Dating Death: An Empirical Comparison of Medical Underwriters in the U.S. Life Settlements Market

Alexander Braun and Jiahua Xu*

May 7, 2017

Abstract

The value of a life settlement investment, which is a traded life insurance policy, is highly dependent on the life expectancy (LE) of the insured. We empirically demonstrate that LE has been the key driver in life settlement pricing, and we illustrate its relationship to the expected internal rate of return (IRR). Based on the analysis of life settlement transaction data from 2011 to 2016, we trace the patterns of LE estimates in both secondary and tertiary markets by major medical underwriters, and investigate systematic differences in their estimation.

Keywords: Medical Underwriting, Life Settlements, Alternative Investments
JEL classification: G11; G22; G28; G32; G38

*Alexander Braun (alexander.braun@unisg.ch) and Jiahua Xu (jiahua.xu@unisg.ch) are from the Institute of Insurance Economics, University of St. Gallen, Tannenstrasse 19, CH-9000 St. Gallen.
We would like to thank attendees of the BVZL conference, the Fasano conference, and the ELSA symposium for their valuable comments.

1 Introduction

1.1 The life settlements market

In the 1980s when AIDS became an epidemic disease in the U.S., many of those infected were willing to sell their life insurance policy in order to alleviate financial hardships due to medical treatment and/or loss of employment (LISA, 2016). If an insured cancels a policy, the person ceases to pay the regular premiums and receives a lump sum equal to the surrender value, while the insurance carrier will no longer pay the death benefit to the original beneficiary. Since this cash-out in most cases would be undervalued (Doherty and Singer, 2002, p. 3), the insured could alternatively sell the policy to an investor who would then become the policy beneficiary. A life insurance transaction, conducted when the original policyholders are chronically or terminally ill, is called a viatical settlement (Stone and Zissu, 2006, p. 66).

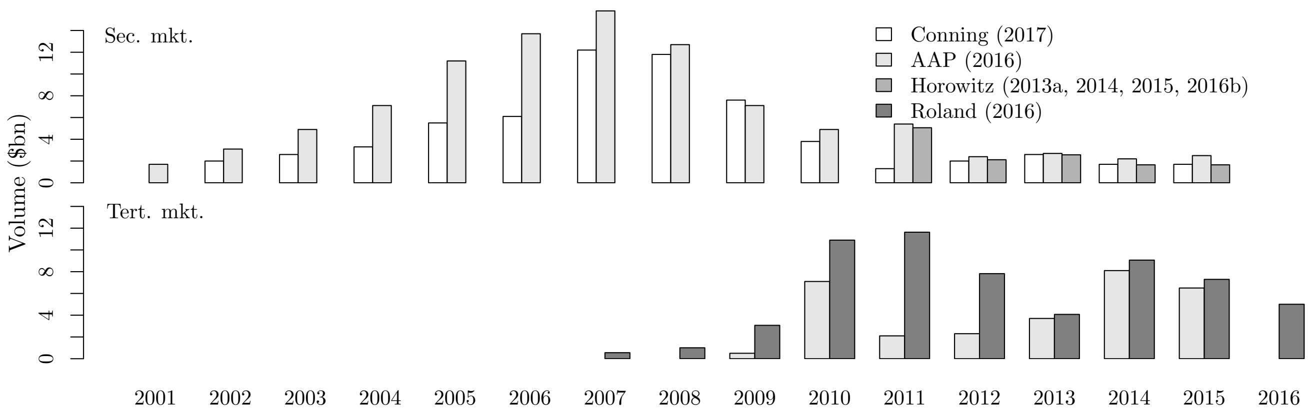
Originating from viatical settlements, the life settlements market emerged and evolved. The trade of life insurance policies nowadays is driven by a different set of factors: policy sellers are not necessarily ill; they sell their life insurance due to unaffordable premiums, urgent need for cash, or deceased beneficiaries (An, 2014, p. 12). With a collective price of severalfold the surrender value, and a double-digit average expected return in some life settlement funds (see e.g. Januário and Naik, 2014, p. 3), the trade of life insurance policies can be attractive to both policyholders and investors. Since the life settlements industry is hardly affected by the traditional financial markets, and its return is uncorrelated with that of conventional investment vehicles (Cowley and Cummins, 2005, p. 220), it is an apt device for funds such as pension or hedge funds in view of investment portfolio diversification. At the moment, life insurance policies worth a total face value of USD 2 billion are traded annually in the secondary market (where insureds sell their life insurance policy directly to investors), and a total face value of USD 10 billion in the tertiary market (where investors trade insurance policies between each other) (Figure 1).

The price of a life settlement is dependent on the insured's life expectancy (LE): the longer the LE, the lower the price an investor is willing to pay for the policy, as the expected premium to be paid by the buyer of the life insurance increases and the death benefit is expected to be received later. Accordingly, in a life settlement transaction investors would wish for an accurate LE forecast to reduce the longevity and liquidity[1] risk, or perhaps even an overestimated LE, so that they could strike a bargain on the price of the policy and achieve a higher actual IRR. Conversely, the sell side would prefer a shorter LE, so that the price would be elevated. Therefore, policy sellers have a natural incentive to attain the shortest possible LE to inflate the price (Braun et al., 2015, p. 188).

The accuracy of LE prediction plays an extremely important role in the life settlements business. The professional determination of LE based on the health and medical information of the insured is called medical underwriting. The entity independently conducting such forecasts is a medical underwriter. Historically, the medical underwriters for the industry have underestimated life expectancy as seniors have

[1]Life insurance was conventionally categorized as an liquid asset (Kohli, 2006, p. 101). As the tertiary market of life settlements grows, it is reclassified as "semi-liquid"(AAP, 2017, p. 8).

Figure 1: Annual face transacted



The secondary market experienced its peak in 2007 while the tertiary market has attracted more and more capital ever since.

been living longer than originally projected. The question is why.

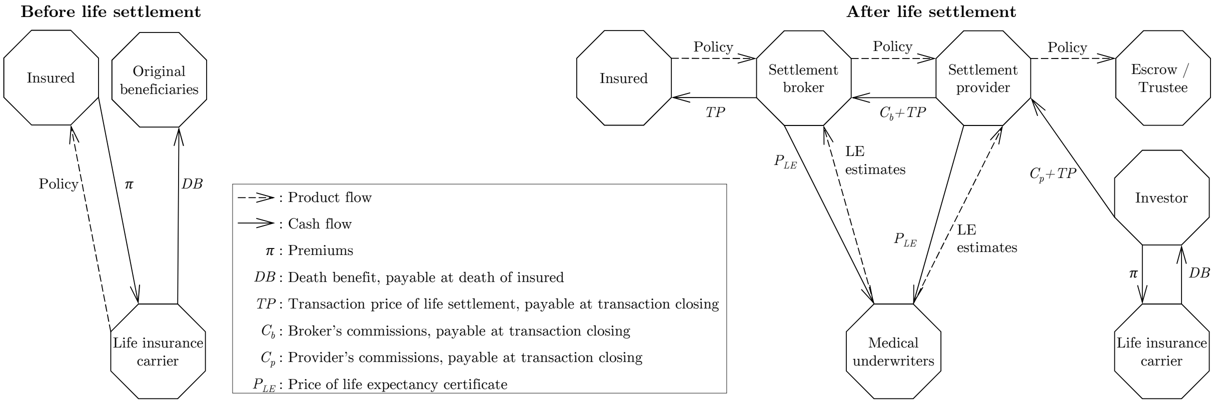
1.2 Object of the study

Dates of death are the determinants of realized IRRs. Empirical evidence suggests LE estimates — predictors of those dates of death — to be the key valuation driver in the life settlements industry. An LE estimate is provided to potential life settlement investors by the sell side or the intermediaries of the life settlement, who usually order LE certificates from one or more medical underwriters. Of all policies considered, only around 10% are eventually traded (Cohen, 2013, p. 3). The rest are discarded due to policyowners reneging, incomplete information on the policies, or financial unattractiveness to either party (price too low for the policy seller or expected return too low for the policy buyer). Not all life insurance policies are worth acquiring for the purpose of investment. If an insured's LE is so long that the present value of the expected future premium stream exceeds the present value of the death benefit, a life settlement investor would not find it economically desirable to purchase the policy[2]. Only policies with a sufficiently low LE can attract investors to bid. Sell-side intermediaries such as life settlement agents and brokers can be bullish in their sale of policies using short LE estimates. While buy-side intermediaries such as providers and fund managers are obliged to serve the investors they represent, they also have the incentive to convince investors to bid as high as possible with short LEs. In this way, they increase the chance to close a transaction and to earn commissions and fees (see Figure 2).

Based on an empirical analysis of life settlement transactions, this paper presents an overview of the industry with an emphasis on medical underwriting. By juxtaposing LE data from various medical

[2]Investors might still be willing to acquire a policy with a negative net present value (NPV). The can occur in a portfolio transaction in the tertiary market. Those economically undesirable policies will be priced zero and the investors will lapse the policies after they purchase the portfolio.

Figure 2: Simplified process of life settlement transaction



Adapted from Januário and Naik (2014, p. 35) and Braun et al. (2015, p. 177), Figure 2 illustrates the process of life settlement transaction in the secondary market, where the ownership of a life insurance policy is transferred from the insured to the investor. Intermediaries such as settlement brokers or providers are usually necessary to prevent direct contact between investors and insureds, since the former benefit from the early death of the latter. Intermediaries generally profit from the closure of a transaction due to commissions and fees they charge. In the tertiary market, policies are traded between sell-side and buy-side investors. Aspinwall et al. (2009, pp. 15-18) and Braun et al. (2012, p. 200) defined and elaborated different roles involved in a life settlement transaction.

underwriters, we seek to identify a pattern of each medical underwriter's forecast, as well as the impact of potential underestimation or overestimation. We indeed discover evidence of systematic, statistically significant differences in LE estimates between medical underwriters. In the absence of comprehensive date-of-death data, or performance analysis, we are restricted to focusing on the relative difference between the underwriters rather than on their absolute performance. However, we argue that the wide empirical variation in life expectancies is itself a contributor to the industry's inability to coalesce around accurate absolute levels. That said, a persisting bias to short LEs is supported by both the limited performance data that was made available to us (Table 1) and also the steady stream of portfolio liquidations (e.g. Robins, 2013), write downs (e.g. Emery, 2011; Tracer, 2014), foreclosures (e.g. Horowitz, 2012) and bankruptcies (e.g. Rivoli, 2011) reported in the press.

Our goal is to promote a better understanding of the prevailing LE landscape, as well as to raise investors' awareness of the status quo of medical underwriting and its significance in the life settlements industry. The names of the medical underwriters are intentionally not anonymized for the sake of market transparency, and the results seek to reveal the facts as opposed to serving promotional or defamatory ends.

The rest of the paper is structured as follows: Chapter 2 describes medical underwriting in the life settlements market and introduces the mortality multiplier k as well as its economic significance; Chapter 3 presents the data and demonstrates empirical analysis; Chapter 4 interprets and discusses the results; the last chapter, Chapter 5 concludes.

Table 1: A/E ratios

		2008	2009	2010	2011	2012	2013	2014	2015	2016	Notes
Underwriters	ITM	—	98%	94%	—	—	—	—	—	—	$A/E = \frac{\text{number of actual deaths}}{\text{number of expected deaths}}$ Adjusted aggregate ratio
	AVS	—	—	—	—	—	—	—	—	—	No publicly available information
	Fasano	—	—	—	—	—	—	—	—	97%	$A/E = \frac{\text{number of actual deaths}}{\text{number of expected deaths}}$ Unadjusted aggregate ratio
	LSI	95%	94%	—	—	—	—	—	—	—	$A/E = \frac{\text{number of actual deaths}}{\text{number of expected deaths}}$ Adjusted aggregate ratio
Funds	EEA	50%	52%	58%	68%	112%	90%	78%	88%	91%	$A/E = \frac{\text{actual maturity}}{\text{expected LE}}$ Original LE used until June 2013, biennially revised LE used from June 2013
	RBS	—	—	—	—	45%	47%	—	—	—	$A/E = \frac{\text{number of actual deaths}}{\text{number of expected deaths}}$ Unadjusted ratio
	Assured	—	—	14%	24%	55%	—	—	—	—	No specification

Sources: 21st Services (2010), 21st Services (2011), Lake Consulting Inc (2016), EMSI (2009), Boger & Associates LLC (2010), EEA Investors' Group (2016), The Royal Bank of Scotland (2013), Assured Fund (2013).
In adjusted ratios, number of expected deaths is calculated using the revised underwriting method as of the reporting date.
In adjusted ratios, number of expected deaths as of the estimation date is used.

2 Medical Underwriting in the Life Settlements Market

2.1 An overview of medical underwriting

Medical underwriting for the life settlement industry is known to be an imprecise science, regulated only in Florida and Texas (Horowitz, 2013b). While Florida prescribes extensive oversight of medical underwriters, including triennial filing of a mortality table and A/E (actual to expected) results (The Florida Legislature, 2016), Texas only requires them to be licensed as life settlement brokers (Texas Department of Insurance, 2016). Today, there are four companies that provide the vast majority of medical underwritings ("life expectancies" or "LEs") for the life settlements market. Those are ITM (ITM TwentyFirst LLC, formerly 21st Services LLC), AVS (AVS Underwriting LLC), Fasano (Fasano Associates Inc) and LSI (Longevity Services Inc, formerly EMSI). Each of these four major medical underwriters have been in business for at least 15 years and they have each updated their mortality tables and/or underwriting methods (debits/credits) over the years[3]. The updates resulted in the overall lengthening of life expectancy estimates as insureds were living longer than originally estimated by the medical underwriters.

In the past, other companies such as ISC Services, Midwest Medical Review and Amscot Medical Labs provided LEs but are no longer in business. New medical underwriters have entered the space in recent years but do not seem to have gained significant market shares. During the years of their operation, Amscot Medical Labs and Midwest Medical Review, both purportedly controlled by M.D. George Kindness (SEC, 2007, p. 8), issued unreasonably short LEs that were below half as long as they were supposed to be (State of Texas, 2011, p. 11), which induced substantial overpayment for policies (State

[3]ITM updated its underwriting method in 2005, 2008 and 2013, AVS in 2008 and 2012, and Fasano in 2008.

of Texas, 2011, p. 10).

Some settlement intermediaries' use of notoriously unscrupulous underwriters has also tainted the image of the industry. Even after the indictment of the sham doctor Kindness, a number of life settlement brokers and providers continued to accept the knowingly unreliable LEs from Kindness's underwriting firm Midwest (SEC, 2007, p. 8). In 2012, the SEC charged Life Partners Holdings Inc. for employing an ineligible medical underwriter, Donald T. Cassidy, to issue unfounded LE estimates, which had been "systematically and materially underestimated" (SEC, 2012).

One of the challenges for the life settlement industry is assessing the accuracy of the medical underwriters. Although each of the medical underwriters will license their historical underwriting data for a fee, there are no publicly available reports. Furthermore, when trying to gauge the accuracy of LE estimates, no perfectly unbiased methodologies exist. For instance, point estimate and mortality distribution methodologies, two widely employed measurements, generate an A/E ratio approaching 100% in the long term (Fasano, 2013, p. 3). In October 2010, AVS Underwriting, 21st Services, EMSI and ISC Services formed Life Expectancy Providers (LEPr) that took a position as to the use of LE estimates that was different than that of the Life Insurance Settlement Association (LISA). While LISA advocated using the original LE estimates provided to the clients (Horowitz, 2010, p. 8), LEPr prefer to include, in addition to historical basis A/E ratios, restated LE estimates in evaluating their forecast accuracy (LEPr, 2011, p. 5). As there is no consensus how the accuracy of LE estimates should be assessed, when reporting their underwriting performance underwriters are free to choose their methods (usually not described in detail in their A/E reports) and to interpret the results. This could partially explain why some underwriters have claimed a high level of accuracy but investors have not seen commensurate results (Table 1).

2.2 Medical Underwriting approaches

ITM

ITM uses a proprietary software system to estimate LEs. Applying ITM's underwriting manual, underwriters exercise judgment in reviewing the insureds' medical records and inputting conditions and other factors (e.g., family history, BMI, lifestyle factors) relevant to the insured into the system. Based on the inputs, the system then calculates the debits and credits and derives a mortality multiplier. The multiplier is applied to ITM's mortality tables based on life settlement data. The end product is a mean life expectancy estimate with a full mortality curve (ITM TwentyFirst, 2016b, p. 1). Both the mortality multiplier and mortality tables are data-driven. ITM reviews its historical data to assess the relative risk of medical conditions and other factors, and assigns them corresponding debits and credits in its software. Their mortality tables include adjustments for expected future mortality improvement. For cases where insureds have terminal conditions, ITM consults with board certified physicians to determine LEs.

This underwriting approach is rule-based. It is designed to limit underwriters' subjectivity and provide consistent, reproducible results. As the underwriters do not calculate their own debits and credits for impairments, no two underwriters will come up with a different life expectancy estimate for insureds with the same conditions. This can become disadvantageous as there are instances where human judgement add value (Siegert, 2010, p. 11). In addition, to ascertain that the system captures all the relevant parameters and that the algorithm correctly colligates all the input information, underwriters need medical data from a statistically sufficient quantity of insureds. However, due to high-paced developments in today's healthcare environment, any historical, data-based algorithm can become obsolete. To keep the system as up-to-date as possible, ITM has to invest substantial time and resources maintaining and analyzing its data, and consulting with leading medical professionals.

AVS

Following intake all AVS files are transferred to two companies in India. These companies organize all files in chronological order, and remove pages that are duplicate or not associated with the insured being reviewed. Each file is then reviewed by a nurse who identifies all relevant medical information and writes a medical summary which is later used for the written report to AVS clients. This information is entered into a proprietary software developed specifically for an LE determination. The file then progresses to a medical underwriter who utilizes the information created by the medical staff to create a debit/credit model for each insured.

AVS uses a continuum for the debit structure, which means it recognizes, e.g., that not all coronary disease has the same debit and that the range can be from mild to severe or beyond. The underwriter at AVS creates debits and credits for each insured but the program itself manages the addition and subtraction of debits and credits with gender, smoking status and age upon review in order to estimate the LE. In all cases the AVS manual is a rule-based system and determines the structure of the process. As such, when underwriting performance of insureds with a specific health impairment turns out to be systematically inaccurate, the company can make adjustments to the rules and correct faulty LEs of that insured group. In addition, AVS can easily recalculate LEs to backtest any changes it plans to implement.

Fasano

Fasano applies a case-driven method where medical professionals review medical records and determine the life expectancy based on their judgment. The process includes four steps for each case. In the first pre-screening step, each case is summarized into a few lines containing the most relevant medical information of the insured. Cases are then roughly categorized into class 1, 2 or 3 per complexity, the higher the class number, the more complicated the case. Medical professionals with diverse specializations and various levels of expertise are then assigned to specific cases according to the case's primary impairment and level of complexity. The medical professionals then decide the underwriting method to use depending on the specifications of each case. The debit-credit method is applied to normal cases, where underwriters book debits to adverse medical conditions that impair health and award credits to positive traits such us adequate therapies and a healthy lifestyle. Research-based clinical judgment is required in complicated cases where insureds suffer from rare diseases and/or multiple conditions that interact with each other. Underwriters qualitatively note comments and explanations in their case-review. Together with specified survival curve and LE, the underwriter passes the notes onto a second underwriter, who is at least as experienced as the primary underwriter, for a peer review. The peer reviewers then issue a second LE based on their own judgement. Usually the primary and secondary LEs are close to each other, which makes their reconciliation fairly easy. Generally, reconcilers select a mortality multiplier that is at or between the two values established by the primary and peer reviewing physicians, before calculating the final LE. On occasion, however, two LEs are years apart from each other. This can occur in the most complex and uncertain cases where, for example, someone needs an organ transplant to survive, but with different underwriter assessments as to whether or not the individual will qualify for — and successfully undertake — a lifesaving transplant.

Fasano's underwriting method takes into account qualifying information that an algorithm-based methodology might not. For example, if an older individual should be brought in for a physical that produces a low FEV1 ratio, which is a measure of pulmonary function, an inflexible approach might assess a high mortality rating based on the low, seemingly objective measure of pulmonary function. However, it is often the case that older people who are brought in by well-intentioned children for physicals, do not come in enthusiastically. In those cases, a low-level effort on a pulmonary function test could produce a misleadingly poor test result for which trained underwriters using a holistic approach would adjust. Underwriters' judgement at this stage is checked and balanced through peer review and further reconciliation. The process is again susceptible to a certain degree of subjectivity and inflexibility since all the reviews are bespoke instead of pre-programmed. The approach is subjective as different underwriters could come up with different results based on their read of the medical records or their own personal biases with respect to specific conditions. It is inflexible in that back-testing is almost impossible whenever a methodological improvement is made. A new underwriting method cannot be practically applied to historical cases, because that would entail those old cases being manually revised all over again. It is thus challenging to empirically test the veracity of new or old methods.

LSI

LSI maintains the clients' database in its Life Expectancy Fulllment System (LEFS). It has a relatively straightforward underwriting method similar to that of AVS. Unlike ITM, which uses an algorithm-driven approach, LSI, together with AVS and Fasano, manually grants debits and credits to various health conditions. While Fasano conducts a peer review for each underwriting case, LSI performs a secondary review only in uncommon or complex cases and audits 50% of each underwriter's case on a monthly basis.

2.3 The mortality multiplier k

A typical procedure for medical underwriters to calculate LE is as follows[4]:

1. Find out the basic mortality rates.

   (a) Select the mortality table.
   Underwriters need to select the suitable mortality table dependent on their calculation basis, and the insured's demographic and medical characteristics. Each underwriter has its own proprietary mortality tables. A publicly available set of tables is provided by the Society of Actuaries (www.soa.org), who issues Valuation Basic Tables (VBT) circa every seven years since 2001. Each VBT table is designed for a certain combination of an age calculation approach (age-nearest birthday (ANB) / age-last birthday (ALB)), a gender (male / female) and a smoking status (smoker / non-smoker)) of insureds.

   (b) Calculate the insured's underwriting age x.
   Under ANB, an insured's age is rounded to the nearest integer, while under ALB, the age is rounded down. If an insured's actual age is 80.34 years old, then the underwriting age is 80 under both ANB and ALB. If the actual age is 80.54 years old, then the underwriting age is 81 under ANB and 80 under ALB. Some underwriters (e.g. ITM TwentyFirst, 2016a, p. 2) use exact age and interpolate mortality rates, which prevents jumps in LE when an insured rolls over a birthday (compared to ALB) or birthday plus 6 months (compared to ANB). With the underwriting age calculated, underwriters can use the corresponding mortality rates $\{_{t}|Q_x\}_{t\in\mathbb{N}}$ as the baseline of their LE estimation.

Table 2: Excerpt of 2015 VBT Male Nonsmoker ANB Mortality Rates, $x = 80$

Duration ($t+1$, in year)	1	2	3	4	5	6	7	8	···
Mortality rates ($_{t}\vert Q_x$)	0.00487 ($_{0}\vert Q_{80}$)	0.00797 ($_{1}\vert Q_{80}$)	0.01386 ($_{2}\vert Q_{80}$)	0.02054 ($_{3}\vert Q_{80}$)	0.02658 ($_{4}\vert Q_{80}$)	0.03391 ($_{5}\vert Q_{80}$)	0.04414 ($_{6}\vert Q_{80}$)	0.05783 ($_{7}\vert Q_{80}$)	···

Source: www.soa.org/files/research/exp-study/2015-vbt-smoker-distinct-alb-anb.xlsx. $_{t}|Q_x$ is the one-year conditional mortality rate, the probability that the person aged x will die in a year, deferred (t) years; i.e. the person will die in the $(t+1)^{\text{th}}$ year.

2. Determine the mortality multiplier k.
   This is a crucial step in underwriting. The multiplier k is a positive number that describes the ratio between the mortality rate of the insured concerned and that of the lives represented in the table.

[4] LE refers to "mean LE" in this paper. In practice, LE can also be short for LE50, or "median LE", which is the time span during which the unconditional survival rate drops from 100% to 50%.

Underwriters use the multiplier to accelerate ($k > 1$) or decelerate ($k < 1$) an insured's mortality rates. By default, someone with a standard health condition in his/her demographic group has a mortality multiplier equal to 100%, or 1. Other things being equal, a greater k implies a worse health condition and results in a shorter LE. Factors considered here include weight, height, alcohol use, illness and its severity, family medical history, lifestyle, etc. (see e.g. TwentyFirst, 2014, p. 2). In addition, underwriters need to take into account that some health impairments exacerbate each other, and that some treatments solve problems for multiple impairments. The capability of boiling all the available qualitative information of the insured down to one single quantitative indicator k demands technical skills and is the core competency of an underwriter. As there is no rule or standardized methodology to date to estimate k, the figure is subjective to some extent.

3. Compute the LE.

$$LE = \sum_{i=0}^{\infty} {}_{i+1}p_x = \sum_{i=0}^{\infty} ({}_ip_x \cdot {}_{i|}p_x) \tag{1}$$

where

$$\begin{aligned} &\forall i \leq 0, {}_ip_x \equiv 1 \\ &\forall i \geq 1, {}_ip_x = \prod_{j=0}^{i-1} {}_{j|}p_x \end{aligned} \tag{2}$$

$${}_{i|}p_x = \sqrt[n]{\max(0, 1 - k \cdot {}_{\lfloor \frac{i}{n} \rfloor|}Q_x)} \tag{3}$$

${}_ip_x$: the probability that the insured will live i periods.
${}_{i|}p_x$: insured's one-period conditional survival probability at time i, the probability that the insured will be alive at the end of $(i+1)^{\text{th}}$ period given that the person is alive at the end of i^{th} period.
n: number of periods in a year, e.g., when i increments in year, $n = 1$; when in month, $n = 12$.

LE is a function of k and $\{{}_{t|}Q_x\}_{t\in\mathbb{N}}$. Ceteris paribus, a greater k implies faster mortality rates and hence a shorter LE. In this paper, we employ the latest VBT (VBT15) as the mortality rate basis. We use ANB to determine an insured's underwriting age, and with the information of gender and smoking status known, we can easily find out the base mortality rates $\{{}_{t|}Q_x\}_{t\in\mathbb{N}}$ from one of the four VBT-ANB tables (gender and smoker distinct). While $\{{}_{t|}Q_x\}_{t\in\mathbb{N}}$ is already age-, gender-, and smoking-specific, k only entails information of an insured's health impairment (excluding smoking) and represents an underwriter's personal judgement. Therefore, we consider k to be a more comparable variable than LE, especially when we compare medical underwriting in demographically heterogeneous cohorts.

2.4 The economic significance of k

For each policy, the death benefit DB and the premium stream $\{\pi_i\}_{i\in\mathbb{N}}$ are fixed for pricing. Given the desired return r and the estimated mortality multiplier k (which further determines the insured's conditional survival rates $\{_i|p_x\}_{i\in\mathbb{N}}$ and conditional mortality rates $\{1 - {}_i|p_x\}_{i\in\mathbb{N}}$), we can calculate the price factor P_0 as follows:

$$
\begin{aligned}
&\text{if } \forall i, {}_i|p_x > 0,\\
&P_0 = -\nu_0 + \sum_{i=1}^{\infty} \frac{{}_{i-1}p_x \cdot (1 - {}_{i-1}|p_x) - {}_ip_x \cdot \nu_i}{(1+r)^i} = \sum_{i=0}^{\infty} \left({}_ip_x \cdot \frac{\delta_i - \nu_i}{(1+r)^i} \right)\\
&\text{if } \exists \tilde{i} \in \mathbb{N}^*, {}_{\tilde{i}-1}|p_x > 0 \text{ and } {}_{\tilde{i}}|p_x = 0,\\
&P_0 = \sum_{i=0}^{\tilde{i}} \left({}_ip_x \cdot \frac{\delta_i - \nu_i}{(1+r)^i} \right) + \frac{{}_{\tilde{i}}p_x}{(1+r)^{\tilde{i}+1}}
\end{aligned}
\tag{4}
$$

where

$$P_0 = \frac{TP}{DB} \tag{5}$$

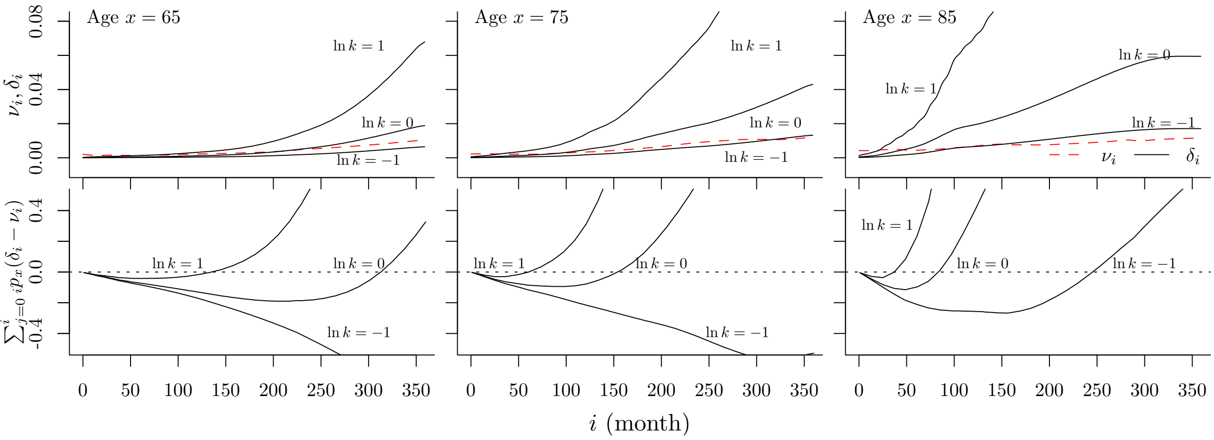
$$\nu_i = \frac{\pi_i}{DB} \tag{6}$$

$$
\begin{aligned}
&\forall i \leq 0, \delta_i \equiv 0\\
&\forall i \geq 1, \delta_i = \frac{1 - {}_{i-1}|p_x}{{}_{i-1}|p_x}
\end{aligned}
\tag{7}
$$

r: expected internal rate of return.
TP: transaction price of the life insurance policy at time 0.
DB: net death benefit at time 0.
P_0: price factor, transaction price as a fraction of net death benefit.
π_i: premium to be paid at time i, for the coverage between i and $(i+1)$, given the insured's survival at time i.
ν_i: premium rate time i, the premium at i as a fraction of net death benefit.
δ_i: ratio between insured's conditional death probability and survival probability at time i, given that the insured is alive at time $(i-1)$.

To achieve a positive P_0, it is important to prevent δ_i from frequently dropping below ν_i, especially in the early period when the discount factor $\frac{1}{(1+r)^i}$ is close to 1 and the unconditional survival rate ${}_ip_x$ is relatively high. The magnitude of δ_i can be elevated by a higher k, as illustrated in the upper plot of Figure 3. We show k in its log form in Figures 3 and 4 to be consistent with further analysis in this paper. To assess the economic influence of k in depth, we simulate three scenarios (the insured being a male non-smoker at age 65, 75 and 85 respectively) using our main sample data (see Section 3.1 for sample description). For each scenario, we extract the relevant transactions according to the corresponding insured's gender, smoking status and age (e.g. only transactions with a 65-year-old male non-smoker considered for the first scenario), and then take the average premium rates of those transactions on a monthly basis to build simulated premium rates $\{\nu_i\}_{i\in\mathbb{N}}$.

Figure 3: k's effect on $\frac{\text{mortality}}{\text{survival}}$ (δ_i) curve and cumulative cash $(\sum_{j=0}^{i} {}_ip_x(\delta_i - \nu_i))$ curve from simulated universal life policies of an x-year-old male non-smoker

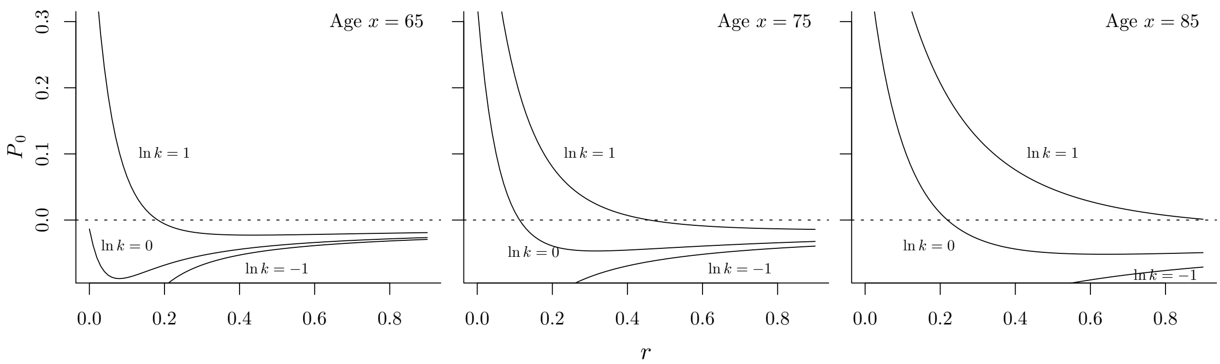


$\ln k = -1 \Leftrightarrow k = 0.368$; $\ln k = 0 \Leftrightarrow k = 1$; $\ln k = 1 \Leftrightarrow k = 2.718$.
We pick out all the universal life policies in our main sample (see Section 3.1 for sample description) of an x-year-old male non-smoker with a positive monthly premium rate throughout 30 years after purchase, i.e., from $i = 0$ to $i = 359$. To simulate a monthly premium rate ν_i, we average the premium rates in month i of all the selected policies.
Higher k elevates δ_i and accelerates the attainment of the break-even-point.

Figure 3 demonstrates how a change in k shifts the position of the δ_i curve relative to the ν_i curve in the upper panel, which further influences the shape of the cumulative undiscounted cash $\sum_{j=0}^{i} {}_ip_x(\delta_i - \nu_i)$ curve as plotted in the lower panel. The cumulative cash curve always goes downwards first, indicating a negative cash flow in the early period. This corresponds to the high probability of premium payment and low probability of death benefit collection. When k is large enough, the cash curve is convex, which means the cumulative premium payment is actuarially offset by the cumulative payout from death benefit at some point (the break-even point, purchase price disregarded). In such cases, a larger k leads to a faster achievement of the break-even point. When k is too small (e.g. $\ln k = -1$ while $x = 65$ or 75), the cash curve is concave, implying that the death benefit will not be sufficient to cover the premium payment, probabalistically speaking. Sensible investors would never purchase a policy with such a small k, or would let it lapse if such a policy has been acquired. We also observe from Figure 3 that the bar of k gets lower as age x gets higher. For the policy to be economically meaningful, k needs to reach a higher threshold when $x = 65$ than when $x = 85$. Therefore in the life settlements market, insureds of the policies should be either senior (large x) or health-wise impaired (large k).

Figure 4 illustrates how different levels of k affect the $r \to P_0$ curve. Given a certain positive r, a higher k indicates a larger P_0. Similarly, given a certain positive P_0, a higher k implies a higher r. Similar to Figure 3, we see from Figure 4 that when k is too small, P_0 can be constantly negative regardless of the choice of r. Policies with such a low k would normally not be able to enter the market, or would be lapsed once purchased. Besides, at the same level of k and r, P_0 increases with the increment of x. This is to say, when an insured is old enough, his / her policy can be worth the investment even if the person is not very sick.

Figure 4: Price factor (P_0) against return (r) by mortality multiplier (k)



When k is not sufficiently high, no r leads to a positive P_0. P_0 being positive and constant, higher k implies higher expected r; r being constant, higher k implies higher P_0.

3 Empirical Analysis

3.1 Data and Sample Selection

Main sample

Our main sample which we used to commence our study was provided by AA-Partners Ltd (AAP), an independent consulting firm specialized in life settlements. AAP maintains a comprehensive network in the life settlements industry through which it collects data from participating firms. AAP receives transaction data with important deal characteristics (e.g. price, face amount, life expectancy) from various life settlement providers (Table 7) on a monthly basis.

This sample consists of life settlement deals data, most of which (2,917 out of 3,236) entail LE data. Out of 2,917 lives, 2,014 were estimated by at least one of the following four firms: ITM, AVS, Fasano, and LSI, which are considered to be among the most important U.S. medical underwriters in the field

(Russ, 2005, p. 5).

The data, covering the period January 2011 to December 2016, include both secondary market transactions and tertiary market transactions. The total face value of all the insurance policies in our sample data amounts to USD 6.4 billion by the date of transaction, while the settling of those policies was priced at USD 1.2 billion in total. Table 3 describes more characteristics of the life settlements sample.

Table 3: Descriptive statistics, main sample

		n	Min	Median	Max	Mean
Full sample	Transaction date	3,236	07/01/2011	24/03/2015	31/12/2016	03/11/2014
	Age (year)	3,234	20.2	80.7	101.0	78.3
	ITM LE (month)	2,026	5.2	63.8	342.0	70.0
	AVS LE (month)	2,794	5.1	81.0	266.1	85.9
	Fasano LE (month)	445	6.0	111.0	280.1	104.2
	LSI LE (month)	185	17.5	97.4	253.1	95.4
Sec. mkt.	Transaction date	2,261	07/01/2011	06/03/2015	31/12/2016	23/10/2014
	Age (year)	2,261	20.2	78.5	101.0	76.3
	ITM LE (month)	1,267	5.2	61.8	312.0	68.2
	AVS LE (month)	1,913	5.1	82.4	266.1	87.8
	Fasano LE (month)	356	6.0	111.5	280.1	104.6
	LSI LE (month)	118	17.5	102.4	253.1	100.7
Tert. mkt.	Transaction date	975	14/02/2011	28/05/2015	31/12/2016	29/11/2014
	Age (year)	973	44.4	84.0	97.8	83.1
	ITM LE (month)	759	7.1	65.0	342.0	73.0
	AVS LE (month)	881	10.0	77.6	260.0	81.9
	Fasano LE (month)	89	10.0	109.0	179.0	102.8
	LSI LE (month)	67	22.3	82.8	217.4	86.2

For every transaction, the age is current as of the transaction date, and each LE is age-adjusted accordingly. We set our focus on ITM and AVS in this study. On Fasano and LSI we mostly apply descriptive analysis because of sparse data, especially in the early sample period and in the tertiary market.

Although Table 3 presents descriptive statistics of LE estimates by the four medical underwriters side by side, the figures need to be compared with caution because not all the underwriters have evaluated the same deals. Deals are distributed across underwriters and markets, the vast majority having two LE estimates. Specifically, out of the 3,236 deals, 2,261 took place in the secondary market, 1,365 of which involve at least two of the aforementioned medical underwriters; and 975 deals were settled in the tertiary market, 807 of which were evaluated by two or more of the four medical underwriters (see Table 4). Deals with at least two LE estimates provide a strong basis for the analysis of the underwriters' practices relative to each other. Table 5 further lists numbers of settlements valued simultaneously by two underwriters. As LE estimates appear to be highly correlated, they may be viewed as manifestation of the true underlying LE. We focus on those settlements to create meaningful comparisons between underwriters. We are particularly interested in the relations between ITM, AVS and Fasano, since the data from LSI are relatively sparse. Later in the paper we discuss the results of a descriptive analysis on the sparse data, for which statistical testing lacks explanatory power.

Table 4: Number of LEs by number of medical underwriters involved

Number of LE estimates	0	1	2	3	4	Total
Secondary Market	83	813	1,257	105	3	2,261
Tertiary Market	26	142	767	40	0	975
Full Sample	109	955	2,024	145	3	3,236

The main sample mostly consists of deals with LEs from two different underwriters. Few deals are evaluated by more than two underwriters.

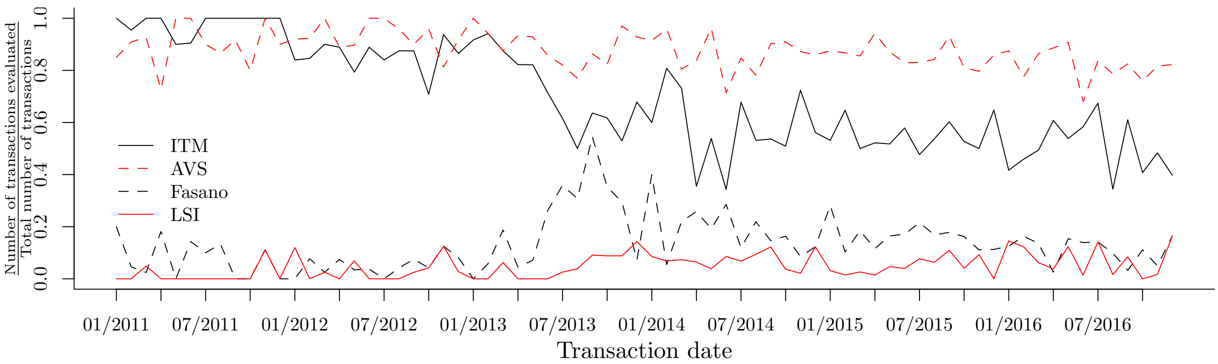
Table 5: Properties of LE pairs, main sample

	Δ \ n	ITM	AVS	Fasano	LSI	p \ ρ	ITM	AVS	Fasano	LSI
Full Sample	ITM	—	1,759	168	92		—	0.83	0.85	0.79
	AVS	12.7	—	311	129		0.000***	—	0.91	0.79
	Fasano	14.1	1.1	—	18		0.000***	0.053	—	0.97
	LSI	9.9	-4.5	2.1	—		0.000***	0.081	0.170	—
Sec. mkt.	ITM	—	1,053	125	60		—	0.84	0.86	0.82
	AVS	14.2	—	248	91		0.000***	—	0.91	0.80
	Fasano	12.1	-0.6	—	13		0.000***	0.600	—	0.97
	LSI	9.7	-7.8	1.1	—		0.005**	0.013*	0.610	—
Tert. mkt.	ITM	—	706	43	32		—	0.82	0.84	0.67
	AVS	10.4	—	63	38		0.000***	—	0.89	0.76
	Fasano	20.1	8.0	—	5		0.000***	0.001**	—	0.99
	LSI	10.4	3.4	4.7	—		0.035*	0.473	0.058	—

We call two underwriters' LEs pertaining to the same transaction a "pair" of LEs.
n: number of LE pairs. Most deals have LEs from ITM paired up with AVS. Few deals involve both Fasano and LSI.
Δ: arithmetic mean of LE difference in LE pairs, calculated by taking the average of row LEs subtracted by column LEs. In the sample concerned, the disparity between ITM and other underwriters is the greatest. On average, ITM is shorter by 12.7 months than AVS, by 14.1 months than Fasano and 9.9 months than LSI.
ρ: correlation between paired LEs. Paired LEs are highly correlated.
p: p-value of a Wilcoxon signed-rank test. Significance levels of 0.05, 0.01 and 0.001 are marked with "*", "**" and "***" respectively (sic passim). We have also conducted paired two-sided Students' t-tests, which render similar results that ITM LEs are consistently and significantly different from other underwriters' LEs.

Figure 5 depicts the relative market shares of the four underwriters. In 2013, ITM's market share dropped dramatically while Fasano's experienced its peak. Shortly thereafter, the market normalized with ITM and Fasano returning to their previous market shares. The change in market share at the time could be explained by that fact that ITM announced in January 2013 a change in its debits/credits and mortality tables which led to an extension of 19%, on average, of its LE estimates (Horowitz, 2013a, p. 2). The methodological modification was in response to the high rate of over-survivorship of insureds previously underwritten by ITM (Granieri et al., 2014, p. 5).

Figure 5: Relative market shares



Relative market shares of Fasano and LSI are comparatively stable. A drastic downturn in ITM's market share as well as a sharp peak of Fasano's can be observed in year 2013.

Side samples

Two anonymous investors also provided us LE-related information on the in-force policies from their life settlements portfolios. All of the policies are evaluated by (and only by) both ITM and AVS. The LE data from the side samples are not incorporated into by the universe of the main sample. The three samples are not mixed together and are analyzed separately. In the later part of the paper, we compare LE landscapes across samples to obtain a view of medical underwriting from the standpoint of both intermediaries and investors.

From the policies we received from the two investors, we filtered out joint policies, and for the sake of comparability omitted the policies where the underwriting dates from ITM and AVS were more than 45 days apart in order to minimize the impact on estimate differences due to health-changing events occurring between the two underwriting dates. Table 6 presents the descriptive statistics of the filtered data from the two side samples. Side sample 1 consists of 584 policies, underwritten between November 2015 and November 2016. Side sample 2 is composed of 552 policies, covering the period June 2009 to October 2016.

Table 6: Descriptive statistics, side sample

		n	Min	Median	Max	Mean
Side Sample 1	ITM undewriting date	584	02/11/2015	14/03/2016	07/10/2016	07/03/2016
	ITM Age (year)	584	64.0	84.7	98.3	84.3
	ITM LE (month)	584	11.0	76.5	283.0	85.1
	AVS undewriting date	584	02/11/2015	28/03/2016	01/11/2016	16/03/2016
	AVS Age (year)	584	64.0	84.7	98.2	84.4
	AVS LE (month)	584	12.0	74.0	180.0	79.3
Side Sample 2	ITM undewriting date	552	26/06/2009	26/05/2015	24/10/2016	18/02/2015
	ITM Age (year)	552	54.8	80.2	98.1	80.8
	ITM LE (month)	552	6.0	132.0	291.0	129.6
	AVS undewriting date	552	25/06/2009	14/05/2015	25/10/2016	15/02/2015
	AVS Age (year)	552	54.9	80.2	98.2	80.8
	AVS LE (month)	552	12.0	125.5	222.0	125.0

For each policy, the age and LE are current as of the underwriting date.

3.2 Findings

We start by looking into the differences in LE estimates between medical underwriters. From Table 5 we observe that in our main sample, ITM provides shorter LEs on average than all the other three underwriters in both the secondary and the tertiary market. While differences in LE estimates also exist among AVS, Fasano and LSI, the magnitude is much smaller and the significance level is much lower.

Since we are looking at the exact same transactions in both sub-samples, there is no difference in age or health impairment that could explain the divergence in LE estimates. One might argue that the time gaps in between underwriters' estimations might also contribute to the LE difference. Yet as a matter of fact, the average time lapse from the LE estimation date to the transaction closing date in the secondary market is merely 3 months. An LE estimate older than six months would be annulled and required to be replaced by a refreshed estimate. Therefore in the secondary market, the LE date difference is negligible, and the LE estimates can all be considered actual by the date of transaction in the secondary market. In the tertiary market, some LE data may be outdated when, for instance, original insureds refuse to provide their latest medical records. In such cases, AAP reverse calculated the implied mortality multiplier k, and reapplied k to standard mortality rates to calculate the LE estimate current as of the transaction date.

As a great many of lives in our sample data are valued by several underwriters simultaneously (Table 4), we can directly compare the LE pairs to see which underwriters tend to give shorter estimates and which longer. However, as long as two LEs are not related to the same insured and/or not evaluated around the same time, the direct comparison of LEs can be misleading. For example, a demographic group of 60-year-old people with a standard health condition naturally has a longer average LE than a group of 90-year-old also with a standard health condition. On account of this, we use the implied mortality multiplier k to proxy the degree of LE adjustment from base mortality, since k serves as a measurement of health impairment that is normalized to age, gender, and smoking status.

To reverse calculate k, we apply the base mortality rates $\{_{t}|Q_x\}_{t\in\mathbb{N}}$ from the four VBT15-ANB tables (gender and smoker distinct). By plugging the known $\{_{t}|Q_x\}_{t\in\mathbb{N}}$ and LE from an underwriter into the equation set (1)-(3), we solve for the implied mortality multiplier k. Since underwriters use their own mortality tables, an implied k can deviate from the original mortality multiplier stated on an LE certificate[5]. Yet by applying the same set of mortality tables to solve each LE-corresponding k, we standardize the k's and make them more comparable. As the value of k in our samples ranges from 0.2 to 6,000, we logarithmize the variable to achieve scalability, and to tone down the impact of those large k's from severely impaired lives on the aggregate results.

For each policy, by plugging an underwriter's implied mortality multiplier k and the transaction price P_0 in equations (4)-(7), we can further calculate the underwriter-specific implied internal rate of return r for that transaction. Ceteris paribus, a greater k is related to a higher r (Figure 4). Figure 6 takes AVS as a benchmark and notes its differences from ITM and Fasano in both $\ln k$ and r. From Figure 6 we observe that AVS's evaluation is closer to Fasano's than to ITM's: compared to $(\ln k_{\text{Fasano}} - \ln k_{\text{AVS}})$, the distributions of $(\ln k_{\text{ITM}} - \ln k_{\text{AVS}})$ are more right-centered (larger μ), more volatile (larger σ), more negatively skewed (larger γ) and more fat-tailed (larger κ). In the distributions of Δr, those features are not only one-to-one mirrored, but also amplified.

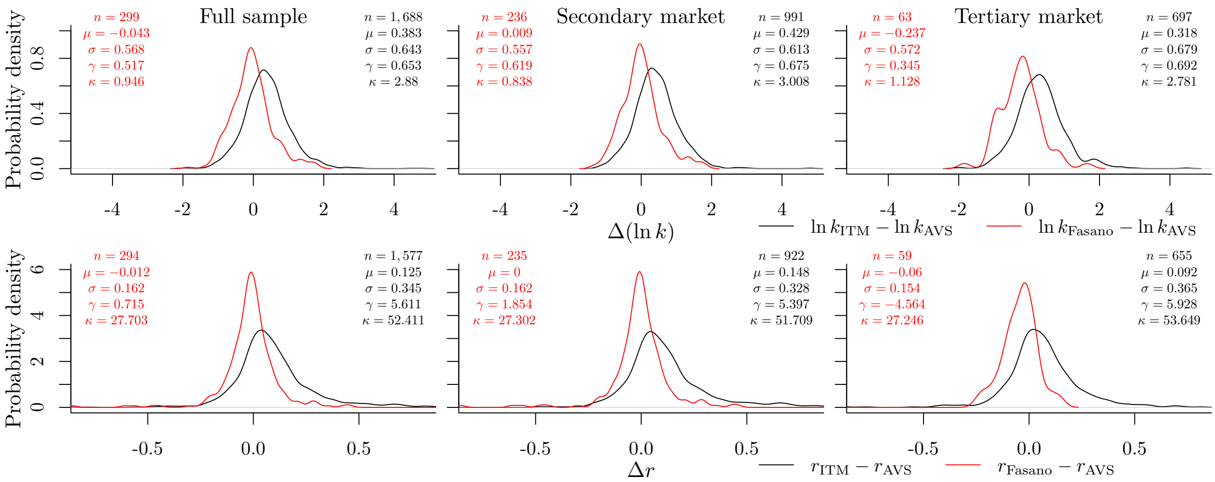
The time series of average $\ln k$ across all transactions in a quarter from ITM and AVS are plotted in Figure 7. The line shapes of the two underwriters are similar, as indicated by the high correlation of their LE estimates in Table 5. The average $\ln k$ of each quarter from ITM is constantly higher than that from AVS throughout the whole sample period in both secondary and tertiary markets. Fasano's and LSI's data are not plotted due to sparse data in some periods and in the tertiary market.

While the main sample demonstrates that ITM tended to issue shorter LEs (represented by higher k's) than AVS, the side samples reveal a different picture (Figure 8). In contrast to the main sample, subset $k_{\text{ITM}} < k_{\text{AVS}}$ accounts for the majority part of the side samples. We also note that the k's in the side samples are generally smaller than those in the main sample.

We compare the demographic characteristics for lives where $k_{\text{ITM}} < k_{\text{AVS}}$ with those for lives where $k_{\text{ITM}} > k_{\text{AVS}}$. For nominal variables such as gender (either male or female) and smoking status (either smoker or non-smoker), we run χ^2-tests to check distribution homogeneity across the two groups. For numeric variables such as age and health impairment, we apply the Kolmogorov-Smirnov test (KS-test)

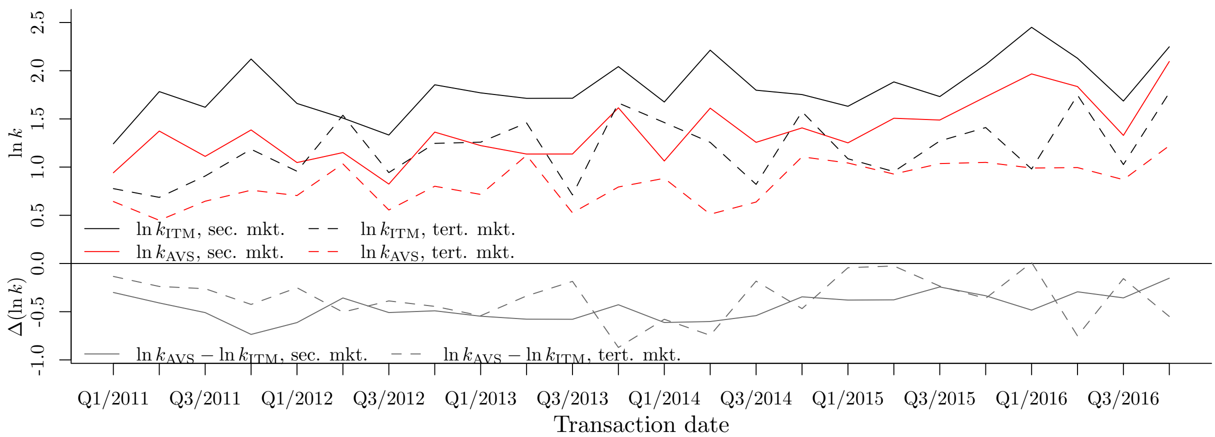
[5]Compared to VBT15-ANB, ITM's base mortality tables have lower rates while AVS's have higher rates. Therefore, a mortality multiplier of 100% stated on an LE certificated issued by ITM implies $k_{\text{ITM}} < 100\%$; analogously, a mortality multiplier of 100% issued by AVS implies $k_{\text{AVS}} > 100\%$, given that k_{ITM} and k_{AVS} are reverse calculated using VBT15-ANB, instead of underwriters' own tables.

Figure 6: Distributions of $\Delta(\ln k)$ and Δr



n: number of observations. μ: mean. σ: standard deviation. γ: skewness. κ: kurtosis. (sic passim)
Differences in $\ln k$ reflect differences in r.

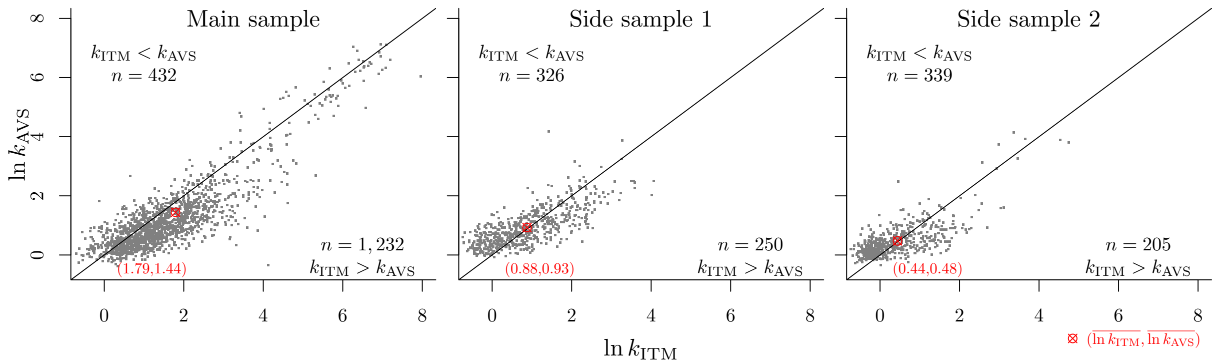
Figure 7: $\ln k$ from ITM and AVS in secondary and tertiary markets, main sample



Only deals with both ITM and AVS LEs are considered. The average $\ln k$ of each quarter from ITM is higher than that from AVS throughout the whole sample period, in both secondary and tertiary markets.

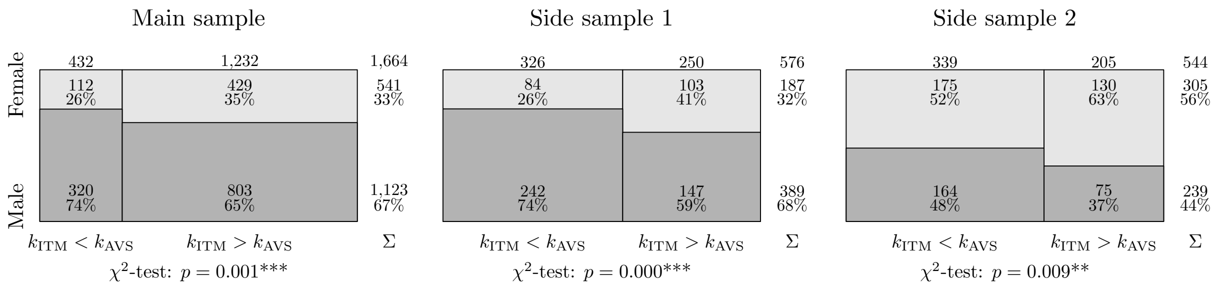
to compare distributions between the two groups. Significant differences can be detected in distributions of gender and health impairment between the two subsets. On a statistically significant level, subset $k_{\text{ITM}} < k_{\text{AVS}}$ is composed of proportionally more male lives (Figure 9), as well as more healthy lives (healthiness proxied by $\frac{\ln k_{\text{ITM}}+\ln k_{\text{AVS}}}{2}$, Figure 10) as comapred with the other subset. No distinguishable patterns are detected when concerning smoking status or age. The distribution of those features is shared among all the three samples.

Figure 8: Scatter plot of $\ln k_{\text{ITM}}$ against $\ln k_{\text{AVS}}$ by sample



Points on the 45° line represent the ideal scenario when $k_{\text{ITM}} = k_{\text{AVS}}$. The main sample consists of more insureds with $k_{\text{ITM}} < k_{\text{AVS}}$ than those with $k_{\text{ITM}} > k_{\text{AVS}}$. The two side samples do not share the same pattern.

Figure 9: Mekko plot of gender against subset $k_{\text{ITM}} < k_{\text{AVS}}$ and $k_{\text{ITM}} > k_{\text{AVS}}$ by sample

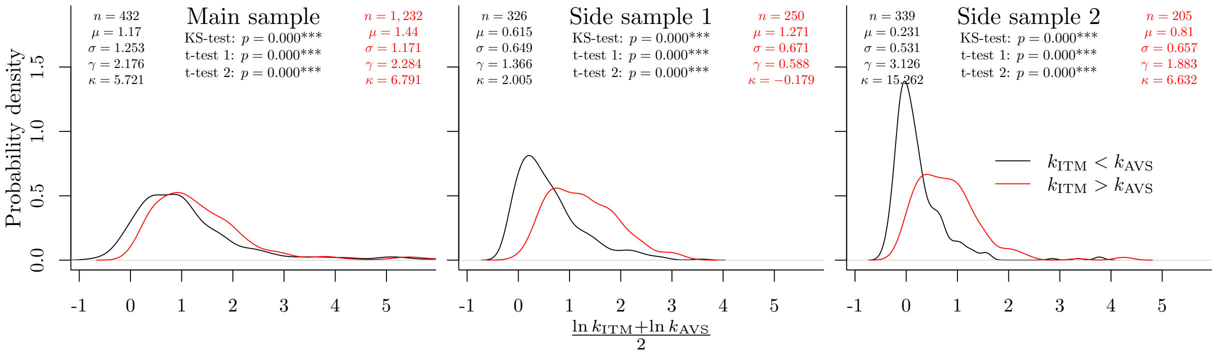


The distributions on gender are significantly different between subset $k_{\text{ITM}} < k_{\text{AVS}}$ and subset $k_{\text{ITM}} > k_{\text{AVS}}$ in all three samples. Specifically, bar male (female) from column $k_{\text{ITM}} < k_{\text{AVS}}$ is always longer (shorter) than that from column $k_{\text{ITM}} > k_{\text{AVS}}$, which means subset $k_{\text{ITM}} < k_{\text{AVS}}$ consists of proportionally more males than subset $k_{\text{ITM}} > k_{\text{AVS}}$.

Despite the common features, a reason must be found to explain differences observed between the main sample and the side samples. One explanation is that the main sample includes LEs prior to the material changes in underwriting methods that ITM implemented in 2013. However, time period and market difference cannot fully explain why cases with $k_{\text{ITM}} > k_{\text{AVS}}$ mostly occurred only in the main sample (Figure 7 shows $k_{\text{ITM}} > k_{\text{AVS}}$ in both markets throughout the sample period 2011-2016). As suggested by ITM, there might have been LEs deliberately omitted from the transactions in the main sample, which has unfairly biased the LE patterns in the sample. To verify this presumption, we compare the subset with only one LE against the subset with multiple LEs (Figure 11). Whichever underwriter is considered, the subset with only that underwriter's LE has generally received a higher k than the subset with additional LEs.

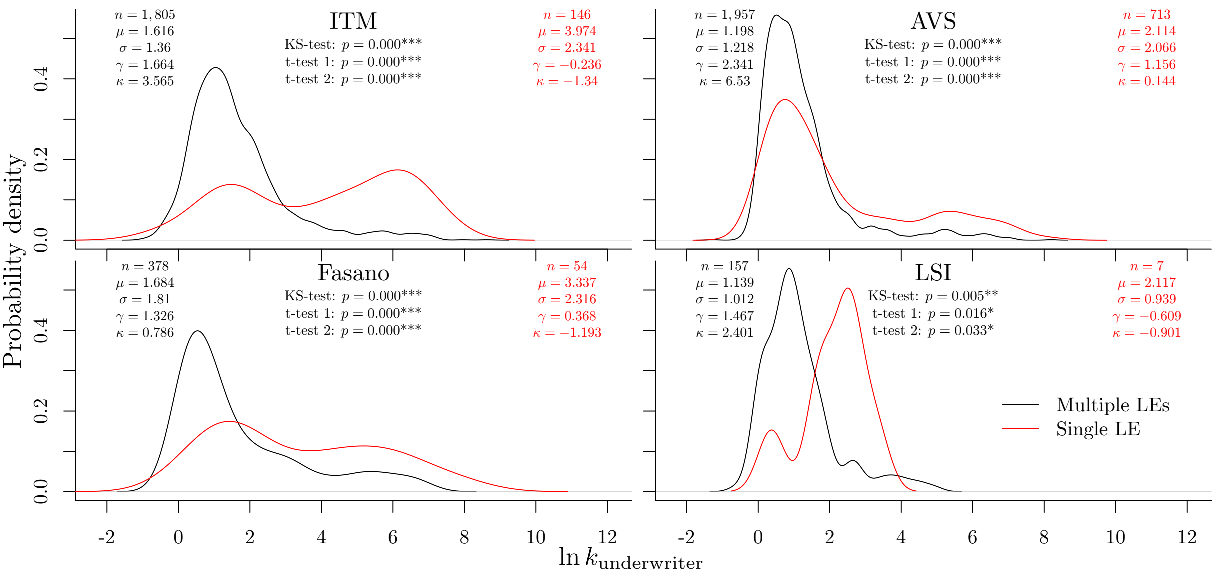
Differences in k also exist between the secondary and tertiary markets. All underwriters appear to accelerate mortality rates in the secondary market more heavily than in the tertiary market, mostly on a highly significant level. The probability curve of $\ln k$ in the secondary market resides on the right-hand

Figure 10: Kernel density of health impairment by sample, subset $k_{\text{ITM}} < k_{\text{AVS}}$ vs. $k_{\text{ITM}} > k_{\text{AVS}}$



Under the alternative hypothesis (H_0) of a Kolmogorov-Smirnov test (KS-test), the distributions of the two subsets differ. Under H_0 of an unpaired one-tailed Student's t-test (t-test 1), the mean of the subset plotted in red is less than that in black. Under H_0 of an unpaired two-tailed Student's t-test (t-test 2), the means of the two subsets differ. (sic passim)
The density distributions on health impairment (proxied by $\frac{\ln k_{\text{ITM}}+\ln k_{\text{AVS}}}{2}$) are significantly different between subset $k_{\text{ITM}} < k_{\text{AVS}}$ and subset $k_{\text{ITM}} > k_{\text{AVS}}$ in all three samples. Specifically, subset $k_{\text{ITM}} < k_{\text{AVS}}$ is in aggregate healthier (smaller $\frac{\ln k_{\text{ITM}}+\ln k_{\text{AVS}}}{2}$) than subset $k_{\text{ITM}} > k_{\text{AVS}}$.

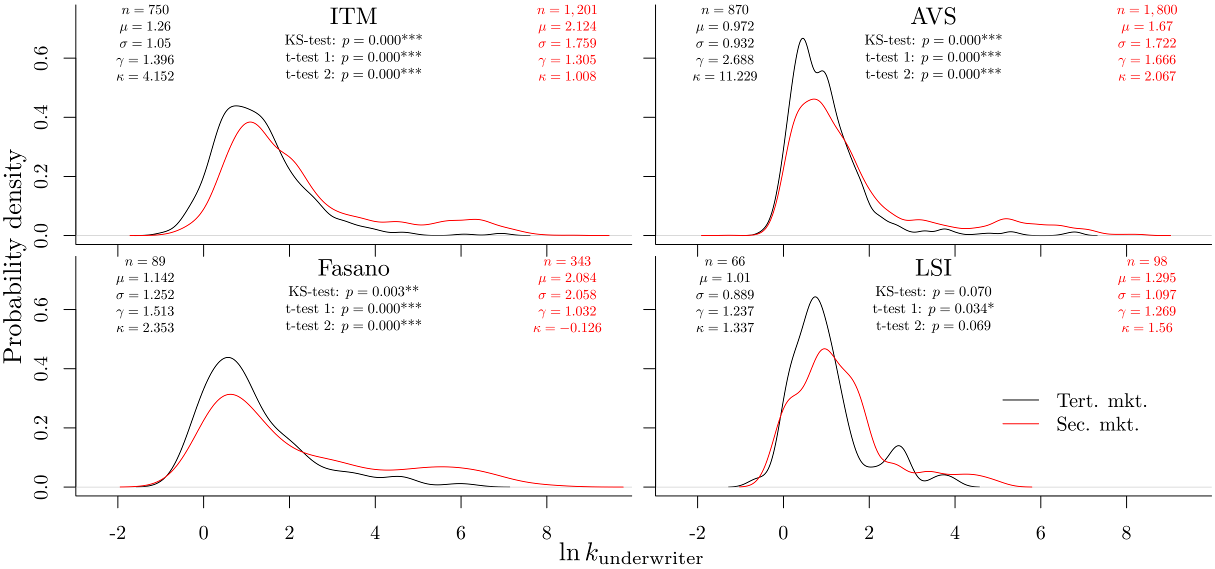
Figure 11: Kernel density of health impairment by underwriter, subset with multiple LEs vs. single LE, main sample



In the upper left plot, ITM's estimation $\ln k_{\text{ITM}}$ is compared between subset of policies with solely one LE estimate from ITM, and subset of policies with LE estimates from ITM and some other underwriter(s). The former subset's $\ln k_{\text{ITM}}$ is in aggregate considerably larger than the latter's. The similar feature, although not as distinct, can be observed when the underwriter is AVS, Fasano, or LSI.

side (the larger $\ln k$ side) of the curve in the tertiary market for all underwriters (Figure 12).

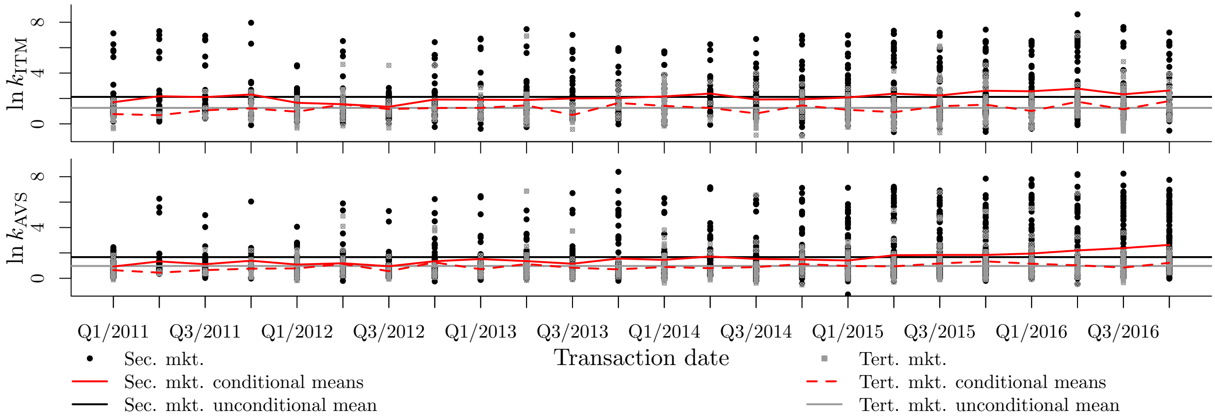
Figure 12: Kernel density of health impairment by underwriter, sec. vs. tert. market



The measures of central tendency (mean, mode, median) of $\ln k$ are larger in the secondary market than in in the tertiary market for all four underwriters.

Both the conditional mean of $\ln k$ per period and unconditional means across the whole sample are higher in the secondary market than in the tertiary markets, both for ITM and AVS (Figure 13). The analysis is based on all transactions for each underwriter, but results do not differ when only those deaths with LE pairs are considered (Figure 7). We also observe a higher likelihood for policies in the tertiary market to receive $k_{\text{ITM}} < k_{\text{AVS}}$ than policies in the secondary market (Figure 14).

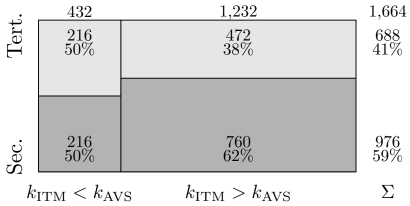
Figure 13: Time series of $\ln k$ distributions by underwriter, sec. vs. tert. market



For both ITM and AVS, the average $\ln k$ of each quarter is always higher in the secondary market than in the tertiary markets throughout the whole sample period.

Figure 14: Mekko plot of markets against subset $k_{\text{ITM}} < k_{\text{AVS}}$ and $k_{\text{ITM}} > k_{\text{AVS}}$ by sample

Main sample



χ^2-test: $p = 0.000$***

The distributions on markets are significantly different between subset $k_{\text{ITM}} < k_{\text{AVS}}$ and subset $k_{\text{ITM}} > k_{\text{AVS}}$ in all three samples. Specifically, bar secondary (tertiary) market from column $k_{\text{ITM}} < k_{\text{AVS}}$ is shorter (longer) than that from column $k_{\text{ITM}} > k_{\text{AVS}}$, which means subset $k_{\text{ITM}} < k_{\text{AVS}}$ consists of proportionally more deals from the tertiary market than subset $k_{\text{ITM}} > k_{\text{AVS}}$.

4 Discussion

4.1 Interpretation of findings

Our analysis shows that there exist significant discrepancies in LE estimates (proxied by k) between underwriters (see e.g. Table 5). Investors still suffer from largely underestimated LEs and face unexpectedly prolonged premium payments and postponed death benefits. Through interviews, practitioners have voiced various personal opinions on these phenomena. Some impute underestimated LEs to mercenary underwriters who intentionally provide low LEs to gain business from intermediaries, as the intermediaries usually present to their investors the LE estimates they order from underwriters. Some blame the skewed market on manipulative sellers and intermediaries of life settlements, who cherry-pick low LEs to artificially elevate policy prices and to collect commissions at the point of transaction closure. Some believe that the investors are also responsible for the malfunctioning market, putting settlement providers under pressure by demanding unrealistically high IRRs.

Underestimated LEs might arise from some myopic underwriters who pursue short-term business gain. However, while underestimation may bring medical underwriters more business from policy sellers in the short term, it compromises investors' interest in the long run, and places the whole life settlements industry in jeopardy. For underwriters valuing sustainability (which we believe are the majority), it could have been an honest mistake on account of varyingly deficient underwriting methods (Section 2.2). No underwriting approach is perfect, and each underwriter has their "quirks": particular medical fields and/or demographic cohorts where they are viewed to be more accurate than their competitors. ITM pointed out one of their underwriting features: their system emphasizes an insured's very positive and very negative health factors, tending to indicate a lower k than their peers' for a very healthy insured, and a higher one for a very unhealthy insured. The underwriter's assessment on its own underwriting is in line with our findings (Figure 10).

Moreover, medical underwriting performance in the life settlements industry is likely to be linked to that in the whole insurance market. Historically, mortality rates on elder populations, which account for the majority part of insureds in life settlements, were seldom statistically robust due to deficient life data. The A/E ratio on insureds between age 80 and 89 of VBT08-ANB, for example, turned out to be a dismal 61.6% (Bahna-Nolan, 2014). As more and more life data on this age group become available, we expect to see continuous improvement in underwriting performance in the future.

On the intermediaries' side, we do detect signs of adverse selection. Based on Figure 10, we have learned that compared to AVS, ITM is more conservative (corresponding to larger LE, or smaller k) when it comes to healthy lives and more aggressive (corresponding to smaller LE, or larger k) in the case of impaired lives. Figure 11 shows that lives evaluated by ITM alone are mostly heavily impaired, for whom AVS would have issued a more conservative LE estimate. On the other hand, lives evaluated solely by AVS are relatively healthy, for whom ITM would have issued a more conservative LE estimate. However, those lives with a single LE were either never given to an underwriter who would have assigned them longer LEs, or another underwriter's LE estimates were issued but then discarded or never disclosed by intermediaries. From Figure 11 we additionally observe that lives with a single LE have received more aggressive LE estimates than lives with multiple LEs. Therefore, we do have reason to believe that certain intermediaries understand the different underwriting patterns of individual underwriters, and tend to accordingly pick the most aggressive underwriter(s) for a particular case.

Some intermediaries maintain that nowadays they are not able to choose medical underwriters at will, since more and more of their investors designate underwriters themselves. LE disparities are said to be tolerated mostly by sophisticated investors. After mastering estimation patterns of different underwriters, those investors price in their confidence in the LEs on a particular trade. Distorted incentives might also appertain to investors, or to be more precise, buy-side representatives such as asset managers and employees from investment firms, who do not necessarily invest with money from their own pocket and hence have little skin in the game. Other parties in the market complain that many investors insist on unattainably high IRRs, that a little LE "maneuvering" is indispensable to convince investors and to drive the business. On top of that, some investors might underestimate the negative impact on return from inaccurate LEs.

The observation that k in the secondary market is larger than in the tertiary market could be explained by two assumptions: (1) k's are deliberately overestimated in the secondary market compared to the tertiary market, and/or (2) health impairments of insureds in the secondary market are more severe than those in the tertiary market.

As discussed in Chapter 2, high k's are desired by settlement intermediaries, who are the underwriters' clients. Therefore, exaggerated k's could attract new business. New business also means valuable information of new lives for medical underwriters in the secondary market, and ample live data is critical for underwriters to test their methods. In addition, underwriters usually get to review lives they have already examined in the secondary market, as, for the sake of consistency, investors tend to stick with the same underwriter for the LE estimate update of a given life. That is to say, an order to estimate the LE on a new life from the secondary market means very likely repeat orders for reviewing that life in the future.

The incentive theory can be challenged on a number of grounds. First, only a small portion of the revenue earned by medical underwriters is generated from the secondary market. The vast majority of their revenue is tied to tertiary market LEs. Second, ITM, for example, issues longer LEs (lower k) for secondary policies than for tertiary policies as their mortality tables for the two types of transactions are different (fewer mortalities in early durations for secondary market cases), which is not directly observable in our data sample. The rationale behind this discrimination is the adverse selection from insureds (21st Services, 2013, p. 3). It is widely understood that insureds are usually a better judge of their own health condition than medical underwriters who evaluate lives solely based on sometimes incomplete medical records. Insureds who are interested in selling their policies are usually those who feel fit themselves (and most likely this feeling accurately reflects their real health condition) despite what their medical records imply (Bauer et al., 2014). They benefit considerably from life settlements on account of the high price of their policies, since their medical records indicate undue impairments (A.M. Best, 2016, p. 15). In addition, the huge backlog suffered by ITM and AVS at the moment (Horowitz, 2016a) may not cause these underwriters to worry about too little business, but too much.

Assumption (2) that insureds are healthier in the tertiary market can be backed by a legacy issue. Historically, most LEs were generally too short. Due to adverse selection, a large number of policies (mostly stranger-originated life insurance, or STOLI) with underestimated LEs were traded in the secondary market. Many of those policies were arguably not supposed to enter the market in the first place as evidenced by poor subsequent performance. With the passage of time, underwriters adjust their estimating methodologies and the LEs extend in general. As a result, underlying insureds of policies originated at the height of the STOLI boom (early-mid 2000's) are generally healthier than their successors. When those early policies from the secondary markets enter the tertiary market, underwriters revalue those lives using updated methods with extended base survival rates, which lowers the implied mortality multipliers. This also partially explains the discrepancy between the secondary market and the tertiary market. The finding that ITM assesses relatively conservative estimates in healthy lives gives credence to this assumption and also explains why ITM is associated with lower k in the tertiary market than in the secondary market.

The finding that ITM appears to be generally more aggressive compared to AVS in the main sample, which consists of data from intermediaries, and more conservative in the investors' side samples also has various explanations. First, intermediaries' adverse selection might have distorted the underwriters' real underwriting pattern. Second, between the transaction date and LE renewal date, some insureds have died and those who survived are relatively healthy. Therefore, the side samples are affected by the survivorship bias, as they include policies in force only, but not purchased and terminated policies whose original insured has died. Since ITM treats healthy lives more conservatively than AVS, side samples show that k_{ITM} is generally lower than k_{AVS}.

4.2 Recommendations

The life settlements industry continues to be troubled by underestimated LEs, and reform is in order. In this chapter, we make a few proposals that could potentially lead towards a more sustainable life settlement investment environment.

First, we recommend regulated or voluntary disclosure of medical underwriters' performance, possibly in the form of A/E ratios using a unified calculation method. An increase in the transparency in underwriters' performance enhances information symmetry, which would help investors identify the most qualified underwriter and push underwriters to constantly strive for accuracy. Disclosing performance would however be difficult to implement universally as some underwriters believe it would expose their intellectual property. AVS, for example, refused to publish their A/E reports arguing in court that their underwriting methodology, namely their core competency, might be deciphered through those reports.

Second, we suggest developing indicators for medical underwriters' aggressiveness or conservativeness in LE estimation. Underwriters who systematically issue LEs that are too low would be indicated "aggressive" while underwriters associated with long LEs would be "conservative". Although the indicator does not directly imply estimation accuracy, it would assist investors in pricing policies or determining expected IRRs: an IRR should be set higher when an LE is provided by a relatively aggressive underwriter compared with a more conservative underwriter. Herein, however, lies a dilemma. On the one hand, it would be improper to associate each underwriter with only one single indicator value. As evidenced in our empirical analysis, underwriters' performance varies depending on the demographic group to which a to-be-evaluated insured belongs, and the health condition of the person. On the other hand, the employment of multiple indicators would complicate matters, a notion to which practitioners would object.

Third, the misalignment of incentives could be mitigated by a deferral of commission payments to settlement intermediaries. It would however be tricky to find the right balance between a front-end and a back-end payment. If the back-end incentive is low enough, settlement intermediaries could just write it off in favor of the front-end fees; yet if the weight on the back end is too high, intermediaries might be deterred from doing business altogether. Hence, in order to effectively incentivize intermediaries to become more long-term oriented, a performance-based pay system must be adopted industry-wide, needless to say a challenging proposition.

5 Conclusion

The present study investigates LE estimates in the life settlement industry. We compare LE estimates between underwriters both within and across samples. Empirical evidence suggests that significant, systematic differences in LEs exist between medical underwriters. In our main sample composed of transaction data provided by life settlements intermediaries, ITM, one of the major medical underwriters in the U.S. life settlement market, has been systematically assigning lower LEs than other underwriters. However, the two side samples from investors show the opposite, indicating intermediaries' adverse selection behavior.

Our findings also demonstrate that underwriters have specific underwriting patterns that are associated with insureds' certain characteristics such as gender and health impairment. For example, ITM's LEs are relatively longer for male and healthy people, while AVS gives more conservative estimation for female and impaired people. In addition, underwriting performance in the life settlements industry could have also been affected by the historically inaccurate LE projection for old demographic in the whole life insurance market.

Irrespective of how the underestimated LEs originate, the end investors would be the victims. To create a more healthy and transparent investment environment, we call for the underwriters' publication of their detailed A/E ratios (Sheridan and Carville, 2012, p. 22). We furthermore suggest buyers analyze underwriters' data and understand their underwriting patterns so that they can price policies accordingly.

Upon availability of data, especially data of insureds' death dates, we recommend future research to evaluate the accuracy of underwriters' forecast. We are also interested to see to what extent naïve predictions (for example using publicly available basic mortality tables) deviate from professional predictions made by medical underwriters. Lastly, the degree to which various factors, such as type of insurance or rating of insurance carrier, affects the pricing of a life settlement also merits further research.

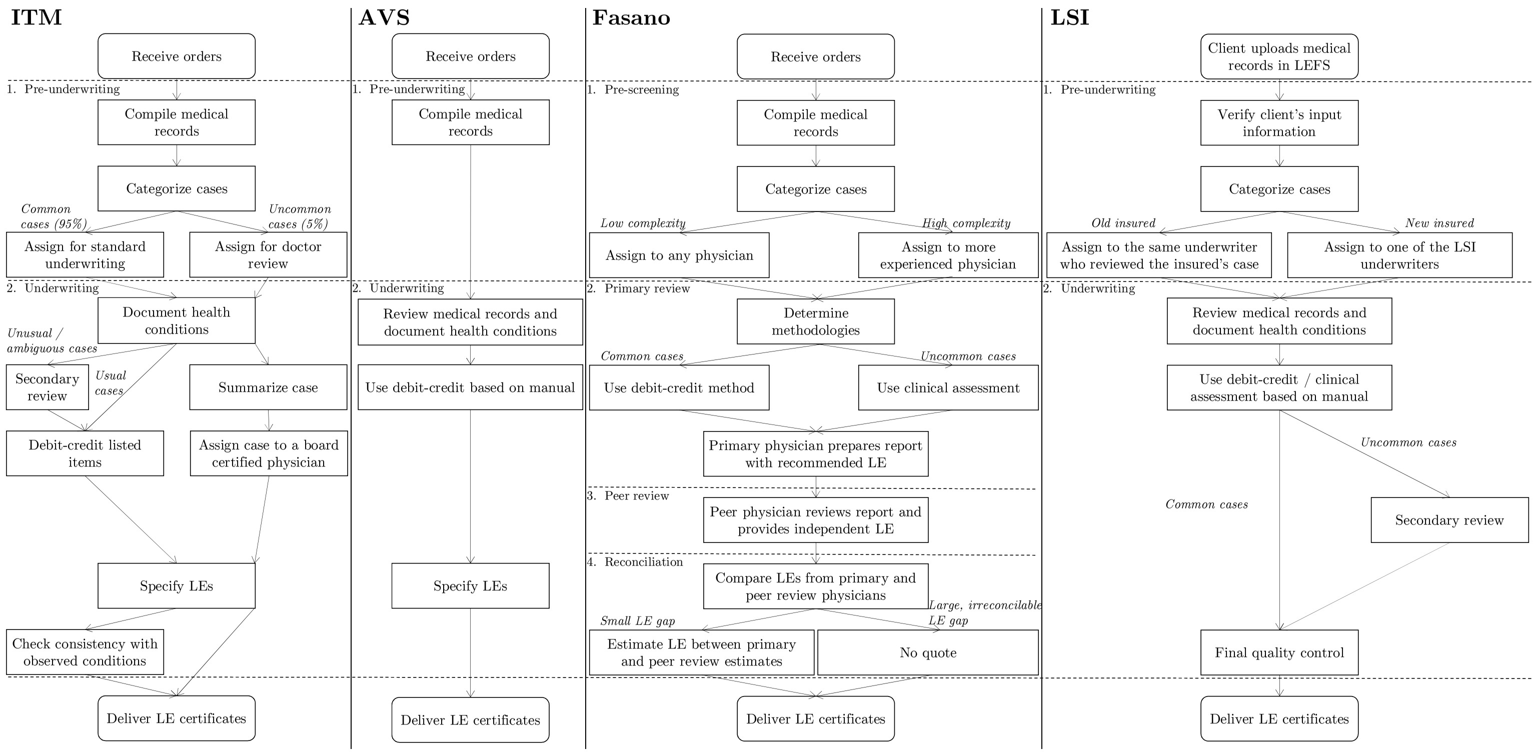
6 Appendix

Table 7: Life settlement providers participant in AAP's monthly data collection

	2011	2012	2013	2014	2015	2016
GWG Life	(✓)					
Legacy Benefits	✓	(✓)	(✓)	✓	✓	(✓)
Q Capital Strategies	✓	✓	✓	✓	✓	✓
Magna Life Settlements	✓	✓	✓	✓	(✓)	
Life Equity	✓	✓	✓	✓	✓	✓
The Lifeline Program	✓	✓	✓	✓	✓	✓
SLG	✓	(✓)				
Settlement Group	(✓)	✓	✓	✓	✓	✓
LifeTrust		✓	✓	✓	✓	✓
Berkshire Settlements		(✓)	(✓)	✓	(✓)	(✓)
Abacus Settlements		(✓)	✓	✓	✓	✓
Institutional Life Settlements		(✓)	✓	✓	✓	✓
Carlisle Asset Management			✓	✓	✓	✓
SL Investment Management			(✓)	✓	✓	✓
Habersham Funding			(✓)	✓	✓	✓
Life Settlement Solutions			(✓)	✓	✓	✓
RiverRock Partners				(✓)	✓	✓
FairMarket Life Settlements					✓	✓
Emergent Capital						(✓)

✓: data provided every month of the year. (✓) : data provided in some, but all months of the year.

Figure 15: Underwriting process



Sources: (ITM TwentyFirst, 2016a, p. 1), LSI (2017).
ITM's underwriting process is mostly algorithm driven, while AVS, Fasano and LSI's underwriting is based on manual review.

References

21st Services (2010). 21st Services' 98.1% Actual-to-Expected Ratio Reflects the Reliability of Our LEs.

21st Services (2011). 21st Services' Actual-to-Expected is 94.7%.

21st Services (2013). Frequently Asked Questions Regarding 2013 Underwriting Adjustments.

AAP (2016). Annual Transaction Volume for Secondary and Tertiary Market & Outstanding Total US Life Settlement Volume.

AAP (2017). Re-think the Tradability of Life Settlement Risks and Returns. In *AAP Life Settlement Roundtable 2017*, Zurich.

A.M. Best (2016). Life Settlement Securitization.

An, J. (2014). EEA Life Settlements Fund - An Independent Case Study.

Aspinwall, J., Chaplin, G., and Venn, M. (2009). The Parties Involved in a Life Settlement Transaction. In *Life Settlements and Longevity Structures: Pricing and Risk Management*, chapter 1, pages 15–18. John Wiley & Sons.

Assured Fund (2013). Assured Fund Shareholder Letter.

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

Bauer, D., Russ, J., and Zhu, N. (2014). Adverse Selection in Insurance Markets: Evidence from the Life Settlement Market. In *Proceedings of the NBER Insurance Workshop2014*.

Boger & Associates LLC (2010). Re: Actual / Expected Analysis.

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

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

Cohen, L. H. (2013). Seeking Alpha in the Afterlife: CMG Life Services and the Life Settlement Industry.

Conning (2017). Life Settlement Market Review. In *LISA Institutional Investor Life Settlement Conference*, New York.

Cowley, A. and Cummins, J. D. (2005). Securitization of life insurance assets and liabilities. *Journal of Risk and Insurance*, 72(2):193–226.

Doherty, N. A. and Singer, H. J. (2002). The Benefits of a Secondary Market for Life Insurance Policies. *Working Paper, Wharton Financial Institutions Center*.

EEA Investors' Group (2016). EEA Fund Facts at December 2016.

Emery, R. (2011). Assured Fund Imposes Exit Restrictions on Investors. *Money Observer*.

EMSI (2009). EMSI Revises Life Expectancy Mortality Tables in Response to 2008 VBT.

Fasano, M. (2013). Underwriting Methodologies.

Granieri, V. J., Heck, G. P., and Heck, G. P. (2014). Survival Characteristics of Three Senior Populations, with a Focus on Life Settlements.

Horowitz, D. D. M. (2010). Life Expectancy Dispute Hurts Market, Key Players Say. *The Life Settlements Report*, IV(19):8–10.

Horowitz, D. D. M. (2012). Wells Fargo Issues Foreclosure Notice Against Lifetrade Fund Sep 2012. *The Life Settlements Report*, VI(15):8–9.

Horowitz, D. T. D. (2013a). Settlement Transactions Continued to Drop in 2012, Market Survey Shows. *The Life Settlements Report*, (Special Edition).

Horowitz, D. T. D. (2013b). Texas Rejects ILMA's Request to Eliminate Life Expectancy Provider Licensing.

Horowitz, D. T. D. (2014). 2013 Saw End of Market's Decline. *The Life Settlements Report*, (Special Report).

Horowitz, D. T. D. (2015). Life Settlement Transactions Plummet Volume. *The Life Settlements Report*, (Special Report).

Horowitz, D. T. D. (2016a). AVS Plans to Increase Prices for Life Expectancy Reports in January.

Horowitz, D. T. D. (2016b). Market Volume Increases 32% in 2015. *The Life Settlements Report*, (2015 League Tables).

ITM TwentyFirst (2016a). Data Subscription & Dictionary.

ITM TwentyFirst (2016b). ITM TwentyFirst - Vendor Diligence, FAQs: Life Settlement Underwriting.

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

Kohli, S. (2006). Pricing Death: Analyzing the Secondary Market for Life Insurance Policies and its Regulatory Environment. *Buffalo Law Review*, 54:101–142.

Lake Consulting Inc (2016). Re: Actual to Expected Analyses: 2008 Through 2015.

LEPr (2011). Life Expectancy Providers Best Practices.

LISA (2016). Life Settlement Industry Timeline.

LSI (2017). LSI Underwriting Process.

Rivoli, D. (2011). Creditors Slam Financing Plan In New Stream's Ch. 11.

Robins, W. (2013). ARM Life Settlement Fund Appoints Liquidators.

Roland, R. (2016). Life Settlement Tertiary Market Dynamics. In *Fasano 13th Annual Longevity Conference*, Washington.

Russ, J. (2005). Wie gut sind die Lebenserwartungsgutachten bei US-Policenfonds? *Working Paper, University of Ulm*.

SEC (2007). Case NO. 2:07-cv-01724-LEW-CMK.

SEC (2012). SEC Charges Life Settlements Firm and Three Executives with Disclosure and Accounting Fraud.

Sheridan, M. and Carville, D. (2012). Advances in the Life Settlement Market and their Relevance to the Macro Longevity Investor. In *Longevity 8 Conference 2012*, Waterloo.

Siegert, P. I. S. I. (2010). Evolution of Life Expectancies in the Life Insurance Secondary Market... Current Trends and New Developments. *Life Insurance Settlement Series*.

State of Texas (2011). CAUSE NO. D-1-GV-10-000454.

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

Texas Department of Insurance (2016). License Application for a Life Settlement Provider or Broker.

The Florida Legislature (2016). Life Expectancy Providers; Registration Required; Denial, Suspension, Revocation.

The Royal Bank of Scotland (2013). Performance Report for ClaridenLeu for the K1 Life Settlement Note.

Tracer, Z. (2014). AIG Has $832 Million Cost on Death Bets as Hedge Funds Gain.

TwentyFirst (2014). TwentyFirst Sample Life Expectancy Certificate.