$$

$$= \sum_{n=1}^{\infty} p_n P[B_i|N = n] (E[v|x_i, B_i, N = n] - b_i)$$

In this model, before their reading of the seller’s health, $x_i$, all firms are exactly alike. This observation motivates our assumption that the firm’s bidding strategies are symmetric. Moreover, we model that separate estimates of the viaticator’s health are independent since bidders each conduct their own medical examinations independently.

To maximize $E[\Pi|x_i, b_i]$, firm chooses $b_i$ to satisfy the first order condition:
\[
\frac{\partial E[\Pi|b_i]}{\partial b_i} = \sum_{n=1}^{\infty} p_n \left( \frac{\partial P[B_i|n]}{\partial b_i} (E[v|B_i,n] - b_i) - P[B_i|x_i,n] \right) = 0
\]  

Equations (2) says firms maximize expected profits by equating the marginal increase in expected revenue due to the higher probability of winning with the marginal cost of paying out that higher bid.

Rearranging the first order condition (2) yields:

\[
b_i = \sum_{n=1}^{\infty} p_n \left( \frac{\partial P[B_i|n]}{\partial b_i} E[v|B_i,n] - P[B_i|n] \right) \sum_{n=1}^{\infty} p_n \frac{\partial P[B_i|n]}{\partial b_i}
\]

Let \( \beta \) be firm \( i \)'s bidding strategy, so \( b_i = \beta(x_i) \), and we claim that symmetric firms share the same strategy. The bidding function, \( \beta \) is monotonically increasing in \( x_i \), so we can write \( x_i = \beta^{-1}(b_i) \). Along with this monotonicity property, firm symmetry permits a simple way to calculate the probability that a bid of \( b_i \) will win in an auction with \( n \) participants.

\[
P[B_i|n] = \int_0^\infty g(v) \left[ F_v(\beta^{-1}(b_i)) \right]^{n-1} dv
\]

Differentiating this equation with respect to \( b_i \) yields,

\[
\frac{\partial P[B_i|n]}{\partial b_i} = \int_0^\infty g(v) (n-1) \left[ F_v(\beta^{-1}(b_i)) \right]^{n-2} f_v(\beta^{-1}(b_i)) \beta'(b_i) dv
\]

Our theoretical goal is to obtain an an analytic expression for \( \beta(x) \) in equilibrium. The next steps manipulate our original first order condition to derive such an expression. First, we distribute equation (3) into two terms:

\[
b_i = \beta(x_i) = \sum_{n=1}^{\infty} p_n \frac{\partial P[B_i|n]}{\partial b_i} E[v|B_i,n] - \sum_{n=1}^{\infty} p_n P[B_i|n] \frac{\partial P[B_i|n]}{\partial b_i}
\]
\[
\beta(x) = \sum_{n=1}^{\infty} p_n E[v|B_i,n] \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} \frac{f_v(x_i)}{\beta'(x_i)} dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} \frac{f_v(x_i)}{\beta'(x_i)} dv \\
+ \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) [F_v(x_i)]^{n-1} dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv
\] (7)

Since \( \beta'(x) \) does not depend on \( n \), we pull these terms out of the summations in equation (7). Cancelling terms then yields:

\[
\beta(x) = \sum_{n=1}^{\infty} p_n E[v|B_i,n] \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv \\
+ \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) [F_v(x_i)]^{n-1} dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv
\] (8)

Next, we solve (8) for \( \beta'(x) \) as a function of \( \beta(x) \). This gives us a first order linear differential equation of \( \beta(x) \) in standard form:

\[
\beta'(x) = \sum_{n=1}^{\infty} p_n E[v|B_i,n] \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) [F_v(x_i)]^{n-1} dv \\
+ \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) (n-1) [F_v(x_i)]^{n-2} f_v(x_i) dv \\
- \sum_{n=1}^{\infty} p_n \int_0^\infty g(v) [F_v(x_i)]^{n-1} dv
\] (9)

The theory of ordinary linear differential equations then gives us that for an equation of the form \( \beta'(x) = Q(x) - R(x)\beta(x) \), the solution for \( \beta(x) \) is:

\[
\beta(x) = \exp \left( - \int^x R(u) du \right) \left[ \int^x Q(u) \exp \left( \int^u R(y) dy \right) du + c \right],
\] (10)

where \( c \) is an arbitrary real number.

Clearly, the terms in equation (9) line up directly with equation (10). Hence,
\[ \int R(u) \, du = \int \sum_{n=1}^{\infty} p_n \int_0^{\infty} g(v) (n-1) [F_v(u)]^{n-2} f_v(u) \, dv \, du \]
\[ = \ln \left[ \sum_{n=1}^{\infty} p_n \int_0^{\infty} g(v) [F_v(u)]^{n-1} \, dv \right] \] (11)

This gives:
\[ \exp \left( \int R(u) \, du \right) = \sum_{n=1}^{\infty} p_n \int_0^{\infty} g(v) [F_v(x)]^{n-1} \, dv \] (12)

Similarly,
\[ \int Q(u) \exp \left( \int R(y) \, dy \right) \, du = \int \left( \sum_{n=1}^{\infty} p_n E[v|B_i,n] \int_0^{\infty} g(v) (n-1) [F_v(u)]^{n-2} f_v(u) \, dv \right) \, du \] (13)

Plugging equations (12) and (13) into equation (10) gives our final solution for \( \beta(x) \):
\[ \beta(x) = \frac{\int_0^{x} \left( \sum_{n=1}^{\infty} p_n E[v|B_i,n] \int_0^{\infty} g(v) (n-1) [F_v(u)]^{n-2} f_v(u) \, dv \right) \, du}{\sum_{n=1}^{\infty} p_n \int_0^{\infty} g(v) [F_v(x)]^{n-1} \, dv} \] (14)

The integration constant must equal zero, since in equilibrium, firms that receive a signal that the value of the viatical settlement is zero will bid zero, \( \lim_{x \to 0} \beta(x) = 0 \).

We define probabilistically the expected value of \( v \), given that \( x \) is the highest signal received among \( n \) bidders, as:
\[ E[v|x_i,B_i,n] = \frac{\int_0^{\infty} v f_v(x_i) g(v) F_v(x_i) \, dv}{\int_0^{\infty} f_v(x_i) g(v) F_v(x_i) \, dv} \] (15)

Though we have constructed this model to predict the behavior of all bids, our empirical work focuses only on winning bids, since losing bids remain unobserved. While this may seem like a drastic loss in data, winning bids are often sufficient for analysis, because they become the upper bounds for all the unobserved bids (Milgrom and Weber 1982). This fact combined with the monotonicity of our equilibrium bid function underpin our investigation.
3 Assumptions for Empirical Analysis

We now turn to the problem of assigning structure to our equilibrium bid function for empirical analysis. To do so, we develop assumptions about the constituent functions of Equation (14):

- $g(v)$, the probability density function of the value of the contract;
- $f_v(x)$, the probability density function of the signal, given the true contract value;
- $F_v(x)$, the cumulative density function of the signal, given the true contract value; and
- $p_n$, the probability that a consumer contacts $n$ firms.

We derive parametrized formulae for these four functions in three main steps. First, we assume that viaticators’ lifespans are drawn from an exponential distribution. Then we derive $f_v(x)$ and $F_v(x)$ based upon assumptions about how estimates of lifespan should be related to actual lifespan. Finally, we argue that the number of firms a policy seller contacts can be well-approximated by a Poisson distribution.

3.1 The Distribution of Contract Values

To derive the distribution of contract values $g(v)$, we first derive the relationship between the value of the contract and the patients’ lifespan. Then we make a distributional assumption about these lifespans, and finally we combine the first relationship with the distributional assumption to determine a parametrization of the probability density function of contract values.

Given the contract face value $C$ and interest rate $r$, value of the contract is given by:

$$v = \frac{C}{(1 + r)^l}, \quad (16)$$

where $l$ is the lifespan of the viaticator. From the perspective of the firm, $C$ and $r$ are observable constants, while $l$ is an outcome of the random variable $L$. Thus, the cumulative distribution of contract values is given by:

$$G(v) = 1 - H\left(\frac{\ln \frac{C}{v}}{r}\right), \quad (17)$$

where $H(l)$ is the cumulative density function of achieved viaticator lifespans, and we apply the small value approximation $\ln(1 + r) \approx r$ for $r << 1$ Differentiating through, we obtain
the probability density function:

\[ g(v) = \frac{1}{rv} h \left( \frac{\ln \frac{C}{r}}{r} \right), \]

(18)

where \( h(l) \) is the probability density function associated with \( H(l) \). Though it restricts us to a constant hazard rate, we model achieved lifespans as following an exponential distribution because of the distribution’s empirical tractability. This generates the following distribution of true settlement values:

\[ g(v) = \frac{\lambda}{rv} \exp \left( -\frac{\lambda}{r} \ln \frac{C}{v} \right) \]

(19)

3.2 The Distribution of Signals of Contract Value

We next turn to deriving parametrizations of the probability and cumulative density functions for the contract value signal measured by bidding firms, conditional on the viaticator actual lifespan. We proceed in four steps. First, we mimic the argument of the last section and derive \( F_v(x) \) and \( f_v(x) \) in terms of a distribution over lifespan signals. Second, we make a strong assumption on the relationship between observed lifespan and actual lifespan. This allows us to find that our model requires only one additional parameter. Third, we derive the probability and cumulative density functions and lastly, we combine these functions with that of the previous section to define the joint distribution.

The signal of contract value observed by the firm may be written as:

\[ x = \frac{C}{(1 + r)^s}, \]

(20)

where \( C \) and \( r \) are constants as before, and \( s \) is an outcome of the random variable \( S \), which itself is a signal of the true achieved lifespan \( l \). As before, the cumulative density function of signals, conditional on the true value may be written as:

\[ F_v(x) = 1 - K_l \left( \frac{\ln \frac{C}{x}}{r} \right), \]

(21)

where \( l = \frac{\ln \frac{C}{r}}{r} \) is the lifespan corresponding to settlement value \( v \) and \( K_l(s) \) is the cumulative density function of lifespan signals. Differentiating through we obtain:

\[ f_v(x) = \frac{1}{rx} k_l \left( \frac{\ln \frac{C}{x}}{r} \right), \]

(22)
where \( k_l(s) \) is the probability density function corresponding to \( K_l(s) \). We next assume that the signal of life expectancy observed by the bidding firms has a Weibull distribution conditional the true lifespan. This assumption is consistent with existing literature; for example, Smiley (1979) also takes the Weibull distribution for signal values in his analysis of offshore oil and gas lease auctions. Hence, the cumulative and probability density of the contract signal given the true lifespan are:

\[
K_l(s) = 1 - \exp\left(-al^{-m}s^m\right)
\]

\[
k_l(s) = aml^{-m}s^{m-1}\exp\left(-al^{-m}s^m\right)
\]

where \( a \) and \( m \) are our two parameters. Next we make the unbiasedness assumption that in expectation, the signal equals the true value, \( E[s|l] = l \).

\[
E[s|l] = \int_0^\infty sk_l(s)ds = la^{-1/m}\Gamma(1 + 1/m) = l
\]

Solving yields \( a = \Gamma^m(1 + 1/m) \):

\[
F_v(x) = \exp\left[-\left(\Gamma(1 + 1/m)\frac{\ln \frac{C_x}{C_v}}{\ln \frac{C_v}{v}}\right)^m\right]
\]

\[
f_v(x) = \frac{m \Gamma(1 + 1/m)}{x \ln \frac{C_v}{v}} \left[\Gamma(1 + 1/m)\frac{\ln \frac{C_x}{C_v}}{\ln \frac{C_v}{v}}\right]^{m-1} \exp\left[-\left(\Gamma(1 + 1/m)\frac{\ln \frac{C_x}{C_v}}{\ln \frac{C_v}{v}}\right)^m\right]
\]

In this construction, \( m \) is the shape parameter of our Weibull distribution and is the second parameter we need to estimate in the joint distribution:

\[
g(v)f_v(x) = \frac{\lambda}{rv} \exp\left(-\frac{\lambda}{r} \ln \frac{C_v}{v}\right) \times
\]

\[
\frac{m \Gamma(1 + 1/m)}{x \ln \frac{C_v}{v}} \left[\Gamma(1 + 1/m)\frac{\ln \frac{C_x}{C_v}}{\ln \frac{C_v}{v}}\right]^{m-1} \exp\left[-\left(\Gamma(1 + 1/m)\frac{\ln \frac{C_x}{C_v}}{\ln \frac{C_v}{v}}\right)^m\right]
\]

3.3 The Distribution of the Number of Bidding Firms

Lastly, we attempt to define the final parametric assumptions of our empirical model, those regarding the distribution over the number of bidding firms, which depends on the number
of potential purchasers contacted by the viaticator. Since we always observe a winning bid, each auction must have at least one bidding firm, so we write:

$$N = 1 + M$$

(29)

where $M$ is a non-negative, integer random variable that represents the number of firms after the first that a policy seller contacts. To approximate $M$, we note that there are relatively many firms to approach, and each firm has a small probability of being contacted within the viaticator’s shopping period. The probability is low, because costs associated with approaching another firm, namely medical examinations, are high. This motivates our conceptualization of $M$ as a Poisson random variable.

We introduce our final variable $\rho$ as the Poisson parameter and write:

$$p_n = \Pr(M = n - 1) = e^{-\rho} \frac{\rho^{n-1}}{(n-1)!}.$$  \hspace{1cm} (30)

This completes the parametrization of our equilibrium bid function.

4 Data

Scrutiny placed on the viatical settlement market has spurred some states into regulating the market. In those jurisdictions, viatical firms are required to register for state licenses and file annual statements for all their transactions. California, New York and Oregon have further mandated that any firm making purchases in their state must also report all their U.S. transactions through that calendar year. Because of these disclosures, we can obtain information about the face value of the policy, settlement amount and life expectancy of the seller at the time of sale.

By the Freedom of Information Act, we were able to request these filed transaction information from 1995-2001 and aggregate them into a large STATA database. After scrubbing nonsensical values (e.g. negative life expectancy or missing face values), our data span 11,877 transactions, mostly from California, New York, Texas and North Carolina. The dataset also contains at least one transaction in every state across the six-year period and includes 32 different viatical firms making purchases. By the identity of the regulated states, we have confidence that our dataset includes nearly the entire population of U.S. transactions, which greatly palliates any fears of sample bias.

Before we conduct our empirical analysis, we first make some descriptive comments about the data. Table 1 shows a dramatic decline in the number of viatical settlements.
especially since 1998 and a 84.2% fall in revenue from 1995 to 2001. We hypothesize that the introduction and adoption of HAART lengthened life expectancies for AIDS patients, making the market less profitable for policy purchasers. This belief is supported in Figure 1, which shows the median life expectancy of viaticators doubling from 1995 to 2001. Table 1 also reports the number of active firms in our dataset remaining relatively steady, but the numbers the belie the market’s great flux. Membership within the active group fluctuated dramatically. Of the 14 active in 2001, only five filed transactions in 1995 and only two firms reported purchases in all six years. This confirms our earlier comment about the high degree of change in the viatical settlement market.

There also exists tremendous variation in the number of transactions made by these firms. In six years, three filed only one purchase, while one firm bought over 2500 policies. This might imply that firms may have very different risk appetites or budget constraints, which would undermine our earlier assumption about bidder symmetry. However, lacking bidder covariates, we overlook firm heterogeneity for this analysis.

Table 2 shows firms on average making more conservative bids over time, even conditional on the same life expectancy. We use nominal price to refer to the ratio of settlement amount and the life insurance’s face value. This normalization is needed to remove face value heterogeneity from our comparisons. The trend of falling prices is most vivid for viaticators with life expectancies longer than 12 months. For expectancy less than a year, we actually observe increases in the nominal price, such that the mean in 2000-2001 is not significantly different from the 1995 mean. Though it could just be small sample bias
(n = 52), the aberrant increase may also be an unexpected consequence of HAART. In general, HAART elongated life expectancies, but for patients whose illness had either progressed too far for HAART or were otherwise resistant to the treatment, the post-1995 technological improvements had no impact. For these sickliest of individuals having exhausted their treatment options, uncertainty about their expected time of death would have been very low, which could drive higher nominal prices. Other trends in Table 2 support this hypothesis. Notice that for life expectancy buckets of greater than two years, number of transactions actually rose before the market’s near dissolution in 2000-2001. On the other hand, the number of policies sold with expectancies under a year declined, even with the sudden spike in transactions in 1998 (see Table 1). One explanation for this is that viaticators who in 1995 would have fallen into the < 12 bucket because of HAART extended their life expectancies and instead fell into a healthier bucket. Thus, the few policy sellers that remained in the most sickly cohort were the ones whose deaths were most imminent and least uncertain. In sum, the success of HAART could have acted as a sieve
to differentiate out patients with the highest mortality risk, and this plausibly explains why nominal price for viaticators with life expectancy < 12 defied the overall industry decline in settlement values.

5 Empirical Strategy

In this section, we describe our empirical strategy, where the goal is to estimate the parameters \((\rho, \lambda, m)\).

Unlike the models found in Rothkopf (1969), Smiley (1979), Thiel (1988) and Levin and Smith (1991) which predict bids as a fixed proportion of signals, our model for viatical settlements does not lend itself easily to a closed-form solution and then a likelihood function. Instead, its severely nonlinear, parametric structure makes more challenging the identification of parameters. We follow the strategy of Hong and Shum (2002) to simulate our auction model and study the effect of parameters on the quantiles of \(\beta(x)\). This method exploits the monotonicity of our equilibrium bidding function, because quantile estimates restrict the shape of the bidding function. Moreover, monotonicity also dictates that the \(q_i\) quantile of health signals maps to the \(q_i\) quantile bid.

We minimize the following quantile objective function, where \(q_i\) indicates the 10\(i\)% percentile:

\[
Q(\hat{\rho}, \hat{\lambda}, \hat{m}) = \sum_{i=1}^{9} \left( \frac{b_{q_i}}{C_{q_i}} - \beta(x_{q_i}; \hat{\rho}, \hat{\lambda}, \hat{m}) \right)^2
\]  

(31)

We again employ \(\frac{b_{q_i}}{C_{q_i}}\) as the nominal price to control for face value heterogeneity. Clearly, the quantile regression should be robust against outlying observations, and another appeal of this quantile estimator is that it greatly relieves the computational burden of simulating Equation (14). The variation shown in Figure 2 given different parameters reassures us about the achievability of identification.
Table 2: Average Nominal Price and Life Expectancy of a Viatical Settlement, by Life Expectancy and Year

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;12 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Price (%)</td>
<td>73.59</td>
<td>78.62</td>
<td>68.20</td>
<td>73.23</td>
</tr>
<tr>
<td>95% CI</td>
<td>[72.77 , 74.42]</td>
<td>[77.84 , 79.40]</td>
<td>[66.05 , 70.35]</td>
<td>[70.42 , 75.94]</td>
</tr>
<tr>
<td>std error</td>
<td>0.420</td>
<td>0.397</td>
<td>1.093</td>
<td>1.350</td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>7.592</td>
<td>8.192</td>
<td>7.878</td>
<td>8.276</td>
</tr>
<tr>
<td>std error</td>
<td>0.107</td>
<td>0.120</td>
<td>0.153</td>
<td>0.307</td>
</tr>
<tr>
<td>n</td>
<td>373</td>
<td>445</td>
<td>273</td>
<td>53</td>
</tr>
<tr>
<td>12-23 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Price (%)</td>
<td>71.43</td>
<td>71.34</td>
<td>60.08</td>
<td>50.60</td>
</tr>
<tr>
<td>95% CI</td>
<td>[71.00 , 71.86]</td>
<td>[70.74 , 71.94]</td>
<td>[59.35 , 60.82]</td>
<td>[47.76 , 53.45]</td>
</tr>
<tr>
<td>std error</td>
<td>0.217</td>
<td>0.306</td>
<td>0.373</td>
<td>1.440</td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>15.761</td>
<td>16.377</td>
<td>15.656</td>
<td>16.207</td>
</tr>
<tr>
<td>std error</td>
<td>0.096</td>
<td>0.104</td>
<td>0.107</td>
<td>0.283</td>
</tr>
<tr>
<td>n</td>
<td>1202</td>
<td>1223</td>
<td>1099</td>
<td>142</td>
</tr>
<tr>
<td>24-35 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Price (%)</td>
<td>61.65</td>
<td>60.74</td>
<td>48.24</td>
<td>38.99</td>
</tr>
<tr>
<td>95% CI</td>
<td>[61.01 , 62.29]</td>
<td>[59.84 , 61.64]</td>
<td>[47.50 , 48.98]</td>
<td>[36.52 , 41.46]</td>
</tr>
<tr>
<td>std error</td>
<td>0.324</td>
<td>0.457</td>
<td>0.375</td>
<td>1.249</td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>25.302</td>
<td>27.541</td>
<td>25.730</td>
<td>26.651</td>
</tr>
<tr>
<td>std error</td>
<td>0.100</td>
<td>0.136</td>
<td>0.088</td>
<td>0.321</td>
</tr>
<tr>
<td>n</td>
<td>624</td>
<td>703</td>
<td>1257</td>
<td>132</td>
</tr>
<tr>
<td>36-47 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Price (%)</td>
<td>48.72</td>
<td>46.92</td>
<td>36.25</td>
<td>29.86</td>
</tr>
<tr>
<td>95% CI</td>
<td>[47.02 , 50.41]</td>
<td>[46.14 , 47.69]</td>
<td>[35.49 , 37.01]</td>
<td>[27.93 , 31.80]</td>
</tr>
<tr>
<td>std error</td>
<td>0.860</td>
<td>0.397</td>
<td>0.386</td>
<td>0.981</td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>37.728</td>
<td>37.096</td>
<td>36.849</td>
<td>36.721</td>
</tr>
<tr>
<td>std error</td>
<td>0.196</td>
<td>0.082</td>
<td>0.066</td>
<td>0.150</td>
</tr>
<tr>
<td>n</td>
<td>212</td>
<td>1026</td>
<td>1152</td>
<td>195</td>
</tr>
<tr>
<td>≥48 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Price (%)</td>
<td>39.31</td>
<td>36.13</td>
<td>28.86</td>
<td>26.91</td>
</tr>
<tr>
<td>95% CI</td>
<td>[36.90 , 41.72]</td>
<td>[34.70 , 37.56]</td>
<td>[28.00 , 29.73]</td>
<td>[24.86 , 28.97]</td>
</tr>
<tr>
<td>std error</td>
<td>1.222</td>
<td>0.729</td>
<td>0.441</td>
<td>1.039</td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>55.066</td>
<td>56.062</td>
<td>58.281</td>
<td>58.250</td>
</tr>
<tr>
<td>std error</td>
<td>0.672</td>
<td>0.553</td>
<td>0.694</td>
<td>0.927</td>
</tr>
<tr>
<td>n</td>
<td>212</td>
<td>492</td>
<td>888</td>
<td>154</td>
</tr>
</tbody>
</table>
Figure 2: Bids with Different Parameters

\[ \rho = 3, \lambda = 0.1, m = 0.5; +: \rho = 3, \lambda = 0.5, m = 1; \diamond: \rho = 3, \lambda = 1, m = 3; \circ: \rho = 3, \lambda = 1.5, m = 1.5 \]

The delta estimation strategy we use to calculate standard errors is explored in the Appendix.

6 Results

Our estimates are presented in Table 3 and graphed in Figure 3 on page 19.
Table 3: Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>4.592</td>
<td>4.468</td>
<td>3.329</td>
<td>2.9911</td>
</tr>
<tr>
<td></td>
<td>(1.279)</td>
<td>(0.091)</td>
<td>(0.224)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.698</td>
<td>0.878</td>
<td>0.797</td>
<td>0.873</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.022)</td>
<td>(0.061)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>$m$</td>
<td>0.756</td>
<td>1.174</td>
<td>1.127</td>
<td>1.125</td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
<td>(0.057)</td>
<td>(0.112)</td>
<td>(0.091)</td>
</tr>
<tr>
<td>$n$</td>
<td>2623</td>
<td>3889</td>
<td>4669</td>
<td>696</td>
</tr>
</tbody>
</table>

Figure 3: Predicted Bids

These results capture the trends we observed previously. Bids conditional on the same
life expectancy are falling over time, except transactions between 1996-1997 for higher
mortality risk settlements. Yet, we predict that 1995 bids are higher than 1996-1997 bids
for life expectancies greater than 32 months. We see this as evidence of rising uncertainty
about the life expectancy readings of the healthier viaticators, as captured in our joint
distribution. This rising uncertainty also manifests as more negative slopes for 1998-1999
and 2000-2001 bid functions. Conversely, bids for the most sickly appear not to have
fallen significantly, which agrees with the data and our hypothesis that HAART helped
differentiate between risky and less risky policies.

6.1 Effect of Increased Competition

We next address claims that purchasers in the viatical market exploited market power to
offer viaticators lower than actuarially fair prices. We also test Paarsch’s prediction that
in common value auctions, increasing the number of bidders drives prices upward initially
but then causes bids to drop as fears of the winner’s curse supersede the competitive effect
(1992). Since our analysis treats number of bidders as unobserved, we rely on comparative
statics on our poisson parameter $\rho$ to investigate market power.

Figures 4, 5 and 6 show simulated bids in response to increasing $\rho$, conditional on
different life expectancies. We also plot the actuarially fair price $AFP$, which is calculated
using $D = time of death$ and an annual insurance premium $z$. We continue to model life
expectancy using an exponential distribution.

$$AFP = \int_{0}^{\infty} P[D = t] \left[ \frac{C}{(1 + r)^t} - zt \right] dt$$

(32)
**Figure 4:** Effect of Competition for Life Expectancy = 12 months

![Graph showing the effect of competition for life expectancy of 12 months](image1)

- o: 1995
- *: 1996-1997
- +: 1998-1999
- ⋄: 2000-2001
- −−−: Actuarially Fair Price

**Figure 5:** Effect of Competition for Life Expectancy = 24 months

![Graph showing the effect of competition for life expectancy of 24 months](image2)

- o: 1995
- *: 1996-1997
- +: 1998-1999
- ⋄: 2000-2001
- −−−: Actuarially Fair Price
Clearly, the three graphs share characteristics. First, we notice that the simulations for 1996-1997 and 2000-2001 track together closely, reflecting the proximity of their respective $\lambda$ and $m$ estimates. This suggests that the sizable disparity in bids evident in Figure 3 was generated by a decline in the number of bidding firms. This conclusion matches Sood, Alpert and Bhattacharya’s (2005) findings of increasing market power driven by firm exit from the viatical insurance market. Moreover, our estimates of $\lambda$ and $m$ for 1996-1997, 1998-1999 and 2000-2001 are not significantly dissimilar at the 95% confidence level. But the post-1995 parameters are different from the 1995 estimates, lending credence to the hypothesis that the arrival of HAART precipitated a lasting shock to the true lifespan and signal distributions of the viatical settlement market.

Figures 4, 5 and 6 all show increasing bids when $\rho < 10$. But for $\rho \geq 10$ and life expectancies longer than one year, we see evidence of winner’s curse as simulated bids become negatively correlated with increased competition. The exception to this pattern is found for post-1995 bids for viaticators with life expectancies equal to one year. Again, we conjecture this is evidence that bidders actually gained confidence in their health readings for the high mortality risk, HAART-ineligible viaticators. But this evidence should be considered with caution, because it derives from extrapolations far outside the bounds of
Instead, the most striking observation is that all our estimates through 1995-2001 fall in the strictly increasing region across all three life expectancies. Realized settlement values are well below the actuarially fair price, and more competition would cause settlement values to grow dramatically. This supports claims that viatical firms enjoyed market power, enabling them to extract surpluses from policy sellers. This analysis also provides empirical evidence that despite the common value nature of this auction, winner’s curse did not play a role in affecting bidding behavior.

7 Conclusion

We have conceptualized transactions in the viatical settlement market from 1995-2001 as first-price, common value auctions. By applying a simulated quantile non-linear least squares estimation to our parametric model, we observe that the market experienced in a lasting shock between 1995 and 1996, likely due to the introduction of HAART, which dramatically extended the life expectancy of HIV/AIDS patients. Our analysis also suggests that throughout the six-year period, viatical firms exercised market power that allowed them to underprice their purchases. Over time, this market power actually increased as a result of firm exit, but market consolidation also coincided with a significant decline in market size.

Our analysis should not necessarily be read as advocating price floors for the viatical market. Such regulation would likely be too heavy-handed and inflexible for this market’s complexities and need to rapidly react to technological improvements. Bhattacharya, Goldman and Sood (2004) have claimed that price floors would reduce social welfare by blocking potential pareto-improving transactions. However, more competition in this market should have been encouraged, and it warrants further study to assess whether the growing life settlement market also suffers analogously from imperfect competition.

In this paper’s introduction, we set forth to propose a novel strategy for evaluating the level of competition in a given market. We have done this for the viatical insurance market and discovered that on average, transactions for life insurance policies between 1995 and 2001 had fewer than five bidders. At that level, we did not see evidence of winner’s curse, since any impact was completely eclipsed by the competitive effect. This conclusion drawn from our model is striking in and of itself, but it also augurs the more general application of our methodology for measuring competition in other markets wherever the object for sale has a common but unknown value.
Appendix: Calculation of Standard Errors

We apply a delta estimation procedure to calculate our standard errors. For \( \theta = (\rho, \lambda, m) \), our objective function in Equation (31) can be rewritten with the following matrix multiplication, where \( g(\hat{\theta}) \) gives the predicted quantile bids and \( y \) represents the actual quantile nominal prices from our dataset. Since we are considering the ten-percentiles, both \( g(\hat{\theta}) \) and \( y \) are 9 \times 1 matrices.

\[
(\hat{\rho}, \hat{\lambda}, \hat{m}) = \min_{\hat{\theta}} \left( g(\hat{\theta}) - y \right)^T I \left( g(\hat{\theta}) - y \right)
\]

We take the first order condition, and let \( H(\hat{\theta}) \) be the Jacobian matrix of \( g(\hat{\theta}) \). We denote the true population parameters as \( \theta_0 \).

\[
0 = H(\hat{\theta})' I (g(\hat{\theta}) - y)
\]

\[
0 \approx H(\hat{\theta})' I \left[ g(\theta_0) - y + H(\hat{\theta})(\hat{\theta} - \theta_0) \right]
\]

by Taylor approximation

\[
H(\hat{\theta})' H(\hat{\theta})(\hat{\theta} - \theta_0) = H(\hat{\theta}) I (g(\theta_0) - y)
\]

\[
\hat{\theta} - \theta_0 = \left[ H(\hat{\theta})' I H(\hat{\theta}) \right]^{-1} H(\hat{\theta})' (g(\theta_0) - y)
\]

\[
Var(\hat{\theta} - \theta_0) = Var(\hat{\theta}) = \left[ H(\hat{\theta})' I H(\hat{\theta}) \right]^{-1} H(\hat{\theta})' Var [g(\theta_0) - y] \left[ H(\hat{\theta})' I H(\hat{\theta}) \right]^{-1} H(\hat{\theta})'
\]

So it suffices to find \( Var [g(\theta_0) - y] \), which is a 9 \times 9 variance-covariance matrix, and by Newey and McFadden (1994) and Paarsch (1994), we note that

\[
\sqrt{n} [y - g(\theta_0)] \rightarrow N(0, \Omega)
\]

To find \( \Omega \), we first introduce a kernel density function \( f(x) \), which denotes the density of the error distribution at different quantiles (Koenker and Hallock 2000). Here, \( n \) is the number of observations, \( q \) is the number of estimated quantiles and \( h \) is a bandwidth term we find by assuming the underlying Gaussian errors and minimizing the asymptotic mean integrated squared error.

\[
f(x) = \frac{1}{qh} \sum_{i=1}^{q} \frac{1}{\sqrt{2\pi}} \exp \left[ \frac{(x - x_i)^2}{2h^2} \right]
\]
Now we return to the topic of calculating $\Omega$ by noting that for the $10k\%$ percentile:

$$0 = \frac{1}{n} \sum_{i=1}^{n} 1[y_i \leq g_k(\theta)] - k$$

$$0 \approx \frac{1}{n} \sum_{i=1}^{n} 1[y_i \leq g_k(\hat{\theta})] - k + f_g(g_k(\hat{\theta}))(y_k - g_k(\theta_0))$$

$$\sqrt{n}(y_k - g_k(\theta_0)) = \frac{1}{f_y(g_k(\hat{\theta}))} \left[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} 1[y_i \leq g_k(\hat{\theta})] - k\sqrt{n} \right]$$

$$n\text{Var}(y_k - g_k(\theta_0)) = \frac{1}{f_y(g_k(\hat{\theta}))^2} \text{Var}\left\{1[y_i \leq g_k(\hat{\theta})]\right\}$$

$$\text{Var}[y_k - g_k(\theta_0)] = \frac{1}{n f_y(g_k(\hat{\theta}))^2} \left[ \frac{k}{10} \left(1 - \frac{k}{10}\right) \right]$$

Next we evaluate the non-diagonal values. For cell $jk, j \neq k$

$$\text{Covar}\left[\sqrt{n}(y_j - g_j(\theta_0)), \sqrt{n}(y_k - g_k(\theta_0))\right]$$

$$= \frac{1}{f_y(g_j(\hat{\theta}))} \frac{1}{f_y(g_k(\hat{\theta}))} \text{Covar}\left[\frac{1}{\sqrt{n}} \sum_{i=1}^{n} 1[y_i \leq g_j(\hat{\theta})], \frac{1}{\sqrt{n}} \sum_{i=1}^{n} 1[y_i \leq g_k(\hat{\theta})]\right]$$

$$= \frac{1}{f_y(g_j(\hat{\theta}))} \frac{1}{f_y(g_k(\hat{\theta}))} \left[ \frac{\min(j,k)}{10} - \frac{j}{10} \frac{k}{10} \right]$$

$$\text{Covar}[y_j - g_j(\theta_0), y_k - g_k(\theta_0)] = \frac{1}{n f_y(g_j(\hat{\theta}))} \frac{1}{f_y(g_k(\hat{\theta}))} \left[ \frac{\min(j,k)}{10} - \frac{j}{10} \frac{k}{10} \right]$$
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Goldstein, Matthew. 2007. “Profiting from Mortality: Death bonds may be the most macabre investment scheme ever devised by Wall Street,” *BusinessWeek*, July 30.


