Fair Value Measurement in the Life Settlement Market

Article *in* The Journal of Fixed Income · January 2020

DOI: 10.3905/jfi.2020.1.084

Jiahua Xu
University College London

Fair Value Measurement in the Life Settlement Market

ALEXANDER BRAUN AND JIAHUA XU

ALEXANDER BRAUN
is vice director at the Institute of Insurance Economics of the University of St. Gallen in St. Gallen, Switzerland.
alexander.braun@unisg.ch

JIAHUA XU
is a research associate at the Ecole Polytechnique Fédérale de Lausanne in Lausanne (EPFL), Switzerland.
jiahua.xu@epfl.ch

KEY FINDINGS

- The authors provide an explanation of historically observed yield spreads for life settlements.
- The authors develop a parsimonious model for the prediction of risk-adjusted discount rates in the life settlements market.
- The results demonstrate that life settlement assets can be marked to market based on observable inputs.

ABSTRACT: *IFRS 13 and the AIFMD require assets to be held at fair value. Life settlement prices are commonly determined by present value calculus. Yet, the asset class lacks an established approach for the determination of adequate discount rates. The authors estimate historical yield spreads used for pricing based on 2,863 transactions that occurred between 2011 and 2016. The cross-section is explained through hedonic regression methodology. Out-of-sample results indicate that market-consistent life settlement prices can be conclusively predicted using discount rates generated by our model.*

TOPICS: ***Fixed income and structured finance, risk management, performance measurement****

Life settlements are traded US whole life, universal life, or term life insurance policies.[1] They originated in the 1980s when terminally ill policyholders monetized their life insurance contracts to fund medical expenses (see, e.g., Braun et al. 2018). Today, the main market comprises policies of senior citizens with preexisting health impairments. The cash flow pattern of life settlement assets resembles that of swaps. One side, the investor, pays regular premiums to keep the policy in force while the other side, the insurance carrier, is obliged to disburse the death benefit when the insured passes away.[2] Hence, unsurprisingly, the price of a life settlement, that is, the amount that the investor hands over to the insured in exchange for the policy, is commonly determined by present value calculus. However, there are two main differences to swap pricing. First, risk-adjusted discount rates are not readily observable, and second, risk-neutral valuation

[1] These differ from endowment policies and participating life insurance contracts (with interest rate guarantees), which are dominant in the UK and continental Europe, respectively (see, e.g., Braun, Fischer, and Schmeiser 2019b; Braun et al. 2019d).

[2] This resembles the cash flow pattern of a credit default swap (CDS). Under such a contract, the protection buyer makes continual payments of the CDS spread in return for a compensation from the protection seller in case a default of the underlying reference entity occurs (see, e.g., Turnbull and O'Kane 2003).

*All articles are now categorized by topics and subtopics. **View at PM-Research.com.**

is not applicable. Instead, actuarial methods are needed to estimate the cash flow probabilities that are governed by the insured's life expectancy (*LE*). Higher *LE*-values are associated with lower prices since the investor will likely have to pay insurance premiums over a longer time horizon and expects to receive the death benefit later (see, e.g., Bayston, Lempereur, and Pecore 2010).

Despite a recent uptick, scholarly research on life settlements remains sparse. Earlier work has mainly considered the impact on policyholder surrender behavior (see Gatzert, Hoermann, and Schmeiser 2009), price determinants (see Brockett et al. 2013; Zhu and Bauer 2013), performance of the asset class (see Braun, Gatzert, and Schmeiser 2012; Giaccotto et al. 2015), impact of adverse selection on expected returns (see Januário and Naik 2014), and risk management aspects for investors (see MacMinn and Zhu 2017). A detailed empirical analysis of yield spreads implied by observed prices, however, is missing to date. It turns out that this is a severe problem for the market's further development since a consistent valuation of life settlement portfolios requires the selection of adequate discount rates (see, e.g., Braun, Affolter, and Schmeiser 2015). While more than USD 100 billion worth of face value in life insurance policies is terminated by senior insureds each year, only USD 2.8 billion could be sold into the life settlement market in 2017 (see Horowitz 2018; Braun et al. 2019).

Fair value measurement in financial statements is governed by International Financial Reporting Standard (IFRS) 13. For many assets, the true fair value is both unobservable and difficult to estimate. Consequently, the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) have established a three-level hierarchy that mirrors the extent of judgment involved in the estimation of fair asset values. The classification of an asset in this hierarchy is ultimately driven by the dominant valuation technique and the existence of reliable inputs. Level 1 assets exhibit price quotes from a liquid market. Level 2 assets can be assessed based on observable market inputs other than prices. Finally, for Level 3 assets, expert judgment is needed since no inputs are observable (see, e.g., Hanley, Jagolinzer, and Nikolova 2018). The managerial discretion involved in the valuation of Level 3 assets can be a blessing and a curse. On one hand, there is evidence that managers may have an information advantage through which they are able to come up with better estimates than models calibrated with market inputs (see, e.g., Altamuro and Zhang 2013). On the other hand, managers may be reluctant to devalue assets despite strong signals of impairment (see, e.g., Hilton and O'Brien 2009).

The Alternative Investment Fund Managers Directive (AIFMD) requires life settlement fund managers to report their assets under management at fair value in line with IFRS 13. Yet, Braun, Affolter, and Schmeiser (2015) revealed differences between the portfolio valuations reported by certain managers and the prices for which similar policies traded in the market, which they attributed to the fact that life settlements are considered to be Level 3 assets in the fair value hierarchy. We address this issue by suggesting a new approach for the ongoing valuation of traded life insurance contracts based on present value analysis, hedonic regression methodology, and real transaction data. More specifically, we econometrically explain the yield spread used for pricing through life settlement attributes motivated by industry know-how and relevant research. This approach is common for other illiquid markets with heterogeneous assets, such as real estate (see, e.g., Shiller 1993; Lin and Vandell 2007). As in the case of property, the immediate trading of life settlements is impossible, and each asset exhibits different characteristics. Our results indicate that longevity risk and premium risk are the most important drivers of life settlement yield spreads and that market-consistent prices can be conclusively predicted by employing risk-adjusted discount rates generated with the proposed model. When calibration is kept up to date, both the in-sample and out-of-sample accuracy of this approach turn out to be encouragingly high. Our results are of substantial practical relevance since we demonstrate that a fair valuation is possible using inputs other than directly observable prices. Put differently, life settlements should be classified as Level 2 assets. We equip investors with a straightforward toolkit for the valuation of life settlement portfolios, which could help unlock the full potential of the secondary market.

For the avoidance of doubt, this article deliberately focuses on the fair value measurement of life settlement assets. We develop a model to predict market-consistent prices but do not (yet) aim to determine if the size of the yield spreads observed in the life settlement market is adequate from a theoretical standpoint. To answer this question, one would need to consider life settlements through the lens of an asset pricing model. This would require realized returns instead of expected yields that only reflect the pricing at the time of sale. The likely result of such an analysis is that life settlements should not pay any risk premium in a competitive market because the covariation between their excess returns and the stochastic discount factor (SDF) is zero, an argument generally used by industry professionals to promote the asset class. When considering the yield spreads analyzed in this article, however, this does not seem to be the case at all. An evident explanation is that the market is not competitive and the observed prices therefore reflect frictions. Possible frictions include but are not limited to (i) the pricing power of capital providers, (ii) market segmentation, or (iii) severe adverse selection.

The remainder of the article is structured as follows. In the next section, we provide a brief introduction to the current practice in life settlement pricing. It is followed by a section in which we develop testable hypotheses with regard to the key drivers of yield spreads. The ensuing section contains our empirical analysis. Here we discuss the data and the procedure for the extraction of yield spreads, show descriptive statistics for our sample, run hedonic regressions to explain the estimated yield spreads, and provide a number of robustness tests. We also assess the in-sample and out-of-sample suitability of our framework for the derivation of risk-adequate discount rates. In the last section, we discuss the limitations of our results and draw our conclusions.

LIFE SETTLEMENT PRICING: A PRIMER

The following is a formal expression for the price of a life settlement asset:[3]

$$TP = \sum_{t=0}^{\infty} -\frac{{}_t p_x \cdot \pi_t}{(1+r)^t} + \sum_{t=0}^{\infty} \frac{{}_t p_x \cdot q_{x+t} \cdot DB}{(1+r)^{t+1}} \tag{1}$$

where

TP = transaction price for the life insurance policy
DB = death benefit
${}_t p_x$ = probability that the insured aged x years survives the next t years
q_{x+t} = probability that the insured aged $x+t$ years dies within one year
π_t = premium to be paid at time t
r = risk-adjusted discount rate

Analogous to CDS pricing terminology, we dub the first summand premium leg and the second death benefit leg. The yield spread YS is embedded in the discount rate. Formally

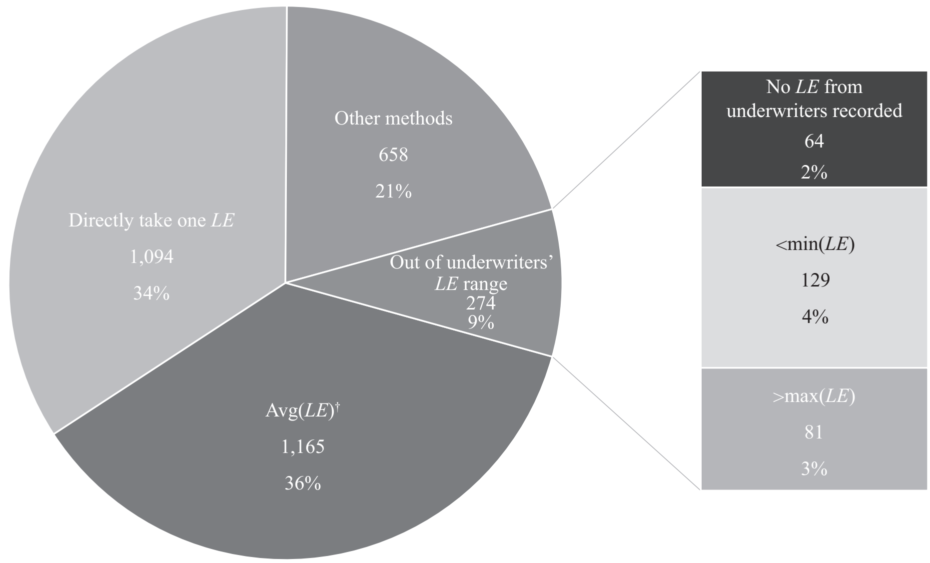
$$YS = r - r_f, \tag{2}$$

where r_f denotes the risk-free rate. Risk-adequate discount rates are chosen by life settlement investors so as to match their specific return targets. Riskier policies should be cheaper than less risky ones. Thus, observed market prices reflect investors' perceptions of the riskiness of a deal and can be employed to extract market-consistent yield spreads. The sizes of DB and the π are known from the policy terms and conditions. Investors that employ Equation (1) to calculate prices or value portfolios need to additionally enter survival rates and discount rates. Both are typically determined subjectively. Mortality profiles, including estimates for LE and the corresponding actuarial probabilities (${}_t p_x$), are provided by specialized medical underwriters. There is a direct link between both magnitudes in that LE consists of the ${}_t p_x$ (see Appendix A for details). Medical underwriters draw on standard actuarial life tables (e.g., VBT 2015) and modify them with so-called mortality multipliers that reflect an insured's health impairment relative to the average individual in that age bracket (see, e.g., Xu 2019). Investors may use a single estimate for LE and hence the survival probabilities or blend those of several medical underwriters (see Exhibit 1).

Exhibit 2 illustrates the pricing relationship based on a hypothetical life insurance policy with a death benefit of 3,645 kUSD from a 75-year-old male non-smoker. The death benefit and the respective premium streams are averages of all universal life policies in our data set (see empirical section for details) with policyholders that fit the aforementioned gender, smoking status, and age at the transaction date. The shapes of the graphs in Exhibit 2 are intuitive. As the price of the policy is equal to the sum of the discounted expected cash flows, it decreases

[3] This discrete-time expression assumes that premiums are paid in advance, that is, the first premium payment (π_0) is due on the transaction date. Hence, the future premium stream starts at time $t = 0$. This is reflected in the counting index of the first summand.

EXHIBIT 1
Methods Used to Derive the Transaction *LE*



Notes: This exhibit summarizes the various methods used to derive the LE for the closing of a life settlement transaction and their frequency. In most cases, investors use an LE that lies within the scope of the estimates issued by medical underwriters. In rare cases, the LE used to close the transaction falls below the lowest estimate, min(LE), or exceeds the highest estimate, max(LE).

†Only if multiple, LE estimates are available.

Source: Authors' illustration based on data from AA-Partners.

nonlinearly in *r*.[4] For an *r* of 0%, the present value equals the sum of expected death benefits less the sum of expected premium payments. In contrast, since premiums are paid in advance, the price converges to $-\pi_0$ as *r* goes to infinity. Note that a negative transaction price does not only occur in extreme cases. As shown in Exhibit 2, *TP* drops below zero at $r = 0.2$ when $LE = 15.1$. In fact, profit-seeking insurance companies set the premiums such that, on average, the expected value of a policy would be negative for a policyholder. Therefore, from the perspective of a life settlement investor, at any given *r*, only policies with a sufficiently reduced *LE* are worth purchasing.

TESTABLE HYPOTHESES

In line with the work of Braun, Gatzert, and Schmeiser (2012), we identify a total of five important risk types associated with life settlements: longevity risk, premium risk, default risk, rescission risk, and liquidity risk. Below we formulate hypotheses regarding their impact on *YS* and introduce variables that are employed to measure them.

Longevity Risk

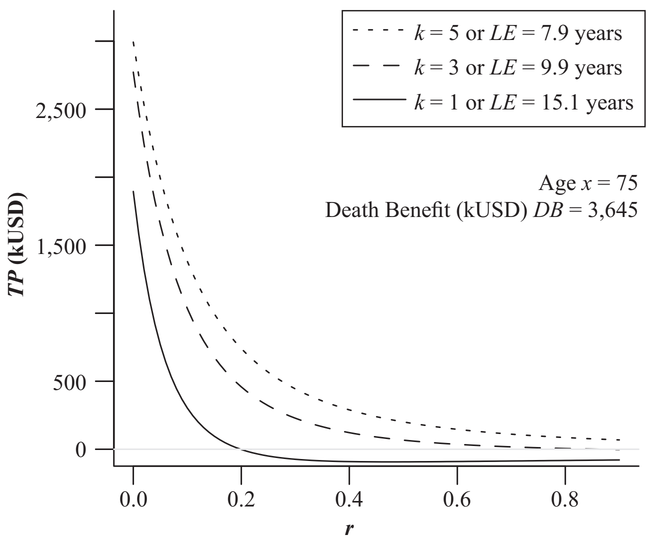
Longevity risk means that an insured may live longer than expected (Stone and Zissu 2006). It is the most prominent risk in life settlements and emanates primarily from the possibility of inaccurate (too short) *LE* estimates. Below, we discuss a number of independent variables that are linked to this type of risk.

LE: Life expectancy used to close the deal. As discussed in the previous section, *LE* estimates for life settlement transactions are issued by specialized firms called medical underwriters. Based on these estimates, policy buyers and sellers agree on the *LE* value that they use to close the deal. Xu (2019) provides empirical evidence that shorter *LE*s are more likely to be underestimated than longer ones, meaning that they exhibit a higher degree of longevity risk. This should be reflected in higher values of *YS*:

[4] Note that the difference in the present values of the two cash flow streams is positive since the sum of expected death benefits exceeds the sum of probability-weighted premiums.

Exhibit 2

Sensitivity of the Transaction Price



Notes: This exhibit illustrates the life settlement pricing relationship in Equation (1) based on a hypothetical policy of a 75-year-old male non-smoker. The respective premium streams are averages of all universal life policies in our data set (see empirical section) with insureds who exhibit the same gender, smoking status, and age. Prices are negatively related to the mortality multiplier k, which represents the degree of the health impairment of the insured. The higher the value of k, the shorter the respective LE for a given age. Put differently, for a constant discount rate r, a higher k is associated with a shorter LE and therefore higher transaction price TP.

H1: YS decreases in LE.

DB: Death benefit. Policyholders whose *DB* is high tend to be wealthy people with access to advanced health care, implying a greater longevity compared to their less-well-off peers (see, e.g., Verdon 2010). *DB*, however, is regularly not disclosed to medical underwriters and consequently not captured in their *LE* estimates. Hence, policies with higher *DB* values can be expected to exhibit a higher degree of longevity risk, leading us to postulate:

H2: YS increases in DB.

DI: Difference in LE estimates. Conventionally, a life settlement requires *LE* certificates from at least two medical underwriters. As *LE* estimation involves different quantitative models and subjective judgment, results concerning the same life can differ notably (see Xu 2019). The variable *DI* denotes the gap between the longest and the shortest available *LE* estimate for a given policy. The larger this deviation, the higher the uncertainty surrounding the accuracy of the *LE* and, in turn, the longevity risk. Therefore, we expect to find the following effect:

H3: YS increases in DI.

MK: Market. *MK* is a binary variable that indicates whether the transaction occurred in the secondary market ($MK = 0$) or the tertiary market ($MK = 1$) for life insurance policies. Ceteris paribus, a policy in the former should carry a higher longevity risk than one in the latter. The reason is an adverse selection effect (see Bauer, Russ, and Zhu 2014). Insureds who are inclined to sell their policies usually think they are healthy, and often this feeling is reflective of their real health condition. Based on this notion, we postulate:

H4: YS is negatively related to MK.

NO: Number of LE estimates. *NO* is a binary variable denoting the number of *LE* estimates from the four biggest medical underwriters (ITM TwentyFirst, AVS, Fasano, and LSI) considered in a transaction. If multiple *LE* estimates are available, $NO = 1$; otherwise $NO = 0$. In line with Januário and Naik (2014), we suppose that buyers associate less longevity risk with a policy for which multiple *LE* estimates are available. Consequently, they are willing to pay a higher price or accept a lower yield spread:

H5: YS is negatively related to NO.

AGE: Insured's age. The life expectancies of older people are more difficult to forecast due to a paucity of historical data (see, e.g., Bahna-Nolan 2014). Consequently, policies of more senior insureds are likely to include a higher degree of longevity risk and should therefore be associated with a higher yield spread:

H6: YS increases with AGE.

CO: Premium convexity. We adopt the notion of premium convexity from Januário and Naik (2014) and define the variable *CO* as the sum of time-weighted premium fractions:

$$CO = \sum_{t=0}^{\infty} \frac{t^2 \cdot \pi_t}{\Sigma_{i=0}^{\infty} \pi_i}, \tag{3}$$

where π_t is the dollar amount of premium to be paid at time t. *CO* captures the latent longevity risk associated with the insureds' outliving their *LE* estimates: ceteris paribus, the more convex a premium stream, the heavier the loss a policy buyer would suffer should the insured live longer than expected. This leads us to assume the following:

H7: YS increases in CO.

Premium Risk

Premium risk pertains to a hike in the premiums of an in-force policy, which means higher cash outflows for investors (see, e.g., Hong and Seog 2018). We measure this risk type by the following variable.

PM/DB: Sum of projected premiums as a fraction of the death benefit. The current premium level is known to be an indicator for the likelihood of increases. Sheridan (2017), for example, suggests that low-premium policies are more likely to experience premium rises. We use the sum of projected premiums *PM* until *LE* normalized to *DB* as a measure for the premium level:

$$PM = \sum_{t=0}^{LE} \pi_t, \tag{4}$$

Other things equal (especially *LE*), the lower the *PM/DB*, the higher a policy's premium risk. Life settlements with lower premium levels should therefore be priced more conservatively, namely with a higher *YS*. Accordingly, we formulate the following hypothesis:

H8: YS decreases in PM/DB.

Default Risk

Despite their relatively high financial strength, insurance carriers may become unable to pay death benefits should financial distress occur. An insurer's A.M. Best credit rating is a good proxy to gauge this risk.

RT: Credit rating. For each policy, *RT* is a binary variable that denotes the insurer's credit rating assigned by A.M. Best, a US-based rating agency that focuses on the insurance industry. For policies issued by A-rated (A–, A, A+, AA–, AA, AA+, AAA) insurers, $RT = 1$; otherwise $RT = 0$. Higher ratings imply a lower default risk associated with the payout of death benefit. Therefore, we expect to find the following relationship:

H9: YS is negatively related to RT.

Rescission Risk

Rescission is the revocation of a contract. In the life settlements market, it means the insurance carriers' refusal to pay the death benefit. This could happen due to a lack of insurable interest or other fraudulent behavior at issuance (Chancy, Thorpe, and Tregle 2010). We proxy this risk by the tenure of a policy (Sadowsky and Browndorf 2009).

TE: Tenure. The tenure of a policy is represented by the time elapsed between the issuance and the settlement date. The sooner a life insurance policy is available for sale after its issuance, the more likely it is that investors would believe the policy was originated with the intention to be life-settled. Such contracts are called stranger-originated life insurance (STOLI). As a carrier can contest a claim in the absence of insurable interest, policies with shorter tenure carry higher rescission risk and should therefore achieve lower prices than policies with longer tenure. Hence:

H10: YS has a positive relation with TE.

Liquidity Risk

Liquidity risk describes the ability of investors to liquidate their assets in a crisis. The nature of the life settlements market per se implies high liquidity risk. We assume the same level of liquidity risk for all policies and let the regression constant capture this risk factor.

Control Variables

We add a control variable *PT* for the policy type. $PT = 1$ designates universal life policies and $PT = 0$ other types. We have also considered variables such as cash surrender value,[5] total projected premiums over a 10-year horizon, transaction date, smoking status, (implied) mortality multiplier, a premium financing dummy, and potential interactions between these variables.

[5] Cash surrender value (*CSV*) is the money that sits in a policy's cash account. If *CSV* is large, the policy owner can enjoy a "premium holiday," meaning that premiums are funded from the account so that no out-of-pocket payment to the insurer is needed. Since *CSV* is immediately obtainable upon lapse, it forms the floor of the policy price. We do not deduct *CSV* from *TP* because the premiums in our sample are optimized. Therefore, any *CSV* effect is already captured through the premium stream.

Furthermore, we have taken into account the US high-yield option-adjusted spread to proxy the premium for liquidity risk. We refrain from reporting these results because there is either a lack of sound theory for these variables or a conceptual overlap with the factors already discussed in this section (e.g., between mortality multiplier k and life expectancy LE). In addition, the inclusion of these regressors does not markedly change our results.

EMPIRICAL ANALYSIS

Data and Sample Selection

We obtained our data from AA-Partners Ltd (AAP), a Zurich-based consulting firm specializing in life settlements. AAP maintains a comprehensive network in the industry, through which it collects audited transaction information from over a dozen life settlement providers on a monthly basis (see Braun, Affolter, and Schmeiser 2015). Based on AAP's own estimation, their data cover approximately 20% of the total deal flow before 2014 and 60% after. Our sample consists of 2,863 life settlement transactions[6] from both the secondary and tertiary markets and spans the time period from January 2011 to December 2016. It allows us to measure all effects discussed in the previous section. The values for *LE*, *DB*, and *AGE* are included in the data set. All remaining variables (*DI*, *MK*, *NO*, *CO*, *PM/DB*, *RT*, *TE*) are coded/computed from the available information. The majority of the recorded policies (56%) were traded in the most recent 2 years. Hence, we are able to analyze a substantial part of the overall market.

Estimation of Yield Spreads

Since the mortality and discount rates that enter Equation (1) are not shared by investors, we need to estimate these magnitudes from our market data. To this end, we rewrite the pricing relation in terms of the yield to maturity *ytm*:

$$TP = \sum_{t=0}^{\infty} -\frac{{}_t p_x \cdot \pi_t}{(1+ytm)^t} + \sum_{t=0}^{\infty} \frac{{}_t p_x \cdot q_{x+t} \cdot DB}{(1+ytm)^{t+1}} \tag{5}$$

YS thus equals the difference between *ytm* and the risk-free rate r_f. For each life settlement transaction, we measure r_f as the probability-weighted average yield of zero-coupon Treasury bonds, formally

$$r_f = \sum_{t=1}^{\infty} {}_{t-1}p_x \cdot q_{x+t} \cdot y_t, \tag{6}$$

where y_t represents the t-year spot rate of the US Treasury zero-coupon bond yield curve at the time of the life settlement transaction. The respective data have been downloaded from FRED Economic Data (https://fred.stlouisfed.org/). Linear interpolation is applied to synthesize rates at maturities where no bonds exist. For example, averaging interest rates of a 3-year bond and a 5-year bond forms the interest rate of a 4-year bond.

Before we can back out *ytm*, we first need to determine the survival probabilities (mortality rates) implied by the *LE* that has been used to close the deal. This is done in three steps:

1. We employ VBT Table 2015 Age Nearest Birthday (VBT15-ANB) as the basis mortality curve for each insured, given gender, smoking status, and age.
2. Using the relationship shown in Appendix A, we estimate the mortality multiplier k implied by the *LE* value reported for each transaction.[7]
3. We combine the estimated k with our basis mortality curves to generate individual mortality curves implied by the market data.

Finally, based on the price, premium stream, and individual mortality curve of each transaction, we can calculate *ytm* and, in turn, *YS*.

Descriptive Statistics

In this section, we provide a variety of descriptive statistics. Exhibit 3 contains the number of observations (n), mean, median, minimum (Min.), maximum (Max.), and standard deviation (StDev.) for the major variables in the sample. To get a sense of the typical transaction characteristics, consider the following values: the average *TP* amounts to USD 368.11 thousand at an average *LE* of 6.64 years, an average *PM/DB* of 26.35%, an average *DB* of USD 1.8 million, and an average *YS* of 21.89%. Both *TP* and *YS* vary consider-

[6] Each transaction corresponds to a policy with a single insured. Joint-policy deals are not considered.

[7] Recall from the second section that k represents the insured's health impairment relative to an average individual.

EXHIBIT 3
Descriptive Statistics I

	n	Mean	Median	Min.	Max.	StDev.
DB (kUSD)	2,863	1,832.78	1,000.00	20.00	30,000.00	2,583.92
TP (kUSD)	2,863	368.11	178.03	0.30	16,191.00	739.69
TP/DB (%)	2,863	26.87	20.84	0.25	85.38	20.66
PM/DB (%)	2,863	26.35	26.62	0.00	96.50	17.28
CSV/DB (%)	2,838	1.64	0.00	–4.02	44.42	4.15
YS (%)	2,863	21.89	16.60	–1.95	247.48	21.59
LE (years)	2,863	6.64	6.26	0.43	28.50	3.76
AGE (years)	2,863	77.89	80.31	20.22	97.80	11.32
TE (years)	2,697	11.99	10.34	1.14	36.92	7.07
k (—)	2,863	67.92	3.31	0.39	4,625.67	273.45

Notes: This exhibit shows the number of observations (n), mean, median, minimum (Min.), maximum (Max.), and standard deviation (StDev.) of the major variables in the sample. The binary variables introduced in the previous section have been omitted.

ably across policies, which is indicated by the respective standard deviations as well as the minimum and maximum values. The extreme *YS* values of −1.95% and 247.48% indicate the presence of outliers. The same is true for *k*. A high standard deviation is also observed for *DB*, for which the minimum and maximum values differ by almost USD 30 million.

Further descriptive statistics for different categories of policies are presented in Exhibit 4. When focusing on gender, we observe that the majority (71%) of the insureds in our sample are male. Even though the average male is 2 years younger than the average female, their respective *LE*s differ only slightly. Apart from that, we notice that non-smokers dominate the sample (97%). The average age of non-smokers (78 years) is significantly higher than that of smokers (72 years). Despite being that much older than the average smoker, the *LE* of the average non-smoker is 1 year longer. In line with the lower *LE*s, both mean *TP/DB* and *YS* are higher for smoker than for non-smoker policies. Furthermore, secondary market transactions make up nearly 70% of the sample. While the mean *LE* is roughly the same for secondary and tertiary market deals, the average insured in the latter is 7 years older. This implies that health impairments are substantially larger in the secondary market, as also reflected by the higher mortality multiplier *k*. Accordingly, secondary market transactions on average exhibit a higher *TP/DB*. Concerning policy type, we notice that the sample comprises mainly universal life contracts (84%). The average *TP/DB*, *PM*, and *DB* are considerably lower for term life and whole life than for universal life policies. It is also evident that the average insured's age differs greatly among the three product categories.[8] In terms of credit ratings, nearly the whole sample (96%) consists of policies from A-rated carriers, which are associated with a lower average *YS* than those of B-rated or unrated insurers. Finally, about 17% of the policies originate from California, and 56% were sold in the years 2015 and 2016. Interestingly, the average *TE* increases with the transaction year, indicating that most issuance dates lie between 2002 and 2004. In this period, the number of manufactured policies, including STOLI, was relatively high.

HEDONIC REGRESSIONS

Historical Composition of the Yield Spread

Consistent with the extant literature on asset valuation in illiquid markets with heterogeneous assets, we explain the market-implied yield spread *YS* with an econometric model of the form:[9]

[8] Understanding these differences requires further analyses of the customers' preferences. In this regard, see, for example, Braun, Schmeiser, and Schreiber (2016).

[9] Recall that we extracted *YS* from the empirically estimated *ytm* since the true underlying values were unobservable. Hence, we work with a market-implied *YS*.

EXHIBIT 4
Descriptive Statistics II

	n (–)	Percent (%)	Ø*DB* (kUSD)	Ø*TP* (kUSD)	Ø*TP/DB* (%)	Ø*PM/DB* (%)	Ø*CSV/DB* (%)	Ø*YS* (%)	Ø*LE* (years)	Ø*AGE* (years)	Ø*TE* (years)	Ø*k* (–)
Gender												
Male	2,025	70.73	1,765.45	354.51	26.17	26.72	1.63	21.30	6.77	77.22	12.42	46.14
Female	838	29.27	1,995.49	400.97	28.57	25.45	1.68	23.32	6.32	79.51	11.00	120.53
Smoker												
Non-smoker	2,784	97.24	1,853.58	371.41	26.77	26.43	1.64	21.74	6.66	78.05	11.98	68.21
Smoker	79	2.76	1,099.97	251.63	30.51	23.38	1.65	27.14	5.87	72.32	12.58	57.61
Market												
Secondary	1,991	69.54	1,772.16	345.79	27.58	24.01	1.77	23.28	6.68	75.71	11.72	92.26
Tertiary	872	30.46	1,971.20	419.08	25.27	31.69	1.36	18.71	6.54	82.88	12.59	12.34
Policy Type												
Universal Life	2,407	84.07	1,959.60	386.55	23.79	28.94	1.77	20.52	7.00	80.24	11.95	20.01
Term Life	161	5.62	534.58	275.30	57.23	4.52	0.01	27.84	3.37	58.02	10.91	490.04
Whole Life	48	1.68	611.17	168.21	41.49	16.27	2.11	28.59	4.35	62.75	14.29	329.72
Others	247	8.63	1,680.52	287.71	34.27	17.24	1.39	30.08	5.76	70.89	12.75	208.70
Rating												
A-*Rated*	2,760	96.40	1,838.95	372.59	26.82	26.57	1.63	21.54	6.67	78.03	11.91	65.73
B-*Rated*	65	2.27	1,533.78	268.34	27.13	22.42	2.17	26.22	6.09	75.36	14.77	81.69
No Rating	38	1.33	1,896.18	213.56	30.13	16.66	2.10	40.03	5.32	72.59	12.70	203.11
State												
California	482	16.84	1,916.54	430.70	25.59	25.99	1.73	22.01	7.01	77.69	11.21	72.85
New York	315	11.00	2,260.75	456.65	25.99	26.68	1.35	18.81	6.91	77.80	10.73	53.90
Florida	252	8.80	2,286.95	428.28	24.28	25.51	1.67	22.84	6.86	79.63	11.39	50.56
Texas	142	4.96	1,167.29	250.20	30.98	21.74	1.34	24.24	6.27	73.94	12.43	138.66
Pennsylvania	130	4.54	1,728.73	297.05	25.75	24.60	1.88	24.81	6.77	78.08	14.14	28.79
New Jersey	105	3.67	1,737.20	382.91	29.18	23.98	1.51	19.56	6.83	76.25	11.96	48.55
Arizona	93	3.25	1,596.87	242.77	24.25	29.63	1.34	19.60	7.12	78.17	10.25	64.89
Others	1,344	46.94	1,721.45	340.48	27.71	27.17	1.72	22.20	6.38	78.17	12.57	70.72
Transaction Year												
2011	191	6.67	1,835.61	344.48	24.19	26.24	1.72	19.52	7.35	78.58	7.72	54.67
2012	246	8.59	2,324.99	467.57	23.70	25.50	2.34	23.99	6.71	79.81	9.19	18.09
2013	344	12.02	2,180.21	317.66	21.73	28.49	1.92	23.56	7.17	78.06	10.58	76.90
2014	480	16.77	1,760.20	332.50	24.26	27.42	1.77	21.20	6.99	78.72	11.68	39.00
2015	807	28.19	1,803.80	426.23	28.78	26.16	1.43	20.16	6.67	77.38	12.82	69.37
2016	795	27.77	1,602.70	327.35	30.37	25.25	1.43	23.26	5.99	77.09	13.91	98.61

Notes: In this exhibit, the sample is classified according to gender, smoking status, market segment, policy type, insurer credit rating, originating state, and transaction year. For each category, we report the number of observations (n) as well as the average death benefit (DB), transaction price (TP), price as a fraction of death benefit (TP/DB), sum of premiums as a fraction of death benefit (PM/DB), cash surrender value as a fraction of death benefit (CSV/DB), yield spread (YS), life expectancy (LE), insured's age (AGE), tenure (TE), and mortality multiplier (k).

EXHIBIT 5

Estimation of the Composition of *YS* (preliminary regression)

	Coeff.	StCoeff.	(StErr.)	Sig.
Intercept	–0.110		(0.279)	
ln*LE*	–0.087	–0.261	(0.012)	***
ln*DB*	0.032	0.176	(0.005)	***
DI	0.013	0.088	(0.004)	***
MK	–0.025	–0.054	(0.010)	***
NO	–0.051	–0.109	(0.011)	***
AGE	0.002	0.091	(0.001)	***
CO	0.001	0.040	(0.001)	
PM/DB	–0.247	–0.195	(0.031)	***
RT	–0.073	–0.063	(0.035)	**
TE	0.001	0.022	(0.001)	
PT	–0.016	–0.027	(0.019)	
	d*f*	SEE	R^2_{adj}	
	2,578	0.200	0.160	

*Notes: This exhibit shows the results for a regression of YS on all potential explanatory variables introduced above. For each considered variable, we present least squares estimates of unstandardized (Coeff.) and standardized (StCoeff.) regression coefficients as well as Newey-West standard errors (StErr.) and their significance levels (Sig.). Significance levels of 0.1, 0.05, and 0.01 are marked with *, **, and ***, respectively.* d*f represents the degree of freedom of the regression model. Standard error of the estimate (SEE) and* R^2_{adj} *indicate the explained variance and goodness of fit of the model.*

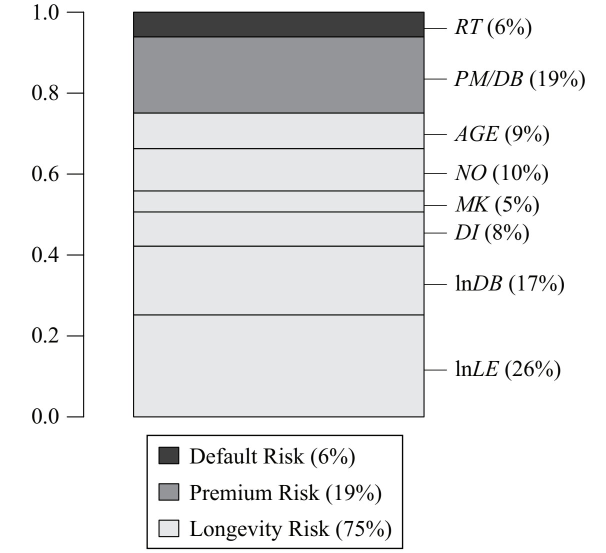
$$YS = \boldsymbol{X}\beta + \epsilon, \quad (7)$$

where the matrix $\boldsymbol{X}$ and the vector β denote the predictors (including constant and control variables) as well as their coefficients, and ϵ is the error term.[10] *LE* and *DB* enter in logarithmic form.

In a first step, we want to test our hypotheses and develop an understanding of the general composition of the life settlement yield spread over the historical time period covered by our sample (January 2011 to December 2016). To this end, we run a preliminary regression with all predictors on the full sample. Exhibit 5 shows the results.[11] The majority of effects are statistically significant, and the respective signs were correctly anticipated. More specifically, we find evidence for all hypotheses presented above, apart from *H7* and *H10*. Therefore, the life settlement yield spread seems to predominantly consist of loadings for longevity risk (measured by the six factors ln*LE*, ln*DB*, *DI*, *MK*, *NO*, and *AGE*). Premium risk and default risk, in contrast, play a much lesser role whereas rescission risk is likely not factored in at all. Exhibit 6 is a graphical illustration of the weights of all the significant components as reflected by their standardized regression coefficients.

EXHIBIT 6

Graphical Breakdown of *YS* Based on the Regression Results in Exhibit 5



Notes: This exhbit illustrates the composition of the historical life settlement yield spread over the time period from January 2011 to December 2016. The weight (in %) of each component is based on its standardized regression coefficient (StCoeff.) shown in Exhibit 5. Only variables with statistically significant coefficients are considered in this breakdown.

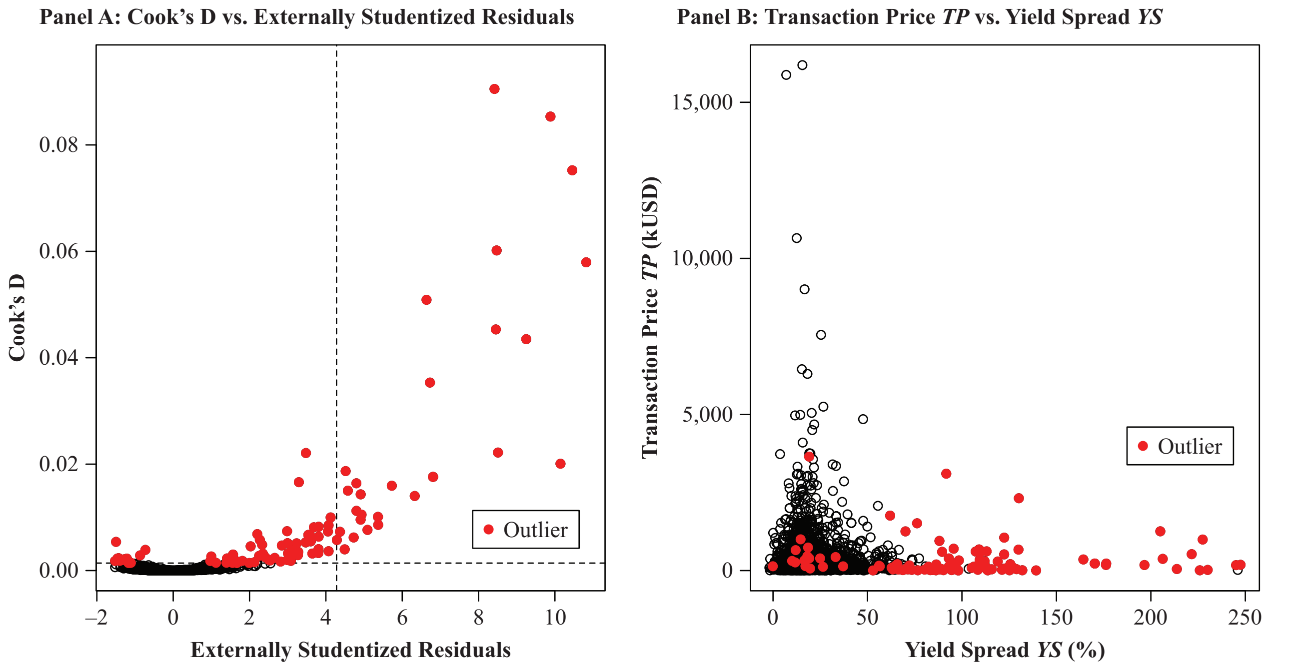
Identification of Abnormal Cases

The descriptive statistics (Exhibits 1 and 2) indicate the existence of extreme values. We now aim to

[10] The existing literature on life settlements does not yet include a model that is well suited to explain *YS*. A promising attempt was made by Januário and Naik (2014), who have used *ytm* as the dependent variable in a regression with various specifications. Their model, however, focuses on the identification of potential adverse selection effects and only explains a minor part of the variance of *ytm*. In addition, they do not assess the suitability of the predicted yields for the market-consistent valuation of life settlement assets.

[11] Note that the variance inflation factor (VIF), which has not been reported, is below 5 for each variable, indicating absence of collinearity.

EXHIBIT 7
Identification of Outliers



Notes: Panel A serves to identify outliers in the data set. For each case, Cook's D has been plotted against the externally studentized residuals. The critical values for both measures are represented by dotted lines, which form a box in the bottom left. Observations outside this box are regarded as outliers. The majority of the selected cases exhibit a low transaction price and an abnormally high yield spread, as shown in Panel B.

exclude abnormal cases since they distort the estimation of the least squares coefficients. To identify outliers, we compute the externally studentized residuals as well as Cook's D of the preliminary regression shown above. The results are shown in Panel A of Exhibit 7. A Bonferroni-corrected confidence level at 0.95 is set for externally studentized residuals (dashed vertical line) whereas a critical value of $\frac{4}{df}$ is set for Cook's D (dashed horizontal line). Data points beyond those thresholds are deemed outliers, which account for 3.5% of the full sample (101 transactions). In Panel B of Exhibit 7 we highlight the previously identified outliers in a *TP-YS* plot, most of which are characterized by very low *TP* values (below USD 1 million) and excessively high *YS* values (above 50%). This might be due to the fact that low-value policies are sometimes priced in an ad hoc fashion instead of strictly following an actuarial pricing formula. Hence, for those policies, the market-implied *YS* values extracted from the *ytm* appear abnormal. After all outliers have been removed, we are left with 2,762 transactions.

Comparison with Fixed-Income Yield Spreads

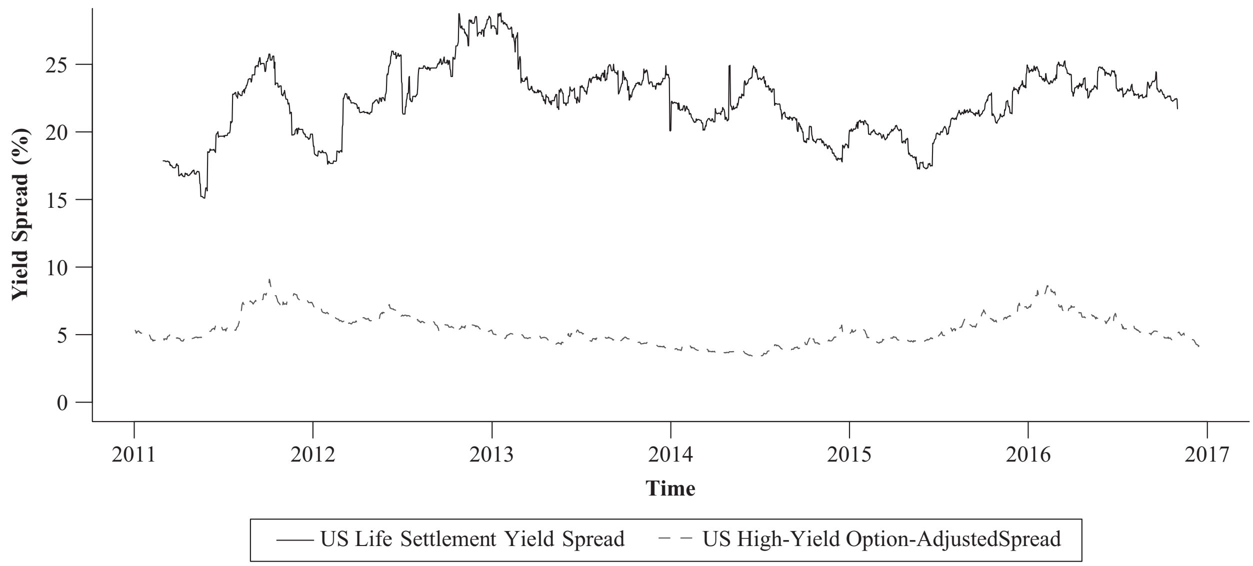
Exhibit 8 is a graphical illustration of the evolution of the average *YS* between January 2011 and December 2016. For comparison purposes, it also includes the historical spreads on high-yield fixed-income securities, which we downloaded from FRED Economic Data. The *YS* time series has been calculated based on a centered 120-day moving average of the truncated sample, without the abnormal cases identified above. We notice that the yield spread for life settlements was historically substantially higher than for corporate default risk. The high volatility of *YS* is likely attributable to the riskiness, heterogeneity, and illiquidity of the asset class.

Prediction of the Life Settlement Yield Spread

We now turn to our main research goal of developing a model for the derivation of risk-adjusted discount rates, which allows for an accurate market-consistent pricing of life settlement assets. Before

EXHIBIT 8

Yield Spread of Life Settlements Compared to US High-Yield Option-Adjusted Spread



Notes: The life settlement yield spread is based on the YS values in our sample, excluding outliers. The time series has been calculated as a centered 120-day moving average. The US High-Yield Option-Adjusted Spread was obtained from FRED Economic Data (https://fred.stlouisfed.org/).

we continue, we divide the overall data set into three equally sized subsamples. Sorted chronologically, the first third of the transactions (training sample) is used for model development, in-sample fitting, and pre-selection of models. We then draw on the second subsample (validation sample) for an assessment of the out-of-sample pricing accuracy of the short-listed models. Based on the respective results, we choose our final model and test its out-of-sample performance on the third subsample (test sample).

Methodologically, we rely on forward selection in a series of 11 ordinary least squares (OLS) regressions with robust standard errors based on the Newey–West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix. In each round, we add the regressor with a statistically significant coefficient that delivers the largest improvement in the model fit.[12] Standard error of the estimate (SEE), adjusted R^2 (R^2_{adj}), and the Bayesian information criterion (BIC) are employed as performance indicators to assess how well a combination of coefficients and variables explains the sample data. For a formal definition of these measures, refer to Appendix B.

The estimation results are presented in Exhibit 9 and mostly confirm our earlier findings. The significance of the intercept in most model specifications indicates the existence of a baseline yield spread, possibly resulting from factors that are not captured by the independent variables, such as liquidity risk.

The results also provide evidence for risk-averse behavior in the life settlements market: the higher the risk that a policy carries, the higher the yield spread demanded by investors. This relationship is most prominent for premium risk (proxied by $\frac{PM}{DB}$) and longevity risk (proxied by $\ln LE$, $\ln DB$, DI, MK, NO).

It should be noted that the positive impact of DB on YS might be attributable not only to a wealth effect (the rich live longer) but also to the interaction of supply and demand in the market, especially with regard to jumbo policies that exhibit a death benefit of over USD 10 million. Since only a limited number of investors can afford and effectively diversify jumbo policies, bidders in those transactions face little competition and thus have the negotiation power to increase YS and ultimately purchase at a low TP.

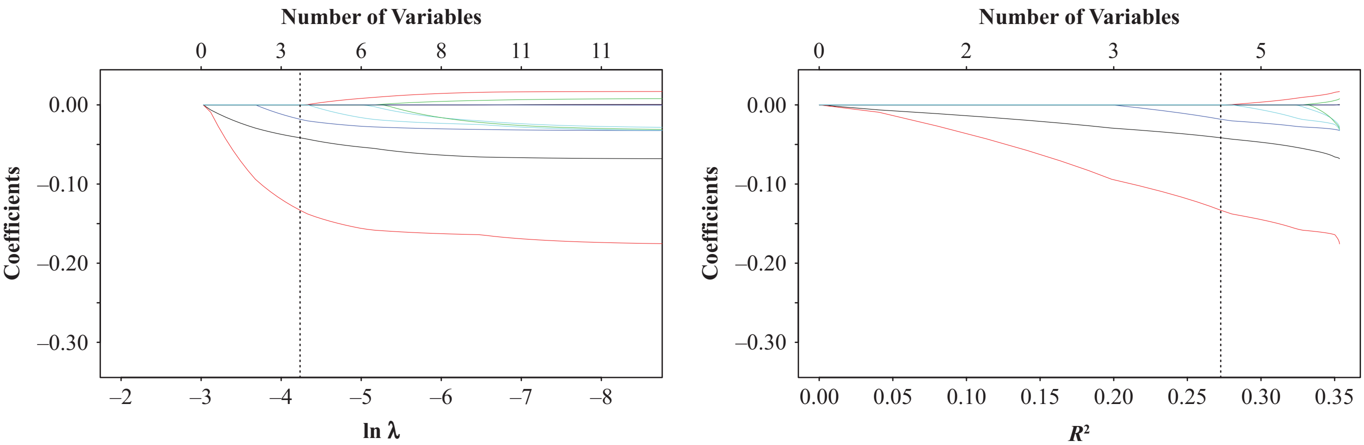
[12] Backward deletion and exhaustive selection deliver virtually the same results and are thus not reported here.

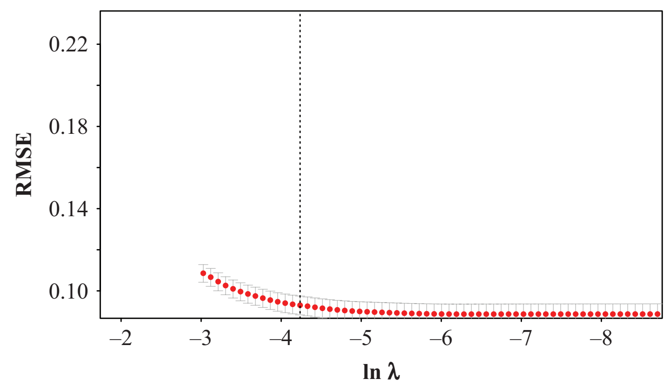
EXHIBIT 9
Regression Model Development for YS with Training Sample

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.	Coeff. (StErr.)	StCoeff. Sig.
Intercept	0.582		0.538		0.541		0.376		0.374		0.379		0.384		0.412		0.410		0.200		0.196	
	(0.034)	***	(0.034)	***	(0.034)	***	(0.046)	***	(0.045)	***	(0.044)	***	(0.045)	***	(0.048)	***	(0.067)	***	(0.261)		(0.264)	
ln*LE*	–0.089	–0.476	–0.067	–0.356	–0.065	–0.347	–0.073	–0.389	–0.069	–0.369	–0.073	–0.392	–0.075	–0.402	–0.075	–0.400	–0.075	–0.399	–0.068	–0.371	–0.068	–0.367
	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.009)	***	(0.009)	***	(0.009)	***	(0.009)	***	(0.009)	***	(0.008)	***	(0.008)	***
ln*DB*							0.014	0.144	0.015	0.154	0.015	0.156	0.016	0.165	0.017	0.173	0.017	0.172	0.017	0.178	0.017	0.179
							(0.003)	***	(0.003)	***	(0.003)	***	(0.003)	***	(0.003)	***	(0.003)	***	(0.003)	***	(0.004)	***
DI											0.005	0.072	0.007	0.099	0.007	0.097	0.007	0.097	0.008	0.111	0.008	0.114
											(0.002)	***	(0.002)	***	(0.002)	***	(0.002)	***	(0.002)	***	(0.002)	***
MK					–0.044	–0.186	–0.040	–0.167	–0.038	–0.157	–0.038	–0.158	–0.036	–0.150	–0.036	–0.151	–0.036	–0.151	–0.033	–0.144	–0.033	–0.142
					(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***	(0.008)	***
NO													–0.021	–0.067	–0.019	–0.061	–0.019	–0.061	–0.026	–0.084	–0.029	–0.093
													(0.010)	**	(0.010)	**	(0.010)	*	(0.010)	***	(0.010)	***
AGE																	0.000	0.003	0.000	0.043	0.000	0.044
																	(0.001)		(0.001)		(0.001)	
CO																			0.001	0.020	0.001	0.021
																			(0.001)		(0.001)	
$\frac{PM}{DB}$			–0.189	–0.269	–0.169	–0.240	–0.168	–0.239	–0.158	–0.225	–0.157	–0.223	–0.151	–0.214	–0.152	–0.217	–0.153	–0.218	–0.173	–0.254	–0.177	–0.258
			(0.026)	***	(0.024)	***	(0.023)	***	(0.023)	***	(0.023)	***	(0.023)	***	(0.023)	***	(0.030)	***	(0.032)	***	(0.032)	***
RT															–0.043	–0.061	–0.043	–0.061	–0.031	–0.047	–0.032	–0.048
															(0.025)	*	(0.025)	*	(0.026)		(0.026)	
TE																					0.000	–0.019
																					(0.001)	
PT									–0.035	–0.090	–0.034	–0.087	–0.031	–0.079	–0.030	–0.077	–0.030	–0.078	–0.034	–0.090	–0.033	–0.086
									(0.012)	***	(0.012)	***	(0.012)	**	(0.012)	**	(0.011)	***	(0.012)	***	(0.012)	***
df	919		918		917		916		915		914		913		912		911		827		788	
SEE	0.099		0.095		0.093		0.092		0.091		0.091		0.091		0.091		0.091		0.087		0.088	
R^2_{adj}	0.226		0.283		0.316		0.334		0.340		0.344		0.347		0.350		0.349		0.345		0.344	
BIC	–1,627		–1,692		–1,729		–1,748		–1,750		–1,750		–1,748		–1,747		–1,740		–1,642		–1,544	

*Notes: This exhibit shows the results for 11 regressions of YS on different combinations of the potential explanatory variables introduced in the third section. For each model, we present the variables' least squares estimates of unstandardized (Coeff.) and standardized (StCoeff.) regression coefficients as well as Newey-West standard errors (StErr.) and the corresponding significance levels (Sig.). Significance levels of 0.1, 0.05, and 0.01 are marked with *, **, and ***, respectively. df represents the degree of freedom of each regression model. SEE and* R^2_{adj} *indicate the explained variance and goodness of fit for each model. The BIC allows us to compare models that differ in the number of variables.*

EXHIBIT 10
LASSO Regression Modeling for *YS*





λ	0.014	Intercept	0.419
ln λ	–4.236	ln*LE*	–0.042
R^2	0.273	ln*DB*	0.000
RMSE	0.093	*DI*	0.000
Number of Variables	3.000	*MK*	–0.018
		NO	0.000
		AGE	0.000
		CO	0.000
		PM/DB	–0.133
		RT	0.000
		VI	0.000
		PT	0.000

Coefficients

Notes: In-sample data are used for the LASSO regression. At λ = 0.014, three variables are selected (lnLE, MK, and $\frac{PM}{DB}$). A decrease of λ, which increases number of variables selected, does not markedly improve the regression performance with regard to both R^2 and RMSE.

Exhibit 9 also shows that model performance can generally be enhanced by adding more independent variables. However, this effect becomes smaller from Model 3 onward. Starting from Model 6, we detect a deterioration in the BIC, although SEE and R^2_{adj} show further improvements. Consequently, we decide to avoid in-sample overfitting by sticking to the most prevalent factors. Of all examined alternatives, we eliminate Models 1, 2, 7, 8, 9, 10, and 11 and continue our analysis with Models 3–6.

For cross validation, we conduct a complementary analysis using the Least Absolute Shrinkage and Selection Operator (LASSO) method (Tibshirani 1996). The LASSO regression presented in Exhibit 10 corroborates the choice of variables based on the set of OLS regressions in Exhibit 9. Specifically, at λ = 0.014, three variables are selected (ln*LE*, *MK*, and $\frac{PM}{DB}$). A decrease of λ, which increases the number of variables selected, does not markedly improve the regression performance with regard to both R^2 and RMSE.

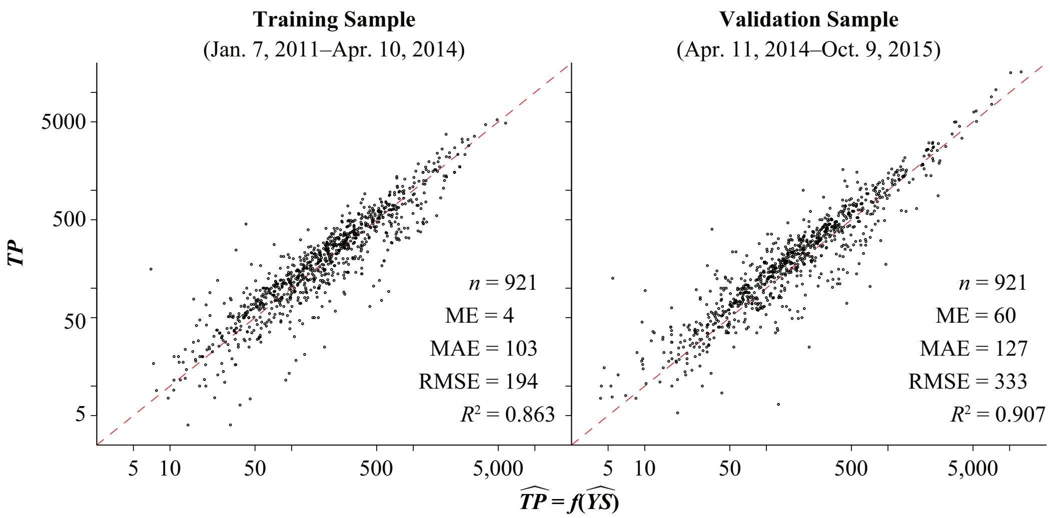
To assess the pricing accuracy associated with Models 3–6, we estimate them based on the training sample (as shown in Exhibit 9) and subsequently generate predictions for the yield spread $\widehat{YS}$. The latter are then inserted into Equation (5) to compute model prices $\widehat{TP}$ for all transactions in the training and the validation sample. Based on the differences between observed and fitted values for the transaction price, we calculate four common performance indicators: mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and (out-of-sample) R^2 (see Appendix B for formal definitions). Exhibit 11 is a graphical illustration of the results in both the training sample (left side) and the validation sample (right side). The 45-degree line (dashed) in each plot implies equality between model prediction $\widehat{TP}$ (horizontal axis) and empirical observation TP (vertical axis). The points above (below) it imply underestimation (overestimation). Deviations from the line correspond to pricing errors.

Overall, the prices generated based on the model-predicted yield spreads, together with the present value relationship in Equation (5), are relatively well aligned along the 45-degree line. A solid precision is also

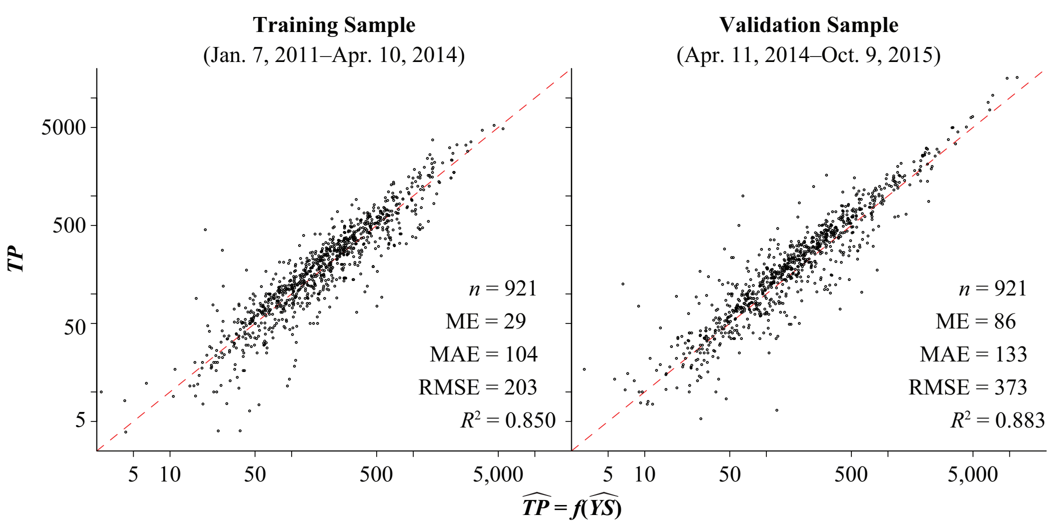
Exhibit 11

Observed versus Fitted Prices Based on Yield Spreads Predicted by Models 3, 4, 5, and 6

Panel A: Model 3: $\widehat{YS} = 0.541 - 0.065 \ln LE - 0.044\, MK - 0.169 \dfrac{PM}{DB}$



Panel B: Model 4: $\widehat{YS} = 0.376 - 0.073 \ln LE + 0.014 \ln DB - 0.040\, MK - 0.168 \dfrac{PM}{DB}$

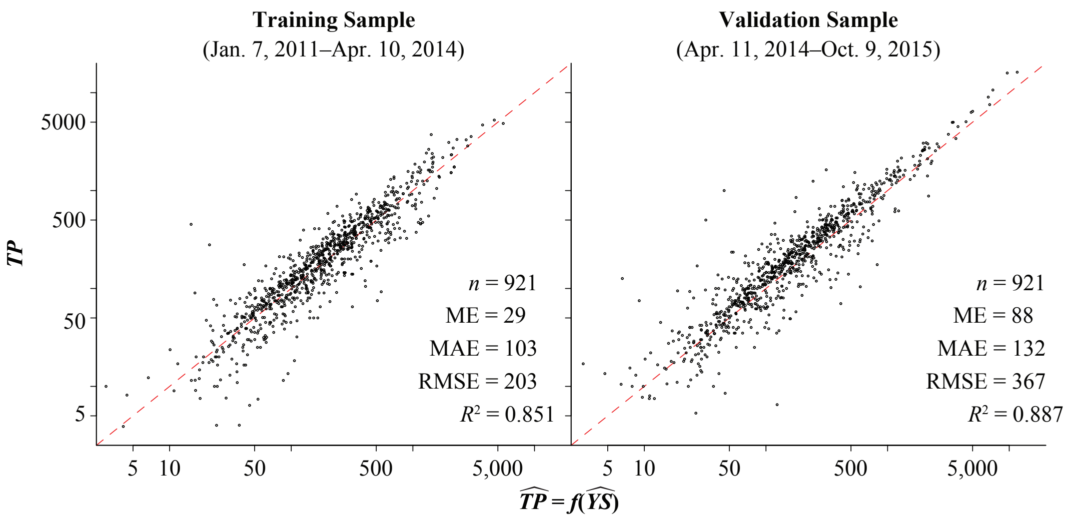


(continued)

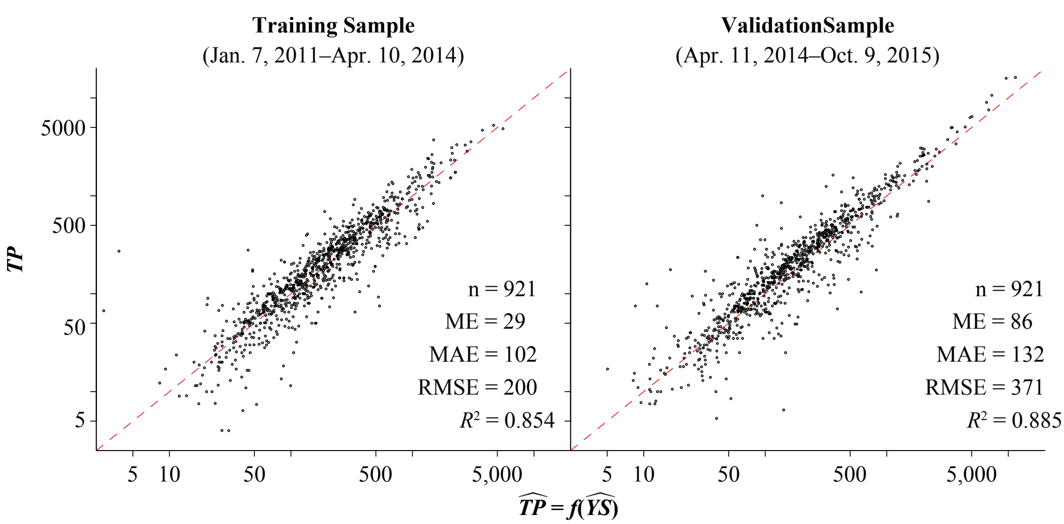
EXHIBIT 11 *(continued)*

Observed versus Fitted Prices Based on Yield Spreads Predicted by Models 3, 4, 5, and 6

Panel C: Model 5: $\widehat{YS} = 0.374 - 0.069 \ln LE + 0.015 \ln DB - 0.038\ MK - 0.158 \dfrac{PM}{DB} - 0.035\ PT$



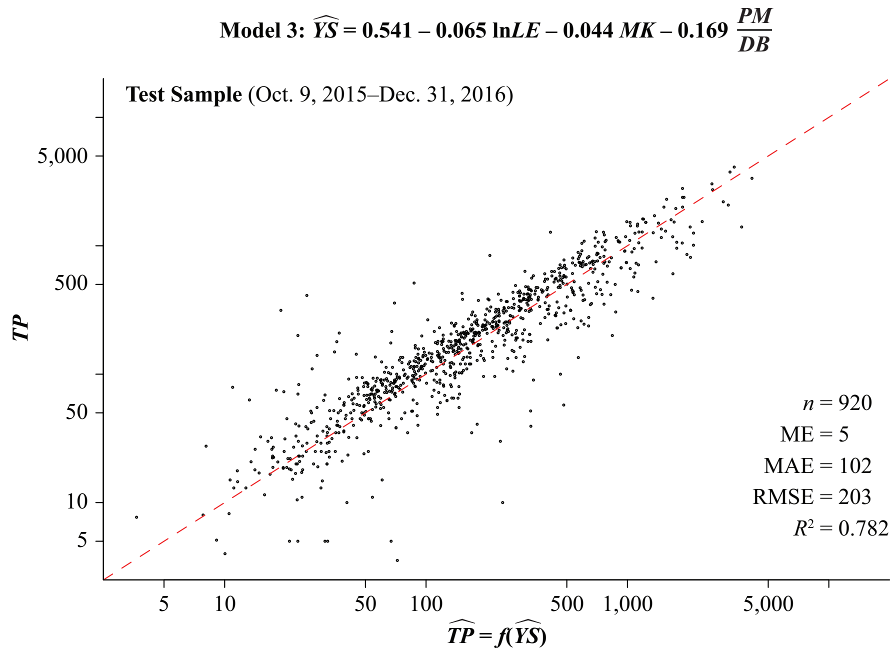
Panel D: Model 6: $\widehat{YS} = 0.379 - 0.073 \ln LE + 0.015 \ln DB - 0.005\ DI - 0.038\ MK - 0.157 \dfrac{PM}{DB} - 0.034\ PT$



Notes: This exhibit is a comparison of predicted transaction prices ($\widehat{TP}$, horizontal axis) and observed transaction prices (TP, vertical axis) in both the training (left side) and validation samples (right side). The $\widehat{TP}$ have been calculated with the present value relationship shown in Equation (5) and the yield spreads $\widehat{YS}$ generated by our regression models estimated on the training sample. The 45-degree line (dashed) in each plot implies equality between $\widehat{TP}$ and TP. The points above (below) it imply underestimation (overestimation). Deviations from the line correspond to pricing errors. Based on the differences between observed and fitted values for the transaction price, we calculate four common performance indicators: ME, MAE, RMSE, and (out-of-sample) R^2.

EXHIBIT 12

Observed versus Fitted Prices Based on Yield Spreads Predicted by Model 3



Notes: This exhibit is a comparison of predicted transaction prices ($\widehat{TP}$, horizontal axis) and observed transaction prices (TP, vertical axis). The former have been calculated with the present value relationship shown in Equation (5) and the yield spreads $\widehat{YS}$ generated by Model 3 estimated on the training sample. The 45-degree line (dashed) in each plot implies equality between $\widehat{TP}$ and TP. The points above (below) it imply underestimation (overestimation). Deviations from the line correspond to pricing errors. Based on the differences between observed and fitted values for the transaction price, we calculate four common performance indicators: ME, MAE, RMSE, and (out-of-sample) R^2.

reflected by the R^2 measures, implying that our framework is capable of describing a large portion of the price variance, both in sample and out of sample.[13]

Although all four short-listed models perform similarly, the quantitative performance measures indicate a superiority of Model 3; it delivers the lowest ME, MAE, and RMSE and the highest R^2. Thus, a linear model for the yield spread, comprising the factors ln *LE*, *MK*, and *PM/DB*, in combination with standard present value calculus, seems to be a very effective way to determine market-consistent life settlement prices. Recall that the variable selection was additionally confirmed by the LASSO regression presented in Exhibit 10. Based on these insights, we move on to the final analysis, in which we run Model 3 on the test sample.

The results are illustrated in Exhibit 12. Evidently, the out-of-sample price predictions based on the estimated yield spreads $\widehat{YS}$ continue to be precise. Hence, Model 3 performs consistently well over all three subsamples, covering different time periods.

Robustness Tests

In the following sections, we want to evaluate the robustness of Model 3 across policy types, carrier ratings, and medical underwriters. We tranche our data accordingly and recalibrate the model separately for each subcategory. Furthermore, we use two-thirds of our overall sample (previously training sample and validation sample) for fitting and one-third (previously test sample) for testing.[14] To calculate $\widehat{TP}$, we again plug the model-predicted yield spreads $\widehat{YS}$ into the pricing

[13] The MAE values, however, are relatively high compared to other asset pricing models for insurance risk (see, e.g., Braun 2016). This observation warrants a discussion of key limitations associated with our approach.

[14] October 9, 2015, separates the two subsamples.

EXHIBIT 13

Robustness Test for Model 3 Using Policy-Type Subsamples

Panel A: Model Calibration on Policy-Type Subsamples

	Universal Life			Term Life			Whole Life		
Policy Type	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**
Intercept	0.407	(0.028)	***	0.489	(0.059)	***	0.271	(0.197)	
ln *LE*	−0.039	(0.006)	***	−0.070	(0.016)	***	−0.020	(0.075)	
MK	−0.031	(0.006)	***	−0.039	(0.024)		−0.073	(0.036)	
PM/DB	−0.173	(0.018)	***	−0.047	(0.119)		0.325	(0.523)	

Panel B: Model Performance for Calibration on Policy-Type Subsamples

	InS.	**OutS.**	**InS.**	**OutS.**	**InS.**	**OutS.**
n	1,601	739	71	82	22	24
ME	11	−18	3	8	5	−17
MAE	115	107	48	50	45	45
RMSE	266	220	101	111	77	118
R^2	0.914	0.752	0.946	0.868	0.943	−0.288

*Notes: Panel A: Model 3 calibrated on subsamples for different policy types. We present the unstandardized (Coeff.) and standardized (StCoeff.) regression coefficients as well as Newey-West standard errors (StErr.) and their significance levels (Sig.). Significance levels of 0.1, 0.05, and 0.01 are marked with *, **, and ***, respectively. Panel B: We plug $\widehat{YS}$, generated with the calibrated model, into the pricing relationship shown in Equation (5) to calculate $\widehat{TP}$. Based on the differences between observed values (TP) and fitted values ($\widehat{TP}$) for the transaction price, we calculate four common performance indicators: ME, MAE, RMSE, and R^2. InS.: In-sample estimation (sample period: Jan. 7, 2011–Oct. 9, 2015). OutS.: Out-of-sample prediction (sample period: Oct. 9, 2015–Dec. 31, 2016).*

relationship shown in Equation (5). We then measure the model performance based on the deviation of $\widehat{TP}$ from TP, using the four performance indicators ME, MAE, RMSE, and (out-of-sample) R^2.

Policy Type

The regression results and performance measures for the subsamples of different policy types are shown in Exhibit 13. Both the in-sample and out-of-sample figures for *universal life* and *term life* contracts are strong. Yet for the *whole life* category, we observe insignificant coefficients and a poor out-of-sample performance. This is likely due to the paucity of *whole life* data, which comprise only 46 cases and thus constitute less than 2% of the full sample. Until this problem can be resolved, it is advisable to exclusively apply the model to *universal life* and *term life* policies. For the latter two categories, model estimation on the specific subsamples does generally not improve pricing accuracy, which can be seen by comparing the results in Exhibit 13 with those for the calibration on the untranched data in Exhibit 12. This confirms our earlier finding that policy type *PT* has a negligible impact on *YS*. Hence, its exclusion from the model was warranted.

Rating

The results for the subsamples of issuing-insurer rating classes are shown in Exhibit 14. Just like the *whole life* subsample, the *no rating* subsample exhibits a very small size. Therefore, its out-of-sample performance is no reliable indication of the model accuracy. Comparing the categories *A-rated* and *B-rated*, we observe that the absolute values of the regression coefficients are higher in the latter. Moreover, we find a larger baseline yield spread (intercept) for policies issued by *B-rated* insurers. In both cases, the model performs similarly as well as on the untranched sample.

Medical Underwriters

The *LE* estimates in our data set come from the four major US medical underwriters (ITM TwentyFirst, AVS, Fasano, and LSI). Most life settlements exhibit at least two of them. In addition, for each transaction,

EXHIBIT 14
Robustness Test for Model 3 Using Rating-Based Subsamples

Panel A: Model Calibration on Rating-Based Subsamples

	A-*Rated*			B-*Rated*			No Rating		
Rating	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**
Intercept	0.410	(0.025)	***	0.806	(0.123)	***	0.727	(0.035)	***
ln*LE*	–0.040	(0.006)	***	–0.111	(0.039)	***	–0.120	(0.012)	***
MK	–0.033	(0.006)	***	–0.056	(0.031)		–0.210	(0.021)	***
PM/DB	–0.166	(0.017)	***	–0.247	(0.141)		0.294	(0.118)	**

Panel B: Model Performance for Calibration on Rating-Based Subsamples

	InS.	**OutS.**	**InS.**	**OutS.**	**InS.**	**OutS.**
n	1,803	873	27	29	12	18
ME	9	–11	10	–8	–5	–33
MAE	109	100	119	71	14	121
RMSE	255	208	232	125	18	201
R^2	0.913	0.777	0.813	0.775	0.984	0.218

*Notes: Panel A: Model 3 calibrated on subsamples for different rating categories. We present the unstandardized (Coeff.) and standardized (StCoeff.) regression coefficients as well as Newey-West standard errors (StErr.) and their significance levels (Sig.). Significance levels of 0.1, 0.05, and 0.01 are marked with *, **, and ***, respectively. Panel B: We plug $\widehat{YS}$, generated with the calibrated model, into the pricing relationship shown in Equation (5) to calculate $\widehat{TP}$. Based on the differences between observed values (TP) and fitted values ($\widehat{TP}$) for the transaction price, we calculate four common performance indicators: ME, MAE, RMSE, and R^2. InS.: In-sample estimation (sample period: Jan. 7, 2011–Oct. 9, 2015). OutS.: Out-of-sample prediction (sample period: Oct. 9, 2015–Dec. 31, 2016).*

there is an *LE* figure, which has been used to close the deal. Recall from the second section that the market lacks a universal rule prescribing how the *LE* for pricing purposes shall be determined. The buy and sell sides (Braun et al. 2018b, 2019c) can agree on the estimate of a single medical underwriter or average the *LEs* from several. Despite the industry jargon "blended LE," the *LE* used to close a life settlement deal is not always a "blend" in the conventional sense; it can exceed (undercut) the highest (lowest) underwriter estimate (Exhibit 1). In the absence of reports from medical underwriters, a "home-brewed" *LE* may be generated. This is common for the pricing of small-face policies where the cost of obtaining an *LE* report is prohibitive. So far, our analyses relied on the blended *LE*. To assess the model's robustness with regard to a change in this input, we will now exclusively employ *LE* estimates of the same underwriter for the recalibration. Consistent with the latter, *PM* is also recalculated according to Equation (4). Exhibit 15 shows that both in-sample and out-of-sample performance remain solid when LEs from different underwriters are employed for parameter estimation.

LIMITATIONS

As noted earlier, the discount rates associated with the transaction prices in our sample are not disclosed by investors. Therefore, we extracted implied yield spreads (*YS*) from yields (*ytm*) that we computed based on Equation (5), given prices, premiums, and mortality rates. However, the mortality rates used for pricing were also unobservable and had to be inferred from the reported *LE* values (via Equation A1 shown in the Appendix). This proceeding relies on two assumptions: (1) *LE* is the mean of an insured's survival distribution; (2) an insured's mortality rates exhibit a constant ratio (the mortality multiplier *k*) with regard to the base mortality rates of the cohort. Differences between our estimates and the true unobserved mortality rates used by investors would cause discrepancies between actual and implied yield spreads. Practitioners sometimes use median *LE* instead of mean *LE* and/or a different mortality table than the VBT15-ANB, which we applied in this study, to extract standard

EXHIBIT 15

Robustness Test for Model 3 Using Subsamples of LEs from Different Medical Underwriters

Panel A: Model Calibration on Medical Underwriter Subsamples

	ITM			AVS			Fasano			LSI		
Underwriter	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**	**Coeff.**	**(StErr.)**	**Sig.**
Intercept	0.378	(0.027)	***	0.384	(0.026)	***	0.379	(0.072)	***	0.614	(0.202)	***
ln*LE*	–0.034	(0.007)	***	–0.036	(0.006)	***	–0.036	(0.016)	**	–0.081	(0.043)	
MK	–0.045	(0.007)	***	–0.037	(0.006)	***	–0.018	(0.012)		–0.011	(0.033)	
PM/DB	–0.139	(0.019)	***	–0.112	(0.019)	***	–0.131	(0.029)	***	–0.075	(0.043)	

Panel B: Model Performance for Calibration on Medical Underwriter Subsamples

	InS.	OutS.	InS.	OutS.	InS.	OutS.	InS.	OutS.
n	1,256	507	1,641	786	293	112	91	63
ME	0	–47	10	–15	61	5	5	68
MAE	108	126	113	108	167	80	114	133
RMSE	205	292	253	229	458	136	175	259
R^2	0.884	0.594	0.918	0.747	0.934	0.913	0.780	0.612

Notes: Panel A: Model 3 calibrated on subsamples of LE*s from different medical underwriters. We present the unstandardized (Coeff.) and standardized (StCoeff.) regression coefficients as well as Newey-West standard errors (StErr.) and their significance levels (Sig.). Significance levels of 0.1, 0.05, and 0.01 are marked with *, **, and ***, respectively.*

*Panel B: We plug $\widehat{YS}$, generated with the calibrated model, into the pricing relationship shown in Equation (5) to calculate $\widehat{TP}$. Based on the differences between observed values (*TP*) and fitted values ($\widehat{TP}$) for the transaction price, we calculate four common performance indicators: ME, MAE, RMSE, and R^2. InS.: In-sample estimation (sample period: Jan. 7, 2011–Oct. 9, 2015). OutS.: Out-of-sample prediction (sample period: Oct. 9, 2015–Dec. 31, 2016).*

mortality rates.[15] In addition, if clinical judgment replaces the medical underwriting, mortality rates are determined ad hoc and not by multiplying *k* with standard rates. It should further be noted that both *LE* and *YS* influence transaction prices. Therefore, we cannot rule out the possibility that investors have taken risks into account by scaling life expectancies instead of yield spreads when valuing a policy.

Another caveat is that we do not know the terminal age associated with each life insurance contract. If the insured reaches the terminal age, the policy would mature without a death benefit payment. Constrained by data availability, we are not able to factor the effect of contract maturity into our model. However, since it is reasonable to assume that investors would only purchase policies with a very high likelihood that the insured will pass away before maturity, this should not materially affect our results. Typically, the survival rates beyond policy maturity are very low.

The economic and formal characteristics of *ytm* as an internal rate of return also contribute to the disjunction between actual and implied yield spreads. First, the *ytm* used for our analysis uses expected returns that incorporate investors' perceptions at the time of the transaction. As such, they will deviate from the realized returns, which can only be assessed at maturity of the life insurance policies. Therefore, the yield spreads derived by means of our model are helpful for pricing but not for performance measurement purposes. Second, if the signs of the probabilistic cash flows change more than once (such as –, +, +, +, –...[16]), the function *TP*(*ytm*) can be non-monotonic, and Equation (5) may have two positive roots. The algorithm that we applied in this study to determine the implied yield spread (*YS*) systematically searches an interval from lower to upper

[15] The crudeness of cohorting in different mortality tables varies. Valuation Basic Tables (VBTs), for example, are gender-smoker-distinct and age-specific. More granular tables also consider primary health impairments.

[16] This barbelled cash flow pattern can occur if probabilistic premiums are greater than probabilistic death benefit receipts at the beginning and the end of the policy coverage period (see Sheridan 2019).

limit for the root (zero) of Equation (5). If multiple roots exist, the smallest is selected. One may consider the usage of the modified internal rate of return, which can resolve the aforementioned problems associated with *ytm*. However, measurement of the former requires assumptions on reinvestment rates, which vary between investors.

CONCLUSION

In deriving risk-adequate discount rates for life settlements, one faces similar problems to those of other illiquid markets with heterogeneous assets, such as real estate or fine arts. The extant literature has not yet come up with a reliable solution to the problem. To fill the gap, we estimate historical yield spreads for life settlement assets based on a large data set of 2,863 transactions that occurred between 2011 and 2016. Subsequently, we explain the cross-section of the yield spreads based on hedonic regression methodology and a comprehensive set of attributes motivated by industry know-how as well as earlier studies. Based on the aforementioned findings, we propose a parsimonious model for the prediction of risk-adjusted discount rates in the life settlements market.

We find evidence for the majority of our hypotheses. More specifically, the life settlement yield spread seems to predominantly consist of loadings for longevity risk. Premium risk and default risk, in contrast, play a much lesser role whereas rescission risk is likely not priced at all. A comprehensive battery of in-sample and out-of-sample tests indicates that market-consistent life settlement prices can be conclusively predicted by employing risk-adjusted discount rates generated with our model. Once its parameters have been estimated, the approach can be used to price new transactions or to run portfolio valuations. Accordingly, life settlements can be marked to market based on observable inputs. They should thus be considered Level 2 assets under IFRS 13.

The composition of the yield spreads merits further research. Although we were able to provide initial evidence on their sizes and constituent parts, our findings are restricted by the fact that we needed to rely on implied instead of observed discount rates. The former were derived using a specifically chosen mortality table and may thus deviate from the values actually applied by investors. Consequently, a confirmation of our results based on the true yield spreads would be desirable. Furthermore, our study revealed high expected returns on life settlement investments. However, there is anecdotal evidence of historical underperformance, which calls the realizability of these return figures into question and raises concerns regarding mispricing. This problem could be addressed by a cash-flow-based performance analysis for open-end life settlement funds. Finally, using expected instead of actual returns also limits the economic interpretation of our results. It remains an open question to what extent the observed yield spreads actually reflect risk premiums. After all, risks that are uncorrelated with economic fundamentals such as capital markets or consumption are fully diversifiable by the global investor and should therefore carry no risk premium. Against this background, much if not all of the excess returns on life settlements might be attributable to frictions.

APPENDIX A

CALCULATION OF *LE*

In actuarial science, life expectancy *LE* is defined as follows:

$$LE = \sum_{i=0}^{\infty} {}_{i+1}p_x = \sum_{i=0}^{\infty} ({}_{i}p_x \cdot {}_{i|}p_x) \qquad \text{(A1)}$$

where

$${}_{i}p_x = \begin{cases} 1, & i \leq 0 \\ \prod_{j=0}^{i-1} {}_{j|}p_x, & i \geq 1 \end{cases} \qquad \text{(A2)}$$

$${}_{i|}p_x = \max(0, 1 - k \cdot {}_{i|}Q_x) \qquad \text{(A3)}$$

- ${}_{i|}Q_x$: standard mortality rate (probability that an average x-year-old insured will die by the end of the $(i + 1)$th period, given that the person is alive at the end of the ith period).
- ${}_{i}p_x$: individual survival rate (probability that the x-year-old insured will live i periods).
- k: customized survival multiplier (describes the relationship between the individual mortality rate and the standard mortality rate).
- ${}_{i|}p_x$: the x-year-old insured's one-period conditional survival probability at time i (probability that the insured will be alive at the end of the $(i + 1)$th period, given that the person is alive at the end of the ith period).

APPENDIX B

MODEL PERFORMANCE MEASURES

Let $\{y_i\}_{i\in 1,2,\ldots,n}$ denote the observed values of a variable and $\{\hat{y}\}_{i\in 1,2,\ldots,n}$ the estimated values using multiple linear regression M that contains q slope parameters.

In-sample performance measurements of model M include:

Standard error of the estimate (SEE):

$$\text{SEE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n - q - 1}} \tag{B1}$$

Adjusted R^2 (R^2_{adj}):

$$R^2_{adj} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2}\frac{q}{n - q - 1} \tag{B2}$$

Bayesian information criterion (BIC):

$$\text{BIC} = (q+2)\ln n - 2\ln p(y|\hat{\theta}, M) \tag{B3}$$

where $\hat{\theta}$ denotes the estimated model parameters.

Out-of-sample performance measurements of model M include (see, e.g., Braun 2016):

Mean error (ME):

$$\text{ME} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \tag{B4}$$

Mean absolute error (MAE):

$$\text{MAE} = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{B5}$$

Root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{B6}$$

Out-of-sample coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \tag{B7}$$

ACKNOWLEDGMENTS

We would like to thank attendees of the 2018 Western Risk and Insurance Association (WRIA) annual meeting, 2018 German Association for Insurance Studies (DVfVW) annual meeting, 2018 Asia-Pacific Risk and Insurance Association (APRIA) annual conference, and 2019 American Risk and Insurance Association (ARIA) annual conference for their valuable comments.

REFERENCES

Altamuro, J., and H. Zhang. 2013. "The Financial Reporting of Fair Value Based on Managerial Inputs versus Market Inputs: Evidence from Mortgage Servicing Rights." *Review of Accounting Studies* 18 (3): 833–858.

Bahna-Nolan, M. 2014. "Mortality Table Development Update 2014 VBT/CSO." *NAIC Life Actuarial Task Force Meeting.*

Bauer, D., J. Russ, and N. Zhu. 2014. "Adverse Selection in Insurance Markets: Evidence from the Life Settlement Market." In *Proceedings of the NBER Insurance Workshop 2014.*

Bayston, D. M., D. R. Lempereur, and A. Pecore. 2010. "Life Settlements: Valuation and Performance Reporting for an Emerging Asset Class." *The Journal of Performance Measurement* 15 (1): 32–51.

Braun, A. 2016. "Pricing in the Primary Market for Cat Bonds: New Empirical Evidence." *The Journal of Risk and Insurance* 83 (4): 811–847.

Braun, A., S. Affolter, and H. Schmeiser. 2015. "Life Settlement Funds: Current Valuation Practices and Areas for Improvement." *Risk Management and Insurance Review* 19 (2): 173–195.

Braun, A., L. Cohen, M. Elvedi, and J. Xu. 2019c. "ClearLife: From Prospect to Platform." Harvard Business School Case 219-119.

Braun, A., L. H. Cohen, C. J. Malloy, and J. Xu. 2018. "Introduction to Life Settlements." Harvard Business School Background Note 218–127.

Braun, A., L. H. Cohen, C. J. Malloy, and J. Xu. 2018b. "Ashar Group: Brokers and Co-opetition in the Life Settlement Industry." Harvard Business School Case 218-109.

———. 2019. "Saving Face: A Solution to the Hidden Crisis for Life Insurance Policyholders."

Braun, A., L. H. Cohen, and J. Xu. 2019d. "fidentiaX: The Tradable Insurance Marketplace on Blockchain." Harvard Business School Case 219-116.

Braun, A., M. Fischer, and H. Schmeiser. 2019b. "How to Derive Optimal Guarantee Levels in Participating Life Insurance Contracts." *Journal of Risk Finance* 20 (5): 445–469.

Braun, A., N. Gatzert, and H. Schmeiser. 2012. "Performance and Risks of Open-End Life Settlement Funds." *The Journal of Risk and Insurance* 79 (1): 193–230.

Braun, A., H. Schmeiser, F. Schreiber. 2016. "On Consumer Preferences and the Willingness to Pay for Term Life Insurance." *European Journal of Operational Research* 253 (3): 761–776.

Brockett, P. L., S. L. Chuang, Y. Deng, and R. D. MacMinn. 2013. "Incorporating Longevity Risk and Medical Information into Life Settlement Pricing." *The Journal of Risk and Insurance* 80 (3): 799–826.

Chancy, S. E., D. L. Thorpe, and M. R. Tregle. 2010. "Senior Life Settlements: A Cautionary Tale." *Supervisory Insight*s, Winter.

Gatzert, N., G. Hoermann, and H. Schmeiser. 2009. "The Impact of the Secondary Market on Life Insurers' Surrender Profit." *The Journal of Risk and Insurance* 76 (4): 887–908.

Giaccotto, C., J. Golec, and B. P. Schmutz. 2015. "Measuring the Performance of the Secondary Market for Life Insurance Policies." *The Journal of Risk and Insurance* 84 (1): 127–151.

Hanley, K. W., A. D. Jagolinzer, and S. Nikolova. 2018. "Strategic Estimation of Fair Values." *Journal of Accounting and Economics* 66 (1): 25–45.

Hilton, A. S., and P. C. O'Brien. 2009. "Inco ltd.: Market Value, Fair Value, and Management Discretion." *Journal of Accounting Research* 47 (1): 179–211.

Hong, J., and S. H. Seog. 2018. "Life Insurance Settlement and the Monopolistic Insurance Market." *Insurance: Mathematics and Economics* 81: 36–50.

Horowitz, D. 2018. "Life Settlement League Tables 2017: Market Grows 19%, Continues Upward Path."

Januário, A. V., and N. Y. Naik. 2014. "Testing Adverse Selection in Life Settlements: The Secondary Market for Life Insurance Policies."

Lin, Z., and K. D. Vandell. 2007. "Illiquidity and Pricing Biases in the Real Estate Market." *Real Estate Economics* 35 (3): 291–330.

MacMinn, R. D., and N. Zhu. 2017. "Hedging Longevity Risk in Life Settlements Using Biomedical Research-Backed Obligations." *The Journal of Risk and Insurance* 84 (S1): 439–458.

Sadowsky, J. T., and M. C. Browndorf. 2009. "Synthetic Longevity Assets—A Primer." *Life Markets: Trading Mortality and Longevity Risk with Life Settlements and Linked Securities* 245–253.

Sheridan, M. 2019. "Managing Life Settlments: In Practice." In *The Stoli Worm: A Practitioner's Guide to Managing Life Settlements and Micro Longevity Risk* 78–129.

———. 2017. "Quantification of Life Settlement Cost of Insurance (COI) Increases." *ELSA Papers*.

Shiller, R. J. 1993. "Measuring Asset Values for Cash Settlement in Derivative Markets: Hedonic Repeated Measures Indices and Perpetual Futures." *The Journal of Finance* 48 (3): 911.

Stone, C. A., and A. Zissu. 2006. "Securitization of Senior Life Settlements: Managing Extension Risk." *The Journal of Derivatives* 13 (3): 66–72.

Tibshirani, R. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society. Series B: Statistical Methodology* 58 (1): 267–288.

Turnbull, S., and D. O'Kane. 2003. "Valuation of Credit Default Swaps." Technical report.

Verdon, L. L. 2010. "Why Do Rich People Buy Life Insurance?"

Xu, J. 2019. "Dating Death: An Empirical Comparison of Medical Underwriters in the US Life Settlements Market." *North American Actuarial Journal*, doi: 10.1080/10920277.2019.1585881.

Zhu, N., and D. Bauer. 2013. "Coherent Pricing of Life Settlements under Asymmetric Information." *The Journal of Risk and Insurance* 80 (3): 827–851.

To order reprints of this article, please contact David Rowe at d.rowe@pageantmedia.com or 646-891-2157.

ADDITIONAL READING

Predicting Longevity: ***An Analysis of Potential Alternatives to Life Expectancy Reports***

Jiahua Xu and Adrian Hoesch

The Journal of Investing

https://joi.pm-research.com/content/27/supplement/65

ABSTRACT: *Retirees, pension funds, and the insurance industry have all been negatively affected by the wrongful estimation of longevity. The inaccuracies in current life expectancy (LE) reports primarily result from misinterpretations of the influence of resilience factors on longevity. This study examines different and more accurate measurement metrics to minimize the risks related to biased LE calculations. By using both qualitative and quantitative research approaches, this research develops a new conceptual model: a two-factor-LE-analysis model with a telomere test as a medical basis (physiological factors) and a big data approach to filter the psychological factors to longevity. The authors suggest that the new model, together with the insights of the existing LE-projection methodologies, has considerable potential to improve LE predictions.*

The Market for Longevity Annuities

Katharine G. Abraham and Benjamin H. Harris

The Journal of Retirement

https://jor.pm-research.com/content/3/4/12

ABSTRACT: *Using a portion of accumulated assets to purchase a longevity annuity—which provides fixed income payments that begin in late old age with a substantial delay from the time the contract is purchased—offers a cost-effective means for individuals to insure against running out of money in retirement. Despite their conceptual appeal, sales of such products to date have been vanishingly small. The article discusses the factors that have inhibited consumers, employers, and insurance providers from participating in the market for longevity annuities and proposes reforms that could help to develop that market. These reforms include stronger efforts to educate consumers about the risks they face in retirement; permitting insurance companies to mention the existence of state guaranty funds when marketing annuity products; creating a more transparent safe harbor for employers who offer annuities within their retirement plans; and taking steps to develop or support the development of longevity bonds, which would allow insurance companies that offer longevity annuities to better hedge against the associated aggregate longevity risk.*