Explaining the risk premiums of life settlements☆

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ABSTRACT

Life settlements may facilitate a more efficient insurance market, generate diversification benefits to investors, and even provide hedging benefits to Asia life insurers. The literature does not investigate what determines the risk premiums of life settlements, and we intend to fill this gap. We find that in spite of the premium for non-systematic mortality risk being substantial, the systematic premium is insignificant. On the other hand, the impact of tax on the life settlements' spreads is material. We further find that life settlements have negative betas and are quality assets when investors face market turmoil. The proprietary information provided by medical underwriters and the surrender behavior of the underlying policyholders are also significant determinants of the rate spreads for life settlements.

1. Introduction

The determinants of rate spreads on various investment products have attracted the attention of scholars as well as practitioners.[2] The renowned CAPM (Capital Asset Pricing Model; Sharpe, 1964), APT (Arbitrage Pricing Theory; Ross, 1976), and other multi-factor models such as Fama and French (1993, 2015, 2018) identify the determinants of the rate spreads on stocks. Many papers examine the determinants of yield spreads on corporate bonds, e.g., Fons (1994), Longstaff and Schwartz (1995), Duffie and Singleton (1997), Elton et al. (2001), Baker et al. (2003), Longstaff et al. (2005), Chen et al. (2007), Yang et al. (2019), and Bai et al. (2019). The literature also looks into the spread determinants of other fixed-income products that linked to a non-financial risk such as catastrophe bonds (Bantwal and Kunreuther, 2000; Zanjani, 2002; Zhao and Yu, 2019; Li et al., 2020).

The determinants of the rate spreads that can be expected from investing in life settlements have not yet been examined despite the importance of this product. Life settlements are life insurance policies sold in the secondary market. The policyholder who engages in a life settlement transaction receives a payment that exceeds the policy's cash value (also called surrender value), but which is less than

the death benefit. The investor involved in such a transaction assumes the role of paying premiums, and the return on investment depends on the quality of the life expectancy estimates provided by medical underwriters. The return will be higher/lower if the insured has a shorter/longer lifespan than expected.

It was these life settlement transactions that brought the secondary market for life insurance into existence. As in the cases of other secondary markets, life settlements have facilitated a more efficient and competitive insurance market (Doherty and Singer, 2003; Seog and Hong, 2019). Life settlements became a popular asset class because they seemed to yield good returns and/or provided diversification benefits to widely-held assets (Gatzert, 2010; Braun et al., 2012; Giaccotto et al., 2017). The life settlement market reached 2.6 billion dollars in 2013 (The Deal, 2015).[3] In addition, understanding the spread determinants of life settlements may shed light on the determinants of the implicit yields of life insurance policies that are relevant to everyone.

In Asia, life settlements are mainly known by few institutional and professional investors asking for higher returns since Asia regulations have been stagnating the market. Only Singapore and Hong Kong have approved the transactions of life settlements up to now. China Insurance Regulatory Commission (CIRC) announced a draft for life settlements in 2018 and conducted a trial run on life settlements for 2 years. Many Asia institutional and professional investors who want to invest in life settlements have to go through offshore markets therefore.

On the other hand, the results of Hsien et al. (2020) demonstrate that even the life settlements originated in other regions may provide significant hedging benefits to the mortality risk of Asia life insurers.[4] This may be one of the reasons why life settlement funds are popular among Japan's pension funds (Yamazaki and Ito, 2011). An unofficial estimate for the investment in life settlements of China reaches 1 billion USD if not more (Song, 2019). We recommend insurance and pension regulators in Asia loosening the regulations on the use of life settlements for the hedging purpose under prudent risk control. For the yield-enhancing purpose, the regulations may also be loosened to some extent for sophisticated investors.[5]

This study aims to extend the scope of the literature on the spread determinants of risky assets in relation to life settlements.[6] Identifying the determinants of life settlements' spreads and understanding their relative significance will help market participants assess the value and risk of life settlements. The results will also shed light on the determinants of the implicit yields of life insurance policies that concern everybody. Actuaries may consider incorporating the identified factors into their pricing to better meet the demands of life insurance buyers. Our results are thus of interest to the buyers, sellers, originators, and other stakeholders in the life settlement market, in addition to scholars.

In estimating the rate spreads of life settlements, we first regard the life expectancy of the insured person on whom the life settlement is based as being comparable to the expected maturity of a corporate bond. The return on a life settlement is subject to mortality risk, while that of a bond is subject to default risk. Therefore, we may calculate the internal rate of return (IRR) of a life settlement to the investor given the insured's life expectancy in a way that is similar to how we calculate the yield-to-maturity (YTM) of a corporate bond.[7]

The assumption behind the above calculation is that the underlying insured lives according to the life expectancy. We further propose a method to incorporate the uncertainty regarding the time of death by applying death probabilities to calculating expected cash flows. We refer this uncertainty as non-systematic mortality risk since the insurer is able to diversify such a risk by accepting more insured lives. The difference between this IRR and the previous one indicates the risk premium from non-systematic mortality risk since the difference originates from the uncertainty surrounding the time of death of the individual insured. Systematic mortality risk, on the other hand, refers to the uncertainty about death probabilities.[8] The uncertainty may come from systematic factors such as medical advances, health system, or pandemics and leads to future mortality improvement or deterioration. To see how systematic mortality risk might affect expected returns, we employ a stochastic mortality improvement model to generate possible mortality tables.

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[3] The market size decreased to 1.7 billion dollars in 2014 (The Deal, 2015) possibly due to legal disputes on market conduct. The market size remained at $1.7 billion in 2015. (http://www.bvzl.de/index.php?language=en&main_id=15&sub_id=60; accessed on May 11, 2016). The life settlement market seemed to have stabilized and embarked on a steady growth trajectory in 2017 and through the first half of 2018 (https://www.conning.com/about-us/news/life-settlements-market-growth-continues-into-2018; accessed on August 30, 2019)

[4] This result is indeed intuitive since mortality rate improvements are a global trend. Because changes of mortality rates in US and Taiwan are positively correlated, a Taiwan life insurer can reduce the risk of its liabilities by buying life settlements issued in US. Similar rationale and implication can be applied to life insurers in other (Asia) countries. Biffis et al. (2017) illustrate the feasibility of hedging the mortality risk with mortality derivatives across countries within the Asia-Pacific region. Other papers also provide support for the diversification benefits across countries and point out that mortality-related derivatives have been issued to facilitate cross-country hedging, e.g., Dowd et al. (2006), Denuit et al. (2007), Lin et al. (2013), and Chen et al. (2017) among others.

[5] We refer to Gatzert (2010) and Braun et al. (2012) stating that life settlements render good returns and/or diversification benefits to major asset classes and infer that such advantages apply to Asia investors as well.

[6] This study extends the boundary of the research on life settlements as well. Many studies have investigated the economic impacts of life settlements on life insurance markets (e.g., Giacalone, 2001; Ingraham Jr and Salani, 2004; Ziser, 2006 and 2007; Smith and Washington, 2006; Seitel, 2006 and 2007; Leimberg et al., 2008; Daily et al., 2008, Seog and Hong, 2019; Fang and Wu, 2020; Fang and Kung, 2020).

[7] Note that the IRR investigated in this paper is *ex ante*, i.e., the expected return. CAPM and APT propose *ex ante* relations between risk and return. Many papers on fixed-income products as cited in the first paragraph investigate the *ex ante* relations as well.

[8] In a single period setup, the non-systematic mortality risk refers to the next year's survival of an age x person I_{x+1}, where $I_{x+1} = \begin{cases} 1, & \text{with probability } {}_1p_x \\ 0, & \text{with probability } {}_1q_x = 1 - {}_1p_x \end{cases}$. The systematic mortality risk refers to the uncertainty of ${}_1p_x$.

The differences between the calculated IRRs and the risk-free rates at the inception of life settlements represent the spreads expected by the investors who bear several types of risk associated with life settlements. We further calculate after-tax spreads to assess the significance of tax in determining the rate spreads for life settlements. Our data on life settlements are obtained from Coventry, a leading market maker in the US. The data initially consist of 353 observations spanning the period from 2009 to 2011. Following the spread determinant literature, we construct independent variables with available data to represent the market risk premium, size, market volatility, default risk, maturity, a factor capturing the proprietary information provided by the medical underwriter, and a factor reflecting the policyholder's tendency to surrender his or her insurance policy.

We find that the IRRs that consider the uncertainty regarding the death time of individual insured have a significantly higher average return than those obtained under the assumption of a certain time of death. This indicates that there are substantial premiums for bearing non-systematic mortality risk. Although expected mortality improvements reduce the expected IRRs to some extent, the systematic mortality risk is negligible, probably due to the stable mortality improvement trend over the long past. Taxes reduce the spreads significantly since the buyers of life settlements are likely to be subject to high tax rates.

We find that the market risk factor consistently has negative coefficients in the regressions. Life settlements can thus be regarded as a negative-beta asset class bringing substantial diversification benefits to vast numbers of investors. We further find that the coefficients of VIX (the CBOE Volatility Index) are negative and significant, suggesting that the life settlement market may serve as a safe harbor for investors when the market is in turmoil. Such demands drive down the expected returns on life settlements. The proprietary information rendered by the medical underwriter regarding the life expectancy of the insured plays a significant role in determining the rate spreads on life settlements. So does the policyholders' behavior in regard to surrendering the policies.

Our further explorations confirm that neither systematic nor non-systematic mortality risk premium is affected by the market risk factor and VIX, which should be the case. The proprietary information, the insurer's rating, policy maturity, and policy age are significant determinants of non-systematic mortality risk premium. This implies that the market of life settlements is not large enough to reach full diversifications across these variables and information asymmetry exists in life insurance and life settlement markets. Rating and policy age are also significant determinants of systematic mortality risk premium.

The remainder of this article is organized as follows. We delineate the life settlement samples in Section 2. In Section 3 we explain the three ways of calculating before- and after-tax IRRs and examine their distributions. In Section 4, we speculate on possible sources of life settlement rate spreads and specify corresponding variables. Sections 5 and 6 contain the regression results and robustness checks, respectively. We draw conclusions and implications in Section 7.

2. Life settlement samples

The data used in this study were obtained from Coventry, one of the major originators and market makers in the US life settlement market. The samples that Coventry provided for us were a subset of its life settlements that originated during the period from July 2009 to April 2011.[9] They are 346 universal life insurance policies, and their descriptive statistics presented in Table 1.

The insureds covered by the policies underlying the sampled life settlements were seniors, with an average age of 76 and an age range from 63 to 87 at the times when the policies were acquired by Coventry. At those times, their life expectancies estimated by one of Coventry's major medical underwriters ranged from 6 years to 20 years with an average of 13 years.[10] About 75% of the insureds were males. The life expectancy of the males aged 75 was 11 years, based on the 2009 US Life Tables accessed from the Human Mortality Database (HMD),[11] and a female of the same age had a life expectancy of 13 years. The life expectancies of the insureds are thus in line with those of the general population.

Most insurance policies were acquired by Coventry at the early stages. The average policy year was about 3 years when the policies were acquired; the longest-held policy was bought in its 24th policy year. Most policies had large amounts of death benefits: the average was 4 million dollars and the largest one reached $20 million. Their acquisition costs had an average of 0.44 million dollars and a range of $20,000 - $6.8 million. The Standard & Poor's ratings on the insurers issuing the underlying policies ranged from BBB- to AAA. We converted the credit ratings to scales from 1 to 5 with A+ and below being equal to 1, AA- equal to 2, AA equal to 3, AA+ equal to 4, and AAA equal to 5.[12]

For each life settlement, Coventry provides a target premium schedule in the data. The premium schedule is a basic pricing assumption reflecting the originator's plan to fund the policy to optimally keep the contract valid. We use the provided premium schedule along with the acquisition cost and death benefit in calculating the expected IRR of a life settlement.

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[9] Since we are unable to secure more recent data, our findings may not be applicable to normal periods (e.g., the period long after the financial crisis of 2008).

[10] The medical underwriter serves as a third party that provides an estimate on the insured's life expectancy based on the insured's health condition. This estimate is used in calculating the acquisition price that Coventry would offer to the policyholder.

[11] HMD is maintained by the Department of Demography at UC Berkeley and the Max Planck Institute for Demographic Research in Germany. It collects the official vital statistics from many countries. Please see their website www.mortality.de for further details.

[12] Eighty-five percent of the underlying insurers are rated by S&P as "very strong." We thus adopted the sub-class (AA-, AA, and AA+) to further differentiate the credit worthiness of the insurers.

Table 1
Descriptive statistics for life settlement sample.

	Mean	Median	Standard Deviation	Minimum	Maximum
Insured's Age	75.63	75.38	4.60	63.42	86.75
Life Expectancy	12.98	13.13	2.78	5.92	19.67
Gender (Male = 1)	0.75	1.00	0.43	0.00	1.00
Policy Year	2.82	2.33	3.22	0.08	23.67
Death Benefit ($million)	4.09	3.00	3.77	0.23	20.00
Acquisition Cost ($million)	0.44	0.23	0.66	0.02	6.80
Rating	2.57	3.00	0.99	1.00	5.00

3. Calculating expected returns and risk premiums

In this section we explain how we calculate the IRRs from the investor's point of view. The first type of IRRs is obtained by solving the following equation:

$$AC = \frac{DB}{(1+IRR)^{LE_{uw}}} - \sum_{t=1}^{LE_{uw}-1} \frac{Premium_t}{(1+IRR)^t},$$ (1)

in which AC represents the acquisition cost (i.e., purchase price) of a life settlement paid by the investor, DB indicates the death benefit to be paid at the expected death time to the investor, LE_{uw} stands for the life expectancy of the insured as evaluated by the medical underwriter, and $Premium_t$ denotes the target premium scheduled to be paid by the holder of the life settlement at time t.[13] The unit of time used in Eq. (1) is one month since the premium schedules of life settlements are in terms of months. We multiply the solved monthly IRR by 12 to obtain an expected annual return and denote it as $IRR^{(1)}$. $IRR^{(1)}$ represents the expected annual IRR under the assumption that the insured would die at the time as the life expectancy predicts.

The distribution and summary statistics of $IRR^{(1)}$ are presented in Fig. 1. The mean and standard deviation of the IRR is 8.62% and 1.21%, respectively. These statistics are comparable with the ex post returns reported by Gatzert (2010), Braun et al. (2012), and Giaccotto et al. (2017).[14] Fig. 1 also displays a longer tail on the left side (with the Skewness being −0.91) and heavier tails (4.22 Kurtosis) than the normal distribution.

Since life expectancy is an expectation of lifetime rather than a sure destiny, we further calculated the expected IRRs of life settlements under the framework of uncertain death time given estimated life expectancies. In other words, the death time becomes uncertain under the premise of the life expectancy LE_{uw}. To take this lifetime uncertainty into account, we incorporate the probability distribution of death time into the present value of life settlement. Since the probability distribution of the policyholder's death time is unknown, we calibrate the population mortality rates according to LE_{uw} and then calculate the expected IRRs.

More specifically, we calculate the expected IRRs through solving the following death-probability-weighted present values of benefits and premiums:

$$AC = \sum_{t=1}^{12(\omega-x)} \frac{{}_{\frac{t-1}{12}}p_x^{adj} \times {}_{\frac{1}{12}}q_{x+\frac{t-1}{12}}^{adj} \times DB - {}_{\frac{t}{12}}p_x^{adj} \times Premium_t}{(1+IRR)^t},$$ (2)

where ${}_{\frac{t-1}{12}}p_x^{adj}$ stands for the adjusted probability that an insured of age x will survive to time $x+\frac{t-1}{12}$ and ${}_{\frac{1}{12}}q_{x+\frac{t-1}{12}}^{adj}$ denotes the adjusted probability that the insured of age $x+\frac{t-1}{12}$ will die within the next month (i.e., $\frac{1}{12}$ year). The first term of the numerator represents the expected death benefit to be received at time $x+\frac{t}{12}$ since ${}_{\frac{t-1}{12}}p_x^{adj} \times {}_{\frac{1}{12}}q_{x+\frac{t-1}{12}}^{adj}$ denotes the probability of an aged-x insured lives to time $x+\frac{t-1}{12}$ and then dies during the next month, while the second term represents the expected premium to be paid

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[13] All IRRs are computed by two algorithms to make sure that they are numerically stable. The first algorithm is a built-in function called "irr" in MATLAB R2015b. We further used the grid-search method on the present value of each life settlement by varying the discount rate between −100% and + 100%. We found that none of them had multiple rates of return (as expected), but detected 2 life settlements as having negative IRRs. These were caused by the feature that the sum of the premium payments exceeded the death benefit. We thus dropped these two life settlements. Winsorizing the data at 1% yielded similar results to those in the following.

[14] Braun et al. (2012) reported the performance of 10 active life settlement funds in the US market during the period from 2007 to 2010. The average return was 6.09%, and the average standard deviation was 1.97%. Gatzert (2010) cited the IRRs of US life settlements were lying between 8% and 12%. Giaccotto et al. (2017) found that the policies purchased in the secondary market by viatical and life settlement companies were about 8% annually over their 1993–2009 sampling period.
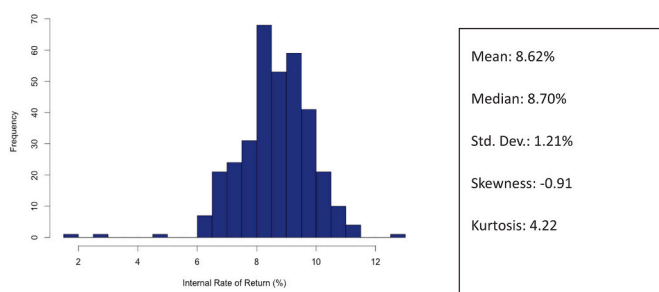
Fig. 1. Histogram of IRRs under Certain Death Time at Life Expectancy (i.e., $IRR^{(1)}$).

when the insured lives to time $x + \frac{t}{12}$. The ultimate age ω is 110 years according to the 2009 US Life Tables compiled by HMD. We refer to this type of IRR as the actuarial IRR since Eq. (2) is used by actuaries to calculate premiums and reserves. The annualized IRR of this type is denoted by $IRR^{(2)}$.

In calibrating the population mortality rates according to LE_{uw}, we first obtain the probability distribution of death time from the US national life table and then adjust the distribution so that the life expectancy would match the life expectancy by the underwriter. Such adjustments allow us to take into account the differences between the policyholders underlying the life settlements and the general public and to facilitate the comparisons between certain and uncertain death time cases. The life table that we use is the 2009 US Life Tables from HMD.

The calibration involves two steps. First, we convert the 2009 US Life Tables from annual to monthly frequency and scale the mortality rate with a constant to account for the discrepancy between the death probabilities of the national population and those of the insureds underlying life settlements. Then we solve, for each of the policy, the scaling constant so that the life expectancy from adjusted life table would be equal to LE_{uw}. We put the details of these two steps in Appendix I.

The distribution of $IRR^{(2)}$ is presented in Fig. 2. The IRRs calculated under the uncertain death time framework have a higher average of 13.4% than that of the IRRs calculated by assuming that the death of the underlying insured occurs as the life expectancy predicts. We justify this higher average return by a technical observation and an economic interpretation as follows.

Take a life settlement as an example that involves a male insured aged 75 with a life expectancy of 13 years. The underlying policy with a death benefit of 2.5 million dollars had been issued about three years before being purchased at a cost of 0.32 million dollars. The cash flows used in calculating $IRR^{(1)}$ and $IRR^{(2)}$ are depicted in Figs. 3 and 4, respectively.

Since the cash outflow takes place only at the end of the contract when calculating $IRR^{(1)}$ while the outflows are spread out over the entire life of the contract when calculating $IRR^{(2)}$, it is easy to infer from Fig. 5 that $IRR^{(2)}$ will usually be larger than $IRR^{(1)}$.

The economic interpretation for $IRR^{(2)}$ having a higher mean than $IRR^{(1)}$ is that $IRR^{(2)}$ incorporates the uncertainty of the time of death. This uncertainty is the non-systematic mortality risk, i.e., the risk that the insured might die earlier or later than expected (with given mortality rates). Law of large number states that if the pool were large enough, the times to the insureds' deaths would be in accordance with the life expectancies but only on average; there will be deviation from the expectation and $IRR^{(2)}$ accounted for such a risk.

The effect of this non-systematic mortality risk is manifested by the convexity of the present value function with respect to time: the positive effect on the IRR resulting from the possibilities of getting the death benefit earlier than the life expectancy and paying fewer times of premiums is larger than the negative effect from the possibilities of getting the death benefit later and paying more premiums than expected. In other words, the insureds underlying life settlements might die earlier or later than expected. The increases in the IRRs of the life settlements due to earlier deaths would be greater than the decreases caused by later deaths. Such asymmetry makes the risk premium be significant: 4.78% (=13.4% - 8.62%) for this pool of life settlements. The significance of the risk premium in bearing non-systematic mortality risk can also be comprehended by the facts that the IRR of a life settlement is sensitive to the death time of the underlying insured and that the full diversification of non-systematic mortality risk is difficult for life settlement buyers to achieve.[15]

Comparing Fig. 2 with Fig. 1 indicates that $IRR^{(2)}$ has a higher standard deviation of 2.68% than $IRR^{(1)}$. This is reasonable due to the introduction of non-systematic mortality risk. There are fewer outliers in $IRR^{(2)}$ since it takes into account the death probabilities across the entire life span. The comparison also shows that $IRR^{(2)}$ has lighter tails (kurtosis being reduced from 4.22 to 0.96) and is less skewed to the left (0.12 skewness vs. -0.91) than $IRR^{(1)}$.

We further estimate the risk premium for bearing systematic mortality risk by incorporating potential changes in the mortality rates of national populations into Eq. (2). More specifically, the solutions of the following Eq. (3) represent the expected returns with the considerations of not only non-systematic but also systematic mortality risks:

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[15] The literature has identified many determinants of mortality including residence, income, education, profession, race, age, and health condition. The scale and scope of life settlement investments have not yet reached the level to achieve full diversification across these determinants.
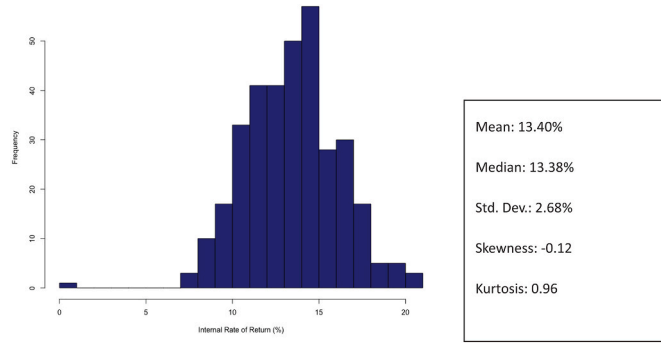
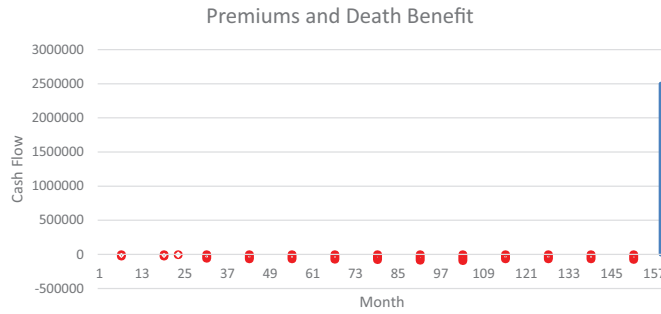**Fig. 2.** Histogram of IRRs under Uncertain Death Time (i.e., $IRR^{(2)}$).

Fig. 3. Cash Flows of a Representative Life Settlement Used in Calculating $IRR^{(1)}$.
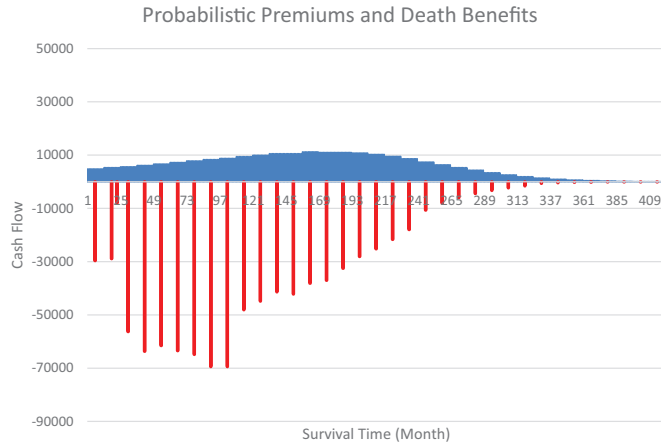
Fig. 4. Cash Flows of a Representative Life Settlement Used in Calculating $IRR^{(2)}$.

$$AC = \sum_{t=1}^{12(\omega-x)} \frac{\frac{t-1}{12}\widetilde{p}_x^{\;adj} \times \frac{1}{12}\widetilde{q}_{x+\frac{t-1}{12}}^{\;adj} \times DB - \frac{t}{12}\widetilde{p}_x^{\;adj} \times Premium_t}{(1+IRR)^t}, \tag{3}$$

where $\widetilde{p}$ and $\widetilde{q}$ (scripts suppressed) denote the survival and death probabilities after considering uncertain mortality rate changes. The annualized IRR of this type is denoted as $IRR^{(3)}$.

To simulate $\widetilde{p}$ and $\widetilde{q}$, we assume that the mortality rate changes of the US population follow the model of Lee and Carter (1992). The Lee-Carter model is chosen for its robustness across ages of adults, sampling periods, and populations (Lee and Miller, 2001; Booth and

Fig. 5. Relations between NPV and Discount Rate in Calculating Alternative IRRs.
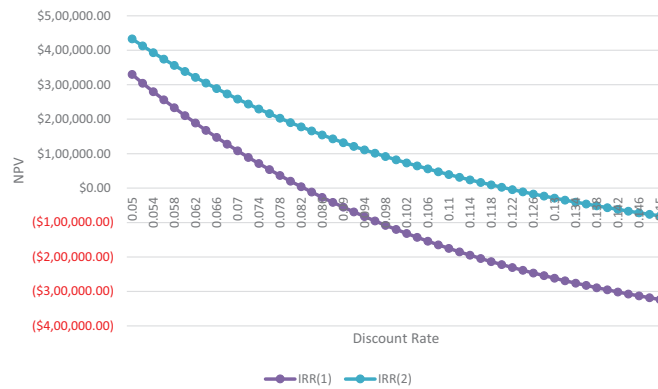
Tickle, 2008). In the Lee-Carter model the dynamics of the central death rate $m_{x,t}$ is specified as[16]:

$$logm_{x,t} = a_x + b_x k_t + \epsilon_{x,t} \tag{4}$$

$$k_t = \mu + k_{t-1} + v_t \tag{5}$$

The parameters a_x and b_x are age-specific constants; they relate to age only and are fixed across time. The k_t parameter captures the time-varying factor of mortality rates.

We follow Lee and Carter (1992) in estimating the parameters a_x, b_x, and k_t and assuming that k_t follows a random walk with a drift. We use 74 years of US central death rates (1933–2006) collected from HMD to estimate the parameters. The estimated models enable us to project the central death rate for each age. We then transform the projection to $_1q_x$ under the assumption of a uniform death distribution (UDD) and scale these $_1q_x$ by applying the same constant α as that used in obtaining $_1q_x^{adj}$ to serve as the inputs in Eq. (3). The estimated model parameters are presented in the Appendix II, and the resulting IRRs are plotted in Fig. 6.

From Fig. 6 it can be seen that the stochastic mortality rates reduce the mean IRR from 13.4% to 10.52%. The main driving force behind the reduction is the trend in mortality improvement. We decompose the differences between $IRR^{(2)}$ and $IRR^{(3)}$ into two components. The first component represents the reductions in IRRs due to expected mortality improvements, and the second reflects the changes in IRRs due to uncertain changes in mortality rates. To observe the impact of the first component, we set $\epsilon_{x,t}$ and v_t equal to zero when simulating future mortality rates using Eqs. (4) and (5). Fig. 7 displays the distribution of the resulting IRRs.

The average of the IRRs displayed in Fig. 7 is 10.55%, which is very close to the 10.52% observed in Fig. 6. This indicates the reduction in IRR is due to the mortality improvement trend. Although the average increase in life expectancy is only about 2.6 years, the compound effect of incremental premium payments and the delayed receipt of benefits causes the mean IRR to decline by 2.85% (13.4% - 10.55%). Take the previous life settlement sample as an example again. The life expectancy increases from 167 months to 175.6 months due to the mortality improvement trend of the general population as predicted by the Lee-Carter model. The IRR of this particular policy thus declines from 14.07% to 12.25%.

The differences between Figs. 7 and 6 result from the uncertainty/risk of mortality improvements. Bearing such systematic risk associated with the mortality improvement of the general population requires a premium, but the risk premium implied by the Lee-Carter model is negligible on average. The average IRR only increases by about 0.03%. The main reason for the minuscule risk premium is that the in-sample fit of the Lee-Carter model is quite good. More specifically, 95% of the male mortality variance and 98% of the female mortality variance are explained by the Lee-Carter model, respectively. The excellent goodness of fit results in small values of $\epsilon_{x,t}$ and v_t in Eqs. (4) and (5). The projected mortality rates hence have small variations, which means that the systematic mortality risk implied by fitting the Lee-Carter model to historical mortality rates is small.

The good fit of the Lee-Carter model can also be seen from the same standard deviations in Figs. 6 and 7. We observe the small difference in the standard deviations of Figs. 2 and 6 (2.68 vs. 2.58) and speculate that the small difference is due to the consistent reductions in the IRR across life settlement samples resulting from the unwavering increases in life expectancies. Similarly, the skewness and kurtosis of Figs. 6 and 7 are almost the same; the differences in these two statistics between Figs. 2 and 6 are minor as well.

We estimate the effect of tax on the returns from purchasing life settlements following Elton et al. (2001). The gains of life settlement investors are treated as ordinary income instead of capital gains according to the Internal Revenue Service (2009).[17] Since we

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[16] The central death rate of the persons aged x is the ratio between the number of deaths at age x and the average population of age x. Given the UDD assumption, the relation between $_1m_x$ and $_1q_x$ is: $_1q_x = \frac{_1m_x}{1+0.5_1m_x}$.

[17] The taxable gain of a life settlement investor is defined as the death benefit minus the sum of the premiums paid and the acquisition cost.
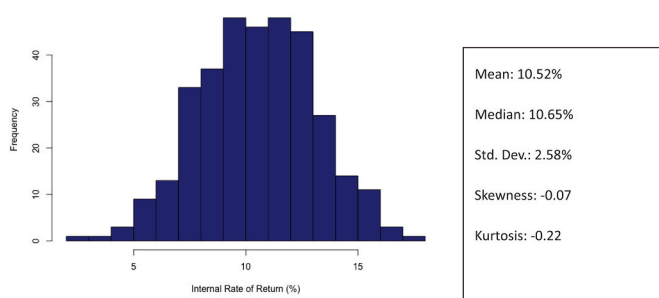
Fig. 6. Histogram of IRRs under Uncertain Death Time with Stochastic Mortality Improvements (i.e., *IRR^(3)*).
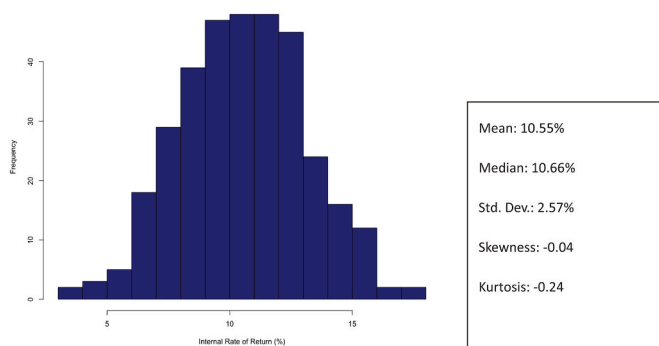

Fig. 7. Histogram of IRRs under Uncertain Death Time with Expected Mortality Improvements.

do not have data on individual investors' incomes but are aware that alternative investments like life settlements are not for low- to medium-income people, we assume the income tax rate to be 33%.[18] The after-tax *IRR^(2)* can then be obtained by solving the following equation:

$$AC = \sum_{t=1}^{12(\omega-x)} \frac{{}_{\frac{t-1}{12}}p_{x}^{adj} \times {}_{\frac{1}{12}}q_{x+\frac{t-1}{12}}^{adj} \times \left[DB - \tau\left(DB - \sum_{i=0}^{t}Premium_i\right)\right] - {}_{\frac{t}{12}}p_{x}^{adj} \times Premium_t}{(1+IRR)^t} \tag{6}$$

where τ is the tax rate. We calculate the after-tax *IRR^(3)* as well as after-tax *IRR^(1)* in a way similar to that using Eq. (6).

Tax lowers IRR by a considerable amount. The mean of *IRR^(1)* falls to 2.08%, from 8.62%, while the means of *IRR^(2)* and *IRR^(3)* decrease by 5.82%and 4.78%, respectively. The percentage reduction is about 24% (=2.08%/8.62%) for *IRR^(1)*, 43% for *IRR^(2)*, and 45% for *IRR^(3)*. The IRRs reflecting mortality risks are affected more by tax because of the higher taxable gain when the insured dies earlier than his life expectancy would indicate. Look at the aforementioned life settlement example again. The expected before- and after-tax death benefits associated with *IRR^(1)* and *IRR^(2)* are plotted in Figs. 8 and 9, respectively. In calculating *IRR^(1)*, death is assumed to occur as expected in the 159th month as Fig. 8 illustrates. The taxable gain is small since many premiums would have been paid before reaching life expectancy. On the other hand, taxable gains are higher in calculating *IRR^(2)* when death occurs earlier and fewer premiums are paid as we can see from Fig. 9.

After we obtain the above three pairs (before- and after-tax) of expected IRRs, we calculate the ex-ante rate spread as the difference between the expected IRR of a life settlement and the matching (after-tax) risk free rate. We first collect the term structure of the zero rates of US government bonds on the first trading day of the month in which the life settlement is purchased.[19] Then we specify the matching risk-free rate to be the spot rate with the same time to maturity as the life expectancy of the life settlement. Since the life expectancy of a life settlement is expressed in terms of months, we interpolate the yield curves linearly to obtain the yield with the maturities matching the life expectancies. Then we obtain the after-tax risk-free rate r_{taxed} by using Eq. (7) to further calculate the after-

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[18] This is the tax rate corresponding to the income bracket of $190,000 to $413,000.
[19] We obtained the Treasury zero rate (Ticker I02503M, I02506M, and I025XXY, where XX = 1, 2, 5, 7, 10, 15, 20, and 30) from the Bloomberg terminal.
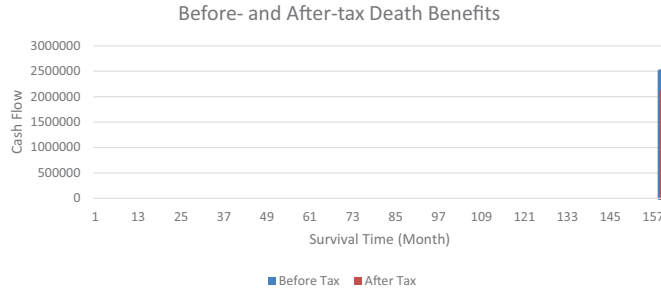
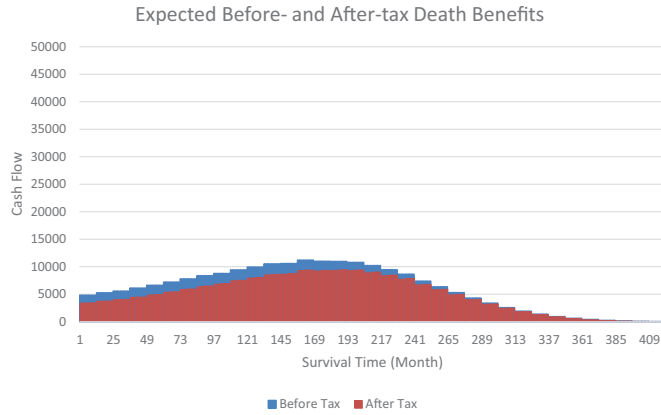**Fig. 8.** Before- and After-Tax Death Benefits of a Representative Life Settlement Used in Calculating IRR[(1)].

Fig. 9. Before- and After-Tax Death Benefits of a Representative Life Settlement Used in Calculating IRR[(2)].

tax spread (denoted as *Sprd[(i)]_taxed*):

$$r_{\text{taxed}} = [(1 - \tau)(1 + r)^n + t]^{\frac{1}{n}} - 1, \tag{7}$$

which is derived from the equation $P = (1 + r)^{-n} = (1 + r_{\text{taxed}})^{-n}(1 - (1 - P)\tau)$.

4. Possible determinants of the spreads and variable specifications

Based on the literature and the data provided by Coventry, we specify possible determinants of the rate spreads on life settlements in the following.

4.1. Market risk factor

The risk premium of the market portfolio has been extensively examined in the literature to see whether it affects the rate spread of a stock, a bond, or other fixed-income products. This factor should be of particular interest to investors because it determines the diversification benefit of life settlements as an asset class. An insignificant correlation between the market portfolio's spread and the spreads of life settlements would imply that life settlements are a zero-beta asset class offering significant diversification benefits. A negative correlation implies greater benefits from a reduction in risk while a positive correlation suggests fewer benefits from diversification.

We surmise the relation between the risk premium of the market portfolio and those of life settlements to be insignificant since the major risk involved with life settlement investments is mortality risk that is probably uncorrelated with the risk factors associated with most other asset classes. Giaccotto et al. (2017) also found that the return of an index of the life insurance policies purchased in the secondary market is relatively uncorrelated with stock or bond returns. We use the market factor in the Fama-French factors data

downloaded from Professor Kenneth French's website as the stock market risk premium.[20]

4.2. Size factor

Fama and French (1993) and subsequent studies raise our interest in investigating whether the size effect exists in the market for life settlements. On the one hand, life settlement investors may like to avoid concentration risk and thus demand a higher spread for a larger-sized policy. On the other hand, policy size might reflect the insured's wealth and wealth is positively related to health (Attanasio and Hoynes, 2000; Attanasio and Emmerson, 2003). A larger-sized policy may thus be initiated by a healthier insured that in turn implies a longer life expectancy and leads to a lower expected return. Therefore, the coefficient of this variable depends on the relative magnitude of concentration risk avoidance and the wealth-health effect.

The logarithm of the death benefit and that of the acquisition cost are used as alternative proxy variables for the size of the transaction/policy. We prefer the death benefit to the acquisition cost because the former represents the demand for insurance that in turn reflects the wealth of the policyholder, while the latter veils the premiums to be paid in the future and thus under-represents the size of the policy.

4.3. Volatility factor

The level of VIX is used to indicate the volatility of the stock market. When the stock market is in turmoil, the investors may try to find safer assets such as high quality bonds (Beber et al., 2009). This is called flight-to-quality. Life settlements can be regarded as bonds with uncertain maturities, and their major risk factor, mortality risk, should be weakly correlated with the movement of the stock market. We thus expect that a higher VIX would drive more funds out of the stock market into the life settlement market, thereby increasing the demand and raising the acquisition prices of the life settlements, and finally reducing the expected IRRs of the life settlements.

The VIX corresponding to each life settlement is the index on the first trading day of the month in which the life settlement is purchased. We obtain the VIX series from the CBOE website.[21]

4.4. Default risk

Default risk has been the focal point of the literature on the yields of corporate bonds. The investor purchasing the life settlement bears the default risk of the life insurer that issues the life insurance policy underlying the life settlement. We thus expect to see that a life settlement originating from a policy issued by a worse-rated insurer will give rise to a higher spread.

4.5. Maturity factor

Baker et al. (2003) identified the maturity/term of a bond to be able to predict the bond's rate spread, and Gottesman and Roberts (2004) found evidence that lenders were compensated for longer-maturity loans. It is thus legitimate to investigate whether the expected maturity of a life settlement is one of the determinants of the rate spread.

We regard the life expectancy of the insured underlying the life settlement as the expected maturity of the life settlement. Considering that the medical underwriter possesses not only public information (on the general population's mortality) but also proprietary information on the insured's health condition, we adopt LE_{uw} as the best estimate of the expected maturity. From the perspective of the maturity spread, we expect to see that the life expectancy regarding the insured has a positive relation with the rate spread of the life settlement as the literature has identified.

A distinction between buying a bond and purchasing a life insurance policy (and a life settlement), however, may reverse the relation: a bond holder receives only cash inflows while a policyholder usually has to pay premiums to keep the policy valid. The longer the insured lives, the more premiums the investor may have to pay and the lower the return will be. The sign of the coefficient of this expected maturity variable is therefore an empirical matter, depending on whether the premium payment effect outweighs the maturity spread effect or not.

4.6. Proprietary information on the health condition of the insured from underwriting

The essential risk associated with investing in the life settlement is the uncertainty in the time of death of the insured, which brings in the role of the medical underwriter. As already mentioned, we speculate that the life expectancy estimated by the medical underwriter contains proprietary information regarding the health condition of the insured. To reflect such information and investigate how it may affect the risk premiums of the life settlements, we calculate the ratio of the life expectancy estimated by Coventry's medical underwriter to that estimated using public information as follows:

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[20] The Fama-French factors are downloaded from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (Accessed on Oct. 10, 2016).

[21] We downloaded post-2004 VIX data on 2016/06/14 from http://www.cboe.com/publish/scheduledtask/mktdata/datahouse/vixcurrent.csv. (Accessed on Aug. 18, 2016)

$$\text{Proprietary Information Ratio} = \frac{LE_{uw}}{LE_{Public}}$$

To calculate LE_{public}, we follow the actuarial practice in adopting the VBT mortality table. Actuaries use the Valuation Basic Table (VBT) from the Society of Actuaries (SOA) to calculate insurance premiums (Bhuyan, 2009) because the sample used in constructing the VBT tables consists of the population of insureds rather than the general population (as in the case of the HMD tables).[22] Since our life settlement sample started being originated from 2009, we have adopted the 2008 VBT Table to represent the up-to-date information at the time the life settlements were issued.

We expect to see a negative coefficient for this variable. The life settlement with an insured who was assessed by the medical underwriter to be healthier than his/her peers and thus has a longer life expectancy will receive death benefits later and pay more premiums than in the case of a life settlement for an insured with average health. The IRR as well as the rate spread associated with a healthier insured will be smaller as a result, and vice versa. A significant, negative coefficient of this variable implies the validity of this proprietary information.

4.7. Surrender behaviors of policyholders

Life settlements can be regarded as substitutes for the policyholders who consider surrendering their life insurance policies for various reasons/motives. Surrendering the life insurance policy is common as life insurance is a prominent tool of human capital risk management (Xiao and Tao, 2020) and the demand of life insurance invariably changes over time (Kung and Yang, 2020). A higher tendency towards surrender implies a greater willingness to sell policies through the life settlement market to avoid surrender charges and/or to secure a higher value than the policy reserve indicates.[23] The selling prices is lower for those policies that have a greater tendency to be surrendered, which implies higher expected returns to the investors in those life settlements. The determinants of the tendency to surrender the policy may therefore also be those of the life settlement's spread.

The insurance literature, including Renshaw and Haberman (1986), Kagraoka (2005), Milhaud et al. (2011), Pinquet et al. (2011), Eling and Kiesenbauer (2014), and Eling and Kochanski (2013), has suggested that the insured's age, gender, and healthiness, policy age, and policy size affect the tendency to surrender the policy. The tendency to surrender the policy decreases with age in general, but the tendency might reverse for people aged 70 and above. The findings about how gender may affect the surrender tendency vary across regions. Hendel and Lizzeri (2003), Pinquet et al. (2011), and Fang and Kung (2020) documented that an unhealthier insured is less likely to surrender his or her policy. The insurance literature has found that younger policies are more likely to be surrendered. Milhaud et al. (2011) found that the surrender tendency is affected by alternative size measures (face amount, savings premium, and risk premium) in different ways. As with the above results, we expect the rate spreads of life settlements to be higher for younger policies and healthier insureds.

The implications of these surrender behaviors on the rate spreads of life settlements may be inconsistent with the non-behavioral perspectives. For instance, the behavioral perspective predicts that the life settlements with healthier insureds will have higher rate spreads. This is inconsistent with the cash-flow perspective as delineated by the variable of proprietary information regarding the health condition of the insured.

In addition, the age and gender of the policyholder affect not only the surrender tendency but also the life expectancy. From the right portion of Eq. (A1) we can see that age and gender are the major determinants of life expectancy since the death and survival probabilities are age- and gender-specific. Age and gender also affect the healthiness of the insured. We will address the potential collinearity and robustness issues in the regression analyses later.

Table 2 shows the correlations among the explanatory variables and the correlations with the three pairs of spreads. The before-tax spreads, denoted as $Sprd^{(i)}$, calculated in alternative ways, are highly correlated with each other. The correlation coefficients between $Sprd^{(1)}$ and $Sprd^{(2)}$, between $Sprd^{(1)}$ and $Sprd^{(3)}$, and between $Sprd^{(2)}$ and $Sprd^{(3)}$ are 0.87, 0.84, and 0.91, respectively. The coefficients among the after-tax spreads $Sprd^{(i)}\_taxed$ are lower: 0.82, 0.64, and 0.92. The impacts of tax on the spreads are more complicated in the framework of the uncertain death time than in the certain-death-time framework. More specifically, the correlation coefficient of 0.99 between $Sprd^{(1)}$ and $Sprd^{(1)}\_taxed$ indicates that tax works like a linear discount factor. The coefficients between ($Sprd^{(2)}$, $Sprd^{(2)}\_taxed$) and ($Sprd^{(3)}$, $Sprd^{(3)}\_taxed$) are, on the other hand, significantly lower (0.82 and 0.83, respectively).

With regard to the correlation coefficients between dependent and independent variables, the market risk factor and information factor are consistently negatively correlated with the dependent variables. The maturity factor and policy age are negatively correlated with five out of six dependent variables. The volatility factor is negatively correlated with before-tax dependent variables, while *Age* and *Gender* have positive coefficients, generally speaking. The size factor has no significant correlations at all. The default risk factor is not correlated with the before-tax spreads; it is negatively correlated with $Sprd^{(1)}$ but positively correlated with $Sprd^{(1)}$.

As for the correlation coefficients among the explanatory variables, age and the maturity spread factor have a large, negative correlation coefficient of -0.72 that raises concerns of collinearity. Age also has notable correlations with the proprietary information

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[22] We did not adopt the VBT tables in calculating $IRR^{(2)}$ and $IRR^{(3)}$ because there are too few tables for us to construct mortality projection models that further allow us to incorporate stochastic mortality improvements into the calculations of IRRs.

[23] The difference between the cash value and policy reserve can be regarded as an implicit surrender charge. The surrender charge usually decreases with the policy's age: it is high in the first few years and eventually decreases to zero. Furthermore, the policy reserve may deviate from its market/fair value since the statutory accounting adopted in the US does not require actuaries to engage in mark-to-market accounting.

Table 2
Correlations among variables.

	$Sprd^{(1)}$	$Sprd^{(2)}$	$Sprd^{(3)}$	$Sprd^{(1)}\_taxed$	$Sprd^{(2)}\_taxed$	$Sprd^{(3)}\_taxed$	Age	Gender	Maturity	Policy_Age	MKT_Prem	logNDB	Prop_inf	Rating
$Sprd^{(2)}$	0.87***													
$Sprd^{(3)}$	0.84***	0.91***												
$Sprd^{(1)}\_taxed$	0.99***	0.87***	0.85***											
$Sprd^{(2)}\_taxed$	0.80***	0.82***	0.90***	0.82***										
$Sprd^{(3)}\_taxed$	0.62***	0.60***	0.83***	0.64***	0.92***									
Age	0.21***	0.13**	0.04	0.14***	−0.05	−0.08								
Gender	0.11**	0.10*	0.18***	0.11*	0.04	0.08	−0.29***							
Maturity	−0.40***	−0.31***	−0.29***	−0.32***	−0.11**	−0.09	−0.72***	−0.12**						
Policy_Age	−0.15***	−0.06	−0.13**	−0.18***	−0.23***	−0.25***	0.04	0.05	−0.17***					
MKT_Prem	−0.15***	−0.13**	−0.12**	−0.13**	−0.15***	−0.13**	−0.03	−0.05	0.09	0.02				
logNDB	0.01	−0.04	−0.04	0	0	0.02	0.11**	−0.16***	0	−0.18***	0.04			
Prop_Inf	−0.23***	−0.25***	−0.29***	−0.22***	−0.25***	−0.22***	0.35***	−0.25***	0.32***	−0.16***	0.07	0.08		
Rating	−0.09	−0.05	0	−0.10*	0.06	0.13**	0.17***	−0.08	−0.12**	0.06	−0.06	0.12**	0.04	
VIX	−0.19***	−0.12**	−0.11**	−0.19***	−0.08	−0.04	0.03	−0.03	−0.01	0.03	−0.56***	−0.04	−0.01	0.09

Note: The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 3
Main regression results: determinants of after-tax life settlement spreads.

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
(Intercept)	11.039***	12.306***	10.075***
	(1.487)	(2.239)	(2.032)
MKT_Prem	−0.093***	−0.095***	−0.078**
	(0.023)	(0.031)	(0.034)
logNDB	−0.086	−0.031	−0.071
	(0.07)	(0.107)	(0.108)
VIX	−0.111***	−0.098***	−0.072**
	(0.026)	(0.034)	(0.036)
Rating	−0.016	0.190**	0.306***
	(0.072)	(0.092)	(0.113)
Maturity	−0.008***	−0.003	−0.002
	(0.002)	(0.003)	(0.003)
Health_Inf	−1.553**	−4.370***	−4.423***
	(0.642)	(1.052)	(1.102)
Policy_Age	−0.083***	−0.182***	−0.186***
	(0.019)	(0.04)	(0.042)
R^2	0.246	0.213	0.178
Adj. R^2	0.230	0.197	0.160
RMSE	1.031	1.623	1.742

Note: Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

factor (0.35). The correlation between the proprietary information factor and maturity factor is notable as well (0.32). The information factor is negatively correlated with gender with a coefficient of −0.25. Gender has a coefficient of −0.29 with age. Having all these variables as independent variables may give rise to multicollinearity and the regression may be mis-specified.

Since the mortality rates used to calculate life expectancy depend on age and gender, we ran a regression on life expectancy with regard to age and gender as the first attempt to investigate the collinearity issue. The coefficients of age and gender are significant and negative, as expected. The R^2 of the regression is 65%. We thus decided to leave age and gender out of the following regression analyses and will provide more justifications for leaving them out in the robustness check section.

5. Primary findings

Based on the above speculations and specifications, we analyze the following regression models:

$$Sprd^{(i)}_{taxed} = \beta_0 + \beta_1 \times Market\ Risk\ Factor + \beta_2 \times Size\ Factor$$

$$+ \beta_3 \times Volatility\ Factor$$

$$+ \beta_4 \times Default\ Risk + \beta_5 \times Maturity\ Factor$$

$$+ \beta_6 \times Information\ Factor + \beta_7 \times Behavior\ Factor + \varepsilon^{(i)}, \tag{8}$$

where $i = 1, 2, or\ 3$ corresponds to the three different ways of calculating the rate spreads. The results are presented in Table 3.

The R^2s of the three sets of regressions range from 18% to 25%, these being reasonable levels of fitness for medium-sized microeconomic samples. The signs of almost all coefficients are consistent across the three types of expected spreads calculated under the assumptions of the certain death time, the uncertain death time, and the uncertain death time with stochastic mortality rates. The significance of the coefficients is also consistent, except for the variables *Rating* and *Maturity* for which one or two coefficients are insignificant. The overall fit of the results seems to be reasonable and robust.

That the coefficient of the *MKT_Prem* is significant and negative indicates that life settlements are an asset class with negative beta and could provide more diversification benefits than we expect. We provide three explanations for this finding. Firstly, stock returns and Treasury bond returns (r_f) are positively related (Campbell and Ammer, 1993; Elton et al., 2001; Connolly et al., 2005). We also have the following relation:

Expected Spreads of Life Settlements = Expected IRR of Life Settlements − r_f

in which the expected IRR is determined by the acquisition cost and future cash flows expected at the time of acquisition. Therefore, increases in stock returns lead to increases in r_f that in turn result in decreases in expected spreads. We thus observe a negative coefficient of the *MKT_Prem* with regard to spreads of life settlements.

The second explanation is a variation of the first one. After the statement of the positive relation between bond yields and stock returns, we argue that the increases in bond yields correlated with stock return increases lead to increases in the discount rates for life
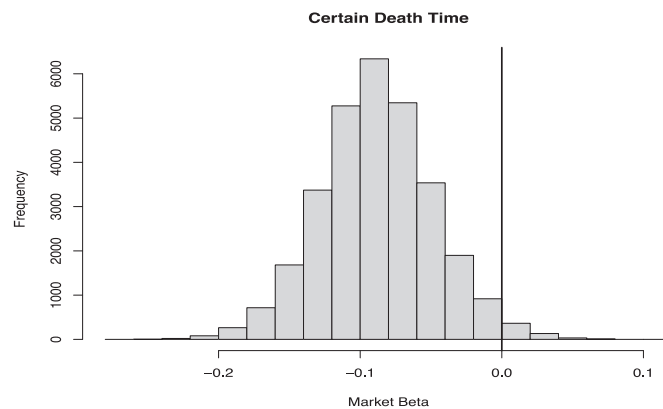
Fig. 10. The bootstrapped distribution of market beta in regression model (1).

settlements since bond yields are the benchmark of the discount rates used in pricing life settlements.[24] On the other hand, the cash flows of life settlements are determined by mortality that is independent of stock returns and bond yields, and the death benefits of the policies underlying life settlements are paid at the end of contracts. Increases in the discount rates thus result in decreases in the values of life settlements, which makes the life settlements an asset class with a negative beta.

The third rationale for the negative beta is related to the emergency fund hypothesis in the insurance literature. The empirical evidences (e.g., Outreville, 1990; Kuo et al., 2003; Kim, 2005; Jiang, 2010; Fier and Liebenberg, 2013) show that policyholders are more prone to surrendering their policies when the economy is bad. This implies that policyholders who have demands for money in economic downturns will be willing to sell their policies at a discount and render life settlement investors higher returns in such times. Since economic downturns usually accompany decreases in stock returns and r_f, the higher IRRs of life settlements during these times imply a negative beta.

Size, measured by the logarithm of the death benefit (*logNDB*), has insignificant coefficients. This implies that the effect of concentration risk avoidance and the wealth-health effect cancel each other out. The market volatility variable, denoted as VIX, has significant, negative coefficients. This confirms the existence of a flight-to-quality phenomenon in which the assets of high quality could be life settlements. The purchasing decisions related to our samples happened to be made right after the financial crisis period, which further supports our view that such a finding is likely to be evidence of flight-to-quality behavior.

The coefficient of the Default Risk variable as represented by the rating of the insurance company underlying the life settlement is significant in two out of three cases. The positive coefficient goes beyond our reasoning, however. While there could be two reasons for the insignificant relation between the rate spread and issuer rating, there is no valid argument for the positive relation. First of all, the life insurance industry is highly regulated to protect the policyholders' benefits from insurer insolvencies. The US Life insurers are strictly regulated by state regulators with the help/coordination of the NAIC (National Association of Insurance Commissioners), and protecting the interests of policyholders has been the top priority of regulators. Through the mechanism of capital requirements, for instance, regulators can even take over an insurance company before the insurer goes into bankruptcy. Furthermore, the actuarial profession has developed rigorous mechanisms to determine the liabilities of a life insurer in relation to its policyholders as shown on the balance sheet and life insurers are required to have adequate assets to cover these liabilities at all times. Secondly, policyholders are protected by the state guarantee funds that play a role similar to that of the FDIC (Federal Deposit Insurance Corporation) in the banking industry. In the cases of insurer insolvencies, the guarantee funds will cover part or all of the insureds' losses. The investors in the life settlements may thus bear the immaterial default risk of the underlying insurers and in turn demand insignificant risk premiums.

With regard to *Maturity* that is used to show how the expected maturity/term of a life settlement affects the spread, its coefficient is significant only in the case of *Sprd$^{(1)}$_taxed*. This means that the term spread effect is balanced out by the premium payment effect in the cases of *Sprd$^{(2)}$_taxed* and *Sprd$^{(3)}$_taxed*. The premium payment effect outweighs the term spread effect only under the framework of the

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[24] Insurance pricing often use bond yield as a benchmark for the discount rate when determining the premium. An example is documented in the Insurance Capital Standard (ICS). In the implementation of the ICS, the International Association of Insurance Supervisors (IAIS), 2020 lays out details on how to use bond yields to estimate the risk premium that is to be used in estimating the liabilities associated with selling life insurance. Paragraph 116 of the ICS Technical Specifications (2020) states: …insurance liabilities are discounted using an adjusted yield curve based on …risk-free yield curve and an adjustment. Paragraph 130 states: This adjustment is determined using the Three-Bucket Approach. The adjustments for the buckets are based on the average spreads of the bonds, loans, and mortgage backed securities held by life insurers to back the portfolio of liabilities (please see section 5.2.5.3 of the ICS Technical Specifications). Therefore, bond yields are the benchmark of the discount rates used in estimating the liabilities associated with selling life insurance. Since life settlements are securitized life insurance policies, bond yields shall be the benchmark of the discount rates used in pricing life settlements.
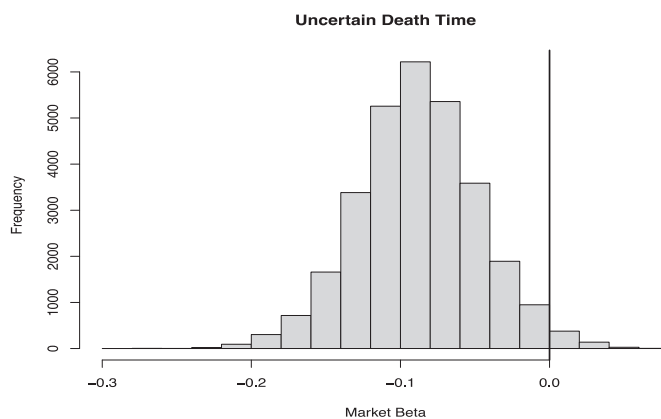
Fig. 11. The bootstrapped distribution of market beta in regression model (2).
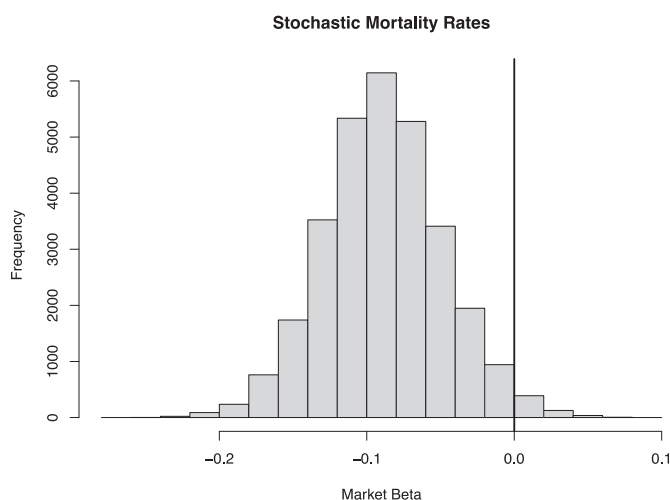

Fig. 12. The bootstrapped distribution of market beta in regression model (3).

certain death time. These results indicate that the feature of multi-premium life insurance (vs. one payment for obtaining a bond) plays a significant role in determining the rate spreads of life settlements.

The coefficients of *Prop_Inf*, serving as a proxy for the proprietary Information on the insured's health, are negative and significant in all three cases. This is consistent with our speculation that a life settlement with an insured who is healthier than his/her peers will have a lower rate spread due to the longer life expectancy that leads to additional premium payments.

With regard to the factor reflecting the surrender behavior of policyholders, we see that *Policy_Age* has significant coefficients. The coefficients are all negative. This supports our speculation that higher tendencies to surrender insurance policies will bring life settlement buyers higher spreads. The behavior of policyholders can indeed be a significant determinant of the rate spreads on life settlements.

6. Robustness checks and further explorations

We conduct robustness checks on the specifications of dependent and independent variables. The results are in Appendix III. The check results confirm that our findings in the previous section are robust.

We further check the robustness of the negative beta by a 3-fold cross-validation. To do this, we divide the full sample into three

Table 4
Other determinants of non-systematic and systematic risk premiums.

Dependent Variable	(2) Non-systematic mortality risk premium	(3) Systematic mortality risk premium
(Intercept)	2.642**	−2.459***
	(1.264)	(0.903)
MKT_Prem	−0.018	0.016
	(0.018)	(0.015)
logNDB	−0.030	−0.011
	(0.065)	(0.044)
VIX	−0.002	0.021
	(0.018)	(0.014)
Rating	0.321***	0.172***
	(0.064)	(0.054)
Maturity	0.007***	−0.0008
	(0.002)	(0.0014)
Health_Inf	−3.050***	−0.286
	(0.607)	(0.469)
Policy_Age	−0.106***	−0.034**
	(0.026)	(0.014)
R^2	0.209	0.065
Adj. R^2	0.192	0.045

Note: Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

sub-samples. Each of the sub-samples is randomly drawn from the full-sample. We draw the sub-sample for 10,000 times and take the subsamples to the main regression to estimate the beta. This gives us a bootstrapped distribution of beta in each of the regression (*i*), *i* = 1,2,3.

Figs. 10, 11, and 12 report the bootstrapped distribution of beta in regression model (1), (2), and (3), respectively. The results demonstrate that the market beta of life settlement is negative in most subsamples by all three regression models. As discussed in the paper, the negative beta is a highly desirable feature for any asset class in the portfolio management. These robustness-check results provide further empirical evidence for the characteristics of life settlement as an attractive alternative asset class.

Then we explore an interesting question: will the independent variables used in the regression analysis affect the two types of mortality risk premiums quantified in section 3? Theoretically speaking, systematic and non-systematic mortality risks have no reason to be related to financial variables. Policy variables, insured's information, and insurer's factor shouldn't be able to affect the systematic mortality risk. This type of risk is affected by pandemics, wars, catastrophes, living environment (such as sewer system and pollutions), medical advances, and health care system. However, non-systematic mortality risk may be affected by policy variables, insured's information, or even insurer's factors since the market of life settlements may not be large enough to reach full diversifications across these variables. Furthermore, the size, maturity, and age of the underlying life insurance policy may be related to mortality risks due to adverse selection, moral hazard, or other information asymmetry.

To explore this question, we conduct two rounds of regression analyses. We use the difference between IRR[2] and IRR[1] and the difference between IRR[3] and IRR[2] to represent the non-systematic and systematic mortality risk spread, respectively. The spreads are dependent variables while financial variables, policy variables, and the insurer's rating are independent variables. The results are in Table 4.

Since the coefficients of MKT_Prem and VIX are insignificant, we confirm that neither systematic nor non-systematic mortality risk premium is affected by financial variables. Two policy variables (Maturity and Policy_Age), one insured's information (Health_Inf), and the insurer's factor (Rating) are significant determinants of non-systematic mortality risk premium. This implies that the market of life settlements is not large enough to reach full diversifications across these variables and information asymmetry exists in life insurance and life settlement markets.

What surprises us is the significance of Rating and Policy_Age in explaining the systematic mortality risk premium. Policy age reflect in which year the policy was issued. Its significance may indicate that the cohorts of the policies issued in different calendar year are priced differently to reflect the differences of life insurance markets across years. For instance, the mortality table is updated from time to time, and policies issued in different years may be priced by using different mortality tables. So is the pricing interest rate. With regard to Rating, our guess is that a better rating insurer tends to adopt a more stringent underlying policy in screening life insurance buyers. We do observe the mortality rates of those who buy life insurance differ significantly from those of the general population. This indicates the underlying practices of life insurers are effective in selecting the "right" customers with regard to profits.

7. Conclusions and remarks

Scholars as well as practitioners pay attention to the determinants of rate spreads on various investment products including common stocks, corporate bonds, sovereign bonds, corporate loans, and catastrophe bonds. The determinants of the rate spreads on life settlements, however, have not yet been examined, even though the market for life settlements has grown to a significant size. This

study extends the scope of the literature on the spread determinants of risky assets to life settlements, in addition to extending the boundary of the literature on life settlements.

In Asia, life settlements are mainly known by few institutional and professional investors asking for higher returns since Asia regulations have been stagnating the market. Only Singapore and Hong Kong have approved the transactions of life settlements up to now. On the other hand, the results of Hsieh, Tsai, and Wang (2020) demonstrate that even the life settlements originated in other regions may provide significant hedging benefits to the mortality risk of Asia life insurers. We thus recommend insurance and pension regulators in Asia loosening the regulations on the use of life settlements for the hedging purpose. The regulations may also be loosened to some extent for the sophisticated investors who want to enhance their yields.

We estimate the IRRs and spreads of life settlements in three ways. First of all, we calculate the IRR of a life settlement given the insured's life expectancy as people calculate the YTM of a corporate bond. Then we calculate the IRRs under the uncertain death time framework to reflect the premiums of non-systematic mortality risk. The third way takes into account stochastic mortality improvements to further capture the systematic mortality risk. The impacts of tax on the IRRs and spreads are then estimated. Our data on life settlements are from a leading market maker in the US, and the data contain attributes of the underlying policies and insureds as well as the life expectancies estimated by a major medical underwriter. The differences between the calculated IRRs and the spot rates of US government bonds that have the maturities matching the expected death time represent the rate spreads expected by the investors. The tested independent variables include the market risk factor, size factor, volatility factor, default risk factor, maturity factor, proprietary information on the insured's health, and a policyholder behavior factor reflecting the tendency to surrender the policy.

Our results demonstrate that the premium for bearing non-systematic mortality risk is quite significant: more than 4% on average. This is reasonable since the insureds underlying life settlements are few in number relative to the general population and the large contract size further hinders diversification.[25] Systematic mortality risk, on the other hand, has only a minor role to play in determining the rate spreads of life settlements. This is probably due to the steady mortality improvements of the general population even though such improvements reduce expected returns and spreads to a significant extent. Tax lowers IRRs considerably, to a greater extent than accounted for by the non-systematic mortality risk.

The regression results show that the market risk factor, volatility factor, information factor, and behavior factor are significant determinants of the rate spreads on life settlements. Life settlements are an asset class with a negative beta and a kind of safe haven for investors to fly to when market volatility increases. The proprietary information provided by the medical underwriter does play an important role in determining expected spreads. So does the surrender behavior of the policyholders behind the life settlements. The maturity factor seems to be an insignificant determinant of the rate spreads of life settlements probably because the maturity spread effect found in bonds and loans is offset by the premium payment effect that pertains to the multi-premium feature of most life insurance policies. The size factor is not significant at all, which implies that the wealth-health effect is balanced out by the avoidance of concentration risk. All these results are robust across alternative specifications of dependent and independent variables. We also confirm the robustness of the negative beta by a 3-fold cross-validation.

Our further explorations confirm that neither systematic nor non-systematic mortality risk premium is affected by the market risk factor and VIX. The proprietary information, the insurer's rating, policy maturity, and policy age are significant determinants of non-systematic mortality risk premium. Their significance implies that the market of life settlements is not large enough to reach full diversifications across these variables and that information asymmetry exists in life insurance and life settlement markets. Rating and policy age are also significant determinants of systematic mortality risk premium.

The above findings show how life settlements share the same risk-premium determinants as stocks and fixed-income products while identifying unique determinants. This secondary market for life insurance policies deserves the attention of finance as well as insurance practitioners to better understand what interconnects and what differentiates the financial markets. Our findings also shed light on the determinants of the implicit yields of life insurance policies concerning the general population. Actuaries may consider incorporating some financial market factors into their pricing to better meet the demand for life insurance that probably changes with the financial markets.

CRediT authorship contribution statement

Ko-Lun Kung: Methodology, Data curation, Formal analysis, Investigation, Writing - original draft. **Ming-Hua Hsieh:** Methodology, Data curation, Software. **Jin-Lung Peng:** Investigation, Resources, Visualization. **Chenghsien Jason Tsai:** Conceptualization, Funding acquisition, Validation, Writing - review & editing. **Jennifer L. Wang:** Project administration, Funding acquisition, Conceptualization.

Appendix A. Adjusting population mortality rates to be consistent with LE_{uw}

The conversion from annual to monthly mortality rates requires an assumption for within-year interpolation. We adopt the assumption of uniform distribution of death (UDD) that is commonly used in actuarial science (Dickson et al., 2020). It assumes the

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[25] This seemingly undiversifiable risk may be hedged with a biomedical research-backed obligation (RBOs). See MacMinn and Zhu (2017) for a discussion on its advantage as a hedging instrument over others for the life settlement industry.

survival of individual decreases linearly within the year. More specifically, the probability of death in duration s ($0 < s < 1$) is

$$_s q_x = s \cdot {}_1 q_x.$$

This relation gives us the monthly mortality rate:

$$_{\frac{1}{12}} q_x = \frac{1}{12} {}_1 q_x.$$

After some algebra we arrive at the probability of dying next month for an age of $x + \frac{t}{12}$ within that year:

$$_{\frac{1}{12}} q_{x+\frac{t}{12}} = \frac{\frac{1}{12} q_x}{1 - \frac{t}{12} q_x}, 0 \le x + \frac{t}{12} + \frac{1}{12} \le x + 1.$$

The life expectancy in months, e_x, is a probability-weighted lifetime and can be written as:

$$e_x\left(\left\{ {}_1 q_{x+t} \right\}_{t=0}^{\omega-x-1}\right) = \sum_{t=1}^{12(\omega-x)} (t-1) \cdot {}_{\frac{t}{12}} p_x \; {}_{\frac{1}{12}} q_{x+\frac{t}{12}}, \tag{A1}$$

where the survival probability $_{\frac{t}{12}} p_x = \prod_{k=0}^{\left[\frac{t}{12}\right]} p_{x+k} \left(\frac{t}{12} - \frac{t}{12} p_{x+\left[\frac{t}{12}\right]} \right)$ and $[\cdot]$ is the gauss (floor) function. Here we explicitly spell out the death probability (as well as the corresponding survival probability) as an argument of the life expectancy function to emphasize mortality rates are variables in the life expectancy calculation.

Next, we specify the moment condition we used to adjust the mortality rate. We use a linear scaling to adjust the annual mortality rate from the life table. In other words, the adjusted annual mortality rate $_1 q_{x+t}^{adj}$ takes the form of

$$_1 q_{x+t}^{adj} = \alpha \cdot {}_1 q_{x+t}, t = 0, 1, 2, ..., \omega - x - 1.$$

This simple form is also used commonly in practice (Actuarial Standard Board, 2013).

We solve for the scaling constant α that satisfies

$$e_x\left(\left\{ {}_1 q_{x+t}^{adj} \right\}_{t=0}^{\omega-x-1}\right) = LE_{uw} \tag{A2}$$

for each policy. Such scaling provides us with the mortality rates maintaining the inter-age relations of the general population while matching with the life expectancy estimates by the medical underwriter.

After obtaining α for each life settlement by solving Eq. (A2) repetitively, we used the adjusted probability of death $_{\frac{1}{12}} q_{x+\frac{t}{12}}^{adj}$ to compute the expected cash flows and obtain the IRR for each life settlement.

We expect α to be less than unity because past actuarial experiences suggested that policyholders have lower mortality rates than the general population. The adjustment results show that the value of α is generally less than 1. The average of α is about 0.76 with a median of 0.67. The range of α is between 0.53 and 3.61, and α has a standard deviation of 0.32.

Appendix B. Parameters of Eqs. (4) and (5)
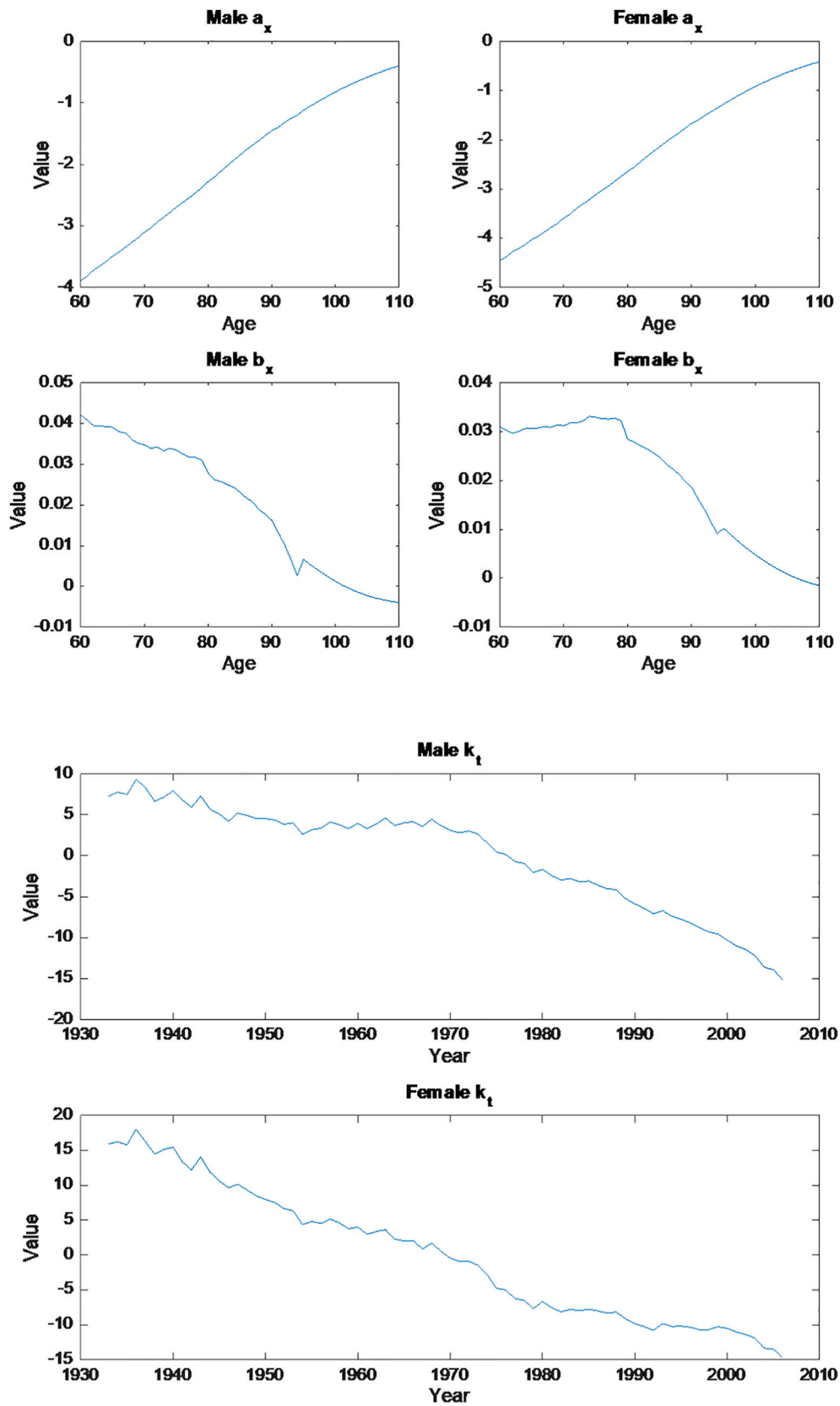
Note: We use the U.S. mortality rates during 1933–2006 to estimate the models for males and females. Data were obtained from the Human Mortality Database. The models were estimated using the central mortality rate $_1m_{x,t}$ as the dependent variable and converted to the death rate $_1q_{x,t}$ by the approximation $_1q_{x,t} = \frac{_1m_{x,t}}{1+0.5\,_1m_{x,t}}$ when inputting Eq. (4). Both male and female mortality trends follow the model of a random walk with drift as follows:

$$k_{t+1} = -0.3059 + k_t + v_t, v_t \sim N(0, 0.4583) \text{ for males,}$$
$$k_{t+1} = -0.4200 + k_t + v_t, v_t \sim N(0, 0.7170) \text{ for females.}$$

Appendix C. Robustness checks on the specifications of dependent and independent variables

The first robustness check is to examine how taxes may alter the above findings. We ran regression (8) on the before-tax spread $Sprd^{(i)}$ and present the results in Table A1.

These results are better and more consistent than those in Table 3. The signs and significance of all variables are consistent across the three ways of calculating rate spreads with comparable R^2. All coefficients of *Maturity* are now significant, which indicates that the premium payment effect dominates the term spread effect in these before-tax cases. Furthermore, all coefficients of *Rating* are insignificant. This liberates us from the previous awkward situation and supports our earlier argument that default risk will not be a concern when investing in life settlements due to stringent solvency regulations and the presence of a sound safety net in the life insurance industry.

The second robustness check is to investigate the potential collinearity between *Maturity* and the set of *Age* and *Gender*. The collinearity originates from the mortality rates used in calculating life expectancy being based on age and gender. We have seen at the end of Section 4 that *Age* is highly correlated with *Maturity* and that the set of *Age* and *Gender* can explain 65% of the variations in *Maturity*. Table A2 contains the results of our further investigation into the collinearity issue.

We first observe from comparing the first three columns of the regression results with the results in Table 3 that replacing *Maturity* with the set of *Age* and *Gender* leaves all results intact. The signs, magnitude, and significance of virtually all coefficients are the same / at the same level.[26] The explanation regarding how life expectancy affects the rate spread remains unchanged as well: a younger person will have a longer life expectancy that in turn results in a smaller rate spread of the associated life settlement. Secondly, we notice from the 4th to 6th columns of the regression results in Table A2 that the standard deviations of the coefficients of *Maturity*, *Age*, *Prop_Inf*, and *Gender* inflate significantly. *Prop_Inf* even becomes an insignificant explanatory variable as a result. We thus conclude that inserting *Age* and *Gender* into Eq. (8) will raise the collinearity and mis-specification concerns and that *Maturity* and the set of *Age* and *Gender* are substitutes for each other. Applying the same robustness checks to the before-tax spreads, $Sprd^{(i)}$, yields the same conclusions.

The third robustness check involves assuming the major investors in life settlements are those with the highest tax bracket (39.6%) instead of the 33%.[27] We re-calculate $Sprd^{(1)}$_taxed and re-run the regressions. All previous findings remain valid as can be seen from Table A3.

The fourth check is to see how the alternative mortality table that can be used in calculating $Sprd^{(2)}$_taxed might affect the regression results. The results in Table A4 confirm that using the VBT table changes no major explanations, but remedies the relation between rating and spread.

We then focus on the specifications of the explanatory variables. Table A5 shows that substituting the death benefit with the acquisition cost merely removes the significance of VIX in the case of $Sprd^{(3)}$_taxed while making *Size* significant in the $Sprd^{(1)}$_taxed case. We suspect that the latter might result from the endogeneity between the acquisition cost and rate spread since the acquisition cost is used in calculating the IRR. A higher acquisition cost will bring down the IRR, which coincides with the negative coefficient.

We tried alternative specifications of *Prop_Inf* in two ways: $LE_{uw} - LE_{Public}$ and $\frac{LE_{uw}}{LE_{HMD}}$ in which LE_{HMD} stands for the life expectancy estimated by using the HMD table instead of the VBT table. From Table A6 we see that the alternatives change nothing of the regression results.

We then tried an alternative specification regarding the volatility factor, the residual from regressing *MKT_Prem* on VIX, since VIX has been identified as a determinant for the risk premiums of the stock market portfolio (Ang et al., 2006; Connolly et al., 2005). This alternative produces the same results as the plain VIX as the comparisons between Table A7 and Table 3 demonstrate. The flight-to-quality story is thus robust.

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[26] The minor exceptions are the coefficient of *Prop_Inf* and the intercept in the case of $Sprd^{(1)}$_taxed.

[27] The tax rates higher than 33% are 35% and 39.6% that are applied to the income brackets of $413,000 ~ $415,000 and $415,000~, respectively. The former bracket is rather narrow and applicable to only a few people. We thus only use the highest marginal tax rate in the robustness checks.

Table A1
Robustness check: determinants of before-tax life settlement spreads.

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
(Intercept)	14.252***	24.364***	21.178***
	(1.840)	(3.657)	(3.264)
MKT_Prem	−0.125***	−0.175***	−0.119***
	(0.030)	(0.053)	(0.045)
logNDB	−0.109	−0.133	−0.110
	(0.089)	(0.169)	(0.158)
VIX	−0.144***	−0.197***	−0.154***
	(0.034)	(0.059)	(0.050)
Rating	−0.012	−0.045	0.086
	(0.093)	(0.155)	(0.138)
Maturity	−0.013***	−0.019***	−0.018***
	(0.003)	(0.006)	(0.005)
Health_Inf	−1.728**	−4.508**	−5.970***
	(0.779)	(1.755)	(1.625)
Policy_Age	−0.099***	−0.124**	−0.217***
	(0.024)	(0.054)	(0.055)
R^2	0.275	0.184	0.218
Adj. R^2	0.260	0.167	0.202
RMSE	1.287	2.560	2.430

Note: Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A2
Robustness check: effects of age and gender.

Dependent Variable	(1)	(2)	(3)	(1)	(2)	(3)
(Intercept)	6.840***	11.141***	9.744***	11.202***	17.576**	26.213***
	(2.065)	(2.508)	(2.615)	(4.192)	(6.929)	(8.600)
MKT_Prem	−0.095***	−0.096***	−0.078**	−0.094***	−0.094***	−0.073**
	(0.023)	(0.031)	(0.034)	(0.023)	(0.031)	(0.034)
logNDB	−0.092	−0.032	−0.063	−0.088	−0.025	−0.044
	(0.072)	(0.109)	(0.108)	(0.072)	(0.109)	(0.108)
VIX	−0.114***	−0.099***	−0.072**	−0.111***	−0.095***	−0.063*
	(0.026)	(0.034)	(0.036)	(0.027)	(0.034)	(0.035)
Rating	−0.018	0.192**	0.315***	−0.017	0.193**	0.319***
	(0.072)	(0.092)	(0.112)	(0.071)	(0.092)	(0.114)
Maturity				−0.008	−0.012	−0.031**
				(0.007)	(0.012)	(0.015)
Health_Inf	−3.064***	−4.822***	−4.462***	−1.563	−2.603	1.232
	(0.686)	(1.147)	(1.102)	(1.506)	(2.505)	(3.045)
Policy_Age	−0.082***	−0.181***	−0.183***	−0.083***	−0.183***	−0.189***
	(0.020)	(0.040)	(0.041)	(0.019)	(0.040)	(0.039)
Age	0.058***	0.015	−0.001	−0.001	−0.072	−0.225**
	(0.016)	(0.024)	(0.026)	(0.052)	(0.090)	(0.111)
Gender	0.129	0.036	0.095	−0.037	−0.207	−0.521
	(0.163)	(0.228)	(0.229)	(0.221)	(0.371)	(0.412)
R^2	0.244	0.212	0.177	0.246	0.215	0.191
Adj. R^2	0.226	0.193	0.157	0.226	0.193	0.168
RMSE	1.034	1.627	1.745	1.034	1.627	1.733

Note: Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A3
Robustness check: alternative tax rate.

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
(Intercept)	10.281***	10.326***	8.081***
	(1.401)	(2.063)	(1.949)
MKT_Prem	−0.086***	−0.084***	−0.066**
	(0.021)	(0.029)	(0.032)
logNDB	−0.080	−0.022	−0.039
	(0.066)	(0.102)	(0.103)
VIX	−0.103***	−0.082***	−0.058*
	(0.025)	(0.032)	(0.035)
Rating	−0.017	0.240***	0.305***
	(0.067)	(0.090)	(0.108)

Table A3 (*continued*)

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
Maturity	−0.007***	0.000	−0.001
	(0.002)	(0.003)	(0.003)
Health_Inf	−1.493**	−4.291***	−3.889***
	(0.608)	(0.991)	(1.060)
Policy_Age	−0.079***	−0.185***	−0.182***
	(0.018)	(0.039)	(0.041)
R^2	0.239	0.217	0.177
Adj. R^2	0.224	0.201	0.159
RMSE	0.969	1.554	1.635

Note: We re-compute the $Sprd^{(1)}\_taxed$ using the highest income tax rate of 39.6% in this regression. Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A4

Robustness check: alternative mortality table.

Dependent Variable	(2) Uncertain Death Time
(Intercept)	11.438***
	(1.887)
MKT_Prem	−0.087***
	(0.026)
logNDB	−0.023
	(0.088)
VIX	−0.096***
	(0.030)
Rating	0.108
	(0.076)
Maturity	−0.004
	(0.003)
Health_Inf	−3.625***
	(0.882)
Policy_Age	−0.148***
	(0.033)
R^2	0.228
Adj. R^2	0.211
RMSE	1.334

Note: We re-compute $Sprd^{(2)}\_taxed$ using the standard 2008 VBT Table in this regression. Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A5

Regression results: alternative specifications of the size factor.

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
(Intercept)	11.331***	11.804***	8.960***
	(1.284)	(1.800)	(1.696)
MKT_Prem	−0.082***	−0.081***	−0.064*
	(0.020)	(0.029)	(0.032)
logAcqCost	−0.165**	−0.134	−0.106
	(0.065)	(0.087)	(0.089)
VIX	−0.099***	−0.080**	−0.056
	(0.024)	(0.031)	(0.035)
Rating	−0.011	0.254***	0.312***
	(0.067)	(0.092)	(0.108)
Maturity	−0.008***	−0.001	−0.002
	(0.002)	(0.003)	(0.003)
Health_Inf	−1.648***	−4.403***	−3.995***
	(0.633)	(1.010)	(1.064)
Policy_Age	−0.084***	−0.191***	−0.186***
	(0.018)	(0.039)	(0.042)
R^2	0.261	0.224	0.181
Adj. R^2	0.245	0.207	0.163
RMSE	0.956	1.548	1.631

Note: The logarithm of the acquisition cost replaces the logarithm of the net death benefit as the size factor in this regression. Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A6

Regression results: alternative specifications of the information factor.

Dependent Variable	(1)	(2)	(3)	(1)	(2)	(3)
(Intercept)	9.499***	7.876***	5.554***	11.017***	12.237***	10.006***
	(1.267)	(2.058)	(2.022)	(1.489)	(2.252)	(2.035)
MKT_Prem	−0.093***	−0.094***	−0.077**	−0.094***	−0.096***	−0.078**
	(0.023)	(0.031)	(0.034)	(0.023)	(0.031)	(0.034)
logNDB	−0.079	−0.010	−0.048	−0.088	−0.037	−0.077
	(0.070)	(0.107)	(0.109)	(0.07)	(0.108)	(0.108)
VIX	−0.110***	−0.095***	−0.069*	−0.112***	−0.099***	−0.074**
	(0.026)	(0.034)	(0.036)	(0.026)	(0.034)	(0.036)
Rating	−0.016	0.193**	0.309***	−0.015	0.193**	0.310***
	(0.072)	(0.092)	(0.114)	(0.072)	(0.093)	(0.115)
Maturity	−0.009***	−0.005	−0.004	−0.009***	−0.005	−0.004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Health_Inf2	−0.007**	−0.021***	−0.021***			
	(0.003)	(0.005)	(0.005)			
Policy_Age	−0.082***	−0.180***	−0.184***	−0.083***	−0.183***	−0.186***
	(0.019)	(0.040)	(0.041)	(0.019)	(0.04)	(0.041)
Health_Inf3				−1.039**	−2.909***	−2.952***
				(0.435)	(0.715)	(0.744)
R^2	0.244	0.211	0.177	0.245	0.21	0.175
Adj. R^2	0.228	0.195	0.159	0.23	0.193	0.157
RMSE	1.033	1.625	1.742	1.032	1.626	1.744

Note: We consider two specifications that may capture the proprietary health information. The first one is *Health_inf2*, defined as $LE_{Coventry} - LE_{Public}$, that measures the difference in expected lifespan. The second specification is *Health_inf3*, defined as $LE_{Coventry}/LE_{Public}$, that measures the life expectancy estimated by the underwriter relative to that by the mortality table of the general population. Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table A7

Robustness check: alternative specifications of the volatility factor.

Dependent Variable	(1) Certain Death Time	(2) Uncertain Death Time	(3) Stochastic Mortality Rates
(Intercept)	8.090***	9.703***	8.156***
	(1.246)	(2.036)	(1.848)
MKT_Prem	−0.037***	−0.045**	−0.041
	(0.014)	(0.022)	(0.027)
logAcqCost	−0.086	−0.031	−0.071
	(0.070)	(0.107)	(0.108)
VIX2	−0.111***	−0.098***	−0.072**
	(0.026)	(0.034)	(0.036)
Rating	−0.016	0.190**	0.306***
	(0.072)	(0.092)	(0.113)
Maturity	−0.008***	−0.003	−0.002
	(0.002)	(0.003)	(0.003)
Health_Inf	−1.553**	−4.370***	−4.423***
	(0.642)	(1.052)	(1.102)
Policy_Age	−0.083***	−0.182***	−0.186***
	(0.019)	(0.04)	(0.042)
R^2	0.246	0.213	0.178
Adj. R^2	0.230	0.197	0.160
RMSE	1.031	1.623	1.742

Note: The residual from regressing *MKT_Prem* on VIX replaces the VIX as the size factor in this regression. Heteroskedasticity-consistent standard errors are reported in the parentheses. The asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

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