The Journal of Risk and Insurance

DOI: 10.1111/jori.12078

Measuring the Performance of the Secondary Market for Life Insurance Policies

Carmelo Giaccotto
Joseph Golec
Bryan P. Schmutz

Abstract

We construct an index of life insurance policies purchased in the secondary market by viatical and life settlement companies. Using the repeat sales method to measure returns over our 1993–2009 sample period, we find that policy returns average about 8 percent annually compared to 5.5 percent for the S&P 500 and 7 percent for corporate bonds, but they are twice as volatile as the S&P and four times as volatile as bonds. Nevertheless, because the index return is relatively uncorrelated with stock or bond returns, life insurance policies make attractive additions to well-diversified portfolios.

Introduction

The secondary market for individual life insurance policies in the United States has grown from about $200 million in 1993 to $44 billion in 2010.[1] The market began with policies on individuals with less than 2 years of life expectancy (called viaticals) and grew to include those with more than 2 years of life expectancy (life settlements). Our data source includes both; hence, we refer to these life insurance investments collectively as viatical life settlements investments (VLSI). Except for recent work by Braun, Gatzert, and Schmeiser (2012) (hereafter BGS) and Davo, Resco, and Barroso (2013) (hereafter DRB), there is little research that systematically analyzes the return characteristics of these investments. We add to this line of research.

Carmelo Giaccotto and Joseph Golec are at the Department of Finance, School of Business, University of Connecticut. Bryan P. Schmutz is at the Department of Accounting and Finance, College of Business, Western New England University. The authors can be contacted via e-mail: CGiaccotto@Business.Uconn.edu, Jgolec@Business.Uconn.edu, and Bryan.Schmutz@wne.edu.
For their helpful comments and suggestions, we would like to thank session participants at the 2009 Eastern Finance Association meetings and the 2012 Swiss Society for Financial Market Research meetings. We thank the Center for International Business and Business Education and Research at the University of Connecticut for support for data gathering.

[1]See the Life Insurance Settlements Association, http://www.lisa.org/content/3/Industry.aspx (accessed June 30, 2013).

BGS provide a detailed analysis of the performance of an index of 17 open-end life settlements mutual funds, covering December 2003–June 2010. They also provide an excellent overview of the life settlements market and the life settlements mutual fund industry. DRB combine two life settlements mutual funds with fixed income and equity index funds over September 2006–February 2010 to form efficient portfolios. To our knowledge, our article is the first to examine the risk and return characteristics of an index composed of direct life insurance policies, including 1,724 policies with a face value of about $300 million. Specifically, we develop a quarterly index of VLSI returns starting from the fourth quarter of 1993 through the fourth quarter of 2009.

We provide three advances compared to BGS and DRB. First, we use data on individual VLSI contracts instead of mutual fund portfolios. This allows us to show that VLSI returns differ across disease types; for example, VLSI from AIDS patients have relatively low returns. Second, we cover a longer sample period; thus we are able to illustrate how major VLSI-related events lead to VLSI return volatility. Third, we use the repeat sales method to compute a VLSI return index, because the method was created by Bailey, Muth, and Nourse (1963) to handle infrequently traded assets such as VLSI. It is used to compute the widely quoted S&P Case–Shiller real estate price index.

Our results are in line with those of BGS and DRB in many respects, except we find that the returns of VLSI computed using the repeat sales method are much more volatile than those self-reported by mutual funds. Indeed, BGS anticipate this possibility, noting that because life settlements investments are illiquid, fund managers can value their investments with a mark-to-model approach instead of a mark-to-market approach, allowing more leeway to smooth their reported returns. They find little correlation between fund returns and the returns of other assets, but this could be due to artificially smoothed fund returns.

Although our VLSI returns are quite volatile, we confirm that they are still little correlated with the returns of more traditional investments, such as stocks and corporate bonds. Indeed, we illustrate some of the reasons why. For example, during the early years of the VLSI market from 1993 through 1996, our VLSI return series is comparable to that of corporate bonds; however, breakthroughs in AIDS drug treatments extended the lives of many AIDS patients, driving down VLSI returns from 1997 to 1999. Changes in institutional investor demand and supply of VLSI could also affect return volatility. The newness and general illiquidity of the VLSI market could partly explain the high volatility.

Our results show that VLSI earn about 8 percent annually compared to 7 percent for long-term corporate bonds, and 5.5 percent for the Standard & Poor's 500 stock index (S&P 500). If we exclude the market crash between 2008 and 2009 from our sample period, we find that VLSI earn about 7.3 percent compared to 8.5 percent for the S&P 500 and about 7.1 percent for bonds. But the VLSI return volatility is about twice that of the S&P 500, and about four times that of bonds.[2]

[2]Our data source for VLSI does not extend beyond 2009 because there is a considerable lag in their availability from the data source. Extended further to include recent stock market appreciation, the superior performance of bonds and VLSI would likely be much less.

Despite the high stand-alone risk, we find that VLSI are subject to little systematic risk measured relative to a stock market index or the stock-based risk factors of Fama and French (1993). The larger volatility of VLSI could reflect liquidity or mortality rate risks. Those risks could be systematic or idiosyncratic in nature, but testing whether our VLSI index represents a priced systematic factor is beyond the scope of this article.

Even though VLSI are much more volatile than corporate bonds and the S&P 500, we show that they are not fully dominated by either one and can still play a role in well-diversified portfolios. The next section provides a brief description of the VLSI industry in the United States and offers a review of recent literature.

INDUSTRY BACKGROUND AND RECENT LITERATURE

VLSI are life insurance policies purchased from terminally ill or health-impaired individuals by investors who agree to pay the remaining premiums in return for the death benefit payout (face value of the policy). The life insurance policies in our data set are typically sold at a discount of between 20 percent and 70 percent of face value, depending on life expectancy, with 72 percent of our observations priced between 50 percent and 79 percent of face value. The VLSI are commonly held until the insured's death, although some are resold.[3]

A unique feature of the data used for our study is that we are able to track the purchase prices and death benefit payouts for VLSI. Policyholders sell to investors who are usually willing to pay more for VLSI than the surrender values offered by the issuing insurance companies, because surrender values usually do not reflect the deterioration in the insured's health. Trinkaus and Giacalone (2002) note that VLSI prices essentially reflect investors' expectations of the insured's life expectancy and medical innovation.

While some form of VLSI date back to public auctions of policies in 18th-century England (Hamwi and Rueggerm, 1994; Sommer, Gustavson, and Trieschmann, 1997), the VLSI industry in the United States essentially started with the AIDS epidemic of the late 1980s. AIDS victims often needed additional liquid assets to fund expensive medical treatments and living expenses, and could not afford to pay premiums once they could no longer work. Because our data start in the early 1990s, the VLSI in the early years of our database are mostly viaticals.

Over the years, other health-impaired individuals have sold their policies for similar reasons (see Ray, 2000; Doherty and Singer, 2003). The term "viatical" is used to connote policies sold by individuals with short life expectancies (less than 2 years) and "life settlements" is used to connote policies sold by individuals with longer life expectances (and typically larger face values).

Recent research mostly focuses on life settlements because they now make up the lion's share of the VLSI market. In their general survey of the longevity risk market,

[3]Each resold policy creates two pairs of transactions. The first pair is from the health-impaired individual to an investor, while the second pair is a transaction between two investors. Both pairs can then be used in the VLSI index construction although our data include only the final transaction.

Blake et al. (2013) discuss the micro-risks associated with life settlements. Zhu and Bauer (2013) examine the effects of asymmetric information on life settlements pricing, and Brockett et al. (2013) show how medical information can be effectively incorporated into life settlements pricing.

BGS and DRB study life settlement mutual fund data that starts in 2003 and 2006, respectively; hence, many of the funds buy only life settlements. This is partly because there are now relatively more life settlements available for sale and they typically have larger values. The larger values help to economize on transactions cost and more quickly compose large portfolios. Furthermore, the market for viaticals is more regulated in many states, although states like New York (in 2009) and California (in 2010) have recently extended the regulation of viaticals to life settlements.[4]

Most other VSLI-related studies do not consider returns, but instead use the unique features of VLSI to test theories of the behavior of life insurance companies or policy sellers. For example, Bhattacharya, Goldman, and Sood (2009) test whether individuals rationally assess their life expectancies when they consider selling their life insurance policies, or whether they act irrationally. They find that individuals tend to overestimate their life expectancies. Daily, Hendel, and Lizzeri (2008) show how VLSI innovation can lead insurance companies to change the contractual nature of their policies. Bhattacharya, Goldman, and Sood (2004) show that when state governments set price floors for VLSI, they reduce the number of VLSI created, implying substantial welfare losses.

Another stream of this literature focuses on the ethical, legal, or regulatory aspects of the VLSI market. Because terminally ill individuals are physically and mentally vulnerable, regulation (mostly at the state level) has grown to try to ensure price fairness and reduce fraud (see Ray, 2000; Giacalone, 2001; Doherty & Singer, 2003).

Some state regulation is aimed at the high fees associated with VLSI. Deloitte (2005) finds that transactions costs include broker's commissions (4–8 percent of face value), selling commissions (5–10 percent of gross proceeds[5]), provider's origination fees (5 percent of gross proceeds), and management fees (5 percent of gross proceeds). They suggest that due to high transactions costs, most individuals with access to other sources of liquidity should avoid selling their policies. Nevertheless, they show that VLSI sell for 109–294 percent of surrender value. Even after steep transactions costs, Doherty and Singer (2003) find that policy sellers in 2002 gained $240 million above surrender values when they sold their policies.

In terms of federal financial regulation, courts have ruled that VLSI do not meet the definition of a "security" established by the Securities Act of 1933, and therefore, are not regulated by the Securities Exchange Commission (Glick, 1993; Rowland, 2003).

[4]See the Life Insurance Settlement Association website listing of state regulations, http://www.lisa.org/state-document-report.aspx (accessed on January 20, 2014).

[5]Gross proceeds are defined as the present value of the life insurance policy's death benefit (face value) at a discount rate of 8 percent (Deloitte, 2005).

BGS are the first to examine the return characteristics of life settlements mutual funds, and their potential benefits to investors. For their Life Settlement Fund Index covering December 2003 and June 2010, they report an annual return mean and standard deviation of 4.85 and 2.28 percent, respectively. Across individual funds in the index, average annual returns ranged widely from 9.09 to −22.71 percent, and standard deviations ranged from 0.24 to 32.42 percent. DRB report average monthly returns for two funds that in annual terms amount to about 1.4 percent (September 2006–February 2010) and 9.6 percent (January 2007–February 2010), respectively. Their associated annualized standard deviations are 5.27 and 0.58 percent, respectively.

By comparison, our portfolio of individual VLSI has a return mean and standard deviation of 8 and 19 percent, respectively. The difference in mean returns partly reflects the larger returns of most assets during the 1990s, which is included in our sample but not those of BGS and DRB. Like them, we find lower returns for VLSI in the 2000s. The additional fees charged by mutual funds likely lower their returns compared to ours. The large difference in return standard deviations is likely due to smoothing by mutual fund managers and the underlying volatility of VLSI during our sample period.

Because VLSI are not widely traded, their values cannot be easily marked-to-market; hence, each fund can value their assets using mark-to-model, which gives managers flexibility to smooth returns by choice of model and model assumptions. For example, estimated life expectancy can be updated at the discretion of the fund manager. By comparison, all of our returns are based on reported purchase price, costs such as discounted premiums, and the face value payout upon death of the insured.

Of course, policies are cashed in at discrete points in time; hence, although it is easy to measure multiperiod returns for individual policies, measuring returns over shorter fixed intervals is problematic. But the repeat sales method can handle this problem and has proven effective in measuring returns for infrequently traded assets like real estate. The method essentially combines the information from the overlapping multi-period returns from groups of VLSI to infer the returns over short fixed intervals of time.

THE DATA AND THE REPEAT SALES METHOD

The Data

Our VLSI data are obtained from the New York State Insurance Department filings for the years ending 1993–2009.[6] Up until 2010, the State of New York required VLSI firms to file annual reports listing all of their VLSI holdings, not just those originating in New York. The report includes several schedules, two of which contain the transaction-level data that we use to compute returns. Table 1 lists the 17 VLSI firms

[6]Since 2011, the department is referred to as the insurance division of the New York State Department of Financial Services. While the annual filings begin in 1995, some policies purchased in 1993 and 1994 are either still "active" in 1995 or have paid out the death benefit in 1995.

Table 1
VLSI Companies Contributing Observations to Index

VLSI Company	Annual Report Range	
	From	To
American Life	1994	1996
Dignity Partners	1993	1995
Habersham	2007	2008
Kelco	1995	2001
Legacy Benefit	1992	2005
Life Benefactors	1993	1997
Life Funding	1993	1996
Life Settlements	1999	2002
Lifetime Entitlements	1994	1996
Lifetime Options	1993	1995
National Benefit	1994	1995
Neuma	1993	2009
Portsmouth	1996	2008
Viatical Settlements	1993	1996
Viaticare	1994	2001
Viaticus	1994	2001
WM Page	1995	2009

Note: This table lists the 17 Viaticals-Life Settlements (VLSI) companies that filed annual reports with the New York State Insurance Department from which we extracted data on their individual VLSI holdings. The range of years for their annual reports are also listed.

used in our study and the range of years for which they conducted business and filed annual reports in New York. The list includes many of the major VLSI firms.[7]

First, Schedule 4 titled "List of All Purchased Policies," lists each policy that the firm purchased, but for which it has not yet received the death benefit (face value) by December 31 of the given year. It lists the issuer, date of issue, face value, settlement paid, expenses, fees, premiums, and total cost. Second, Schedule 7 titled "List of Paid Viatical Settlements Where Viator's Death Occurred During the Current Year," lists all policies on which the firm has collected the face value. Schedule 7 shows the date of death, age at death, cause of death, duration from VLSI purchase to the insured's death, and state of residence, as well as the date of purchase, estimated life expectancy, face value, and settlement paid.

The terminology used in the New York filings is a bit misleading. In the early 1990s, when the filings were first developed, viaticals essentially comprised the whole market, hence, the title of Schedule 7. Once VLSI firms started buying life settlements in the 2000s, they were required to report the same information for them alongside their viaticals using the

[7]A notable exception is Coventry First which filed annual reports but did not report the data on their individual LSI holdings.

same form.[8] The life settlements funds studied by BGS (fund data start in 2003) and DRB (fund data start in 2006) may restrict their holdings to life settlements.[9]

We use data in Schedule 4 to estimate up-front expenses and commissions for each settlement listed in Schedule 7. Up-front expenses are estimated by finding the average up-front expense reported on Schedule 4, for each dollar of face value, and applying that percentage to the Schedule 7 settlements. Commissions are calculated in the same manner with the average commissions reported on Schedule 4 applied to settled VLSI reported in Schedule 7. Across all firms, up-front expenses are 5.90 percent on average, and commissions are approximately 4.5 percent of face value. Premiums paid are also taken from Schedule 4, and average $16.47 per $1,000 of face value (1.647 percent) per year.

We use these data to compute a VLSI return index using the repeat sales method. Quarterly data on other asset class returns, including certificates of deposit, U.S. long-term corporate bonds, S&P 500, S&P 400, and Russell 1000, are obtained from Ibbotson Associates and the CRSP database. We obtain the market portfolio return and the Fama–French factors from Kenneth French's website. These are required to estimate systematic risk from the capital asset pricing model (CAPM) and the Fama–French three-factor model.

The Repeat Sales Method

The repeat sales method was created by Bailey, Muth, and Nourse (1963) and has been widely used to construct real estate price indices (Case and Shiller, 1989, 1990; Clapp and Giaccotto, 1992). It has also been applied to other illiquid assets including wine, collectables, and art (Burton and Jacobsen 1999, 2001; Pesando 1993; Biey and Zanola 1999; Ginsburgh, Mei, and Mosses, 2006).

Many nontraditional assets do not trade identical units at fixed intervals like widely held stocks or bonds, making it difficult to accurately measure returns over fixed intervals. This problem has been handled for real estate assets by using the hedonic regression method or the repeat sales regression method (RSR) to create index values at points in time, and returns for fixed time intervals. RSR allows us to compute a quarterly VLSI index series even though most policies do not settle after 3 months.

We start with the hedonic model that expresses house value as a function of time (the valuation date) and hedonic characteristics like the number of bedrooms,

[8]Information obtained from personal contact with George Brady, Supervising Insurance Examiner, Life Bureau, New York Department of Financial Service, November 18, 2013.

[9]We tried to obtain financial reports for some life settlements funds, but could only find a few that provided some data to nonshareholders. We found portfolio-level data on only one, EEA Life Settlements Fund PCC Limited. In their earliest annual report available (2008), EEA reports that they held 196 policies, whose insureds had an average life expectancy of 38 months (http://www.cisx.com/listedsecuritynews.php?companyID = 1549&offset = 125; accessed January 9, 2014). Similarly, the policies in our VLSI index covering the 2006–2009 period had insureds with an average life expectancy of 31 months. Therefore, although EEA only invested in life settlements, the expected maturities of their policies were similar to those in our index.

number of bathrooms, etc. The logarithm of V_{it} , the price of house i, sold at time t, is expressed as:

$$\log(V_{it}) = X_{it}\beta_t + \delta_t + \epsilon_{it}, \tag{1}$$

where X_{it} is a vector of house i's hedonic characteristics, and ϵ_{it} is a mean zero random error. This error term captures variation in house prices unrelated to hedonic characteristics or the price level (e.g., randomness in tastes and preferences of buyers and sellers, or variation in bargaining power; see Shiller, 1993). The vector β_t measures the implicit price of the hedonic characteristics, and the intercept δ_t measures the overall time t price level. This method works well for a consistent set of data on hedonic characteristics recorded at the time of sale.

The RSR method is an extension of the hedonic model that works well even when consistent data on the hedonic characteristics are not available. Consider a home that sells twice over a particular time horizon, first at time s and again at time t. The rate of price change (continuously compounded) is given by the difference in log prices: $y_i \equiv \log(V_{it}) - \log(V_{is})$. Using Equation (1) we obtain:

$$y_i = X_{it}\beta_t - X_{is}\beta_s + \delta_t - \delta_s + \epsilon_{it} - \epsilon_{is}. \tag{2}$$

The RSR method assumes that home characteristics and their implicit prices remain constant between the first and second sales. When these assumptions are met, the first two terms on the right-hand side of Equation (2) cancel, leaving the repeat sales regression.

There are two issues to consider when applying the RSR method to VLSI. First, the health of the insured changes over time and is not easy to observe. Second, the VLSI payoff of face value is not a negotiated price between buyer and seller. Indeed, this value is known at the time of the first sale (ignoring the possible default by the insurer). To address these concerns, we develop a variation of the repeat sales model.

Our goal is to develop an index that tracks the price path of a portfolio of VLSI; let e^{δ_t} be the level of this index at time t. Without loss of generality, we set $\delta_0 = 0$, so that the index starts at 1.0. We assume that the market value, or price, of each VLSI (V_{it}) is related to the index in a log-linear fashion:

$$V_{it} = c_{it}e^{\delta_t + \pi_{it}}, \tag{3}$$

where c_{it} represents time-varying characteristics, such as health of the i^{th} insured individual, and π_{it} is a mean zero disturbance that reflects random deviations of each policy from the overall index. This model is similar to a single-factor stock market model in levels (Fama, 1976); the time-varying "beta" of the ith VLSI is measured by c_{it}.

Let V_{is} be the purchase price paid at time s by an investor for the ith VLSI. In our application, this price includes up-front expenses and the present value of premiums. One can argue that premiums should be discounted at a relatively low rate because VLSI buyers must pay the premiums; otherwise, they forfeit the face value, and because premiums can sometimes be deferred during bad economic times and paid later in good economic times. On the other hand, systematic mortality risk could support a higher rate found in Affolter, Braun, and Schmeiser (2014). Unfortunately, there is no theoretical or empirical model of a VLSI risk premium. We use the 3-month U.S. Treasury bill rate to discount premiums. Robustness checks using a number of different discount rates show only a marginal effect on the estimated return series.[10]

At the time of purchase, investors know the face value that they will receive upon death of the insured. But the timing of this payment is uncertain, and may change substantially as a result of medical innovations, or other idiosyncratic events. Let V_{it} be the face value of the ith policy received as the death benefit at time t. Then, the cumulative return for each VLSI is given by: $y_i = \log(V_{it}) - \log(V_{is})$. Clearly, this return must be characterized as a random variable because the timing of the final cash flow is unknown.

From Equation (3), the following is used to explain the cross-section of returns:

$$y_i = \delta_t - \delta_s + \log(c_{it}) - \log(c_{is}) + \pi_{it} - \pi_{is}. \tag{4}$$

Changes in the (log) index, $\delta_t - \delta_s$, reflect the total return obtained from time s to t after the ith policy has been paid off. Furthermore, a comparison of Equations (2) and (4) shows that changes in the natural log of c_{it} correspond to changes in individual hedonic characteristics and their implicit prices. The term $\log(c_{it}) - \log(c_{is})$ captures idiosyncratic randomness in the original price paid for the VLSI, as well as the random timing of the final cash flow. The last two terms in Equation (4) reflect random deviations from the overall index.

Note that our model does not require the strong assumptions of the repeat sales method. However, since we do not have data on the insured's health, we model unobservable changes in the health of the ith individual with a zero mean random walk: $\xi_i = \Delta\log(c_i)$. The assumption of zero mean is consistent with the notion that a rational buyer is equally likely to over- or underestimate the life expectancy of each insured.

[10]Using the Treasury bill rate allowed us to use a rate that changed over time. The average rate during our sample period applied to our VLSI was 4.73 percent annualized. We also considered using a fixed rate of 1 percent or 8 percent. The 1 percent rate can be rationalized because the premium payments could actually be countercyclical. The 8 percent could be rationalized because DRB note that their funds set target returns of 8 percent and BGS find the same for some of their funds. Both BGS and DRB, however, find that the funds typically earn much less than 8 percent. We find that if we use a fixed 1 (8) percent, the quarterly return for our VLSI index falls (rises) by about 6 basis points. A recent (unpublished) study by Affolter, Braun, and Schmeiser (2014) finds that over the period 2011 to 2013 implied internal rates of returns (IRR) on VLSI funds were in the range of 15 to 30 percent. Using a 15 percent discount rate increases our average quarterly return by 10 basis points roughly, and further increasing the discount rate to 25 percent adds an additional 10 basis points to the average. However, we note that using the IRR in place of an appropriate cost of capital is contrary to accepted financial theory because the IRR exceeds the cost of capital by the return due to profitable investments (Brealey, Myers, and Allen, 2013).

From Equation (4) we get a cross-sectional regression:

$$y_i = D_{i1}\delta_1 + D_{i2}\delta_2 + \ldots + D_{iT}\delta_T + \varsigma_i, \tag{5}$$

where D_{is} $(s = 1, 2, \ldots, T)$ is a time dummy variable that equals -1 if the ith VLSI was purchased in quarter s, $+1$ if the death benefit was collected in s, and 0 otherwise. Given the time dummies D_{is} for each quarter, the regression coefficients $(\delta_1, \ldots, \delta_T)$ can be estimated by ordinary least squares (OLS) or weighted least squares (WLS), because the random disturbance term in Equation (5) consists of white noise plus a random walk: $\varsigma_i = \xi_i + \varepsilon_{it} - \varepsilon_{is}$.

The random walk assumption implies that the variance of ς_i is a function of the actual difference between the time the policy is sold and the time the face value is received. This choice is consistent with Case and Shiller's (1989) finding of heteroskedasticity associated with a longer time between the purchase and payoff. Therefore, we use WLS to estimate Equation (5), where the weight for each observation is the policy holding period.

To avoid perfect collinearity, we fix one of the coefficients in Equation (5). To start the VLSI index at 1.0, we set $\delta_0 = 0$, which is equivalent to excluding the first column of data. Thus, δ_1 represents the average appreciation of the VLSI held during the first period, and the single period (quarterly) returns are obtained from the differences: $\delta_t - \delta_{t-1}$.

EMPIRICAL RESULTS

Summary Statistics for the VLSI Sample

Table 2 presents the summary statistics for our sample of VLSI. Across the entire sample, the average policy seller is 54 years old, sells a policy with a face value of $170,435 for $103,615, and lives approximately 33 months after the policy is sold. The average cost to the settlement company including fees and premiums is $134,780. On average, discounted premiums are approximately $6,171, provider's origination fees plus manager's and servicer's fees are about $14,938, and the remaining $10,056 costs are the broker's up-front fee. Clearly, origination fees and broker fees are substantial, representing about 20 percent of the total costs, and are much larger than the cost of premiums.

Table 2, Panel A shows the summary statistics for our sample of VLSI transactions broken down by cause of death. The largest portion comes from individuals suffering from AIDS (804 observations or 46.64 percent of the sample), followed by various "other" diseases (649 observations or 37.65 percent of the sample), cancer (212 observations or 12.30 percent of the sample), and heart disease (59 observations or 3.42 percent of the sample).

Note that VLSI from AIDS patients provide the lowest average returns, and those from heart and cancer patients provide the highest average returns. The differences in returns across diseases can be partly explained by the amount by which VLSI firms have underestimated patients' life expectancies. They estimated AIDS patient life expectancy at 17.70 months on average, but they lived for 30.58 months on average. The 12.91 difference likely reflects progress on new AIDS drugs after some of the VLSI were purchased.

TABLE 2
Summary Statistics for VLSI Where Death of the Insured Has Occurred

Panel A

	Entire Sample	AIDS	Heart	Cancer	Other
Face value	170,435	93,522	192,860	344,636	206,385
Amount paid to seller	103,615	61,905	99,073	212,684	112,833
Total cost to company	134,780	78,348	133,855	273,832	150,717
Discounted premiums	6,171	2,416	12,122	12,480	8,205
Origination & manager's fees	14,938	8,383	13,543	29,087	17,738
Broker's upfront fees	10,056	5,644	9,117	19,581	11,941
Age of seller	54	50	60	59	56
Estimated life expectancy	20.54	17.67	28.92	18.53	24.27
Time until death	33.04	30.58	34.69	26.18	38.19
Total return	23.47%	17.70%	36.52%	23.00%	31.43%
Expected annual return	13.11%	11.71%	13.79%	14.34%	14.47%
Actual annual return	7.96%	6.61%	11.37%	9.95%	8.97%
Number of VLSI	1724	803	59	213	649

Panel B

	Pre-1996	1996–2000	2001–2005	Post-2005
Face value	79,113	89,407	190,906	574,609
Amount paid to seller	55,422	61,202	99,735	251,169
Total cost to company	73,403	75,252	136,556	389,594
Discounted premiums	1,701	2,105	7,877	23,837
Origination & manager's fees	9,730	7,139	17,299	68,485
Broker's upfront fees	6,550	4,806	11,645	46,103
Age of seller	58	47	54	63
Estimated life expectancy	13.99	17.28	25.46	31.12
Time until death	10.06	16.86	48.47	86.91
Total return	7.49%	17.24%	33.50%	38.86%
Expected annual return	6.39%	11.68%	14.59%	13.49%
Actual annual return	9.00%	11.98%	7.42%	4.64%
Number of VLSI	441	516	594	173

Note: Data were obtained from annual reports filed by VLSI firms with the New York State Insurance Department. Specifically, we use data from Schedules 4 and 7 of the annual reports. All figures are averages except Number of VLSI. Face value, amounts paid, costs, premiums, and fees are in dollars; age is in years; and life expectancies and time until death are in months.

VLSI firms underestimated life expectancies for the other disease categories as well, although less so for heart and cancer patients. If the policies had been purchased at prices that reflected patients' actual times until death life, the VLSI firms would have earned an average return of 12.50 percent versus 8.00 percent across all policies. The median would have increased from 8.03 percent to 10.70 percent. Therefore, had the individuals' life expectancies not been underestimated, the VLSI firms would have achieved substantially higher returns.

Our figures are consistent with criticism of VLSI companies who advertised high expected returns to investors but delivered much lower ones.[11] Nevertheless, the average returns of VLSI are still comparatively good, so that VLSI pricing appears to include a large enough margin to absorb the negative return effects of medical treatment progress on average. This margin was apparently relatively small for AIDS patients compared to patients with other diseases, where the underestimate of life expectancy is also large but the average returns are not as low (but still lower than for heart and cancer).

Table 2, Panel B shows the summary statistics for our sample of VLSI transactions broken down by subperiods within our 1993–2009 sample period. Note that the average face value and cost to the VLSI company has increased over time as companies focus on purchasing larger VLSI. Purchasing fewer but larger VLSI saves on transactions costs. The differences between estimated life expectancy and actual time until death also grows across the subperiods. In the pre-1996 period, before AIDS drug breakthroughs had taken hold, the average estimated life expectancy exceeds the average actual time until death, and actual returns exceed expected returns.[12] The reverse is true for later subperiods.

The estimated life expectancy and the actual time until death increase in each period, reflecting medical treatment progress as well as the growth of the VLSI market, from mostly viaticals (less than 2 years life expectancy) to more life settlements (greater than 2 years life expectancy). The discrepancy between estimated life expectancy and the actual time until death gets larger for at least two possible reasons. First, the number of VLSI firms grew from about 30 in 1994 to 170 in 1999, and more competitive bidding for policies may have led to higher prices.[13] Higher prices can also be rationalized if VLSI firms obtain estimates of policyholder life expectancies that are relatively short. Second, the sharp drop in interest rates during the sample period is likely to have driven VLSI prices higher.

The average returns in Panels A and B are not directly comparable. Panel B presents the average annual returns for VLSI for which the face value was collected during the given period. Hence, the increasing discrepancy between expected life expectancy and the actual time until death partly reflects the fact that later periods include some cases where the seller ended up surviving much longer than expected, forcing the VLSI company to pay more premiums and wait longer for the death benefit payoff.

---

[11]In a page 1 article in the *Wall Street Journal*, Maremont and Scism (2010) describe how a major life settlement company sold VLSI to investors after touting large returns. The large projected returns were driven by life expectancy estimates, purchased by the company from a doctor, which were too low 95 percent of the time. The longer actual life expectancies meant that investors had to pay more premiums and receive the policy death benefit later than expected, cutting their returns. A.M. Best (2008) and Milliman (2009) also find that life expectancies for VLSI were consistently underestimated.

[12]The Food and Drug Administration approved the first protease inhibitor, the first highly effective AIDS drug, in June 1995. See aids.gov/hiv-aids-basics/hiv-aids-101/aids-timeline/ (accessed July 9, 2013).

[13]See Taylor (1994) and Opdyke (1999).

There are relatively fewer long-survivors in the pre-1996 period because the industry largely started in the early 1990s.

VLSI Index Construction

We compute the VLSI index returns based on the repeat sales method using a quarterly interval to ensure that there are enough VLSI policies in each period to get reliable index values. Most of the individual quarterly index values (the δ_t in Equation (3)) are statistically significant (59 of 64), even though they are quite volatile. Some of the volatility is due to the changing distribution of policy sellers' diseases over time, shocks to mortality (e.g., breakthrough drug treatments), and changes in institutional supply and demand for VLSI.

Table 3, Panel A presents a comparison of the VLSI index descriptive statistics with those of the S&P 500 and long-term corporate bonds over our sample period of 1993:Q4 though 2009:Q4. VLSI display a higher average quarterly return than either long-term corporate bonds or the S&P 500 (1.96 percent for VLSI vs. 1.36 percent for the S&P 500 and 1.69 percent for long-term corporate bonds). However, this attractive

TABLE 3
VLSI Comparison to S&P 500 and Long-Term Corporate Bonds

	VLSI	S&P 500	LT Corp
Panel A: Entire Sample (1993:Q4–2009:Q4)			
Mean	1.96%	1.36%	1.69%
Standard deviation	19.85%	8.63%	4.93%
Skewness	−0.47	−0.72	0.46
Kurtosis	3.84	0.83	3.42
Semivariance	195.56	40.73	8.17
Sharpe (T-bill)	0.055	0.057	0.17
Sharpe (T-bond)	0.035	0.012	0.087
Panel B: Excluding Financial Crisis Years (1993:Q4–2007:Q4)			
Mean	1.77%	2.05%	1.72%
Standard deviation	19.95%	7.58%	3.51%
Skewness	−0.61	−0.62	−0.04
Kurtosis	4.42	0.92	−0.61
Semivariance	209.64	26.87	3.8
Sharpe (T-bill)	0.040	0.144	0.217
Sharpe (T-bond)	0.023	0.097	0.118

Note: Panel A presents selected descriptive statistics and performance measures for the quarterly VLSI index, the S&P 500, and long-term corporate bonds over the entirety of our sample (1993:Q4–2009:Q4). Panel B presents the same descriptive statistics and performance measures as Panel A, but excludes the financial crisis years of 2008 and 2009. The risk-free rates used in the calculation of the Sharpe ratio is the average of the 3-month U.S. Treasury bill or the 10-year U.S. Treasury bond rate over our sample. The target rate for the below-target semi-variance is the average 3-month T-bill rate.

return comes with substantially higher volatility. The standard deviation for our VLSI index is more than double that of the S&P 500 and about four times that of long-term corporate bonds (19.85 percent vs. 8.63 percent and 4.93 percent, respectively). The large volatility results in a Sharpe ratio of only 0.055 for VLSI compared to 0.057 for the S&P 500 and 0.170 for long-term corporate bonds.[14]

The return skewness for VLSI is between that of the S&P 500 and long-term corporate bonds. VLSI returns have negative skewness of −0.47, compared to −0.72 for the S&P 500 and positive skewness of 0.46 for long-term corporate bonds. VLSI have excess kurtosis of 3.84 indicating a fairly peaked distribution. The excess kurtosis of VLSI exceeds that of the S&P 500 (0.83) and that of long-term bonds (3.42).

Finally, Table 3, Panel A shows a below target semivariance for the VLSI index as well as the S&P 500 and long-term corporate bonds.[15] This means that in quarters with returns below the average risk-free rate, VLSI (195.56) are much riskier than the S&P 500 (40.72) or long-term corporate bonds (8.17).

Panel B of Table 3 repeats the comparisons above but excludes the financial crisis period of 2008 and 2009. The largest change in results is that average VLSI returns (1.77 percent) no longer exceed those of the S&P 500 (2.05 percent), and their advantage over long-term corporate bonds (1.72 percent) is diminished. Also, the S&P 500 and corporate bonds display a smaller standard deviation when compared to the entire sample, but there is no reduction for VLSI. Furthermore, the below-target semivariance decreases for both the S&P 500 and corporate bonds, but it increases slightly for VLSI.

Figure 1 illustrates the VLSI index cumulative returns from 1993 to 2009 compared to those of the S&P 500 and long-term corporate bonds. A $1,000 investment in VLSI grows to about $3,500, compared to $2,400 for an S&P investment, and $3,000 for a corporate bond investment. The relative underperformance of the S&P can be attributed to the extreme financial crisis of 2008 and 2009. Indeed, the VLSI index stays below the S&P index for most of the period, except during the financial crisis.

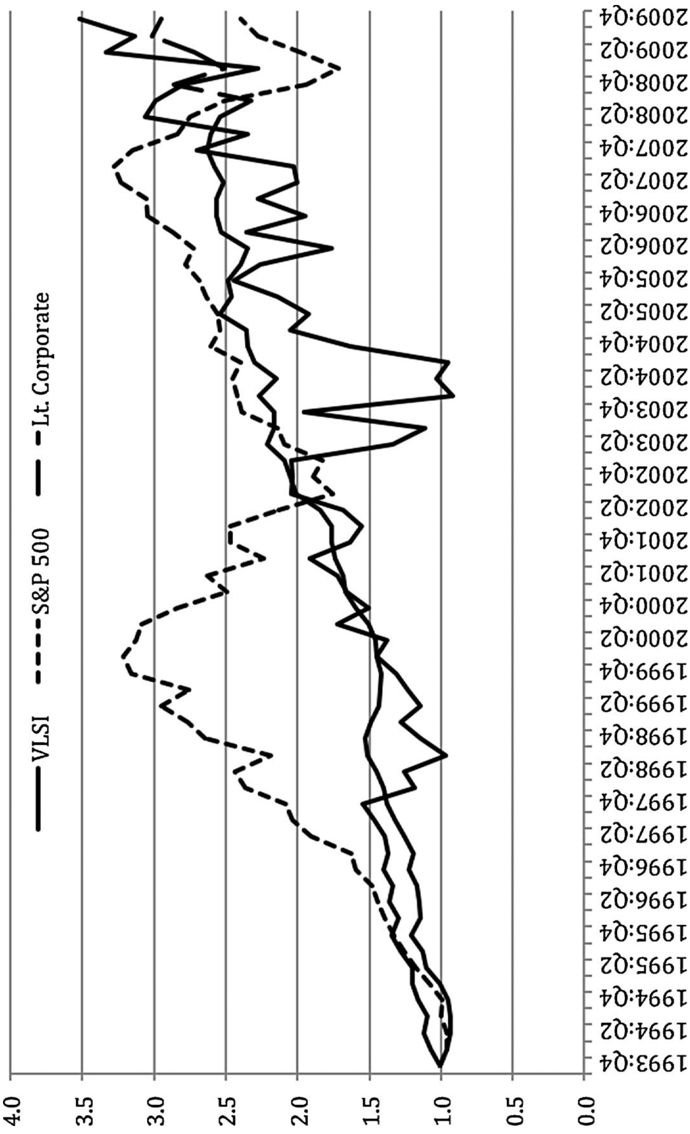
Fitting a smoothed trend line to the VLSI index would more closely approximate that of long-term corporate bonds, except from 2003 through 2006. This makes sense in that VLSI are fixed-payment instruments like bonds, except with negative coupons (premium payments). Their underlying default risk is that of the insurance company backing the policy. However, VLSI also carry other risks like mortality risk associated with the diseases of the policy sellers and liquidity risk.

The estimated VLSI returns are more volatile than those of the S&P 500 and corporate bonds. That volatility can be traced to some major events that occurred during the development of the VLSI market. Many of the first VLSI were from AIDS patients in the late 1980s and early 1990s, before effective drugs like protease inhibitors became

[14]These ratios are computed using the average 3-month U.S. Treasury bill rate as the risk-free rate. When using the average 10-year Treasury bond rate, the ratios are 0.05, 0.012, and 0.87 for VLSI, the S&P 500, and long-term corporate bonds, respectively.

[15]The target rate used to calculate semivariance is the same average risk-free rate described in footnote 1 above.

FIGURE 1
VLSI Index From 1993:Q4 Through 2009:Q4 Compared to S&P 500 and Long-Term Corporate Bonds



Note: The figure illustrates the growth of $1.00 invested in the VLSI index, the S&P 500, or long-term corporate bonds from 1993:Q4 to 2009:Q4.

available. These VLSI provided stable returns that tracked close to corporate bonds until 1997.

The VLSI index underperformed from 1997 to 1999, at least partly due to AIDS patients living longer than expected. In June 1995, the Food and Drug Administration approved the first protease inhibitor and others followed. The drugs started to extend AIDS patients lives during the 1997–1999 period, reducing VLSI returns.[16]

VLSI returns rebounded during the next 2 years. Asinof (2002) describes how the VLSI market expanded from 2000 through 2002, from the limited market for viaticals, to the market for senior life settlements. Senior life settlements are typically larger face-value policies of relatively wealthy older policyholders with impaired health. Corporations also started to sell their key-man policies covering top executives who had retired or left the firm. These new supplies of policies brought down VLSI prices, offering higher returns.

VLSI returns fell substantially in 2003 and 2004. Jenkins (2005) describes how large institutional investors started to enter the VLSI market then, including AIG and Berkshire Hathaway. Entry by such large investors likely drove prices up and returns down.

VLSI returns rebounded in 2005 and 2006. During these years, Pleven (2006) describes how a new supply of VLSI came from policyholders who did not take out policies on their own. Instead, they were investor-initiated policies in which VLSI firms approached wealthy individuals and offered to lend them the money to pay policy premiums for 2 years. After 2 years, the policyholder would sign over the policy to the VLSI firm as payment for the loan (insurance companies require the original policyholder to own the policy for at least 2 years). This new supply likely drove down VLSI prices and raised returns.

Finally, during 2007 through 2009, changes in both demand and supply drove VLSI returns sharply higher. Tergeson (2008) describes how large numbers of cash-strapped policyholders approached VLSI firms to sell their policies as the U.S. economy weakened. Then in 2008, the financial crisis caused many investors to limit or withdraw funds from the VLSI market. Larger effective supply and smaller demand drove returns higher. The exception was the first quarter of 2009, at the depth of the financial crisis. This is when many life insurance stocks plunged, and VLSI investors could have worried that some life insurance companies would default on their policy payments.

Analysis of Systematic Risk

We observe from Figure 1 that VLSI returns are volatile, but they do not look highly related to the S&P 500 index (except for 2009:Q1); hence, they may have little systematic risk. We examine the systematic risk component of the VLSI index by estimating betas from the Fama–French (1993) three factor model.

[16]See aids.gov/hiv-aids-basics/hiv-aids-101/aids-timeline/ (accessed July 9, 2013).

Fama and French (1993, 1996) use three factors to capture systematic risk: a market factor, a size factor (SMB), and a value factor (HML). Applied to VLSI we have:

$$R_{V,t} - R_{f,t} = \alpha + \beta(R_{M,t} - R_{f,t}) + \beta_S(R_{SMB,t}) + \beta_H(R_{HML,t}) + \epsilon_t, \tag{6}$$

where R_V is the quarterly VLSI index return, R_M is the market return, R_f is the risk-free rate, R_{SMB} is the size factor, R_{HML} is the value factor, and β, β_s, and β_H are the associated factor loadings. ζ_t is a zero mean error term.

We estimate Equation (6) with OLS and find estimates of the β, β_s, and β_H factor loadings of 0.258, −0.385, and −0.071, respectively. The p-values of the factor loadings are 0.67, 0.42, 0.45, and 0.81, respectively. Therefore, none of the VLSI loadings are statistically significant. As a robustness check, we estimated the beta for the VLSI index from the CAPM and found a small positive but statistically insignificant estimate (estimate = 0.19, p-value =0.78). Overall, these results support the notion that VLSI have little systematic risk, at least when that risk is measured by stock-based single factor (CAPM) or multifactor models (Fama–French). Of course, some other nonstock systematic factor such as a longevity or mortality risk factor, could be driving VLSI returns. Testing whether such a systematic factor exists is beyond the scope of this article, but is worth considering in future research.

We next consider the impact of VLSI in a portfolio. The large volatility of VLSI returns could make them poor investments, even as a small part of a portfolio.

VLSI in Optimal Portfolios

To get an idea of whether VLSI have a role to play in portfolios of traditional assets, consider the correlations between VLSI returns and those of the S&P 500 and long-term corporate bond returns reported in Panel A of Table 4. There is little correlation among any of these asset's returns over the entire sample, with the correlations between VLSI and the S&P 500 and corporate bonds of 0.067 and 0.020, respectively. After excluding the financial crisis period of 2008:Q1–2009:Q4, VLSI displays correlations with the S&P 500 and corporate bonds of −0.038 and −0.038, respectively. None of these correlations are statistically significant.

Panel B of Table 4 shows the quarterly return means and standard deviations for each asset, along with its optimal weight in a minimum variance portfolio. Using the full sample period, VLSI carry a small weight of 3.24 percent, mostly because of their high volatility and the goal of minimizing variance. Excluding the crisis period, the weight falls to 2.99 percent.

Panel C of Table 4 presents optimal tangency portfolios based on the Sharpe ratio criterion.[17] VLSI play a larger role in the optimal portfolio because the Sharpe

[17]The Sharpe ratio is the difference between the portfolio return and the risk-free rate, divided by the standard deviation of that difference. For the risk-free rate, we consider both the average 3-month U.S. Treasury bill and the U.S. Treasury bond (data from Ibbotson Associates). Although the most common proxy for the risk-free rate is a short-term Treasury bill rate, Damodaran (2008) suggests that a Treasury bond rate can be appropriate for long-term investments.

TABLE 4
Asset Correlations and Optimal Portfolio Weights, Returns, and Standard Deviations

	Entire Sample: 1993:Q4–2009:Q4			Excluding Financial Crisis: 1993:Q4–2007:Q4		
	VLSI	S&P 500	LT Corp	VLSI	S&P 500	LT Corp
			Panel A: Correlations			
VLSI	1			1		
S&P 500	0.067	1		−0.038	1	
LT Corp	0.020	−0.058	1	−0.038	−0.126	1
			Panel B: Minimum Variance Portfolios			
Weight	3.24%	24.68%	72.08%	2.99%	20.02%	76.99%
Return	1.96%	1.36%	1.69%	1.77%	2.05%	1.72%
St. dev	19.85%	8.63%	4.93%	19.95%	7.58%	3.51%
Portfolio return	1.61%			1.70%		
Port st. dev	4.12%			2.96%		
			Panel C: Sharpe Optimal Portfolios			
Risk free rate: T-bill						
Weight	5.45%	16.80%	77.75%	3.00%	23.25%	73.35%
Return	1.96%	1.36%	1.69%	1.77%	2.05%	1.72%
St. dev	19.85%	8.63%	4.93%	19.95%	7.58%	3.51%
Portfolio return	1.65%			1.80%		
Port st. dev	4.21%			2.97%		
Risk-free rate: T-bond						
Weight	7.89%	8.13%	83.98%	2.95%	27.76%	69.29%
Return	1.96%	1.36%	1.69%	1.77%	2.05%	1.72%
St. dev	19.85%	8.63%	4.93%	19.95%	7.58%	3.51%
Portfolio return	1.68%			1.81%		
Port st. dev	4.49%			3.03%		

Note: Panel A presents the correlations between the annual returns on the VLSI index, S&P 500, and U.S. long-term corporate bonds. Panel B presents the minimum variance portfolio constructed from a mix of the VLSI index, S&P 500, and U.S. long-term corporate bonds. Panel C presents the Sharpe optimal portfolios constructed from the VLSI index, S&P 500, and U.S. long-term corporate bonds using either the short-term Treasury bill or the longer-term Treasury bond as the risk-free rate.

criterion sets a return–risk trade-off goal rather than a minimum variance goal. The optimal portfolio allocates 5.45 (7.89) percent to VLSI when the short-term (long-term) Treasury bond rate is used.

VLSI in Portfolios Ranked by Investor Risk Tolerance

Next, we consider the effects of adding VLSI to a number of portfolios designed to fit the levels of risk tolerance for typical investors. Canner, Mankiw, and Weil (1997) and

TABLE 5
Portfolio Asset Allocation According Level of Investor Risk Tolerance

	Conservative	Moderate	Aggressive
Panel A: Portfolios Without VLSI			
Money market	23.90%	0.00%	0.00%
Corp. bonds	54.90%	70.70%	34.30%
Blue chips	0.00%	5.10%	10.50%
Small caps	21.10%	24.20%	55.20%
Panel B: Portfolios With VLSI			
Money market	22.80%	0.00%	0.00%
Corp. bonds	44.10%	59.80%	16.60%
Blue chips	0.00%	0.00%	6.20%
Small caps	19.40%	23.90%	49.80%
VLSI	13.70%	16.30%	27.40%

Note: This table presents optimal asset weights for the portfolios of investors with HARA utility functions and risk aversion parameters of 5, 2.5, and 0.25, associated with conservative, moderate, and aggressive allocations, respectively. The portfolios include up to five assets: a money market instrument (3-month certificates of deposit), bonds (U.S. long-term AAA corporate), blue chip stocks (S&P 500), small cap stocks (Russell 1000), and VLSI. Panel A presents the asset allocation when VLSI are excluded from the set of asset choices, and Panel B reports the allocations when VLSI are included.

Ingersoll (1987, chap. 5), identify three risk categories used by investment advisors to separate investors into risk tolerance groups: conservative, moderate, and aggressive. We use the hyperbolic absolute risk aversion (HARA) utility function to capture the degree of risk aversion:

$$U(W_1) = \frac{W_1^{1-\eta} - 1}{1 - \eta}, \tag{7}$$

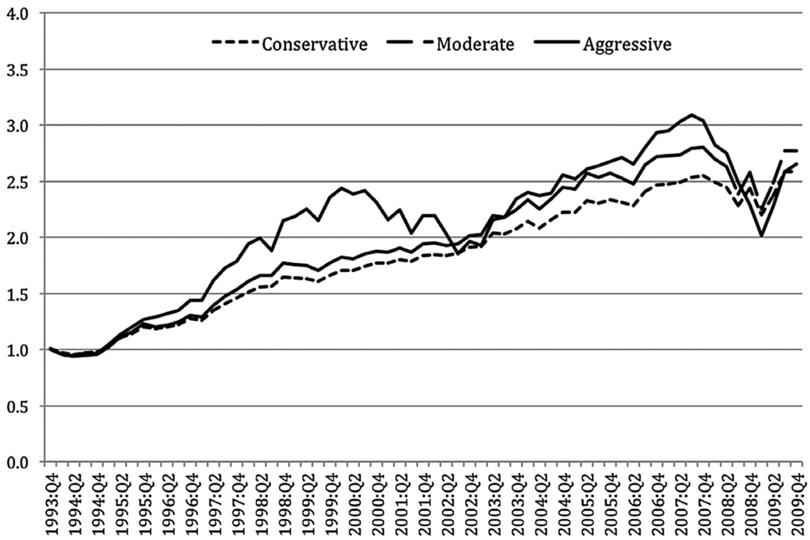
where W_1 represents end-of-period wealth. A risk-neutral investor is characterized by values of η close to 0, while larger η implies greater risk aversion. We set $\eta = 0.25$, 2.5, and 5 to describe, aggressive, moderate, and conservative risk-taking behavior, respectively.

An investor's terminal wealth is given by her initial wealth times one plus her portfolio return. The portfolio of an investor with a given risk tolerance is constructed from up to five assets; a money market instrument (the 3-month CD rate), long-term corporate bonds (AAA corporates), blue chip stocks (S&P 500), small cap stocks (Russell 1000), and VLSI. We select the asset weights to maximize the expected utility of an investor with a given risk tolerance, subject to the constraints of non-negative weights that sum to one.

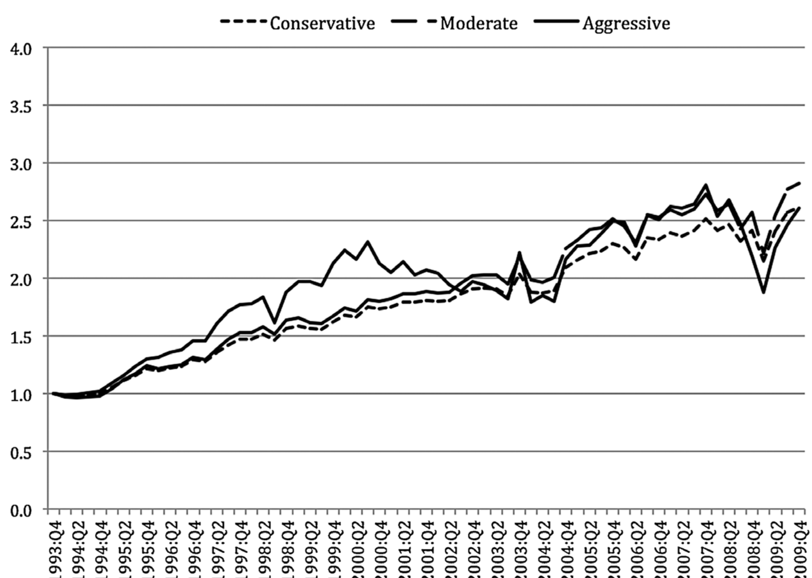
Table 5, Panel A presents the optimal asset weights for each investor type with VLSI excluded from the maximization. Panel B presents recomputed weights with VLSI included.

FIGURE 2
Cumulative Investment Performance From 1993:Q4 Through 2009:Q4 for Portfolios Ranked by Investor Risk Tolerance

Panel A: Investment Portfolios without VLSI



Panel B: Investment Portfolios with VLSI



Note: The figure illustrates the growth of $1.00 invested in portfolios optimized for conservative, moderate, and aggressive investors from 1993:Q4 to 2009:Q4.

TABLE 6
Quarterly Return Statistics for Portfolios Ranked by Investor Risk Tolerance

	Conservative	Moderate	Aggressive
Panel A: Portfolios Without VLSI			
Total return over period	158.28%	176.92%	165.36%
Mean return	1.55%	1.69%	1.71%
Median return	1.24%	1.29%	1.74%
Standard deviation	3.24%	4.25%	5.90%
Maximum	9.06%	11.89%	14.15%
Minimum	−9.57%	−12.70%	−11.98%
Skewness	−0.42	−0.37	−0.08
# Negative returns	21	22	21
Panel B: Portfolios With VLSI			
Total return over period	161.23%	182.09%	160.59%
Mean return	1.59%	1.76%	1.79%
Median return	1.46%	1.65%	1.70%
Standard deviation	3.98%	4.96%	7.61%
Maximum	11.83%	14.74%	22.10%
Minimum	−10.76%	−13.93%	−19.17%
Skewness	−0.161	−0.156	0.145
# negative returns	22	22	24
Panel C: Portfolios Without VLSI (Financial Crisis Period 2008:Q1–2009:Q4)			
Total return over period	1.31%	−0.94%	−12.47%
Mean return	0.37%	0.24%	−1.22%
Median return	−0.87%	−1.23%	−4.75%
Standard deviation	6.47%	8.47%	9.39%
Maximum	9.06%	11.89%	13.61%
Minimum	−9.57%	−12.70%	−11.98%
Skewness	−0.036	−0.019	0.720
# negative returns	5	4	5
Panel D: Portfolios With VLSI (Financial Crisis Period 2008:Q1–2009:Q4)			
Total return over period	3.88%	3.41%	−7.09%
Mean return	0.48%	0.42%	−0.92%
Median return	1.97%	2.08%	−1.08%
Standard deviation	6.85%	8.84%	11.40%
Maximum	11.83%	14.74%	20.53%
Minimum	−10.75%	−13.93%	−14.12%
Skewness	−0.138	−0.170	0.515
# negative returns	3	3	4

Note: This table presents the risk and return statistics for three portfolios constructed for conservative, moderate, and aggressive investors. Panel A presents portfolio performance without VLSI, and Panel B presents portfolio performance after adding VLSI to an investor's choice set. Panels C and D present the portfolio characteristics during the financial crisis from 2008:Q1 to 2009:Q4 for portfolios without and with VLSI, respectively.

Not surprisingly, Panel A of Table 5 shows that conservative investors heavily weight the money market instrument and bonds. Conversely, aggressive investors heavily weight small cap stocks. The relatively large weighting for bonds by each investor type reflects their relatively good returns and low volatility during the sample period.

Panel B of Table 5 includes VLSI and shows similar relative weights, for example, more stocks for aggressive investors. But now aggressive investors also hold relatively more VSLI, with VLSI allocations of 13.7 percent, 16.3 percent, and 27.4 percent for conservative, moderate, and aggressive investors, respectively. VLSI allocations displace some of the bond allocation, by as much as half for aggressive investors. This is perhaps not that surprising; VLSI can be considered fixed-income assets with larger volatility that is less distasteful to risk-tolerant investors.

Figure 2, Panels A (without VLSI) and B (with VLSI) illustrate the effects of VLSI on cumulative portfolio returns over our sample period for each investor type. Adding VLSI in Panel B tends to increase the volatility of the returns, but also increases the return in most cases. During the stock market booms of 1993–2000 and 2003–2007, the aggressive portfolio outpaces both the conservative and moderate ones, but they catch up in the sharp market declines of 2001–2002 and 2008–2009.

Table 6 presents the return distribution statistics for each portfolio. Panels A and B cover returns over the full sample period for portfolios with and without VLSI, respectively. For each portfolio, the mean return and standard deviation increases with VLSI added, and skewness improves, becoming positive for the aggressive portfolio.

Panels C and D of Table 6 examine portfolio performance with and without VLSI during the financial crisis period of 2008:Q1 through 2009:Q4. Again, both mean and standard deviation increases when VLSI are added. Overall, these results show that adding VLSI can increase mean portfolio returns, but at a cost of additional volatility.

CONCLUSION

We have analyzed the risk and return characteristics of VLSI (life insurance policies purchased on the secondary market). First, using the repeat sales method initially developed to analyze real estate returns, we construct an index of VLSI returns covering the fourth quarter of 1993 to the fourth quarter of 2009. Second, we show that VLSI earned more than corporate bonds and stocks during the period; however, VLSI returns are much more volatile than either stocks or corporate bonds.

The volatility we find in VLSI returns differs substantially from the smoother return series reported in BGS and DRB for life settlement mutual funds. It confirms BGS's suspicion that fund managers could smooth their performance. We discuss a number of VLSI-related events that could have caused some of the volatility.

It is possible that our VLSI return series is more volatile than the VLSI market as a whole. All of our data come from the New York State Insurance Department and may not be representative of the whole market. But because VLSI firms operating in New York operated throughout the country, and were required to report all of their VLSI transactions, we believe that the sample is reasonably representative of the industry.

Most of our other results corroborate those found by BGS and DRB for mutual funds. We show that VLSI have low correlations with traditional investments in stocks and bonds. We also find that VLSI have little stock-based systematic risk.

REFERENCES

Affolter, S., A. Braun, and H. Schmeiser, 2014, Life Settlement Funds: Current Valuation Practices and Areas for Improvement Funds, Working Paper on Risk Management No. 143, University of St. Gallen.

A.M. Best, 2009, Methodology, Life Settlement Securitization, November 24. World Wide Web: http://www.hyperionfunds.com/media/2292/a.m.%20best%20-%20life%20settlement%20securitization%20 (2009).pdf (accessed June 29, 2014).

Asinof, L., 2002, Selling off Life Insurance: Good Policy? *Wall Street Journal*, (May 15): D2.

Bailey, M. J., R. Muth, and H. O. Nourse, 1963, A Regression Model for Real Estate Price Index Construction, *Journal of the American Statistical Association*, 58: 933-942.

Bhattacharya, J., D. Goldman, and N. Sood, 2004, Price Regulation in Secondary Insurance Markets, *Journal of Risk and Insurance*, 71(4): 643-675.

Bhattacharya, J., D. Goldman, and N. Sood, 2009, Market Evidence of Misperceived Mortality Risk, *Journal of Economic Behavior & Organization*, 72(1): 451-462.

Biey, M. L., and R. Zanola, 1999, Investment in Paintings: A Short-Run Price Index, *Journal of Cultural Economics*, 23(3): 209-219.

Blake, D., A. Cairns, G. Coughlan, K. Dowd, and R. MacMinn, 2013, The New Life Market, *Journal of Risk and Insurance*, 80(3): 501-557.

Braun, A., N. Gatzert, and H. Schmeiser, 2012, Performance and Risks of Open-End Life Settlement Funds, *Journal of Risk and Insurance*, 79(1): 193-229.

Brealey, R., S. Myers, and F. Allen, 2013, *Principles of Corporate Finance*. (New York: McGraw-Hill).

Brockett, P., C. Shuo-li, D. Yinglu, and R. D MacMinn, 2013, Incorporating Longevity Risk and Medical Information Into Life Settlement Pricing, *Journal of Risk and Insurance*, 80(3): 799-825.

Burton, B. J., and J. P. Jacobsen, 1999, Measuring Returns on Investments in Collectibles, *Journal of Economic Perspective*, 13(4): 193-211.

Burton, B. J., and J. P. Jacobsen, 2001, The Rate of Return on Investment in Wine, *Economic Inquiry*, 39(3): 337-350.

Canner, N., G. Mankiw, and D. Weil, 1997, An Asset Allocation Puzzle, *American Economic Review*, 87(1): 181-191.

Case, K. E., and R. J. Shiller, 1989, The Efficiency of the Market for Single-Family Homes, *American Economic Review*, 79(1): 125-137.

Case, K. E., and R. J. Shiller, 1990, Forecasting Prices and Excess Returns in the Housing Market, *Real Estate Economics*, 18(3): 253-273.

Clapp, J. M., and C. Giaccotto, 1992, Estimating Price Trends for Residential Property: A Comparison of Repeat Sales and Assessed Value Methods, *Journal of Real Estate Finance and Economics*, 5(4): 357-372.

Clapp, J., M. Carmelo, and C. Giaccotto, 1995, Which Real Estate Price Index Is Right for Mortgage-backed Securities? *Real Estate Finance*, 12: 41-47.

Daily, G., I. Hendel, and A. Lizzeri, 2008, Does the Secondary Life Insurance Market Threaten Dynamic Insurance? *American Economic Review*, 98(2): 151-156.

Damodaran, A., 2008, What Is the Risk-free Rate: A Search for the Basic Building Block, New York University working paper. World Wide Web: http://people.stern.nyu.edu/adamodar/pdfiles/papers/riskfreerate.pdf (accessed January 30, 2014).

Davo, N. B., C. M. Resco, and M. M. Barroso, 2013, Portfolio Diversification With Life Settlements: An Empirical Analysis Applied to Mutual Funds, *Geneva Papers on Risk and Insurance*, 38(1): 22-42.

Deloitte Consulting and University of Connecticut Actuarial Center, 2005, The Life Settlements Market: An Actuarial Perspective on Consumer Economic Value, May www.quatloos.com/uconn_deloitte_life_settlements.pdf (accessed July 16, 2013).

Doherty, N., and H. J. Singer, 2003a, The Benefits of a Secondary Market for Life Insurance Policies, *Real Property, Probate and Trust Journal*, 38(3): 449-457.

Doherty, N., and H. J. Singer, 2003b, Regulating the Secondary Market for Life Insurance Policies, *Journal of Insurance Regulation*, 21(4): 63-79.

Fama, E. F., 1976, *Foundations of Finance: Portfolio Decisions and Securities Prices* (New York: Basic Books).

Fama, E. F., and K. R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33(1): 3-56.

Fama, E. F., and K. R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, 51(1): 55-84.

Giacalone, J. A., 2001, Analyzing an Emerging Industry: Viatical Transactions and the Secondary Market for Life Insurance Policies, *Southern Business Review*, 27(1): 1-7.

Ginsburgh, V., J. Mei, and M. Moses, 2006, The Computation of Prices Indices, in: V. A. Ginsburg and D. Throsby, eds., *Handbook on the Economics of Art and Culture* (Boston: Elsevier), pp. 947-979.

Glick, S. D., 1993, Are Viatical Settlements Securities Within the Regulatory Control of the Securities Act of 1933? *University of Chicago Law Review*, 60(3-4): 957-984.

Hamwi, S. I., and D. Rueggerm, 1994, Past and Present Changes in Living Policy Values, *Journal of the American Society of CLU & ChFC*, 48(6): 76-87.

Ibbotson Associates, 2010, *Stocks, Bonds, Bills, and Inflation Classic Yearbook* (Chicago, IL: Morningstar Inc.)

Ingersoll, J., 1987, *Theory of Financial Decision Making* (Totowa, NJ: Rowman & Littlefield).

Jenkins, H. W., 2005, The Liberalization of Life Insurance, *Wall Street Journal*, (June 22): A11.

Maremont, M., 2010, Odds Skew Against Investors in Bets on Strangers' Lives, *Wall Street Journal*, December 21: A1.

Masset, P., C. Henderson, and J. Weisskopf, 2010, Wine as an Alternative Asset Class, Working Paper.

Milliman, 2008, Life Settlement Characteristics and Mortality Experience for Two Providers, April. World Wide Web: us.milliman.cominsightresearchinsurancepdfs Life-settlement-characteristics-mortality-RR-04–01–08.pdf (accessed June 29, 2014).

Opdyke, J., 1999, States Probe Sales Practices for Viaticals, *Wall Street Journal*, (April 7): NW1.

Pesando, J., 1993, Art as an Investment: The Market for Modern Prints, *American Economic Review*, 83(5): 1075-89.

Pleven, L., 2006, Life-Settlements Deals Scrutinized, *Wall Street Journal*, (May 4): B2.

Ray, L. M., 2000, The Viatical Settlement Industry: Betting on People's Lives Is Certainly No Exacta, *Journal of Contemporary Health Law and Policy*, 17: 321-347.

Rowland, R., 2003, The Brewing Storm: Securities Regulation and Lifetime Settlements, *Journal of Financial Service Professionals*, 57(3): 76-84.

Shiller, R. J., 1993, *Macro Markets: Creating Institutions for Managing Society's Largest Risks* (Oxford, UK: Oxford University Press).

Sommer, D., W. Sandra, G. Gustavson, and S., T. James, 1997, Viatical Settlements: Perspectives of Investors, Regulators, and Insureds, *Journal of the American Society of CLU & ChFC*, 51(2): 54-67.

Taylor, J., 1994, SEC Sues Life Partners Inc., Alleging Illegal Brokering of Insurance Policies, *Wall Street Journal*, (August 26): A2.

Tergeson, A., 2008, Source of Cash for Seniors is Drying Up, *Wall Street Journal*, (November 13): D1.

Trinkaus, J., and J. A. Giacalone, 2002, Entrepreneurial "Mining" of the Dying: Viatical Transactions, Tax Strategies and Mind Games, *Journal of Business Ethics*, 36(1-2): 187-194.

Zhu, N., and D. Bauer, 2013, Coherent Pricing of Life Settlements Under Asymmetric Information, *Journal or Risk and Insurance*, 80(3): 827-851.