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

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The value of a life settlement investment, manifested through a traded life insurance policy, is highly dependent on the insured's life expectancy (LE). LE estimation in life settlements relies heavily on medical underwriting. Employing different evaluation processes, underwriters rarely agree on LE estimates, leading to valuation disparities. We use the natural logarithm of the implied mortality multiplier ($\ln k$) to compare the underwriting results of the four major U.S. medical underwriters (ITM, AVS, Fasano, and LSI). $\ln k$ is normalized in terms of gender, age, and smoking status, and is therefore a more suitable indicator than LE estimates for high-level comparisons, especially when the compared groups have a heterogeneous make-up. Based on the analysis of life settlement samples from 2011 to 2016, we trace patterns of underwriters' $\ln k$ in both secondary and tertiary markets of life settlements, and investigate systematic differences in their estimation. Our results show that an underwriter can, relative to peers, act more conservatively (issuing longer LE estimates) for one cohort while more aggressively (issuing shorter LE estimates) for another. We also detect signs of intermediaries' cherry-picking behavior and discuss additional theories that shed light on the convoluted LE landscape.

1. INTRODUCTION

In the 1980s when AIDS became an epidemic in the United States, many of those infected were willing to sell their life insurance policy to alleviate financial hardships due to medical treatment and/or loss of employment (LISA 2016). A life insurance trade, conducted when the original policyholders are 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 trading of life insurance policies nowadays is usually driven by a different set of factors: policy sellers are not necessarily severely ill; they sell their life insurance for reasons such as unaffordable premiums, urgent need for cash, or deceased beneficiaries (An 2014, p. 12). 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 no longer pays the death benefit to the original beneficiary. Since this cash-out would in most cases be undervalued (Doherty and Singer 2003, p. 451), the insured could alternatively sell the policy to an investor, who would then become the policy beneficiary.

With a collective price 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 trading of life insurance policies can be attractive to both policyholders and investors. Since the life settlements industry is hardly affected by traditional financial markets, and its risks are 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 portfolio diversification (Braun et al. 2018a). At the time of writing, life insurance policies with a total face value of \$2 to \$3 billion are traded annually in the secondary market (where insureds sell their life insurance policy directly to investors), and up to \$10 billion in the tertiary market (where investors trade insurance policies between themselves) (Fig. 1).

Dates of death are the determinant of realized return in life settlements investment. Life expectancy (LE) estimates—predictors of those dates of death—are the key valuation driver in the life settlements industry: ceteris paribus, the higher the LE estimate, the lower the price an investor is willing to pay for the policy, as the expected number of premiums to be paid by the buyer of the life insurance increases and the death benefit is expected to be received later. In the life settlements industry, the

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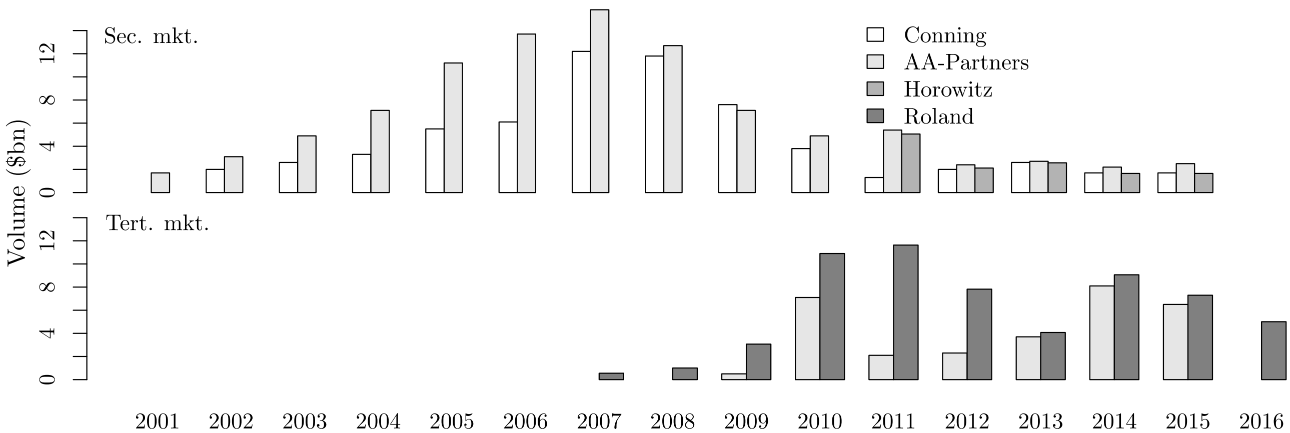

FIGURE 1. Annual Face Value Transacted. *Sources:* Conning (2017), AA-Partners (2016), Horowitz (2013a, 2014, 2015, 2016b), Roland (2016). *Note:* The estimation by the four sources on the dollar amount varies, but the trend shown is similar. The secondary market experienced its peak in 2007, while the tertiary market has attracted increasingly more capital ever since.

professional determination of LE, based on the health and medical information of the insured, is called medical underwriting. The independent entities conducting such forecasts are known as medical underwriters. An LE estimate is usually provided to potential life settlement investors by the sell-side intermediaries of the life settlement transaction, who usually order LE certificates from one or more medical underwriters.

Today, four companies provide the vast majority of medical underwritings for the life settlements market: ITM (ITM TwentyFirst LLC, formerly 21st Services LLC), AVS (AVS Underwriting LLC), Fasano (Fasano Associates Inc.), and LSI (Longevity Services Inc., formerly Examination Management Services Inc.). These four U.S. medical underwriters have all been in business for at least 15 years and are considered to be among the most important in the field (Russ 2005, p. 5).[1] Assessing the accuracy of the medical underwriters has been a big challenge for the life settlement industry. Although each of the medical underwriters will license their historical underwriting data for a fee, there are no publicly available reports. Furthermore, there is no consensus as to how the accuracy of LE estimates should be assessed,[2] and no perfectly unbiased methodologies exist (Fasano 2013; Bauer et al. 2018). When reporting their underwriting performance, underwriters are free to choose their methods (usually not described in detail in their performance reports) and to interpret the results. While professional actuaries can find some guidance in the Actuarial Standard of Practice on how to interpret and assess life settlements underwriters' reports, the standard leaves actuaries with considerable leeway to exert their own judgement, in terms of, for example, mortality table selection (Actuarial Standards Board 2013, p. 17).

Medical underwriting for the life settlement industry is known to be an imprecise science (Xu and Hoesch 2018), affected by the inaccurate baseline mortality tables inherited from the wider life insurance market. Mortality rates of elder populations, which account for the majority of insureds in life settlements, were difficult to accurately estimate due to deficient life data. The A/E (actual to expected) ratio on insureds between age 80 and 89 of VBT08-ANB,[3] for example, turned out to be a dismal 61.6% (Bahna-Nolan 2014). Historically, the medical underwriters for the industry have underestimated life expectancy as insureds have been living longer than originally projected (Seitel 2008, p. 56). Over the years, underwriters have updated their underwriting methods multiple times,[4] resulting in an overall lengthening of LE estimates (Sheridan 2019).

Adding to the historical LE underestimation from the underwriters' side (Cook and Ezell 2008) is the natural incentive of intermediaries to obtain the shortest possible LE estimates. Sell-side intermediaries such as life settlement agents and brokers

[1]Many former underwriting companies such as Midwest Medical Review and Amscot Medical Labs are no longer in business. While new medical underwriters have entered the space in recent years, they do not seem to have gained significant market shares.

[2]In October 2010, AVS Underwriting, 21st Services, EMSI, and ISC Services formed Life Expectancy Providers (LEPr), which took a position as to the reporting of A/E (actual to expected) that was different than that of the Life Insurance Settlement Association (LISA), where Mike Fasano, President of Fasano Associates, was a board member. While LISA advocated using the original LE estimates provided to the clients (Horowitz 2010, p. 8), LEPr preferred to include, in addition to historical basis A/E ratios, restated LE estimates in evaluating their forecast accuracy (LEPr 2011, p. 5).

[3]The Society of Actuaries (www.soa.org) has issued 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/nonsmoker) of insureds (see Table 2).

[4]ITM updated its underwriting method in 2005, 2008, 2013, and 2014, AVS in 2008 and 2012, and Fasano in 2008.

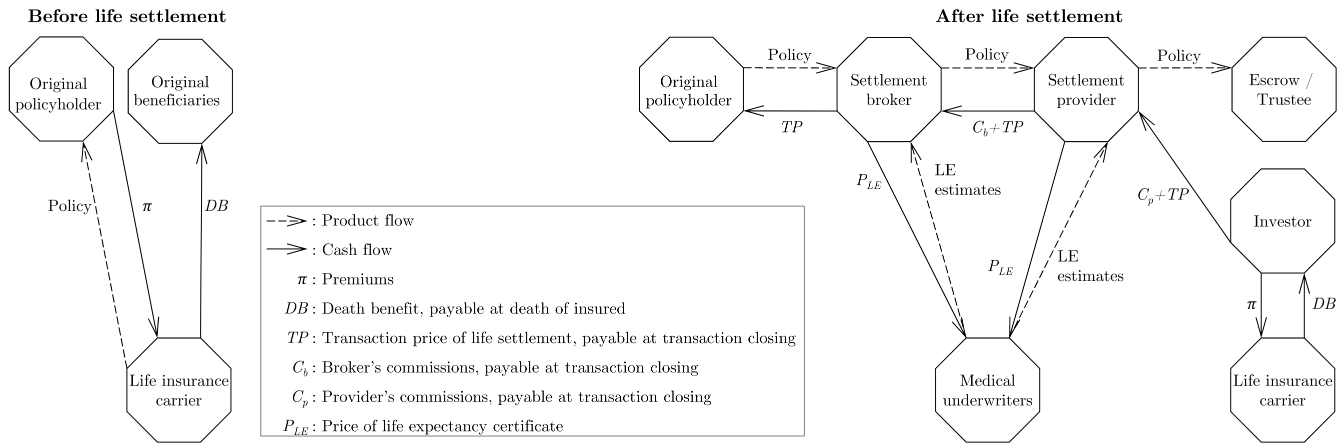

FIGURE 2. Simplified Process of a Life Settlement Transaction. *Sources:* Adapted from Januário and Naik (2014, p. 35) and Braun, Affolter, and Schmeiser et al. (2015, p. 177). *Note:* Intermediaries, including brokers and providers, generally earn income from the closure of a transaction due to commissions and fees they charge. Aspinwall, Chaplin, and Venn (2009, pp. 15–18) and Braun, Gatzert, and Schmeiser (2012, p. 200) define and elaborate on the various roles involved in a life settlement transaction.

are motivated to inflate the policy price using short LE estimates (Braun, Affolter and Schmeiser 2015, p. 188). Buy-side intermediaries such as providers and fund managers, although obliged to serve the investors they represent, also have an incentive to convince investors to bid as high as possible with short LE estimates (see, e.g., Braun et al. 2018b), increasing the chance of closing a transaction[5] and earning commissions and fees (see Fig. 2). Only policies with a sufficiently low LE relative to premiums can attract investors. If an insured's LE estimate 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.[6] Intermediaries shopping for short LE estimates could be a reason why some underwriters have claimed a high level of accuracy, but investors have not seen commensurate results (Table 1). A persisting bias to short LE estimates is also evidenced by the steady stream of negative publicity, including portfolio distresses (e.g., Trinkwon 2017), liquidations (e.g., Robins 2013), write downs (e.g., Emery 2011; Tracer 2014), foreclosures (e.g., Horowitz 2012), and bankruptcies (e.g., Rivoli 2011).

Based on an empirical analysis of LE estimates from ITM, AVS, Fasano and LSI with an emphasis on the first two,[7] we seek to identify underwriters' patterns in LE forecasting and to promote a better understanding of the prevailing landscape of LE estimates. In the absence of comprehensive date-of-death data, we are restricted to focusing on the relative difference between the underwriters rather than on their absolute performance. We indeed discover evidence of systematic, statistically significant differences in LE estimates between medical underwriters and detect signals of intermediaries' cherry-picking behavior.

The rest of the article is structured as follows: in Section 2 we describe medical underwriting in the life settlements market and introduce the mortality multiplier k as well as its economic significance; in Section 3 we present the data and demonstrate empirical analysis; in Section 4 we discuss potential remedies for a more sustainable market; in Section 5 we conclude.

2. MEDICAL UNDERWRITING AND THE ECONOMIC SIGNIFICANCE OF THE MORTALITY MULTIPLIER

In Figure 3 we juxtapose the process flows of the four largest medical underwriters in the United States: ITM, AVS, Fasano, and LSI. ITM's underwriting process is mostly algorithm driven, while AVS, Fasano, and LSI's underwriting is based

[5]Of all policies ever considered for settlement, 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).

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

[7]Because of the higher market share of ITM and AVS compared to the other two underwriters, we have abundant data to conduct diverse statistical analyses on ITM and AVS, whereas for Fasano and LSI we mostly apply descriptive analyses due to sparse data, especially in the early sample period and in the tertiary market.

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
	Life Bond	—	34%	—	—	—	—	—	—	—	$A/E = \frac{\text{number of actual deaths}}{\text{number of expected deaths}}$, expected deaths estimated by EMSI (now LSI)

Sources: EMSI (2009); Boger & Associates LLC (2010); 21st Services (2010); 21st Services (2011); Assured Fund (2013); The Royal Bank of Scotland (2013); EEA Investors' Group (2016); Lake Consulting Inc (2016); Xu and Hoesch (2018).

Note: The actual to expected ratio (A/E ratio) describes the relationship between an actual value and its expectation (Bauer et al. 2018). An A/E less than 1 implies LE underestimation and greater than 1 overestimation. The exact definition of A/E varies (see, e.g., footnote 2). In adjusted ratios, number of expected deaths is calculated using the revised underwriting method as of the reporting date. In unadjusted ratios, number of expected deaths as of the estimation date is used.

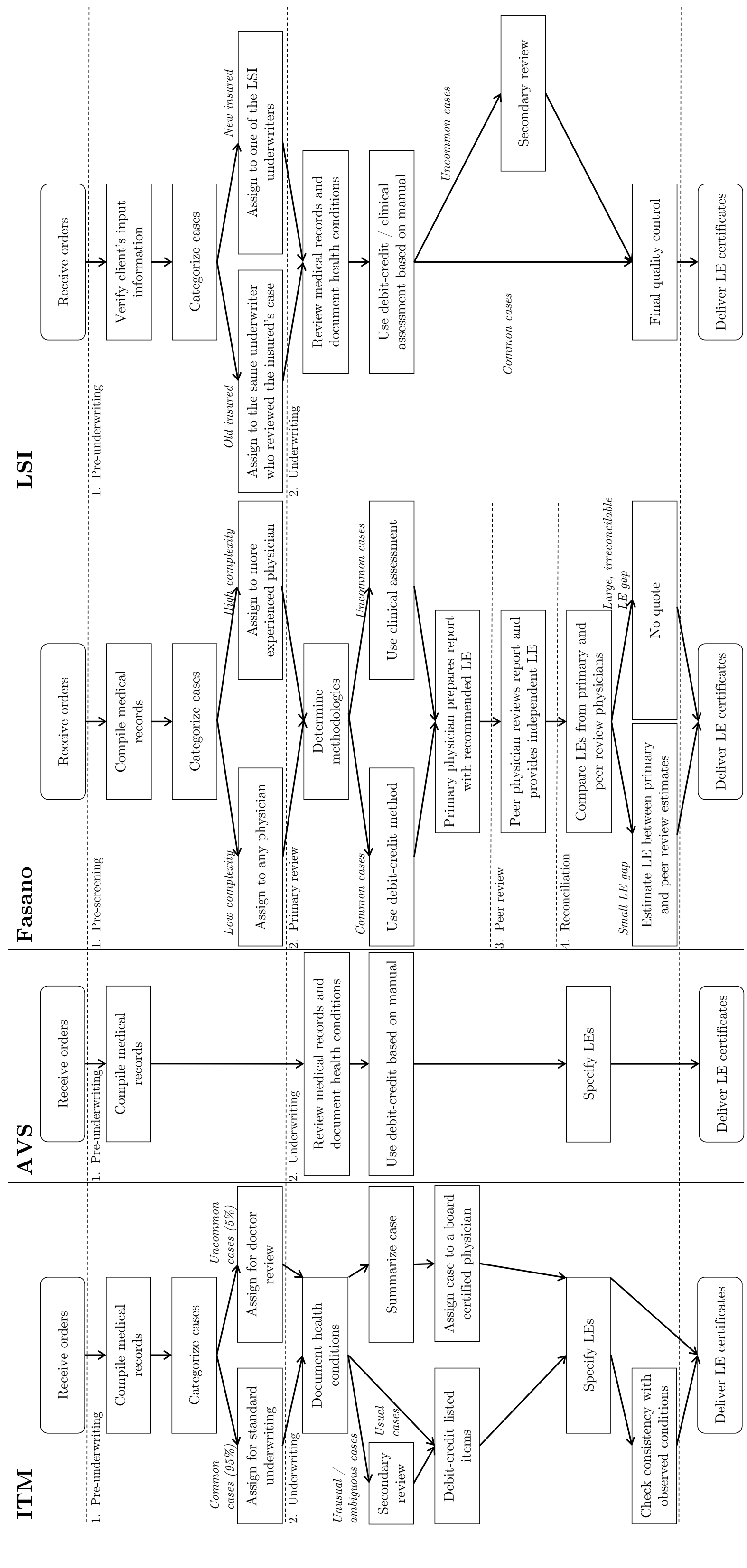

FIGURE 3. Underwriting Process. *Sources:* ITM TwentyFirst (2016, p. 1); LSI (2017).

on manual review. Each method has its pros and cons. An algorithm-based approach can limit underwriters' subjectivity and provide consistent, reproducible results. Nevertheless, due to high-paced developments in today's health care environment, any historical, data-based algorithm needs to be continuously updated. A case-driven approach enables human judgement to add value in some instances (Siegert 2010, p. 11).[8] However, manual underwriting can be inflexible as back-testing is almost impossible whenever a methodological improvement is made, because that would entail all of the pre-improvement cases being manually re-underwritten.

To estimate an insured's LE, an underwriter selects the suitable mortality table corresponding with the insured's demographic and medical characteristics. Underwriters usually have their own proprietary mortality tables and employ some version of the debit-credit underwriting approach. Starting from a base mortality multiplier of 100%, an insured's individual mortality multiplier is "debited" (increased) in the case of a negative health record (e.g., a smoking habit, need for assistance with activities of daily living) and is "credited" (decreased) in the case of a positive one (e.g., athletic lifestyle, absence of family disease history). The applied mortality multiplier is the determinant of the insured's mortality curve, from which an LE estimate is derived. The derivation process is formally described below.

Denote the basic mortality rates of an x-year-old insured as $\{_i|Q_x\}_{i\in\mathbb{N}}$ and the insured's mortality multiplier as k. The insured's mortality rates can thus be expressed as

$$_i|q_x \quad = \begin{cases} 0, & i \le 0 \\ \min(1-\epsilon, k\cdot{}_i|Q_x), & i \ge 1 \end{cases}, \tag{1}$$

where ϵ is a small, positive, arbitrarily predetermined number (e.g., 10^{-5} or 10^{-6}). The individual survival rates are

$$_i|p_x = 1-{}_i|q_x \quad = \begin{cases} 1, & i \le 0 \\ \max(\epsilon, 1-k\cdot{}_i|Q_x), & i \ge 1 \end{cases}. \tag{2}$$

Thus, we can calculate $_ip_x$, the probability that the insured is alive at the end of the ith period given that he or she is alive at time 0, as

$$_ip_x \quad = \begin{cases} 1, & i \le 0 \\ \prod_{j=0}^{i-1} {}_j\Big|p_x, & i \ge 1 \end{cases}. \tag{3}$$

A typical LE measurement, the curtate life expectancy,[9] is calculated as follows (see, e.g., Olivieri and Pitacco 2015, p. 173):

$$LE = \sum_{i=0}^{\omega} {}_{i+1}p_x, \tag{4}$$

where ω represents the terminal age, typically 121 years old.[10] Ultimately, LE is a function of two inputs: (1) base mortality rates $\{_i|Q_x\}_{i\in\mathbb{N}}$ and (2) individual mortality multiplier k. The first input, $\{_i|Q_x\}_{i\in\mathbb{N}}$, entails the demographic information of the cohort to which a reference insured belongs. If, for example, one uses VBT tables to determine the mortality rate basis as per industry standard, then $\{_i|Q_x\}_{i\in\mathbb{N}}$ is age-, gender-, and smoking-specific. The second input, k, only entails information of an insured's health impairment relative to the cohort average and represents an underwriter's personal judgement. Ceteris paribus, a greater k implies faster mortality rates, hence a lower LE and a higher policy value. The positive relationship between k and policy price is elaborated in a formal fashion below.

Let TP denote the transaction price of a life policy, DB the death benefit, $\{\pi_i\}_{i\in\mathbb{N}}$ the premium stream, and r the internal rate of return (IRR) used for pricing. A policy can be priced as

[8]For example, if an older individual is brought in for a physical that produces a low FEV1 ratio (a measure of pulmonary function), an inflexible approach might assess a high mortality rating based on the low, seemingly objective result. However, it is often the case that older people who are brought in by well-intentioned children for physicals are not in the best of moods. 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.

[9]The curtate LE is the expected number of complete periods lived. In this paper, LE refers to "mean LE." 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%.

[10]To date, the only person verified to have lived more than 121 years is Jeanne Calment of France (1875–1997), who died at age 122 (Whitney 1997).

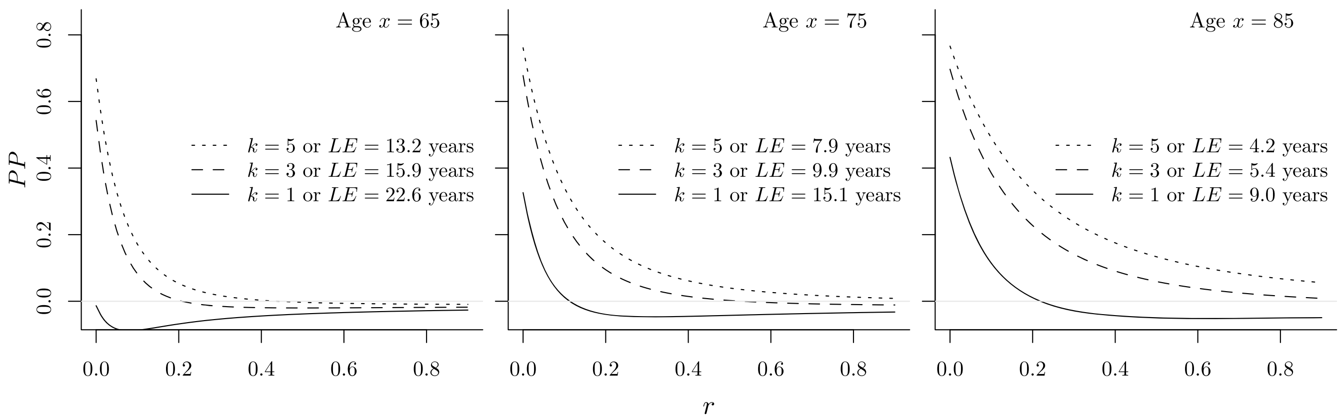

FIGURE 4. Price Factor (*PP*) against Return (*r*) by Mortality Multiplier (*k*). *Note:* *k*'s effect on the $r \to PP$ curve from simulated universal life policies of an *x*-year-old male non-smoker. When *k* is not sufficiently high, *PP* can be always negative irrespective of *r*. *PP* being positive and constant, higher *k* implies higher expected *r*; *r* being constant, higher *k* implies higher *PP*.

$$TP = -\pi_0 + \sum_{i=1}^{\omega} \frac{{}_{i-1}p_x \cdot {}_{i-1|}q_x \cdot DB - {}_ip_x \cdot \pi_i}{(1+r)^i} = \sum_{i=0}^{\omega} \left({}_ip_x \cdot \frac{\frac{{}_{i-1|}q_x}{{}_{i-1|}p_x} \cdot DB - \pi_i}{(1+r)^i} \right). \tag{5}$$

Let $PP := \frac{TP}{DB}$, $\nu_i := \frac{\pi_i}{DB}$, $\delta_i := \frac{{}_{i-1|}q_x}{{}_{i-1|}p_x}$. We can thus express *PP*, policy price normalized to policy death benefit, as

$$PP = \frac{TP}{DB} = \frac{\sum_{i=0}^{\omega} \left({}_ip_x \cdot \frac{\frac{{}_{i-1|}q_x}{{}_{i-1|}p_x} \cdot DB - \pi_i}{(1+r)^i} \right)}{DB} = \sum_{i=0}^{\omega} \left({}_ip_x \cdot \frac{\delta_i - \nu_i}{(1+r)^i} \right). \tag{6}$$

To assess the economic influence of *k* in depth,[11] we simulate three universal life policies (the insured being a male non-smoker at age 65, 75, and 85, respectively) using our main sample data (see Section 3.1.1 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 nonsmoker are 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 4 illustrates how different levels of *k* affect the $r \to PP$ curve. Given a certain positive *r*, a higher *k* indicates a larger *PP*. Similarly, given a certain positive *PP*, a higher *k* implies a higher *r*. When *k* is too small, *PP* can be constantly negative regardless of the choice of *r*. Policies with such a low *k* would not enter the market normally or would be lapsed once purchased.

An economically viable life settlement requires $PP > 0$; that is, the price of a policy must be positive.[12] To achieve a positive *PP*, *k* must be sufficiently large. We observe from Figure 4 that the bar of *k* becomes 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 $x = 85$. Furthermore, we notice that at the same level of *k* and *r*, *PP* increases with the increment of *x*. This is to say, when an insured is old enough, his or her policy can be worth the investment even if the person is relatively healthy. As shown in Figure 4 with the insured's age $x = 75$ or 85, a policy from an insured with standard health ($k = 1$) can also have a positive net present value (NPV). In reality, this can happen when, for instance, the policy was issued as "preferred" by the insurance carrier—which reflects an above-average health status at policy issuance and consequently lower premium rates as compared with the "standard" class—but the insured's health status deteriorates to "standard" after issuance. Another explanation might be "front-loading," a premium pricing scheme commonly employed by insurance carriers to enhance policyholders' commitment (Hendel and Lizzeri 2003, p. 323; Gottlieb and Smetters 2016, p. 1; Bauer et al. 2017, p. 489). A front-loaded policy overcharges at the beginning of the coverage and undercharges at a later stage, such that a policy from a senior insured, provided that he or she purchased the policy at a young age, is cheap to maintain. The policy is thus also economically viable to life settlement investors even if the insured has an average health status.

[11]We later show *k* in its log form in Figure 4 to be consistent with further analysis in this article.

[12]In the case of a positive surrender value, the policy price needs to exceed the surrender value for a transaction to be viable.

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

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

Source: www.soa.org/files/research/exp-study/2015-vbt-smoker-distinct-alb-anb.xlsx.

Note: ${}_{i}|Q_x$ is the one-year conditional mortality rate, the probability that the person aged x will die in a year, deferred i years, i.e., the person is dead at the end of the $(i+1)$th year given that the person is alive at the end of the ith year.

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
Secondary market	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
Tertiary market	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

Note: For every transaction, the age is current as of the transaction date, and each LE is age-adjusted accordingly.

3. EMPIRICAL ANALYSIS

3.1. Data

3.1.1. Main Sample

The main sample that we used to commence this study was provided by AA-Partners Ltd (AAP), an independent consulting firm specializing 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 salient deal characteristics (e.g., price, face amount, premiums,[13] LE estimates) from various life settlement providers on a monthly basis. This sample consists of life settlement transaction data, most of which (3,127 out of 3,236) entail LE data. Out of 3,127 lives, 2,172 were estimated by at least one of the main U.S. medical underwriters (ITM, AVS, Fasano, or LSI). The data, covering the period January 2011 to December 2016, include both secondary and

[13]Premiums are current to the date of settlement. Note that recently, life insurance carriers have been raising premiums on in-force policies, exposing premium risk into the life settlement business.

TABLE 4
Number of Transactions by Number of Medical Underwriters Involved

No. 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

Note: 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

$\Delta\backslash n$		ITM	AVS	Fasano	LSI	$p\backslash\rho$	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	—
Secondary market	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	—
Tertiary market	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*	—

Note: 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.

p: p value of a Wilcoxon signed-rank test. Significance levels of 0.1, 0.05, and 0.01 are marked with "*", "**", and "***", respectively. 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.

tertiary market transactions. The LE estimates are deemed actual by the date of transaction.[14] In our sample, 84% of the transacted policies are universal life policies, and according to AAP, the premiums of most of those policies have been optimized to the bare minimum payment that keeps the policy in force.[15] The total face value of all the insurance policies in our sample data amounts to $6.4 billion, while the settling of those policies was priced at $1.2 billion. Table 3 summarizes characteristics of the life settlements sample.

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

[14]To be precise, the average time elapsed from LE estimation date to the transaction closing date in the secondary market is merely three months. An LE estimate older than six months would typically be annulled and replaced by a refreshed estimate. Therefore in the secondary market, the LE date difference is negligible. 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 retrospectively calculate the LE estimate as of the transaction date.

[15]The most common policy type in life settlements is universal life (UL), which is characterized by flexible premiums (Blake and Harrison 2008, p. 11). UL combines life insurance and savings and allows the policyholder to control the amount of money devoted to the savings component. Life settlement investors almost exclusively devote zero dollars to the savings account.

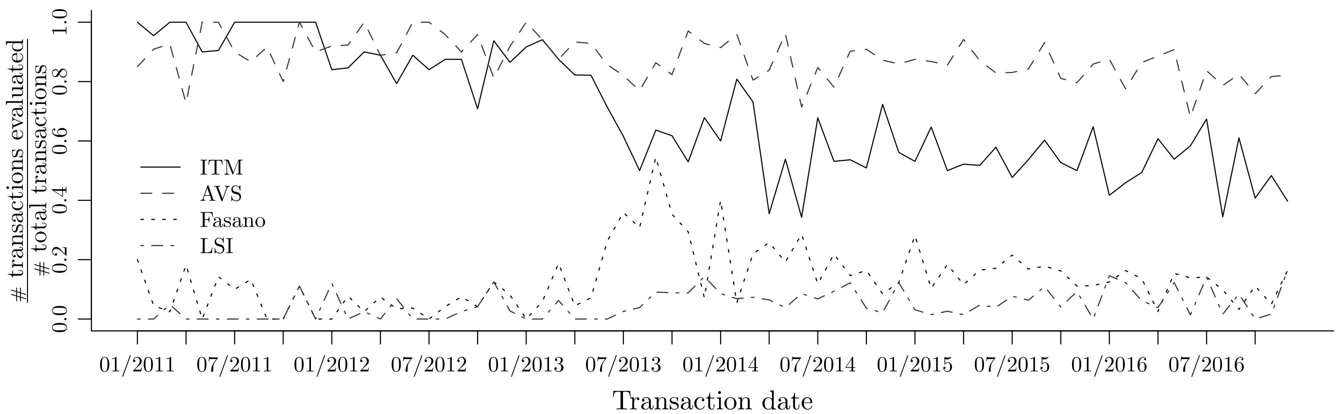

FIGURE 5. Relative Market Shares. *Note:* Relative market shares of Fasano and LSI are comparatively stable. A sharp downturn in ITM's market share as well as a sharp peak of Fasano's can be observed in 2013.

underwriters and markets, the vast majority involving 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 the numbers of settlements evaluated simultaneously by two underwriters. As LE estimates appear to be highly correlated, they may be viewed as a manifestation of the true underlying LE. We focus on those settlements to create meaningful comparisons between underwriters. We are particularly interested in the relationships between ITM and AVS, since the data from Fasano and LSI are relatively sparse. Later in the article we discuss the results of a descriptive analysis on the sparse data, for which statistical testing lacks explanatory power.

Figure 5 depicts the relative market share 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 in January 2013 ITM announced a change in its debit-credit system and mortality tables that 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 and Heck 2014, p. 5).

3.1.2. Side Samples

Two anonymous investors also provided LE-related information on the in-force policies from their life settlements portfolios. All of the policies are from the tertiary market and have been evaluated by (and only by) both ITM and AVS at the request of investors. The LE data from the side samples are not covered by the universe of the main sample, that is, there is no overlap. The three samples are not mixed together but analyzed separately. Later in this article, we compare LE landscapes across samples to obtain a view of medical underwriting from the standpoint of both intermediaries and investors.

From the policies included in the side samples, 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 to minimize the impact on estimate differences due to potential health-changing events occurring between the two underwriting dates.[16] Table 6 presents the descriptive statistics of the filtered data from the two side samples.[17] 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.

3.1.3. Reverse Engineering of $k_{underwriter}$

As a great many of lives in our sample data are simultaneously evaluated by several underwriters (Table 4), we can directly compare the LE pairs to see which underwriters tend to give shorter estimates and which longer. However, whenever two series of LE estimates are not referenced to the same group of insureds and/or were not issued around the same time, the direct comparison of those LE estimates can be misleading. For example, a demographic group of 60-year-old people with a standard

[16]While an *actual* dramatic health change within 45 days might be rather rare, an *estimated* health status is likely to be largely influenced by, e.g., a medical test report issued between two underwriting dates.

[17]We have conducted additional analyses using data without applying the filter of underwriting date difference, and the findings do not change.

TABLE 6
Descriptive Statistics, Side Sample

		n	Min	Median	Max	Mean
Side Sample 1	ITM underwriting 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 underwriting 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 underwriting 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 underwriting 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

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

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. We consider k to be more suitable than LE, especially for a comparison of medical underwriting in demographically heterogeneous cohorts, since k serves as a measurement of relative health impairment that is normalized to age, gender, and smoking status.

Since underwriters' base mortality curves are not publicly available, we employ the four VBT15-ANB tables (gender and smoker distinct) as input for $\{_i|Q_x\}_{i\in\mathbb{N}}$. By plugging $\{_i|Q_x\}_{i\in\mathbb{N}}$ together with $LE_{\text{underwriter}}$ into Equations (2)–(4), we solve for the implied mortality multiplier $k_{\text{underwriter}}$, where underwriter $\in \{\text{ITM}, \text{AVS}, \text{Fasano}, \text{LSI}\}$. The value of k in our samples ranges from 0.2 to 6,000. Extremely high k's are associated with severely ill individuals with a future mortality curve significantly different from the baseline table. Since underwriters' own mortality tables might differ from VBT15-ANB, an implied k can deviate from the original mortality multiplier stated on an LE certificate.[18] Yet by applying the same set of mortality tables to solve each LE-corresponding k, we standardize the k's and make them directly comparable. To tone down the impact of those large k's from severely impaired lives on the aggregate results, we employ a log transformation for the variable.[19]

3.2. Findings

3.2.1. Comparison between Underwriters

We start by investigating the differences in LE estimates between medical underwriters. From Table 5 we observe that in our main sample, ITM provides shorter LE estimates on average than all the other three underwriters in both the secondary and the tertiary markets. 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 subsamples, there is no difference in age or health impairment that could explain the divergence in LE estimates.

When LE estimation is proxied by k, there remain significant discrepancies between underwriters. Figure 6 takes AVS as a benchmark and notes its differences from ITM and Fasano with regard to $\ln k$. 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).

The time series of average $\ln k$ across all transactions from ITM and AVS per quarter 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. $\ln k_{\text{ITM}}$'s quarter average is constantly higher than $\ln k_{\text{AVS}}$ throughout the whole sample period in both secondary and tertiary markets. Fasano's and LSI's data are not plotted because of a dearth of data. Discrepancies in LE estimates between ITM and AVS do

[18] Compared to VBT15-ANB, ITM's baseline mortality tables have lower rates while AVS's have higher rates. Therefore, a mortality multiplier of 100% stated on an LE certificate 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.

[19] We also conduct additional analyses excluding outlier transactions with $\ln k_{\text{underwriter}} > 4$ (10% of total sample), and the findings do not change. For brevity, those results are not reported but are available upon request.

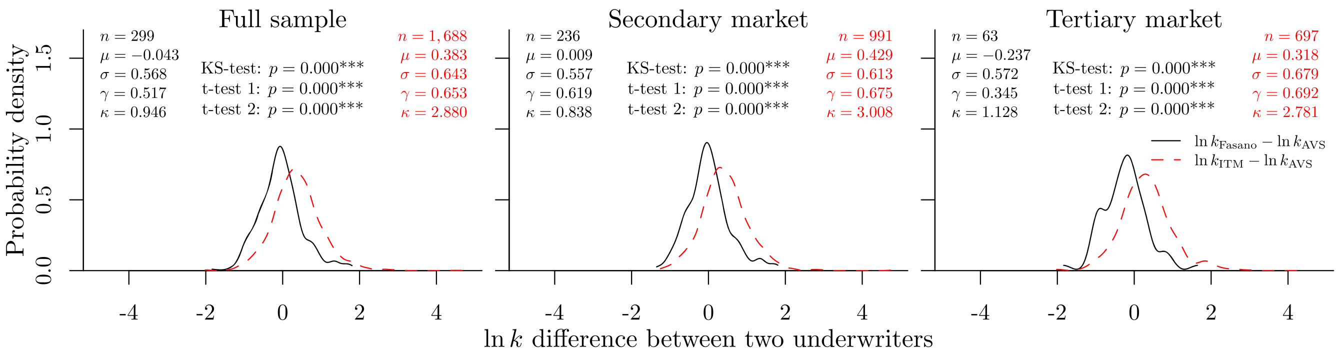

FIGURE 6. Distributions of $\ln k$ Differences. *Note:* n: number of observations. μ: mean. σ: standard deviation. γ: skewness. κ: kurtosis. Under the alternative hypothesis (H_0) of a Kolmogorov-Smirnov test (KS test), the distributions of the two subsets differ. Under H_0 of an unpaired one-tailed Student's t-test (t-test 1), the mean of the subset plotted in dashed lines is less than that in solid lines; under H_0 of an unpaired two-tailed Student's t-test (t-test 2), there is no difference between the means of the two subsets (sic passim). The figure illustrates the distribution of $\ln k$ difference in the main sample.

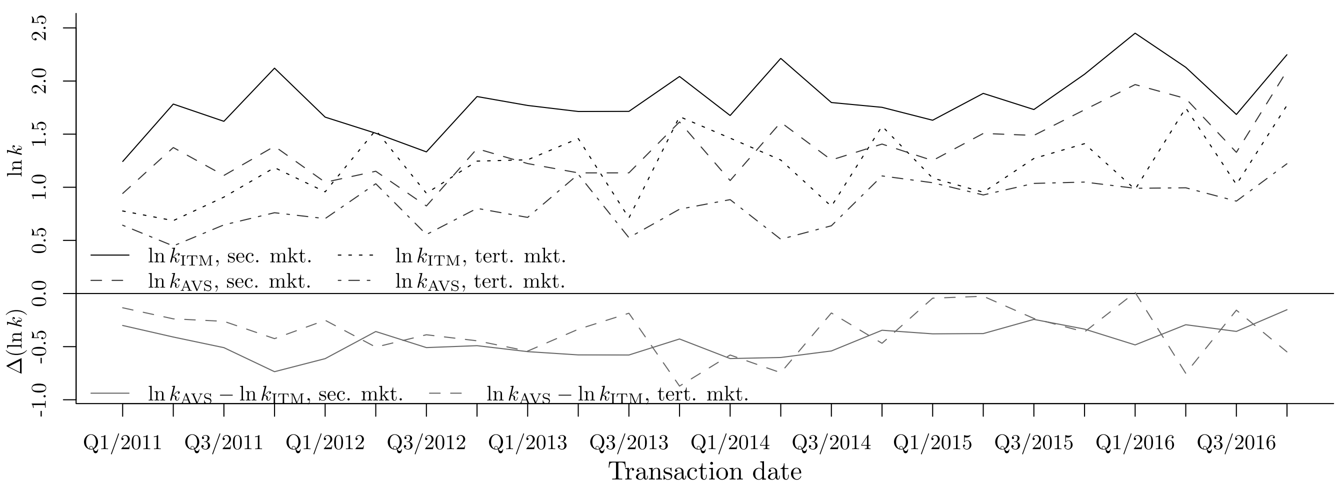

FIGURE 7. $\ln k$ from ITM and AVS in Secondary and Tertiary Markets, Main Sample. *Note:* Quarterly average $\ln k$ of ITM and AVS throughout the sample period. Only deals with both ITM and AVS LEs are considered. The mean $\ln k$ of each quarter from ITM is higher than that from AVS throughout the whole sample period, in both secondary and tertiary markets.

not seem to diminish over time, possibly because LE disparities are tolerated, presumably by sophisticated investors. After mastering estimation patterns of different underwriters, those investors price in their confidence in the LE estimates on a particular trade.

Underestimated LEs might arise due to myopic underwriters who intentionally provide low LE estimates to gain business from intermediaries, as the intermediaries usually present to their investors the LE estimates they order from underwriters. However, while underestimation may bring medical underwriters more business from policy sellers in the short term, it compromises investors' confidence and interest in the long run and places the whole life settlements industry in jeopardy. For underwriters valuing sustainability (which we believe are the majority), a wrong LE projection could have been an honest mistake on account of varyingly deficient underwriting methods (Fig. 3). Hence, we pursue more in-depth analyses.

3.2.2. Comparison between Cohorts

Underwriters apply differing mortality tables and debit-credit methodologies (see Section 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. To explore the underwriting pattern between ITM and AVS, in all three samples 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

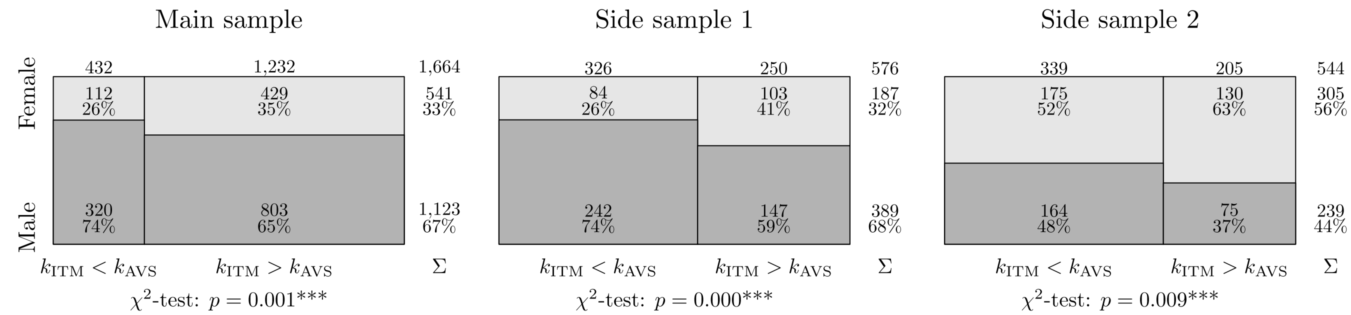

FIGURE 8. Mekko Plot of Gender against Subset $k_{\text{ITM}} < k_{\text{AVS}}$ and $k_{\text{ITM}} > k_{\text{AVS}}$ by Sample. *Note:* The distributions on gender are significantly different between subset $k_{\text{ITM}} < k_{\text{AVS}}$ and subset $k_{\text{ITM}} > k_{\text{AVS}}$ in all three samples. Specifically, bar male (female) from column $k_{\text{ITM}} < k_{\text{AVS}}$ is taller (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 $k_{\text{ITM}} > k_{\text{AVS}}$.

variables such as gender (either male or female) and smoking status (either smoker or nonsmoker), 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) to compare distributions between the two groups. Significant differences can be detected in distributions of gender and health impairment between the two subsets.[20] On a statistically significant level, subset $k_{\text{ITM}} < k_{\text{AVS}}$ is composed of proportionally more male lives (Fig. 8), as well as more healthy lives (healthiness proxied by $\frac{\ln k_{\text{ITM}} + \ln k_{\text{AVS}}}{2}$; Fig. 9) as compared with the other subset. The distribution of those features is shared among all three samples.

For robustness checks, we run regressions on the difference in LE estimates between ITM and AVS with respect to policy characteristics, including health status (proxied by average log mortality multiplier, $\overline{\ln k}$), gender, and smoking status (Table 7). The results show that $(LE_{\text{ITM}} - LE_{\text{AVS}})$ increases when an insured is healthier (smaller $\overline{\ln k}$) and is male, indicating that when using AVS' underwriting as a benchmark, ITM's underwriting appears more conservative (higher *LE*) with healthy and male lives than with unhealthy and female lives. The finding holds throughout our three samples and corroborates Figures 8 and 9.

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 k for a very unhealthy insured. ITM's assessment of its own underwriting is thus in accordance with our findings (Figs. 8–9 and Table 7).

3.2.3. Comparison between Secondary and Tertiary Markets

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 at a highly significant level. We observe from Figure 10 that the density curve of $\ln k$ in the secondary market runs to the right (the larger $\ln k$ side) of the tertiary market curve for all 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, for both ITM and AVS (Fig. 11). The analysis is based on all transactions for each underwriter, but the same conclusion can be drawn when only those deals with LE pairs are considered (Fig. 7). While we observe $k_{\text{ITM}} > k_{\text{AVS}}$ in both the secondary and the tertiary markets, the discrepancy $(k_{\text{AVS}} - k_{\text{ITM}})$ is smaller in the tertiary market (Fig. 7). In addition, we detect a higher likelihood for policies in the tertiary market to receive $k_{\text{ITM}} < k_{\text{AVS}}$ than policies in the secondary market (Fig. 12). This finding is in line with Table 7, which shows that using AVS as a benchmark, ITM's underwriting is more conservative (higher $LE_{\text{ITM}} - LE_{\text{AVS}}$) in the tertiary market than in the secondary market.

The observation that k in the secondary market is larger than in the tertiary market might be due to the fact that health impairments of insureds in the secondary market could indeed be more severe than those in the tertiary market. The finding that ITM assesses relatively conservative estimates in healthy lives gives credence to this assumption, since it explains why $k_{\text{ITM}} < k_{\text{AVS}}$ is observed more frequently in the tertiary market than in the secondary market (Fig. 12).

Lives being healthier in the tertiary market than in the secondary market might be explained by the survivorship bias. The more health-impaired policyholders die first before even a chance of a tertiary transaction to take place. Therefore, those whose policies are settled in the tertiary market are naturally healthier ones who still remain alive at a future time since the initial secondary transaction. Second, the conjecture that insureds are healthier in the tertiary market can be backed by a legacy

[20] No distinguishable patterns are detected concerning smoking status, age, or policy face value.

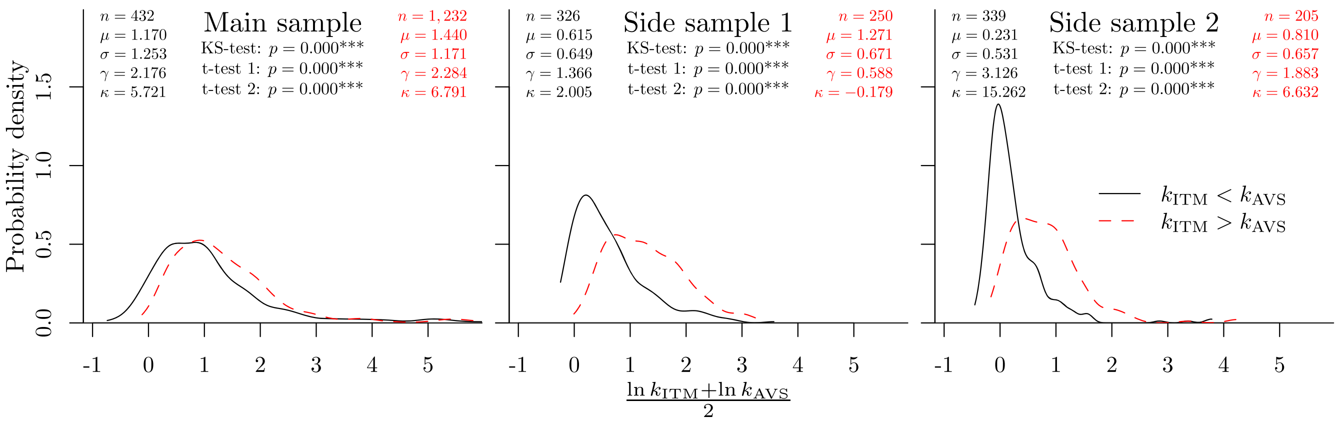

FIGURE 9. Kernel Density of Health Impairment by Sample, Subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ vs. $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$. *Note:* The density distributions on health impairment (proxied by $\frac{\ln k_{\mathrm{ITM}} + \ln k_{\mathrm{AVS}}}{2}$) are significantly different between subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ and subset $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$ in all three samples. Specifically, subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ is in aggregate healthier (smaller $\frac{\ln k_{\mathrm{ITM}} + \ln k_{\mathrm{AVS}}}{2}$) than subset $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$.

TABLE 7
Regression: The Effect of Policy Characteristics on the Difference in Underwriters' LE Estimates

Dependent variable	$LE_{\mathrm{ITM}} - LE_{\mathrm{AVS}}$		
Sample	Main Sample	Side Sample 1	Side Sample 2
(Intercept)	–12.028***	13.199***	8.657***
	(1.288)	(1.770)	(1.464)
$\overline{\ln k}$	–2.298***	–18.939***	–20.583***
	(0.484)	(1.169)	(1.538)
Gender (male)	1.417	14.266***	12.143***
	(1.214)	(1.845)	(2.043)
Smoking Status (smoker)	2.574	1.872	–7.664
	(3.863)	(7.386)	(11.840)
Market (tertiary)	3.139**		
	(1.176)		
df	1,683	580	548
Adjusted R^2	0.019	0.338	0.259

Note: Regressions include controls for insured's health status (proxied by average log mortality rate $\overline{\ln k}$) and indicator variables for insured's gender (male = 1), smoking status (smoker = 1), and transaction market (tertiary market = 1). Standard errors are in parentheses. Significance levels of the explanatory variables at 0.1, 0.05, and 0.01 are marked with "*", "**", and "***", respectively.

issue. Historically, most LE estimates were generally too short. During the early-to-mid-2000s, 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 adjusted their estimating methodologies, and the LE estimates extended in general. As a result, underlying insureds of policies originated at the height of the STOLI boom 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.

One might also argue that k's are deliberately inflated by medical underwriters in the secondary market. As discussed in Section 2, high k's are desired by settlement intermediaries, who are 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 data of lives are critical for underwriters to test their methods. In addition, underwriters usually get to

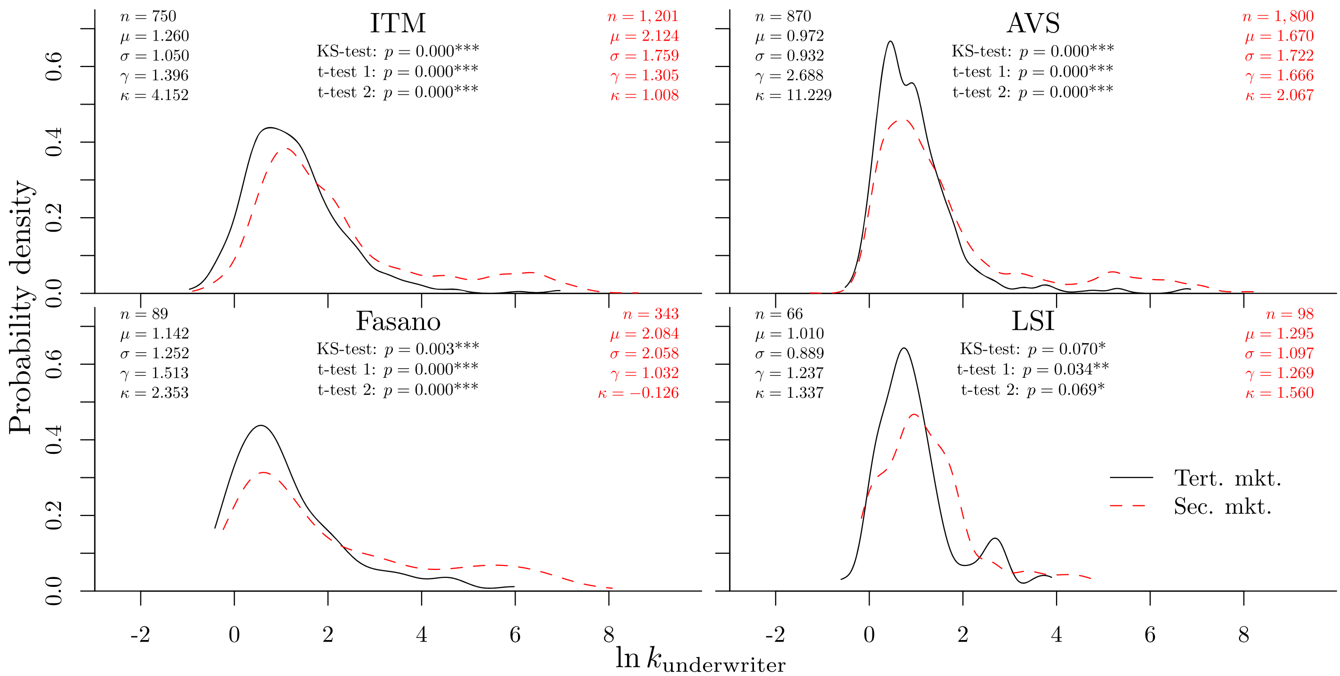

FIGURE 10. Kernel Density of Health Impairment by Underwriter, Secondary versus Tertiary market. *Note:* The measures of central tendency (mean, mode, median) of $\ln k$ are larger in the secondary market than in in the tertiary market for all four underwriters.

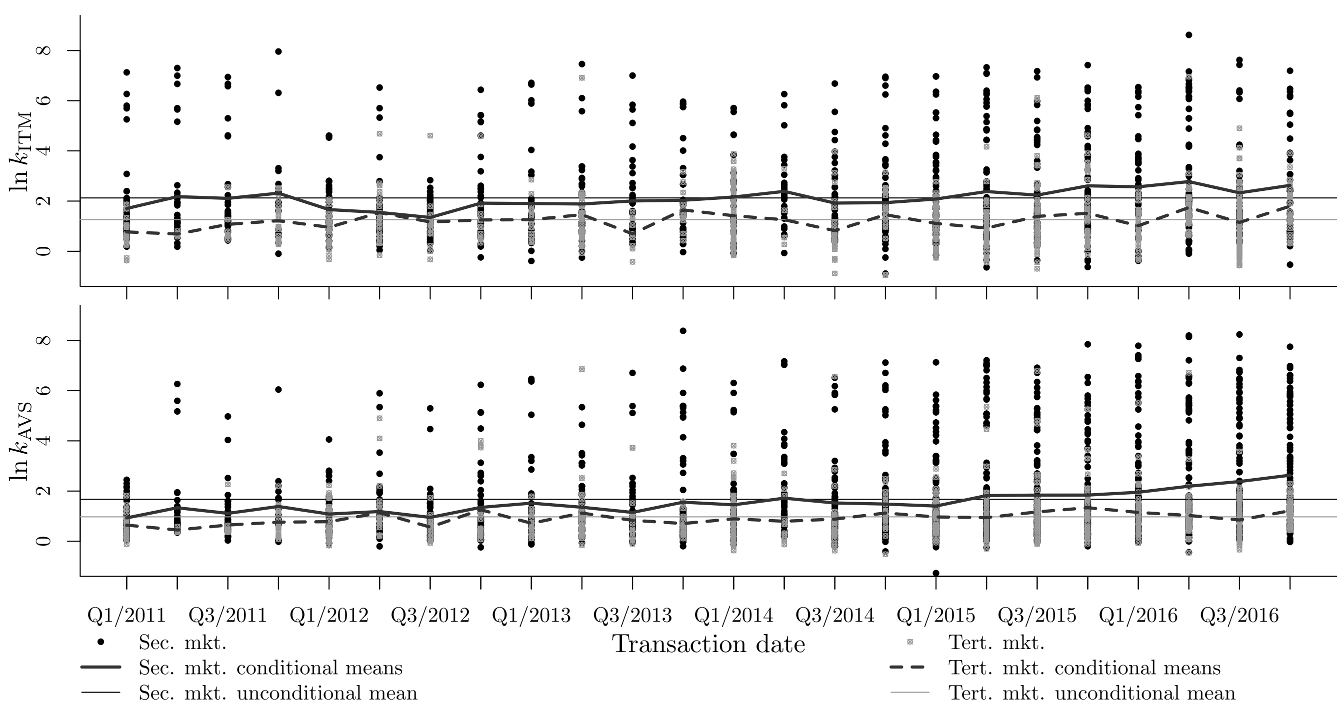

FIGURE 11. Time Series of $\ln k$ Distributions by Underwriter, Secondary versus Tertiary market. *Note:* For both ITM and AVS, the average $\ln k$ of each quarter is always higher in the secondary market than in the tertiary markets throughout the whole sample period.

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. In short, 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. This argument has been challenged by

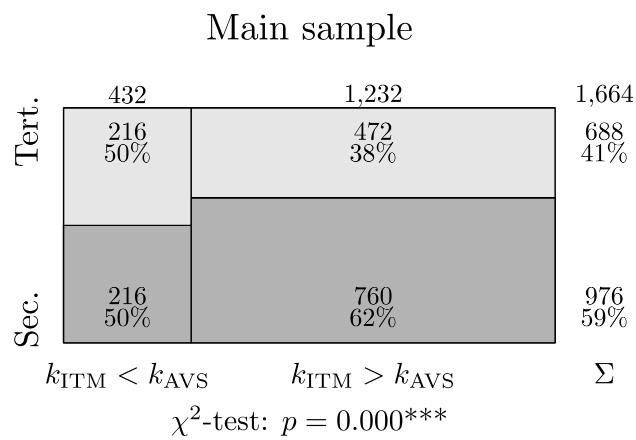

FIGURE 12. Mekko Plot of Markets against Subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ and $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$ by Sample. *Note:* The distributions on markets are significantly different between subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ and subset $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$ in all three samples. Specifically, bar secondary (tertiary) market from column $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$ is taller (shorter) than that from column $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$, which means subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ consists of proportionally more deals from the tertiary market than subset $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$.

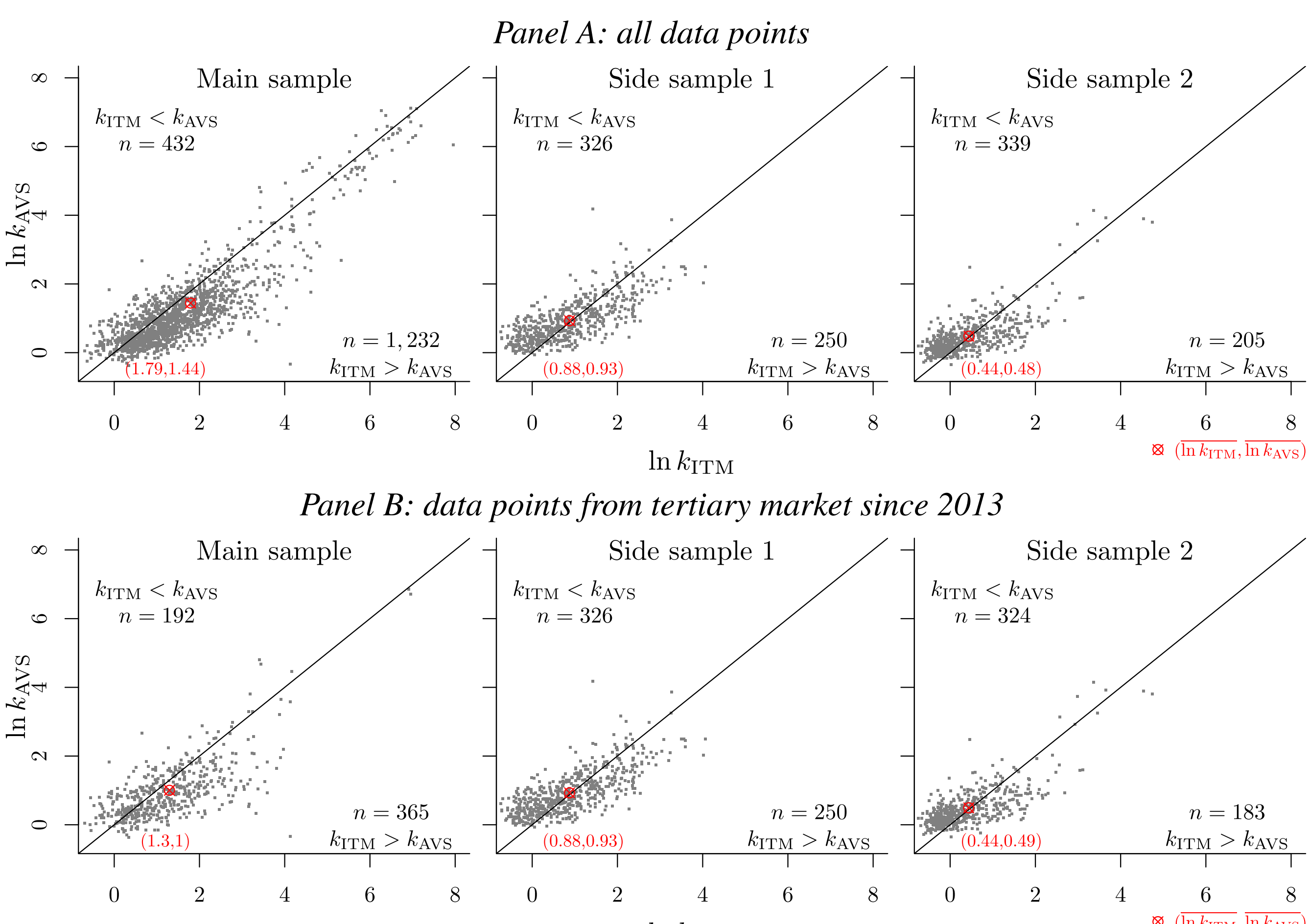

FIGURE 13. Scatter Plot of $\ln k_{\mathrm{ITM}}$ against $\ln k_{\mathrm{AVS}}$ by Sample. *Note:* Points on the 45° line represent the ideal scenario when $k_{\mathrm{ITM}} = k_{\mathrm{AVS}}$. Panel A consists of all data points from our sample. In *Panel B*, we remove the secondary market data from the main sample (side samples only consist of tertiary data) and the data before 2013 (given the considerable change in ITM's underwriting methodology around January 2013). The main sample consists of more insureds with $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ than those with $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$. This pattern is not shared by the two side samples.

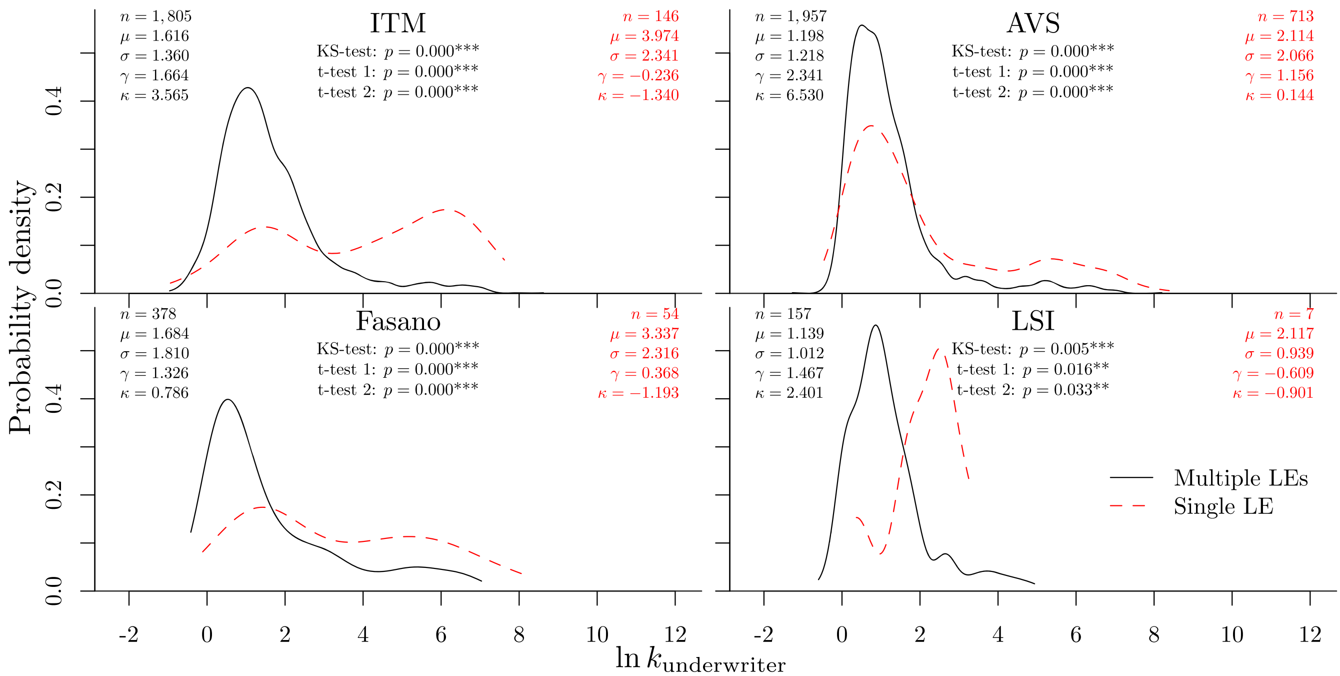

FIGURE 14. Kernel Density of Health Impairment by Underwriter, Subset with Multiple LEs versus Single LE, Main sample. *Note:* In the upper left plot, the distribution of $\ln k_{\mathrm{ITM}}$ is compared between the subset of policies with a single LE estimate from ITM, the and subset of policies with LE estimates from ITM and some other underwriter(s). The former subset's $\ln k_{\mathrm{ITM}}$ is in aggregate considerably larger than the latter's. This effect, although not as distinct, can be observed when the underwriter is AVS, Fasano, or LSI.

underwriters. ITM, specifically, claims to issue longer LE estimates (lower k) for secondary policies than for tertiary policies, as their mortality tables for the two types of transactions differ (21st Services 2013, p. 3), which, however, is not directly observable in our data sample. The rationale behind this discrimination is the adverse selection by insureds (Zhu and Bauer 2013; Bauer et al. 2017). 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 (and most likely this feeling accurately reflects their real health condition) despite what their medical records imply (Bauer, Russ, and Zhu 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). Based on their own data, ITM has observed that the adverse selection's effect on mortality rates disappears a few years after the settlement, hence fewer mortalities in early durations for secondary market cases. In addition, the huge backlog suffered by ITM and AVS (Horowitz 2016a) may not cause these underwriters to worry about too little business, but rather the opposite.

3.2.4. Detection of Intermediaries' Cherry-Picking

While the main sample demonstrates that ITM tended to issue shorter LE estimates than AVS (indicated by points representing $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$), the side samples reveal a different picture (Fig. 13). In contrast to the main sample, subset $k_{\mathrm{ITM}} < k_{\mathrm{AVS}}$ accounts for the majority of the side samples. We also note that the k's in the side samples are generally smaller than those in the main sample. Despite the common features, there must be a reason for the differences observed between the main sample (intermediaries' data) and the side samples (investors' data), specifically why cases with $k_{\mathrm{ITM}} > k_{\mathrm{AVS}}$ mostly occurred only in the main sample.

A possible explanation is that life settlement intermediaries of the transactions in the main sample might have shopped for LE estimates in their favor and/or discarded LE estimates that might impede the closing of a deal. Such cherry-picking by intermediaries can cause a skewed picture of the underlying underwriting pattern. To verify this, we compare the subset with only one LE estimate against the subset with multiple LE estimates (Fig. 14). Whichever underwriter is considered, the subset with only that particular underwriter's LE estimate generally received a higher k than the subset with additional LE estimates. In other words, lives with a single LE have received more aggressive LE estimates than lives with multiple LE estimates.

Insureds with their LE only estimated by a single underwriter might *appear* less healthy, possibly because the other, longer LE estimates were withheld. The lives with a single LE estimate might have never been given to an underwriter who would have assigned them longer LE estimates. Alternatively, other underwriters' LE estimates might have been issued but then discarded or never disclosed by intermediaries.

When focusing on ITM and AVS, we detect additional evidence that supports the cherry-picking theory. Based on Figure 9, we have learned that compared to AVS, ITM is more conservative (reflected by larger *LE*, or smaller *k*) when it comes to healthy lives and more aggressive (reflected by smaller *LE*, or larger *k*) in the case of impaired lives. Figure 14 shows that lives evaluated by ITM alone are mostly heavily impaired, for whom AVS would likely have issued a more conservative LE estimate. On the other hand, lives evaluated solely by AVS are relatively healthy, for whom ITM would likely have issued a more conservative LE estimate. Therefore, we do have reason to believe that certain intermediaries understand the inherent biases of individual underwriters, and, accordingly, tend to select the most aggressive underwriter(s) for a particular case.[21]

Distorted incentives might also pertain 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 due to many investors' insistence on such unattainably high IRRs, a little LE "maneuvering" is indispensable to satisfy investors and to drive the business. Furthermore, some investors might underestimate the negative impact on return from inaccurate LE estimates.[22]

Cherry-picking from sell-side intermediaries coupled with tolerance from buy-side intermediaries could also explain the large A/E gap between the underwriters and the funds in Table 1. Most settled policies have been transacted through intermediaries. Therefore, considering the two insured groups—(1) those who have been underwritten by the underwriters and (2) those who have been underwritten by the underwriters *AND* eventually settled their policies—such behavior of intermediaries would lead to more severe LE underestimation with the latter group.

Last, we cannot rule out the possibility that the lives in the side samples are healthier than those in the main sample in the first instance. Particularly, the side samples might have been subject to survivorship bias, as they include in-force policies only, but not purchased and terminated policies whose original insureds have died. Between the transaction date and LE renewal date, some insureds have died, and those who survived tend to be relatively healthy. Therefore, k_{ITM} being generally lower than k_{AVS} in the side samples (Fig. 13) falls in line with this possibility, since ITM treats healthy lives more conservatively than AVS.

4. DISCUSSION

Investors still suffer from largely underestimated LEs and face unexpectedly prolonged premium payments and postponed death benefits. Some practitioners impute underestimated LEs to mercenary underwriters who pursue short-term business gain. Some blame the skewed market on manipulative intermediaries of life settlements, who select low LE estimates to artificially elevate policy prices and to collect commissions at the point of transaction closure. Others believe that investors are also responsible for the malfunctioning market, putting settlement providers under pressure by demanding unrealistically high IRRs. Irrespective of how the underestimated LEs originate, end investors are the victims. A number of steps would potentially result in a more sustainable life settlement investment environment.

First, we recommend regulated or voluntary disclosure of medical underwriters' performance using a unified calculation method that gauges underwriting accuracy. So far, medical underwriting for the life settlement industry is regulated only in Florida and Texas (Horowitz 2013b).[23] Disclosing performance has been difficult to implement universally as some underwriters claim it would expose their intellectual property.[24] However, it is practically impossible to reverse engineer the underlying methodology simply using an aggregate performance indicator. Life settlement associations can play a vital role in enforcing standards. An increase in the transparency in underwriters' performance enhances information symmetry, which would help investors identify the most qualified underwriters and push underwriters to constantly strive for accuracy.

Second, 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

[21]See also Braun et al. (2018b), which documents a sell-side intermediary's acknowledgement of their pursuit of short LE estimates in order to sell policies at the highest possible price for their insured clients.

[22]This is based on conversations with anonymous practitioners.

[23]While Florida prescribes extensive oversight of medical underwriters, including triennial filing of a mortality table and A/E (actual to expected) results (Florida Legislature 2016), Texas requires them only to be licensed as life settlement brokers (Texas Department of Insurance 2016).

[24]AVS, for example, refused to publish their A/E reports, arguing that their underwriting methodology, namely, their core competency, might be deciphered through those reports (Horowitz 2016a).

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, to effectively incentivize intermediaries to become more long-term oriented, a performance-based pay system must be adopted industry-wide, which is needless to say a challenging proposition.

5. CONCLUSION

The present study investigates LE estimates of four major medical underwriters in the U.S. life settlement industry: ITM, AVS, Fasano, and LSI. We compare LE estimates between underwriters both within and across samples. Empirical evidence suggests that significant, systematic differences in LE estimates exist between medical underwriters. Our main sample, composed of transaction data provided by life settlements intermediaries, shows that ITM has been generally assigning lower LE estimates than its peers. However, the two side samples from investors suggest the opposite, indicating intermediaries' cherry-picking behavior. Our findings also demonstrate that underwriters exhibit patterns in LE projection associated with insureds' specific characteristics such as gender and health impairment. For example, ITM's LE estimates are relatively longer for males and healthy people, while AVS is more conservative for females and those more impaired.

Human longevity has significantly increased over the last decades, and an expanding amount of life data on the senior insured group will become available. Thus, we expect to see continuous improvement in underwriting performance in the future. We suggest buyers beware of intermediaries' cherry-picking and analyze underwriters' data on a regular basis to understand their underwriting patterns for a sensible valuation of life settlement deals. Furthermore, we call for the underwriters' publication of their detailed A/E ratios, to create a more healthy and transparent investment climate.

Upon availability of data, especially data of insureds' death dates, we recommend future research to evaluate the accuracy of underwriters' forecasts. 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. Last, 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.

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