Asymmetric Information in Secondary Insurance Markets: Evidence from the Life Settlements Market

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Abstract

We use data from a large US life expectancy provider to test for asymmetric information in the secondary life insurance—or *life settlements*—market. We compare realized lifetimes for a subsample of settled policies relative to all (settled and non-settled) policies, and find a positive settlement-survival correlation indicating the existence of informational asymmetry between policyholders and investors. Estimates of the "excess hazard" associated with settling show the effect is temporary and wears off over approximately eight years. This indicates individuals in our sample possess private information with regards to their near-term survival prospects and make use of it, which has economic consequences for this market and beyond.

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1 Introduction

Asymmetric information in insurance markets is an important and intensive area of research.[1] This paper makes two primary contributions to the existing body of knowledge. First, we provide evidence for asymmetric information in the secondary life insurance market—the market for so-called *life settlements*—between policyholders and investors. To the best of our knowledge, this is the first empirical study of informational frictions in a secondary personal insurance market.[2] This complements research from primary insurance markets, where the decision problem is different in nature but the underlying risk is the same. Second, by studying dynamic patterns in our data, we are able to provide insights on the nature of the informational friction. Our analyses suggest that policyholders in our sample possess and make use of private information with regards to their *relative* survival prospects over the near future, in a situation where they are prompted with relevant information and where there are significant monetary consequences to their decision. This complements research from the behavioral literature suggesting that individuals fare poorly at appraising their own *absolute* mortality.

Within a life settlement, a policyholder sells—or *settles*—her life-contingent insurance payments for a lump sum to a life settlement (LS) company, where the offered price depends on an individualized estimation of her survival probabilities by a third party *life expectancy* (LE) *provider*. Clearly, ceteris paribus, an LS company will pay more for a life insurance policy with shorter estimated life expectancy since, on average, survival-contingent premiums will be paid for a shorter period whereas the death benefit is disbursed sooner. The company profits from a short realized lifespan relative to the estimate. The policyholder, on the other hand, benefits from a life expectancy estimate that is (too) short—whereas she may walk away from the transaction if the estimate notably overstates her true life expectancy. This wedge creates the possibility of asymmetric information between the policyholder and the life settlement company influencing the transactions.

We use the dataset of a large US LE provider to test for this informational asymmetry. Leaning on the literature that studies asymmetric information in primary insurance markets, we derive a test that hinges on the correlation between selling insurance coverage and (ex-post) risk. We find that individuals selling their policy live significantly longer (relative to their estimate conditional

[1] While seminal theoretical contributions have emphasized the importance of informational frictions since the 1960s (Arrow, 1963; Akerlof, 1970; Rothschild and Stiglitz, 1976; Stiglitz and Weiss, 1981), the corresponding empirical literature has flourished only relatively recently (Puelz and Snow, 1994; Cawley and Philipson, 1999; Chiappori and Salanié, 2000; Dionne et al., 2001; Cardon and Hendel, 2001; Finkelstein and Poterba, 2004, 2014; Chiappori et al., 2006; Finkelstein and McGarry, 2006; Cohen and Einav, 2007; Cutler et al., 2008; Fang et al., 2008; He, 2009; Einav et al., 2010a,b; Cannon and Tonks, 2016, among others).

[2] Our findings are in line with a recent industry study by Granieri and Heck (2014) that postdates earlier drafts of our paper. More precisely, based on simple comparisons of survival curves for different populations, the authors conclude that within the life settlements market "insureds use the proprietary knowledge of their own health to select against the investor."

on observables) than those retaining the insurance coverage, providing evidence for the existence of asymmetric information. It is important to distinguish our result from the notion that individuals wishing to sell their insurance coverage, as a group, live longer, e.g. because they are wealthier per se or because the absence of dependents requiring protection implies the availability of resources to spend on their own care. Rather, what we find is that among individuals seeking out the opportunity to sell their policy, those deciding to pull the trigger will on average live longer, conditional on all observables. The identification then relies on the idea that for two individuals with the same observable characteristics, the quoted price will be more attractive to the one (privately) expecting a longer life, ceteris paribus. Example calculations for an average 75-year old male policyholder suggest that the effect amounts to a roughly four percent difference in LE or roughly ten percent difference in the present value of the underlying insurance policy, although this result is sensitive to underlying assumptions.

To analyze the pattern of the deviation in mortality between the two groups, we derive non-parametric estimates of the *excess hazard* (or excess mortality) for policyholders choosing to settle. These show that the difference in the hazard rate is most pronounced immediately after settling the policy but wears off over the course of roughly eight years. Survival regressions confirm this observation: When including a time trend interacted with the settlement dummy, the model fit improves markedly and the effect becomes stronger at settlement but weakens over time, zeroing after the same approximately eight-year time frame. Thus, while there is a large asymmetry immediately after selling the insurance coverage, the influence of the factors leading to the difference in mortality dissipates over time.

The time trend in the mortality deviation helps make more accurate LE predictions for the settled group. Indeed, our analyses indicate that not accounting for the time pattern roughly doubles the effects in terms of impact on LE and policy present value mentioned above. Furthermore, the observed structure allows us to draw inference on the nature of the informational friction. Based on different hypotheses on the origin of the asymmetry, we run regression and simulation experiments to analyze whether a certain underlying mechanism produces the empirical patterns. We demonstrate that selection on persistent unobservables, changes in behavior of policyholders that settled their policy (moral hazard), or information revealed during the settlement process are unlikely to be the (sole) underlying mechanism. In contrast, the pattern closely resembles situations where there exists additional information on a policyholder's *initial* health state. We conclude that while potentially a number of aspects could be relevant, our analyses point to adverse selection on near-term survival prospects as a key driver of the informational asymmetry. Thus, individuals participating in the life settlements market appear competent in evaluating their propensity to survive in the near future.

We perform extensive robustness analyses probing for concerns related to specification and sample selection, as well as for omitted variables. We address the former by running additional regressions using alternate samples and specifications, finding similar results. In view of the latter, we show theoretically that additional information on the individuals' mortality that the LS company may possess, e.g. a second LE estimate or other pricing-relevant information, will lead to a bias *against* our results *if* the proportion of settlements is increasing in estimated mortality—which is true in the data. The intuition is that in the absence of asymmetric information, settlement will be indicative of a low second LE estimate, leading to a negative settlement-survival correlation. Hence, our finding of a *positive* settlement-survival correlation is robust to the availability of additional information. We also provide evidence that holders of medium-sized policies are most selective in their settlement decision, which is in line with predictions of a simple expected utility model.

Related Literature and Organization of the Paper

Our paper relates to the large literature on asymmetric information in insurance markets (see Footnote 1 for a list of references). In this context, several contributions highlight the merits of insurance data for testing theoretical predictions (Cohen and Siegelman, 2010; Chiappori and Salanié, 2013), although heterogeneity along multiple dimensions may impede establishing or characterizing informational asymmetries (Finkelstein and McGarry, 2006; Cohen and Einav, 2007; Cutler et al., 2008; Fang et al., 2008). We contribute by carrying out tests in a secondary insurance market, which offers the same benefits of insurance data but considers a different decision problem—namely selling rather than purchasing insurance coverage. To our knowledge, this aspect has not been explored thus far.

Our results are of immediate interest and have applications in the life settlements market, for instance in view of pricing the transactions (Zhu and Bauer, 2013) and regarding equilibrium implications (Daily et al., 2008; Fang and Kung, 2019; Fang and Wu, 2019). We return to this point in the Conclusion. In addition, our findings corroborate empirical results from the primary life insurance market that policyholders, or at least a subset of policyholders, possess superior information regarding their mortality prospects (He, 2009; Wu and Gan, 2013). We complement these studies in that we are able to provide insights on the characteristics of the informational advantage.

More broadly, our results provide positive evidence on individuals' ability to make financial decisions that depend on their mortality prospects. This contrasts research from the behavioral literature comparing individual forecasts of *absolute* life expectancies to actuarial estimates, which suggests that individuals fare poorly at appraising their own mortality prospects (Elder, 2013; Payne et al., 2013; and references therein). Our results indicate that individuals participating in the life settlements market are competent in evaluating their *relative* life expectancy, when prompted with relevant information on population mortality. This may be the more material task in situations where there are significant monetary consequences and when appropriate "default" choices that are suitable for average individuals are provided, such as retirement planning.

In what follows, we first provide background information on life settlements and the possible relevance of asymmetric information in this market in Section 2. We then describe our dataset and our basic empirical approach in Section 3. The next two sections present our analysis of the time trend of the informational asymmetry and a corresponding discussion of the economic impact and origin. Section 6 conducts a variety of robustness and cross-sectional analyses, and the final section concludes. An online appendix collects details on derivations and supplemental results.

2 Life Settlements and Asymmetric Information

2.1 The Life Settlements Market

Originating from the so-called viatical settlements market in the late 1980s that targeted HIV/AIDS patients in need of liquidity (Doherty and Singer, 2003), according to Braun et al. (2018) the most prevalent reason for settling today is that elderly individuals no longer have a need for their insurance policy (see e.g. Fang and Kung (2019) or Fang and Wu (2019) for equilibrium models where loss of a bequest motive drives settlement). Within a secondary market transaction, a policyholder offers her life insurance contract, typically via a broker, to an LS company. The LS company—or, in some instances, the broker—then obtains individualized LE reports (typically two) from established LE providers. Based on these reports, the company makes an offer. The average time between the LE report date and the transaction closing date is a mere three months, with LE reports older than six months being discarded (Xu, 2019). If the offer is accepted, the policy—including all life-contingent insurance benefits and premiums—will be transferred to the LS company, who then holds it in its own portfolio or on behalf of capital market investors. In some instances, investors sell their interest in a policy at a later stage to a different investor within a so-called *tertiary* market transaction, in which the insured is not directly involved.

Settling presents a beneficial option relative to lapsing or retaining a non-needed contract especially for policyholders facing medical impairments. In the underwriting process, the LE provider determines an individual mortality multiplier by applying *debits* and *credits* based on these impairments.[3] The LE estimate is then calculated by applying this multiplier to a given mortality table. There are three large LE providers in the US market. While there exist nontrivial differences between these providers (Xu, 2019) and while LE providers were more aggressive by assigning

[3] According to Fasano (2019), the majority of debits are associated with cancer (37% of total debits), cardiovascular disease (21.1%), liver/kidney disease (9.7%), and neurological conditions/dementia (8.1%).

higher multipliers (equivalent to shorter LE estimates) in early market years, recent LE estimates from the underwriter used in our study, Fasano Associates (Fasano), do not exhibit a bias.[4]

Roland (2016) estimates that in 2016, roughly 47,000 individuals had traded policies totaling to roughly USD 100 billion in face value, which is less than one half percent of the total US life insurance market. However, size estimates differ substantially. For instance, a frequently cited report by the research firm Conning (2017, p.11) reports a 2016 market size of a mere \$25.1 billion in face value. Similarly, estimates on the average face value vary. While Roland (2016) reports an average face amount of \$2.15 million, the market overview by Magna (2018) reports average face values between 1.24 and 1.95 million for years 2014 through 2018. We provide descriptive statistics for our dataset in Section 3.1. Despite these differences, it is clear that typical policies are relatively large (the average face value of a US life insurance policy is roughly \$150,000, according to the American Council of Life Insurers). One potential reason are transaction costs. For instance, the price for a basic LE estimate is roughly \$300-400 depending on the provider, which can be significant for smaller policies but is marginal for a high face value policy. Life settlement investment returns average between roughly 5-8% and are volatile relative to e.g. aggregate equity indices—although they exhibit low correlation to stock or bond returns giving rise to diversification opportunities in investors' portfolios (Giaccotto et al., 2017, and references therein). According to Evans (2019), life settlements are regulated in some capacity by 46 states in the US, where several states require disclosure of settlement as an alternative to lapsing a policy.

2.2 Asymmetric Information in Life Settlement Transactions

An LS company will pay more for a policy with shorter life expectancy, ceteris paribus, and the investor profits from a relatively short realized lifespan. The policyholder, on the other hand, gains from a short life expectancy estimate relative to her true expected lifespan. This creates the possibility for asymmetric information affecting the transactions.

To illustrate, we consider a simple one-period model. We assume that at time zero, the policyholder is endowed with a one-period life insurance policy that pays $\$f$ at time one in case of death before time one and nothing in case of survival thereafter. The probability for dying (mortality probability) before time one is $\mathbb{P}(\tau < 1) = q$, where τ is the time of death. Suppose the policyholder is offered a life settlement at price π. For simplicity, we assume she assesses her settlement decision $\Delta = \mathbf{1}_{\{\text{policyholder settles}\}}$ by comparing the settlement price to the present value of her contract (the risk-free rate is set to zero):

$$\Delta = 1 \Leftrightarrow \pi > f\,q - \psi, \tag{1}$$

[4] More precisely, Table 1 in Bauer et al. (2018) shows that the difference in realized and estimated temporary life expectancies for the period 2006-2013 is not statistically different from zero.

and ψ characterizes the policyholder's proclivity for settling.[5]

Online Appendix A.1 provides a version of this simple setup—and particularly an expression for ψ—in a one-period expected utility framework. More precisely, the policyholder makes settlement and (contingent) consumption decisions in order to maximize expected utility, where in addition to consumption at time zero and one, the policyholder receives utility from her dependents' consumption. We show that in the case of logarithmic utility and bequest function with proportional bequest motive $b \in [0,1]$, the policyholder's proclivity for settling ψ decreases in wealth, decreases in bequest motive b, increases in face value f; and the proclivity for settling per dollar of face value, ψ/f, increases in f for large face values (see Proposition A.2 in Online Appendix A.1). In other words, the upper bound (ψ) for the markdown relative to the present value of the policy ($f\,q - \pi$) that is acceptable for the holder is smaller for wealthy policyholders, since they are less financially constrained. Similarly, the acceptable markdown is greater for holders of high face value policies even in terms of the markdown per unit of face value, since such a policy presents the more substantial asset. We return to these predictions in the context of our empirical analyses (see Sections 5.2 and 6.3). However, we note that our general specification (1) accommodates a variety of different settings, including models with policyholders' subsequent actions affecting mortality rates (e.g., healthier lifestyle choices). The key assumption is that the policyholder is more inclined to settle when offered a higher price—or, equivalently, a smaller markdown.

From the policyholder's perspective, the question of whether or not to settle the policy based on Equation (1) is deterministic. However, this may not be the case from the perspective of the LS company offering to purchase the policy since it may have imperfect information with respect to q and/or policyholder characteristics that are captured in ψ.[6] More precisely, assume that the policyholder has private information on the mortality probability q and the LS company solely observes the expected value, $\mathbb{E}[q]$, conditional on various observable characteristics such as age, medical impairments, etc. Then we obtain for the mortality probability conditional on the observation that the policyholder settles her policy:

$$\mathbb{P}(\tau < 1|\Delta = 1) = \mathbb{E}\left[q|\Delta = 1\right] = \mathbb{E}\left[q\,|q < (\pi + \psi)/f\,\right] \leq \mathbb{E}[q] = \mathbb{P}(\tau < 1). \quad (2)$$

Hence, if there exists private information on q, we will observe a *negative* relationship between

[5] We do not consider partial settlement. While private information may affect the contract choice in theory, the possibility of owning multiple policies, the non-exclusivity of the contractual relationship, and the presence of different sources of uncertainty (q and ψ) may hinder screening. Importantly, partial settlements have not been common in the marketplace.

[6] Of course, such an informational asymmetry may affect the pricing of the transaction, i.e. the choice of π. We refer to Zhu and Bauer (2013) for a corresponding analysis. Here, we focus on the implications when the settlement price is given.

settling and dying.

While the basic model and its implication may appear straightforward, it clarifies our empirical approach and it facilitates the discussion of robustness of our results in Section 6 (e.g. via an extension of the model, see also Online Appendix A.5). The former point is particularly relevant in light of recent controversy with regards to so-called *correlation tests* for the presence of asymmetric information (Chiappori et al., 2006; de Meza and Webb, 2017), which are closely related to our approach. To illustrate, note that we can alternatively represent the result in (2) as:

$$\mathbb{E}[\, \boldsymbol{1}_{\{\tau<1\}}\, \Delta] - \mathbb{E}[\, \boldsymbol{1}_{\{\tau<1\}}]\, \mathbb{E}[\Delta] \leq 0 \Leftrightarrow \text{Corr}\left(\Delta,\ \boldsymbol{1}_{\{\tau<1\}}\right) \leq 0 \Leftrightarrow \text{Corr}\left(\Delta,\ \boldsymbol{1}_{\{\tau\geq 1\}}\right) \geq 0. \tag{3}$$

Hence, our result is a version of the *positive correlation property* asserting that under asymmetric information, (ex-post) risk and insurance coverage are positively related (Chiappori and Salanié, 2000, 2013). However, since we are considering secondary market transactions, the mechanism is reversed: A policyholder will be more inclined to settle—i.e., sell—her policy if she is a low risk from the insurer's perspective—i.e., if she has a low probability of dying. The intuition is straightforward: If the policyholder has private insights on her lifetime distribution, she will gladly agree to beneficial offers from her perspective while she will walk away from bad offers. Hence, if individuals are equivalent based on observables, but those deciding to settle display relatively longer average lifespans, asymmetric information must be present—although welfare implications of possible market interventions are not immediately clear (de Meza and Webb, 2017).

Asymmetric information with respect to ψ alone, e.g. arising from heterogeneous preferences, wealth, or liquidity constraints, cannot yield a negative relationship. More precisely, while these factors may affect the settlement decision according to Equation (1), if the unobserved heterogeneity does not relate to mortality risk q, neither will the sorting in settled versus non-settled contracts. Hence, we will obtain an equality in Equation (2).

However, it is possible that heterogeneity in ψ and q can jointly affect the relationship. Indeed, de Meza and Webb (2001) argue that the relationship may even be flipped in such situations with *multidimensional* private information, although Chiappori et al. (2006) and Fang and Wu (2018) clarify that the inversion is only possible under certain conditions. Specifically, Fang and Wu (2018) show that multidimensional private information will not overturn the correlation test in equilibrium if the market is competitive and administrative costs are low—which likely is warranted at least for a portion of the life settlements market (see the previous subsection). Hence, a negative relation between settling and dying will—directly or indirectly—originate from an informational asymmetry with respect to the time of death, and our basic empirical approach analyzes this relationship.

3 Evidence for Asymmetric Information

To test for the existence of asymmetric information in the life settlements market, we analyze the relationship between settling and the realized future lifetime based on individual survival data. We first describe our data, then introduce our empirical approach, and finally present our baseline results.

3.1 Data and Sample Selection

Our primary dataset consists of $n = 53,947$ distinct lives underwritten for the purpose of life settlement by Fasano between beginning-of-year 2001 and end-of-year 2013. More precisely, we are given survival information for each individual and, particularly, the realized death times for individuals that died before January 1st, 2015. In addition, we are given individual characteristics including sex, age, smoking status, primary impairment (PI_1 through PI_{15}), as well as one or more LE estimates at certain points in time.[7] Therefore, we can use the LE estimate in combination with the underlying life table (also provided by Fasano) to derive the mortality multiplier, and then use it to obtain the estimated hazard, $\hat{\mu}_t^{(i)}$, for individual i.

This dataset contains LE estimates for policyholders that decided to settle (*close*) their policy as well as for policyholders that walked away from a settlement offer. The LE provider typically does not receive feedback on whether or not a policy closed, so that this aspect is unknown for our full dataset—and it is clearly unknown (not yet known) when compiling the *initial* LE estimate used for an offer. However, we also have access to a secondary dataset of overall $13,221$ lives underwritten by Fasano that settled their policy. We will refer to this secondary dataset as the subsample of *closed* cases, whereas we will refer to the rest as the *remaining* sample. While roughly 8% of the closed cases originate from portfolios of individual investors, more than 90% of the sample comes from a third-party service provider that handles policy origination and policy servicing (premium payments, annual reviews, valuation, etc.) for a broad set of investors—so that our sample is not affected by idiosyncrasies of a single or a small number of investors. This dataset covers a substantial fraction of the total market for life settlements, although it is difficult to appraise exactly how much given the divergent total market size estimates cited in Section 2.1.

Within our primary dataset, there are $140,257$ LE evaluations, so many of the lives occur multiple times in it. There are various reasons of why individuals are underwritten several times. For instance, multiple investors bidding on same policies may request separate reports in a relatively short time frame. Individuals that walked away from a transaction may want to offer their policies again at a later point in time, possibly after a health event. Policyholders may own several policies

[7] Since they are not material to our results, we do not list the primary impairments to protect proprietary information of our data supplier.

and sell different policies at different times. Also, some investors re-underwrite parts of their portfolio in regular intervals to receive updated information on its value. For the vast majority of closed cases (12,904 out of the 13,221), we are able to determine the underwriting record that was used for the transaction. For approximately 50% of them, this date corresponds to the first underwriting date, and for roughly 82%, this date is within six months of the first underwriting date, with an average delay over all cases of a little under 5 months. However, for the remaining 18% where the transaction underwriting record succeeds the first underwriting date by more than six months, the average delay is roughly 25 months—so that it is likely that many of these present tertiary transactions. Since we are interested in the influence of informational frictions on the settlement decision, we focus on the earliest underwriting date for each individual in our baseline analysis. This has the advantage that we can use all 13,221 cases and that we can treat closed and remaining cases equivalently. Furthermore, we believe that the first underwriting date presents a better proxy for the decision time for tertiary transactions. However, we repeat our analyses using the matched settlement records in the context of our robustness analyses (Section 6.2).

Summary statistics are provided in Table 1. In line with our summary from Section 2.1, participants in the life settlements market are elderly with an average (earliest) underwriting age of roughly 75 years and an average life expectancy estimate of roughly 11.5 years. There are two offsetting factors that affect this figure: On the one hand, participants in the life settlements market frequently suffer from some medical impairment—so that settling is advantageous relative to surrendering their policy—pushing down their average life expectancy; on the other hand, they are relatively wealthy, pushing up their LE relative to the general population. To illustrate the latter point, Figure 1 plots the distribution of policy face values available in our sample. More precisely, our dataset includes face values for a subset of 10,504 cases (2,672 cases in the closed subsample and 7,832 cases in the remaining sample), where there does not seem to be a systematic relationship.[8] As is evident, face values tend to be large, with the first, second (median), and third quartiles at $800,000, $2,000,000, and $5,000,000, respectively. The proportion of current and former smokers is lower than in the aggregate population,[9] which is also not surprising considering the typical socioeconomic profile of life settlements participants. The three most common medical impairments cover more than 50% of the full sample.

3.2 Empirical Approach

Our empirical strategy follows studies of asymmetric information in primary insurance markets: We regress ex-post realized risk on ex-ante coverage (Cohen and Siegelman, 2010). If, conditional

[8] Clients can submit policy face value in the underwriting process, but it is not a required field.

[9] According to the Centers for Disease Control and Prevention (CDC), about 8.2% of adults aged 65 years and older are current smokers.

	Average (Std. Dev.)			Percentage	
	Closed	Remaining		Closed	Remaining
Life Expectancy Estimate			*Male*	66.31%	62.40%
	11.54	11.93	*Observed Deaths*	25.83%	24.56%
	(4.00)	(4.37)	*Smoking*	4.89%	3.51%
Underwriting Age			PI_{15}	17.16%	22.66%
	75.40	75.00	PI_{13}	19.13%	19.91%
	(6.50)	(7.71)	PI_{7}	16.54%	13.41%

Table 1: Summary statistics for the subsample of closed cases ("Closed"; 13,221 lives, earliest observation date) and the remaining cases ("Remaining"; 40,726 lives, earliest observation date). We include the three most common primary impairments (PIs). The average relative difference between the PI in the Closed and Remaining group is 13.78%.

on all observed covariates, coverage has a positive and significant influence on risk, one can infer the existence of asymmetric information. In the setting of a secondary life market, risk is given by the realized death time, whereas (elimination of) coverage is given by the settlement decision. Thus, we analyze the relationship between settling and the individual hazard (cf. Equations (2) and (3)).

We use a conventional proportional hazards model (we consider an alternative additive specifications in Online Appendix B.1). More precisely, we assume the hazard for individual i, $\mu_t^{(i)}$, satisfies:

$$\begin{aligned} \mu_t^{(i)} &= \beta_0(t) \times \exp\Bigg\{\beta_1 \ln(\hat{\mu}_t^{(i)}) + \beta_2 \ln(1+\text{DOU}_i) + \beta_3 \ln(1+\text{AU}_i) + \beta_4\, \text{SE}_i \\ &\qquad + \sum_{j=1}^{15} \beta_{5,j}\, \text{PI}_{i,j} + \sum_{j=1}^{2} \beta_{6,j}\, \text{SM}_{i,j} + \gamma\, \text{SaO}_i\Bigg\},\ i = 1,\dots,n. \end{aligned} \tag{4}$$

Here $\beta_0(t)$ is a non-parametric term. $\hat{\mu}_t^{(i)}$ is the estimated hazard recovered from the provider's LE assessment. DOU_i is the underwriting date, measured in years and normalized so that zero corresponds to January 1st, 2001. AU_i is the individual's age at underwriting, measured in years. SE_i is a sex dummy, zero for female and one for male. $\text{PI}_{i,j}, j = 1,\dots,15$, are primary impairment dummies for various diseases. $\text{SM}_{i,j}, j = 1, 2$, are smoker dummies, where $\text{SM}_{i,1} = 1$ for a smoker and $\text{SM}_{i,2} = 1$ for an "aggregate" (unknown/uncertain smoking status) entry.

We include all covariates that are available for the full dataset in our regression (4),[10] although

[10] Chiappori and Salanié (2000) and Dionne et al. (2001) emphasize the importance of incorporating all pricing-relevant variables in asymmetric information tests.

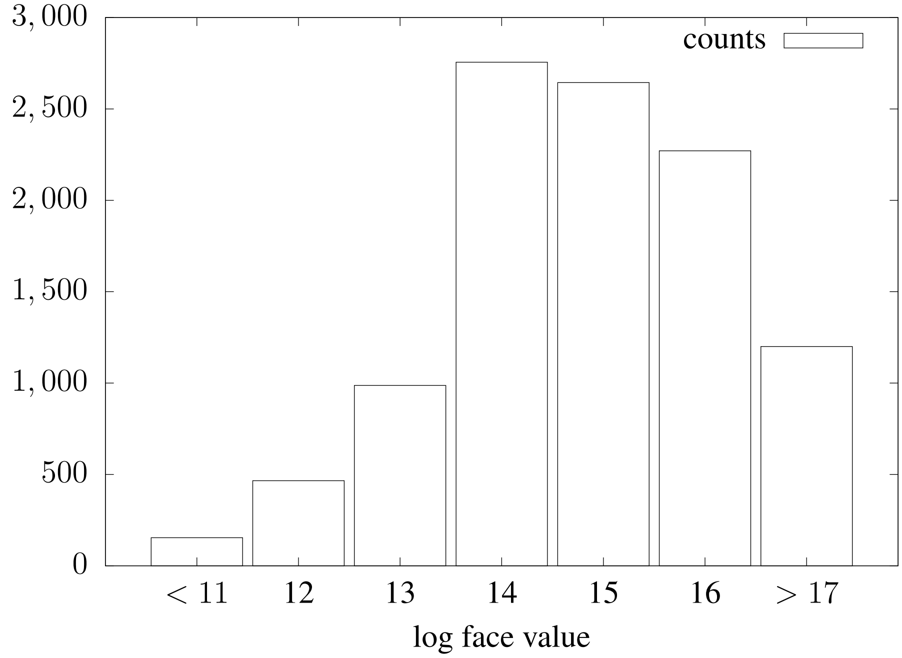


Figure 1: Histogram of the $10,478$ log face values in our sample. The median is $14.5087 = \ln\{\$2,000,000\}$. The first and third quartiles are $13.592 = \ln\{800,000\}$ and $15.4249 = \ln\{5,000,000\}$, respectively.

we also run a specification with just the estimated hazard for robustness (so we set $\beta_2 = ... = \beta_{6,2} = 0$). The estimated hazard $\hat{\mu}_t^{(i)}$ serves both to capture the basic shape of the mortality curve over time and to pick up the information from the underwriting process. Hence, the coefficients for age, sex, primary impairments, etc. reflect residual effects beyond the LE provider's estimate. We include log-linear effects for underwriting date and age for ease of presentation and interpretation; specifications with dummies for date and age are provided in Online Appendix B. We omit information that is only available for a fraction of the dataset in our basic regressions. However, we run checks including these variables and address the possible impact of omitted variables and sample selection issues in our robustness analyses (Sec. 6).

Finally, we include a Settled-and-Observed dummy SaO_i that is set to one for the subsample of closed cases and zero otherwise. We test for asymmetric information by inferring whether the estimate $\hat{\gamma}$ for the corresponding coefficient is *negative* and significant. Since the life expectancy for individual i is (Bowers et al., 1997):

$$LE_i = \mathbb{E}\left[\tau_i\right] = \int_0^\infty \underbrace{\exp\left\{-\int_0^t \mu_s^{(i)}\, ds\right\}}_{=\mathbb{P}(\tau_i > t)}\, dt, \tag{5}$$

where τ_i is the individual's remaining lifetime, a negative coefficient γ *increases* life expectancy, yielding the positive settlement-survival correlation indicative of asymmetric information (see Eq. (3) in Sec. 2). We rely on the conventional partial maximum likelihood method to estimate the coefficient vector (Cox, 1975) and calculate robust standard errors using the "sandwich estimator" from Lin and Wei (1989) to account for possible misspecification.[11]

Before presenting our results, we note that the remaining cases include policyholders that rejected the settlement offer as well as individuals that settled but are not contained in our closed subset. This brings about two complications. On the one hand, we are actually comparing closed cases relative to a mix of closed and non-closed cases, making it more difficult to establish asymmetric information. In other words, analyzing the difference presents a more conservative test than when directly comparing closed versus non-closed cases. On the other hand, even if we find evidence for asymmetric information, our quantitative estimate may be biased—and pinpointing this bias is difficult. To elaborate, our estimate would be accurate if for some reason only the portfolios we have access to were subject to asymmetric information, but not the remaining part of the market. In the (more tangible) case that our findings carry over to the set of all settled policies, i.e. if we assume our closed cases are a random sample of all settled policies, our estimate will be biased, with the size of the bias depending on how many individuals in the remaining sample settled. To appraise this bias, we derive "correction" formulae under the random sample assumption that give estimates for the more relevant settled- vs. non-settled comparison using the (unknown) proportion of closed policies in the full data set p as an input in Online Appendix A.3. It is clear that a substantial fraction of the underwriter's portfolio did not settle in the end. Therefore, in presenting our results on the economic significance in Section 5, we use several different choices for this proportion p.[12]

3.3 Results

Columns [A] and [B] in Table 2 present the results for our basic regression when only using the estimated hazard as a covariate and when using all observables, respectively, where for the latter we do not show the coefficient estimates for the primary impairments although we control for them. Our key finding is that for the Settled-and-Observed variable, the corresponding coefficient estimate is negative, highly statistically significant, and similar across both specifications. The coefficient is also economically significant. More precisely, we find that for two individuals with otherwise the same observables that are both included in our dataset, the one that is known to have settled her policy will exhibit a $1 - e^{\hat{\gamma}} \approx 11.3\%$ *lower* hazard—and thus will, on average, live

[11] Online Appendix A.2 provides technical details on the estimation approach and the expression of the partial log-likelihood.

[12] We note that this situation of a mixed comparison sample is similar to what individual investors in the LS market face, since they know what policies they purchased and bid on, but do not generally know what happened to the policies that they did not submit a (successful) bid on. Hence, our econometric approach is relevant to them as well.

	[A]	[B]	[C]	[D]
$^1/_{14} \times \int_0^{14} \beta_0(t)\, dt$	0.4228	0.0187	0.4184	0.0184
Estimated hazard, $\hat{\mu}_t^{(i)}$	0.8962^{***}	0.8986^{***}	0.8945^{***}	0.8968^{***}
	(0.0065)	(0.0102)	(0.0065)	(0.0102)
Underwriting date, $\ln(1 + \text{DOU}_i)$		0.3101^{***}		0.3043^{***}
		(0.0286)		(0.0286)
Age at underwriting, $\ln(1 + \text{AU}_i)$		0.5796^{***}		0.5852^{***}
		(0.0852)		(0.0853)
Sex, SE_i		-0.1022^{***}		-0.0986^{***}
		(0.0198)		(0.0198)
Smoker, $\text{SM}_{i,1}$		0.3743^{***}		0.3736^{***}
		(0.0429)		(0.0429)
"Aggregate" smoking status, $\text{SM}_{i,2}$		0.2114^{***}		0.2120^{***}
		(0.0553)		(0.0553)
Settled-and-Observed, SaO_i	-0.1105^{***}	-0.1203^{***}	-0.4941^{***}	-0.4929^{***}
	(0.0198)	(0.0200)	(0.0638)	(0.0635)
Settled-and-Observed $\times$ trend,			0.2294^{***}	0.2225^{***}
$\text{SaO}_i \times \ln(1 + t)$			(0.0358)	(0.0356)
Log-likelihood value	$-134,533.38$	$-134,032.02$	$-134,512.64$	$-134,012.44$

Table 2: Proportional hazards survival regression results. Column [A]: Only using estimated hazard and Settled-and-Observed, earliest observation date; [B]: Basic regression (Eq. (4)), earliest observation date; [C]: Only using estimated hazard and Settled-and-Observed with time trend, earliest observation date; [D]: Basic regression plus time trend, earliest observation date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

longer. Therefore, we find a strong negative relationship between settlement and mortality, which indicates the existence of asymmetric information in the life settlements market.

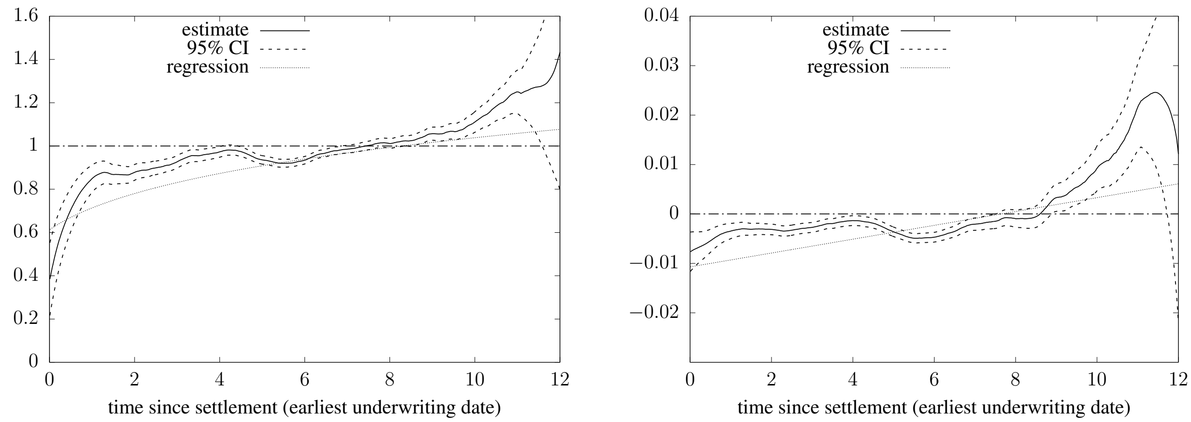
As for the remaining coefficients, we find that the estimated hazard $\hat{\mu}_t^{(i)}$ is highly significant, with a coefficient $\hat{\beta}_1$ of around 0.9—and, thus, close to one as would be the case for (ex-post) "perfect" estimates by the LE provider. The non-parametric term varies across the years and, in particular, averages below one in the basic specification [A]. This indicates that, across the entire time period, the LE provider over-estimates mortality as discussed in Section 2.1. As also discussed there, this is primarily driven by (too) aggressive underwriting in the early market years, in line with the significant and positive estimate for date-of-underwriting (DOU) in specification [B]: The downward correction of overestimation is particularly relevant in early years. It is also not surprising that the coefficients for age at underwriting and smoking status are positive in [B]. For robustness, we also run specifications with year and age dummies rather than the log-linear trends, finding equivalent results (see column [C] in Table A.2 and Figure A.1 in Online Appendix B). The negative coefficient for male policyholders is more surprising, indicating that underwriting has been more aggressive for males relative to females. Due to all these (predominantly positive) corrections, the non-parametric term for specification [B]—as well as for other specifications that involve all observables—is small on average.

Aside from its relevance to the life settlements market, our finding of asymmetric information complements analyses in primary life insurance markets, where several papers fail to find evidence for the existence of asymmetric information based on correlation tests (Cawley and Philipson, 1999; McCarthy and Mitchell, 2010). As discussed in detail by Finkelstein and Poterba (2014), these results may originate from (unobserved) related confounding factors such as risk aversion or wealth also affecting insurance decisions, or also from risk factors not included in the pricing—so that researchers may fail to reject the null hypothesis of symmetric information within a correlation test even if there exists private information about risk type. For example, underwriting is limited in certain segments of the primary market (such as life annuities) and regulation in some instances restricts factors that can be considered in pricing (such as gender or genetic information). In contrast, the evaluation of mortality for the pricing of life settlements is highly individualized. Furthermore, while risk aversion is a key driver for purchasing life insurance, the decision of whether or not to sell a policy for an affluent senior is frequently driven by investment or estate planing considerations—so that risk aversion may be less relevant. Therefore, our analysis may not be subject to the same confounding influences as purchasing coverage in the primary market, or at least not to the same extent. Our result that individuals possess private information is in line with He (2009) and Wu and Gan (2013), who find evidence for asymmetric information in primary life insurance when accounting for certain biases.

Our results may be due to selection on unobservables beyond whether or not the individual settled, implying the existence of unobserved heterogeneity. While our standard proportional hazards estimate remains consistent for the *mean function* or the *cumulative rates* in this case (Lin et al., 2000) and differences to estimators that explicitly account for unobserved heterogeneity are usually small (Liu, 2014), issues may arise for resulting life expectancy estimates. We will return to this point in Section 5.1.

4 Time Trend of the Excess Hazard

The previous section provides evidence for asymmetric information by establishing a negative relationship between settling and dying, following the logic of Equation (3) in Section 2.2. More precisely, our regression (4) states that for two individuals with identical observable characteristics and the sole difference that one is in the settled-and-observed subgroup (S—with hazard μ_t^S) and



(a) multiplicative excess hazard $\alpha(t)$ (b) additive excess hazard $\beta(t)$

Figure 2: Non-parametric estimate of the multiplicative excess hazard $\alpha(\cdot)$ and the additive excess hazard $\beta(\cdot)$ for an individual in the closed subsample relative to an individual in the full sample (solid curve), with point-wise 95% confidence intervals (dashed curves) and the corresponding trend line from the survival regression (dotted curve); earliest observation date.

for the other one we do not have that information (R—with hazard μ_t^R), we obtain:

$$\mu_t^S = \mu_t^R \times e^{\gamma}, \tag{6}$$

where $\gamma \approx -0.12$ (or $\mu_t^S = \mu_t^R + \gamma$ in the context of the additive model from Online Appendix B.1). That is, there exists private information that, when projected onto the information that the individual settled, results in a lower hazard—and, thus, a longer expected lifetime via Equation (5). We can generalize Equation (6) by writing:

$$\mu_t^S = \alpha(t) \times \mu_t^R \text{ or } \mu_t^S = \mu_t^R + \beta(t), \tag{7}$$

where $\alpha(t)$ and $\beta(t)$ are called the (multiplicative and additive, respectively) *excess hazard* in the survival analysis literature (Andersen and Vaeth, 1989). That is, we can allow for the projection to vary with time since settlement.

We obtain non-parametric estimates for the multiplicative and additive excess hazard $\alpha(\cdot)$ and $\beta(\cdot)$ by repeated application of the excess hazard estimators from Andersen and Vaeth (1989), which in turn are based on the well-known Nelson-Aalen and Kaplan-Meier non-parametric estimators, respectively. More precisely, we first adjust all hazard estimates from the LE provider $\hat{\mu}_t^{(i)}$ based on the survival experience in the full sample, and then derive the excess hazard to the adjusted hazard estimate based on the survival experience in the closed subsample (see Online Appendix A.4 for more details). Figure 2 shows the resulting estimates (solid curves).

Clearly, if the estimate for the multiplicative (additive) excess hazard had the shape of a horizontal line at *one* (*zero*) given by the horizontal dashed line, or if the horizontal line at one (zero) fell within the (point-wise) 95% confidence intervals given by the dashed curves, we would conclude that there is no significant relationship between settling and an individual's hazard. The observation that the estimate is overall less than one (zero) illustrates the negative association between settling and the hazard, in line with the regression results from the previous section. With an approximately 60% (0.007) reduction in hazard, the relationship is very pronounced immediately after the settlement decision. However, the effect is wearing off over the course of about eight years. While the point estimate continues to increase after year eight, the confidence intervals become wider due to the limited data in this region, making it difficult to infer the existence or the sign of the trend in the later years after settling. Hence, the key characteristic that emerges is a negative hazard-settlement relationship that is receding over time since settlement.

Survival regressions confirm these observations. We augment the basic specification from Equation (4) by a logarithmic time trend interacted with the Settled-and-Observed variable $\text{SaO}_i \times \ln(1+t)$ in the exponent. Column [D] in Table 2 presents the resulting estimates. The coefficients for the covariates that are not related to the settlement decision are similar to the basic specification in column [B]. The coefficient for the Settled-and-Observed dummy (intercept of the trend) again is negative and strongly significant, with its absolute value being more than four times that of the basic specification. Hence, in line with the non-parametric estimate, we find a pronounced negative relationship between settling and mortality shortly after the settlement decision. The slope of the trend is highly significant and positive, implying that the relationship weakens over time since settlement, which is again congruent with the pattern as observed in the non-parametric estimate.[13]

Indeed, the regression model suggests a multiplicative excess hazard for individuals in the closed subsample relative to the remaining sample of the form:

$$\alpha(t) = \exp\{-0.49\} \times (1+t)^{0.22} \approx 0.61 \times (1+t)^{0.22},$$

which we also plot in Figure 2a (dotted curve).[14] In particular, the trend suggests a reduction in the hazard of roughly 40% immediately after settlement but that the effect wears off zeroing after roughly 8 years, with a decreasing slope so that the effect after the 8-year time window is minor. The log-likelihood of the model increases markedly when adding the time trend, compared with the basic specification. Alternative trend specifications (e.g., a linear trend in the exponent) yield similar results, although corresponding model likelihoods are lower. We refer to Online Appendix B for corresponding results.

[13] We draw the same conclusion when using the simpler specification with only the estimated hazard as a covariate, as shown in column [C] of Table 2.

[14] Similarly, when including a time trend into the additive regression model from Online Appendix B.1, we obtain an additive excess hazard $\beta(t) = -0.01 + 0.0014 \times t$, which we include in Figure 2b (dotted line).

The relevance of these findings is twofold. On the one hand, the estimated LE is a key pricing input, and adjusting the hazard for settlement based on Equation (6) results in a very different expected lifetime estimate relative to adjusting based on (7). On the other hand, the time pattern allows us to draw conclusions with regards to the nature of the informational friction. More precisely, a number of potential mechanisms can yield a negative relationship between settling and dying, but only a subset will result in the patterns as observed from Figure 2. We provide more details on both of these aspects in the next section.

5 Impact and Origin of the Informational Friction

5.1 Economic Impact

To demonstrate the quantitative impact of our results on life settlement transactions, we provide example calculations based on our proportional hazards regression results. More precisely, we are looking to quantify the average difference of LE estimates and policy valuations for an individual that decided to settle their policy relative to an individual that walked away from the transaction.

We face three difficulties. First, as discussed in Section 3.2, our regression estimates are based on analyses of the known closed policies relative to the remaining policies, with the latter including a mix of closed and non-closed cases. Since we are interested in the direct closed versus non-closed comparison, we adjust our point estimate based on different parameter values of the (unknown) proportion of closed policies in the full sample p. More precisely, we inflate the coefficient γ based on the analysis in Online Appendix A.3 (Eq. (A.6)). Second, our regressions give us estimates for the overall impact, but not for a specific individual. Hence, we rely on US population mortality data to evaluate the impact on average policyholders at different ages that are roughly in line with the aggregate statistics from our dataset (ages 70, 75, and 80).[15] And, third, as pointed out at the end of Section 3.3, unobserved heterogeneity may yield a prediction bias for LEs calculated based on survival regression estimates. Since we are mainly interested in the difference of LE estimates between the settled and the non-settled group, we accept this limitation and refer to Liu (2014) for possible remedies, e.g. by relying on the so-called retransformation method.

Table 3 presents results for US male policyholders, where we rely on two different approaches to adjust the baseline mortality for settlement: A time-constant effect assumption as in Equation (6) with results shown in the bottom part of the table, and an effect that weakens and wears off over eight years according to the time trend in our regression model with results shown in the

[15]The mortality data are taken from the Human Mortality Database; University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany); available at *www.mortality.org* or *www.humanmortality.de*. More precisely, we calculate life expectancies based on expected future survival probabilities, where we use the Lee and Carter (1992) method to produce forecasts.

	Proportion of closed policies (p)					
	24.5%	30%	40%	50%	60%	70%
Proportional hazards; time-weakening effect						
Age 70 (non-adjusted LE 13.93*, value* 0.2092*)*						
Difference in LE (%)	2.51	2.65	2.95	3.32	3.81	4.48
Difference in value (%)	−8.21	−8.67	−9.63	−10.85	−12.44	−14.62
Age 75 (non-adjusted LE 10.48*, value* 0.2520*)*						
Difference in LE (%)	3.87	4.08	4.54	5.12	5.88	6.93
Difference in value (%)	−9.71	−10.25	−11.40	−12.86	−14.76	−17.36
Age 80 (non-adjusted LE 7.50*, value* 0.3024*)*						
Difference in LE (%)	6.00	6.34	7.06	7.97	9.17	10.83
Difference in value (%)	−11.33	−11.97	−13.33	−15.05	−17.30	−20.40
Proportional hazards; time-constant effect						
Age 70 (non-adjusted LE 13.93*, value* 0.2092*)*						
Difference in LE (%)	5.48	5.89	6.79	8.03	9.81	12.62
Difference in value (%)	−14.64	−15.70	−18.09	−21.35	−26.03	−33.33
Age 75 (non-adjusted LE 10.48*, value* 0.2520*)*						
Difference in LE (%)	6.19	6.65	7.68	9.08	11.11	14.31
Difference in value (%)	−13.44	−14.43	−16.64	−19.64	−23.98	−30.78
Age 80 (non-adjusted LE 7.50*, value* 0.3024*)*						
Difference in LE (%)	6.93	7.44	8.59	10.16	12.44	16.03
Difference in value (%)	−11.90	−12.77	−14.74	−17.41	−21.28	−27.36

Table 3: Comparisons of average life expectancies as well as net policy values for a standard whole life insurance purchased 10 years ago, between population-level and settled US male policyholders; proportional hazards model with time-weakening effect or time-constant effect.

top part of the table. As pointed out at the end of Section 3.3, our estimates for the adjustment are consistent for the cumulative hazard rates independently of its genesis. We determine the LE according to Equation (5) for the adjusted and the unadjusted rates, and we report the LE change in percent. In addition, we report the percentage change in value for a whole-life insurance policy that was purchased ten years prior with a constant face value, constant annual premiums, and using an interest rate of 4%. Online Appendix B presents additional results for female policyholders as well as for additive specifications of the excess hazard.

The first column of the table presents results based on the observed proportion of closed policies ($13,221/53,947 \approx 24.5\%$), so without inflating the coefficient estimate. Since the actual proportion p can only be higher, these estimates provide lower bounds for the differences between settlers and non-settlers with identical observable characteristics. The remaining columns present results based on various assumptions of p that range from 30% to 70%. Our calculations for the time-weakening assumption suggest that the LEs for individuals that settled their policy exceed those for non-settlers by between roughly 2.5% to 11%. In particular, for a 75-year old policyholder and assuming that the proportion of closed cases in the full sample is 50%, we obtain roughly half a year (5%) of additional LE relative to a non-settler's LE of a little over 10 years. For the differences in value of the insurance policy, we obtain figures between roughly -8% to -20% for settlers relative to non-settlers. Of course, the results are based on rather specific assumptions. Nevertheless, these magnitudes suggest that asymmetric information has an economically significant impact on the life settlements market, and should be accounted for in market operations—e.g. in view of pricing and risk management.

The results increase substantially if we use a time-constant adjustment. For instance, they roughly double for a 75-year old for all considered proportions p. This documents the relevance of accounting for the dynamic pattern of the excess hazard. Furthermore, as we will discuss in the next subsection, it allows us to shed some light on the nature of the informational friction.

5.2 Nature of the Informational Friction

Identifying the origin of the informational asymmetry is a difficult problem since different explanations have similar empirical implications, particularly the positive risk-coverage relationship we observe (Chiappori and Salanié, 2013). In our setting, there are a number of ways how asymmetric information can affect the transactions, including:

(i) *Selection on persistent unobservables*: There exists a permanent hidden characteristic that affects both mortality and the proclivity to settle.

(ii) *Hidden actions* (moral hazard): Settling leads individuals to adjust their behavior (relative to when retaining their policy).

(iii) *Settlement process*: If bidders imperfectly account for hidden information, the positive relationship may arise from the transaction process ("winner's curse").

(iv) *Selection on temporary unobservables*: There exists a temporary hidden characteristic that affects both mortality and the proclivity to settle.

However, different mechanisms for asymmetric information lead to different risk-coverage patterns over time.[16] In what follows, we discuss and evaluate these explanations by appraising of whether they will yield the empirical pattern.

We consider a simulation experiment, where we assume individual i's hazard is of the form:

$$\mu_t^{(i)} = \theta_i \times B \times C^{x_0+t}, \tag{8}$$

where $B \times C^{x_0+t}$ is a basic Gompertz form for baseline mortality and θ_i is a random variable associated with unobserved heterogeneity. We simulate 50,000 independent lifetimes, with 25,000 individuals that settled (S) and 25,000 that did not settle (N), using starting age $x_0 = 70$, Gompertz parameters $B = 0.0003$ and $C = 1.07$ (Dickson et al., 2003), and making different assumptions on (the conditional distribution of) θ_i within the two groups S and N. We then determine the multiplicative and additive excess hazard $\alpha(t)$ and $\beta(t)$, respectively, for members of the S group following the same procedure as in Section 4, and compare the results to Figure 2. We show results for a single simulation in Figure 3, Panels (a) through (d), (f), and (g). We carried the experiment out several times obtaining virtually identical results.

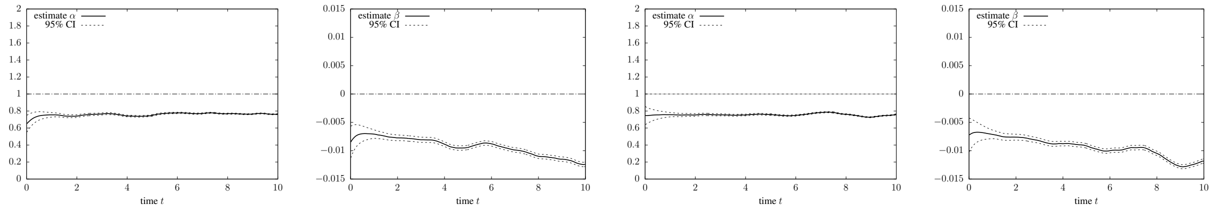
(i) Selection on Persistent Unobservables

Policyholders heterogeneity can be the root cause for an informational asymmetry. As we discuss in the context of our simple model in Section 2.2, policyholder characteristics will influence the decision to settle (via the parameter ψ) and may also be related to their propensity to survive. While heterogeneity in wealth is not likely to deliver the observed result,[17] *risk aversion* presents a viable explanation. Indeed, persistently higher risk aversion may directly increase the incentive to settle or it may lead individuals to hold more (relinquishable) life insurance in the first place,[18]

[16]The idea to rely on dynamic relationships to characterize asymmetric information already appears in Abbring et al. (2003) in the context of experience ratings in automobile insurance.

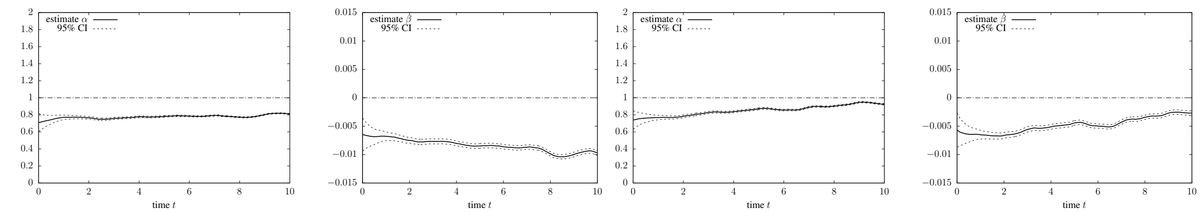
[17]Our expected utility model from Online Appendix A.1 predicts that wealthier policyholders are *less* likely to settle (Proposition A.2) but wealthier policyholders generally also have greater life expectancies, ceteris paribus, so settling will be associated with lower wealth—or shorter average lifetimes.

[18]Proposition A.2 shows that the propensity to settle increases in policy face value, ceteris paribus. And while the model from Online Appendix A.1 assumes $\log$-utility and thus does not allow for a direct analysis of risk aversion, since $\log$-utility exhibits decreasing absolute risk aversion, an increase in risk aversion is similar to a decrease in wealth, which increases the incentive to settle (see de Meza and Webb (2001, p. 252) for a similar argument).



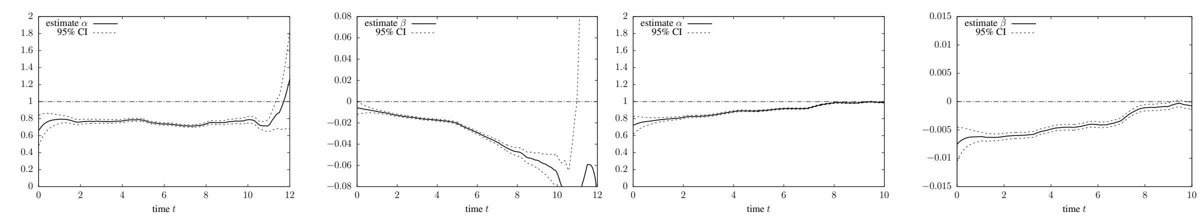
(a.i) mult. ex. hazard (a.ii) add. ex. hazard (b.i) mult. ex. hazard (b.ii) add. ex. hazard

(a) S has permanently lower mortality (b) S has permanently lower mortality, with equivalent frailty



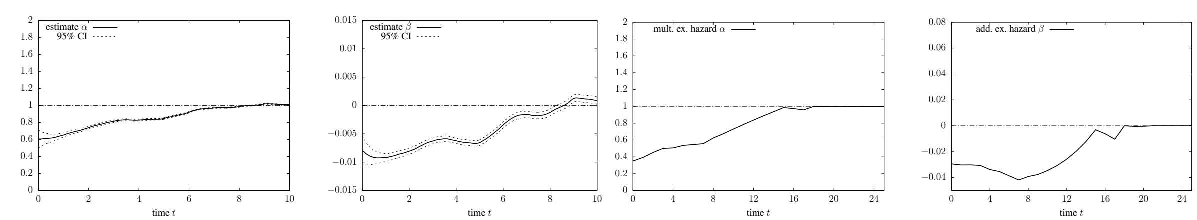
(c.i) mult. ex. hazard (c.ii) add. ex. hazard (d.i) mult. ex. hazard (d.ii) add. ex. hazard

(c) S has permanently lower mortality, N has higher variance (d) S has permanently lower mortality, N has much higher variance



(e.i) mult. ex. hazard (e.ii) add. ex. hazard (f.i) mult. ex. hazard (f.ii) add. ex. hazard

(e) Monte Carlo experiment on settlement process ("winners curse") (f) S has temporarily lower mortality



(g.i) mult. ex. hazard (g.ii) add. ex. hazard (h.i) mult. ex. hazard (h.ii) add. ex. hazard

(g) S has temporarily lower mortality, matching Figure 2 (h) Comparison to CSO life table selection effect

Figure 3: Multiplicative and additive excess hazard. Panels 3a through 3d, 3f and 3g: Monte-Carlo experiment according to Equation (8) and 25,000 lives in the settled (S) and non-settled (N) groups based on various specifications. 3a: $\theta_i|\{i \in N\} = 1$ and $\theta_i|\{i \in S\} = 0.6$; 3b: $\theta_i|\{i \in N\} = \Gamma(1, 0.2)$, and $\theta_i|\{i \in S\} = 0.6 \times \Gamma(1, 0.2)$, where $\Gamma(a, b)$ stands for a random variable that follows a Gamma distribution with mean a and standard deviation b; 3c: $\theta_i|\{i \in N\} = \Gamma(1, 0.4)$, and $\theta_i|\{i \in S\} = 0.6 \times \Gamma(1, 0.2)$; 3d: $\theta_i|\{i \in N\} = \Gamma(1, 1)$, and $\theta_i|\{i \in S\} = 0.6 \times \Gamma(1, 0.2)$; 3f: $\theta_i(t)|\{i \in N\} = 1$ and $\theta_i(t)|\{i \in S\} = 0.6 + 0.04 \times t$, $0 \leq t \leq 10$; 3g: $\theta_i(t)|\{i \in N\} = 1$ and $\theta_i(t)|\{i \in S\} = 0.44 + 0.066 \times t$, $0 \leq t \leq 8.5$. 3e: Monte-Carlo experiment on the settlement process, see Online Appendix C for details. 3h: at age 75 as a function of time since underwriting for the Society of Actuaries 2001 Commissioner's Standard Ordinary (CSO) preferred life table.

but may also positively affect survival prospects, e.g. by limiting engagement in risky activities or more engagement in preventative health care.

To illustrate the impact of persistent unobserved heterogeneity, consider the simulation experiment outlined above with different assumptions on θ_i conditional on being in the N(ot-settled) and S(ettled) groups. A necessary condition for the negative settlement-mortality relationship right at settlement as observed in Figure 2 is:

$$\mathbb{E}\left[\theta_i|\{i \in S\}\right] < \mathbb{E}\left[\theta_i|\{i \in N\}\right]. \tag{9}$$

To see this, note that the multiplicative excess hazard at settlement is:

$$\alpha(0) = \frac{\mu_0^S}{\mu_0} = \frac{\mathbb{E}\left[\theta_i|\{i \in S\}\right]}{\mathbb{P}(i \in S) \times \mathbb{E}\left[\theta_i|\{i \in S\}\right] + \mathbb{P}(i \in N) \times \mathbb{E}\left[\theta_i|\{i \in N\}\right]},$$

and similarly the additive excess hazard at settlement is:

$$\beta(0) = \mu_0^S - \mu_0 = B \times C^{x_0} \times \mathbb{P}(i \in N) \times \left(\mathbb{E}\left[\theta_i|\{i \in S\}\right] - \mathbb{E}\left[\theta_i|\{i \in N\}\right]\right).$$

The two panels (b) in Figure 3 provide the multiplicative and additive excess hazard when assuming $\theta_i|\{i \in N\}$ is Gamma distributed with mean 1 and standard deviation 0.2, and when an individual in the settled group exhibits a 40% lower hazard rate throughout her lifetime ($\theta_i|\{i \in S\} \sim 0.6 \times \theta_i|\{i \in N\}$). The plots look similar to the situation when assuming there is no conditional heterogeneity, i.e. $\theta_i|\{i \in N\} = 1$ and $\theta_i|\{i \in S\} = 0.6$, provided in panels (a). In particular, we observe a flat shape for the multiplicative excess hazard and a diverging shape for the additive excess hazard, in contrast to Figure 2. Hence, selection on persistent heterogeneity with identically distributed frailty factors does not appear to yield the observed pattern.

However, different patterns can emerge from differences in higher-order moments. Indeed, for a flat heterogeneous hazard, $\mu_t^{(i)} = \theta_i$, by expanding the moment-generating function of θ_i:

$$\mu_t^{S/N} \times \mathbb{P}\left(\tau_i > t|\{i \in S/N\}\right) = \mathbb{E}\left[\theta_i|\{i \in S/N\}\right] - t \times \mathbb{E}\left[\theta_i^2|\{i \in S/N\}\right] + \frac{1}{2}t^2 \times \mathbb{E}\left[\theta_i^3|\{i \in S/N\}\right] + ...,$$

so an increasing pattern in the quotient $\alpha(t) = {}^{\mu_t^S}/_{\mu_t}$ or the difference $\beta(t) = \mu_t^S - \mu_t$ must stem from differences in the conditional moments, particularly from $\mathbb{E}\left[\theta_i^2|\{i \in N\}\right]$ exceeding $\mathbb{E}\left[\theta_i^2|\{i \in S\}\right]$. The intuition is as follows: While individuals in the S group have a lower hazard on average, individuals in the N group show a higher dispersion; thus, after the individuals with the lowest hazard realizations in the N group deceased, the distribution of the N group *conditional on* having survived till time t becomes closer and closer to the distribution of survivors in S. An example may be more risk-averse individuals in S showcasing lower—but also a more concentrated distribution of—mortality.

To illustrate, for the two panels (c) in Figure 3, we use the same conditional distribution for the settled subgroup ($\theta_i|\{i \in S\}$) as before but now double the standard deviation for the frailty factor in the non-settled subgroup ($\theta_i|\{i \in N\}$) to 0.4. As is evident from the plot, we now observe a slightly increasing multiplicative excess hazard but the increase in variance is not sufficient to overturn the decreasing pattern in the additive excess hazard, which originates from the underlying Gompertz form. In part (d), we repeat the exercise but now further increase the standard deviation of $\theta_i|\{i \in N\}$ to one. In this case, we do observe an increasing shape similar to Figure 2. However, a standard deviation of one for the unobserved heterogeneity—conditional on observables, including the underwriter's estimated hazard—is a relatively extreme assumption. Indeed, this assumption would imply a chance of close to 40% that the true hazard of individuals in the N group is less than half of the estimated hazard, and a chance of close to 14% that the true hazard is more than twice the estimated hazard. Thus, even though differences in the conditional distributions in theory could generate the observed pattern, it seems rather unlikely that persistent unobserved heterogeneity is the sole driver.

(ii) **Hidden Actions/Moral Hazard**

In the present context, "moral hazard" may take the form of healthier lifestyle choices after relinquishing the life insurance coverage, seeking improved medical care using the proceeds from settling, or other positive changes in health-related behavior. If *permanent* changes in behavior were the sole driver for the informational asymmetry, two policyholders with exactly the same observable characteristics but only differing in their settlement decision should display exactly the same hazard rate right up until settlement, and we would expect to see a diverging relationship thereafter. In particular, if there were differences in care or in lifestyle, we would arguably expect (at least) a *persistent* effect on the hazard—in contrast to the *subsiding* pattern we identify in Figure 2.

However, if settlement is driven by the need of funds for treatment of an acute medical condition, it is conceivable that the effect of settling is immanent. And once the condition is treated, mortality may revert to population levels. To probe for this explanation, we rerun our regression analysis focusing on relatively healthy individuals. More precisely, we repeat the exercise for the 32,317 individuals in the full dataset with a mortality multiplier of less than 150% (the corresponding closed dataset comprises 7,122 cases), thus excluding the individuals that were rated as very impaired. Columns [E] and [F] of Table 4 show the results with and without time trend, respectively. For the Settled-and-Observed variable, the point estimate of the coefficient in the specification without time trend ([E]) barely changes, although standard errors increase given the smaller sample size. We observe some decrease in the slope of the time trend from 0.22 in the baseline analysis [D] to about 0.15 in specification [F], with an accompanying decrease in the intercept so that the duration of the effect roughly remains the same. Hence, while we see some relevance of the treatment of acute conditions, it appears that the observed pattern still emerges when considering only relatively healthy individuals.

(iii) ***Settlement Process***

If life settlement companies imperfectly account for missing information in their pricing, the *winner's curse* can yield a negative settlement-mortality correlation (Thaler, 1988). More precisely, a wedge could arise from brokers forwarding shorter LEs to LS companies or policyholders picking the highest among several bids for their policy, although it is not clear whether or not the LE from our provider was actually used in the settlement process.

Consider the following thought experiment in opposition to this explanation: Suppose there are several identically distributed LE estimates with different associated multipliers but the broker only forwards the one with the highest multiplier and the "winning" LS company prepares a bid on this basis; now, assuming the multiplier is simply a relatively high random realization, the multiplicative excess hazard will be constant over time at a level below one and the additive excess hazard will necessarily need to diverge to sustain this constant multiplicative trend. The panels in part (e) of Figure 3 show the multiplicative and additive excess hazard for a Monte Carlo implementation of this thought experiment in the context of our dataset (see Online Appendix C for details), which is congruent with the predictions but in contrast to the pattern depicted in Figure 2. Thus, again, the dynamic pattern does not sustain this explanation as the sole driver.

(iv) **Selection on Temporary Unobservables**

Unsurprisingly, allowing the heterogeneity between the two groups to converge with time since settlement (t) can generate the observed patterns from Figure 2. To illustrate, we generalize Equation (8) to allow for dependence on t in the unobserved heterogeneity θ_i:

$$\mu_t^{(i)} = \theta_i(t) \times B \times C^{x_0+t}. \tag{10}$$

The panels in part (f) of Figure 3 plot the multiplicative and additive excess hazard for the S relative to the N group under assumption (10), where we set $\theta_i(t)|\{i \in N\}$ to one and let $\theta_i(t)|\{i \in S\}$ start at 0.6 and linearly increase to one at time 10. Similar to part (a) versus (b), adding frailty with positive variance does not substantially change the pattern.

The resulting shape is similar to Figure 2, although this is not a like for like comparison due to differences in the definition of the N(ot settled) and the R(emaining) comparison group. In order to replicate the trends in Figure 2 as closely as possible, we need to choose $\theta_i(t)|\{i \in S\}$

	[E]	[F]	[G]	[H]	[I]	[J]	[K]	[L]
$^1/_{14} \times \int_0^{14} \beta_0(t)\, dt$	0.0000	0.0000	0.6171	0.0198	0.0193	0.0140	0.0230	0.5818
Estimated hazard, $\hat{\mu}_t^{(i)}$	0.5651***	0.5749***	0.8386***	0.8961***	0.8948***	0.8914***	0.8787***	0.8384***
	(0.0735)	(0.0734)	(0.0265)	(0.0102)	(0.0102)	(0.0104)	(0.0097)	(0.0267)
Underwriting date, $\ln(1 + \mathrm{DOU}_i)$	0.2492***	0.2500***	−0.0134	0.2712***	0.2683***	0.3032***	0.2480***	−0.0150
	(0.0735)	(0.0734)	(0.1754)	(0.0285)	(0.0285)	(0.0289)	(0.0260)	(0.1753)
Age at underwriting, $\ln(1 + \mathrm{AU}_i)$	5.2342***	5.1351***	0.5243***	0.5753***	0.5822***	0.6273***	0.5364***	0.5246***
	(0.7582)	(0.7579)	(0.2089)	(0.0849)	(0.0849)	(0.0874)	(0.0843)	(0.2097)
Sex, SE_i	−0.0037	−0.0081	−0.0943	−0.1008***	−0.1006***	−0.1012***	−0.0735***	−0.0960*
	(0.0436)	(0.0436)	(0.0582)	(0.0198)	(0.0198)	(0.0199)	(0.0197)	(0.0583)
Smoker, $\mathrm{SM}_{i,1}$	0.6537***	0.6481***	0.4004***	0.3611***	0.3610***	0.3757***	0.3112***	0.4019***
	(0.0917)	(0.0917)	(0.1153)	(0.0431)	(0.0432)	(0.0434)	(0.0435)	(0.1155)
"Aggregate" smoking status, $\mathrm{SM}_{i,2}$	0.2394**	0.2373**	0.2550	0.2217***	0.2223***	0.2124***	0.2250***	0.2637
	(0.1184)	(0.1184)	(0.1614)	(0.0550)	(0.0550)	(0.0557)	(0.0551)	(0.1618)
Face Value, $\ln(1 + \ln(1 + \mathrm{FV}))$			−1.1458***					−1.1223***
			(0.3412)					(0.3721)
Settled-and-Observed, SaO_i	−0.1225***	−0.3922***	−0.2847*	−0.0886***	−0.3673***	−0.3835***	−0.1111**	
	(0.0342)	(0.1307)	(0.1509)	(0.0201)	(0.0620)	(0.0664)	(0.0525)	
Small Face Value × Settled-and-Observed,								−0.2054
$\boldsymbol{1}_{FV \leq 500{,}000} \times \mathrm{SaO}_i$								(0.1747)
Medium Face Value × Settled-and-Observed,								−0.3473**
$\boldsymbol{1}_{500{,}000 < FV < 5{,}000{,}000} \times \mathrm{SaO}_i$								(0.1552)
Large Face Value × Settled-and-Observed,								−0.1907
$\boldsymbol{1}_{FV \geq 5{,}000{,}000} \times \mathrm{SaO}_i$								(0.2006)
Settled-and-Observed × trend,		0.1524**	0.2094**		0.1701***	0.1638***	0.0711**	0.2308**
$\mathrm{SaO}_i \times \ln(1 + t)$		(0.0709)	(0.1023)		(0.0355)	(0.0372)	(0.0326)	(0.1026)
Log-likelihood value	−46,659.58	−46,657.25	−13,472.47	−133,986.91	−133,975.36	−132,337.92	−132,918.00	−13,471.36

Table 4: Supplemental proportional hazards survival regression results. Column [E]: Only considering cases with mortality ratings ≤ 150%, earliest observation date; [F]: Only considering cases with mortality ratings ≤ 150% and with time trend, earliest observation date; [G]: Only considering cases with known face value (in the entire dataset) and with time trend, face value as covariate, earliest observation date; [H]: Basic regression, using matched observation date for observed settled cases; [I]: Basic regression plus time trend, using matched observation date for observed settled cases; [J]: Excluding cases with times of death within six months of underwriting (in the remaining sample) and with time trend, earliest observation date; [K]: Basic regression plus time trend, latest observation date; [L]: Only considering cases with known face value (in the entire dataset) and with time trend, face value and its interactions with observed settlement as covariates, earliest observation date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

starting at roughly 0.44 and linearly increasing to one at approximately time 8.5, as shown in the panels (g) of Figure 3. The resulting patterns—and also the relative magnitudes—are reminiscent of so-called *select-and-ultimate* life tables in actuarial studies that capture selection effects due to underwriting. To illustrate, in the panels in part (h) of Figure 3, we plot the multiplicative and additive excess hazard, respectively, for a preferred male life underwritten at age 75 as a function of time since underwriting relative to ultimate hazard rates based on the Society of Actuaries 2001 Commissioner's Standard Ordinary (CSO) preferred life table.[19] Here the "selection effect" comes from the underwriting process allowing insurers to use lower hazard rates in the *select* period, so the origin for the deviation is not an informational asymmetry. The relevant analogy is that insurers will only have information on the policyholder's *health state* at the point of sale (time of underwriting), and the relevance of this information dissipates as time progresses, producing the converging pattern.

Thus, all-in-all, while there are several possible aspects contributing to the informational asymmetry, the pattern over time is most in line with policyholders adversely selecting on private information regarding their near-term survival prospects.

6 Robustness and Cross-Sectional Analyses

To demonstrate that our results do not originate from model misspecification and that they are not driven by biases, we conduct a series of robustness analyses. We first discuss the possible influence of omitted variables and then comment on sample selection issues, overall concluding that our qualitative findings are robust. Finally, we investigate differences in selection effects in the cross section of individuals.

6.1 Omitted Variables

In preparing the offer price, the LS company will have access to additional information. For example, policy information such as the face value may proxy for variables not included in our dataset, and the company may have available additional LE estimates from different LE providers or insights from their own experience.

To analyze the impact of policy face value or potentially unobserved correlated variables on our findings, we first repeat the regression analyses when only considering cases for which we have information on the policy face value ($2,650$ cases in the *closed* subsample and $7,723$ cases in the

[19]For information on the 2001 CSO table, see `https://www.soa.org/Research/Experience-Study/ind-life/tables/intl-2001-cso-preferred-class-structure-mortality-tables.aspx`.

remaining sample) and including face value as a covariate.[20] We present the results in column [G] of Table 4. We observe that the settlement-related variables are again significant with consistent signs. This reinforces our main prediction of a negative and receding relationship between settling and mortality. Moreover, the coefficient for face value is negative and significant, providing evidence that high face values are associated with longer realized lifetimes, i.e., a residual wealth effect.

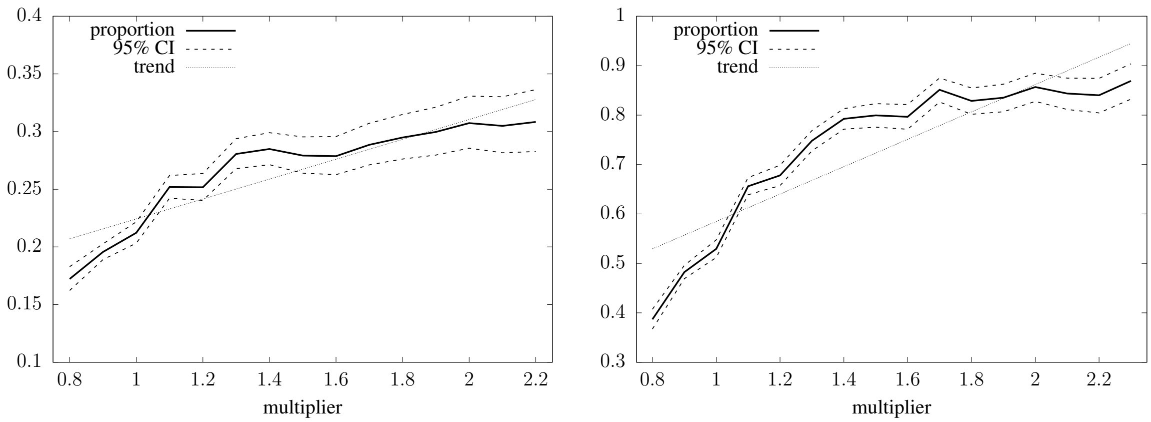
Beyond face value, the LS company may have available additional pricing-relevant information that is unknown to *our* LE provider, particularly the underwriting results from different LE providers (typically there are at least two evaluations). More precisely, we only have access to one LE provider's estimate $\hat{\mu}_t^{(i)}$ and not necessarily the LE used for pricing. To the extent that the difference is substantial, a second estimate may affect the pricing and thereby the decision to settle, giving rise to possible endogeneity and a potential bias.

However, since we are primarily interested in the sign of the settlement coefficient, a positive (conditional) relationship between the omitted estimate and settlement yielding a positive bias will not be critical in view of our result whereas a negative relationship may pose problems.[21] It is important to note that there are two relevant influences: On the one hand, a relatively high second hazard estimate will typically lead to a higher offer price rendering settling more likely; on the other hand, a relatively high second estimate is indicative of a higher *true* hazard rate, which will make settling less likely for an unchanged offer price. Hence, in order to assess whether the relationship is positive or negative, the key question is whether or not the proclivity for settling increases in the estimate. Online Appendix A.5 corroborates this insight by working out a version of the simple model from Section 2.2 with uncertainty in the offer price originating from additional information on the mortality probability estimate. In line with the arguments here, the model shows that the average difference between the unconditional mortality probability and the mortality probability conditional on settling will be larger in the presence of additional information *if* the fraction of policyholders deciding to settle is increasing in the unknown mortality probability estimate.

We can assess this relationship in the context of the available estimate by analyzing the proportion of policyholders that decided to settle their policy as a function of the corresponding mortality multiplier. As discussed in Section 3.1, this multiplier is used relative to a life table that accounts for basic characteristics such as gender, age, etc., so that it controls for observable characteristics and reflects the assessment of the LE provider. In Figure 4, we plot the proportion of policyholders within our subsample of closed policies, both relative to the full sample (left panel) and relative

[20]Due to data quality concerns for collected face values, we limit our sample to face values between \$50,000 and \$50mn, eliminating the most extreme (and potentially erroneous) values.

[21]Consider e.g. the extreme and stylized case where the company has full information (such that the *true* coefficient γ will be zero) and the correlation between $\mu_t^{(i)}$ and SaO_i is 1 (-1). Then clearly the estimated $\hat{\gamma}$ from Eq. (4) will be positive (negative).



(a) full sample

(b) sample with known policy face values

Figure 4: Proportion of policyholders that settled their policy as a function of the mortality multiplier (solid curve), with point-wise 95% confidence intervals (dashed curves); earliest observation date. Left panel: Proportion calculated based on the full sample. Right panel: Proportion calculated based only on policies with known face values in the remaining sample.

to only the policies with known face value in the remaining sample (right panel). In constructing the figures, we consider bins of multipliers of length 0.1 and derive the proportion (solid curve) as well as 95% confidence intervals (dashed curves) based on a binomial assumption. Since we have many outliers with relatively (very) small or (very) large multipliers and the calculation of reliable proportions is difficult in this range, we disregard the 5% of the sample with the lowest multipliers and the 15% with the highest multipliers, so that the plots show 80% of the sample. As is evident from the figures and the trend lines (dotted lines), we find a generally positive relationship. This suggests our analysis is robust with regards to additional information on LEs.

6.2 Sample Selection

As discussed in Section 3.1, we use the first underwriting date as a proxy for the time the individual decides whether or not to settle her policy—which is the relevant point in time for exploiting the informational advantage. However, as was also pointed out there, we are able to match the underwriting records that were used for the transactions for a majority of cases ($12,904$ out of $13,221$). We repeat our survival regressions (with and without time trend) using the matched underwriting record in the settled group and keeping the earliest records for the remaining group. We note that doing so might create a bias *against* our hypothesis of a negative settlement-mortality correlation, as we artificially prolong the (relative) duration of the remaining cases in our analysis. Nonetheless, as can be seen from columns [H] and [I] in Table 4, while the effect slightly decreases due to the aforementioned bias, the intercept and the slope of the settlement dummy are still highly significant and remain similar to our baseline results.

To ascertain that our results are not driven by individuals dying during the settlement process, we rerun our analysis eliminating cases where the policyholder died within six months of the (earliest) underwriting date in our remaining sample. Thus, all policyholders that might have considered settling but died before having the opportunity will be excluded from the analysis. Since by doing so we also exclude policyholders that did settle but are not observed as well as policyholders that would not have settled, and since being in the remaining subsample now implies a survival of at least six months, this procedure again creates a bias against our main hypothesis. The results are provided in column [J] of Table 4, where we again find highly significant settlement coefficients that are consistent with the baseline results.

Finally, we rerun the regressions using the latest observation date for each policy in the full dataset, i.e. we evaluate the relationship between settlement and survival experience relative to the last time the life was underwritten by our LE provider. Results are presented in column [K] of Table 4. The estimates for the non-settlement-related variables are similar to the earliest observation date (column [D]). For the settlement-related variables, the qualitative observations are analogous, although—as is to be expected given the results on the time trend from Section 4—the effect is less pronounced since it weakens over time. In particular, the results indicate that the effect wears off after approximately four years. Thus, while these estimates are less in line with our objective of studying the existence and pattern of private information when selling the policy, we are able to identify the residual effect—lending force to our results.

6.3 Cross Sectional Analyses

Our simple model from Section 2.2, and particularly the expected utility version presented in Online Appendix A.1, provide information on policyholder characteristics associated with settlement. More precisely, according to Equation (2), the policyholders accepting the settlement offer are those whose (private) mortality rate q is low relative to the offer price and the *proclivity for settling* ψ:

$$q < \pi/f + \psi/f, \tag{11}$$

where ψ varies among policyholders with differing wealth, bequest motive, face value, etc. Since a "key feature" of markets with selection is that firm outcomes depend on which consumers (endogenously) choose to participate (Einav et al., 2010b), understanding policyholders' incentive to settle is important—and may allow to shed light on how asymmetric information varies in the cross section of policyholders.

To illustrate, assume that settlement price π is roughly linear in face value and that transaction costs are homogeneous, then the set of participating policyholders according to Equation (11) is governed by ψ/f. If ψ/f associated with certain characteristics is very large, nearly everyone will settle, irrespective of the given price. Hence, the effect of a marginal change in π on the set of policyholders that settle—and, therefore, the effect on expected revenue from their policies—is minor. This situation is equivalent to a flat or only mildly sloped marginal cost curve in Einav et al. (2010b), indicating no or minor selection effects. In particular, in this case Equation (2) will be close to an equality, and we should not identify a strong relationship between settling and dying. In contrast, if ψ/f is small, price changes will have a substantial impact on the set of settlers, suggesting a strong settlement-survival relationship originating from asymmetric information.

Hence, we can investigate (cross-sectional) heterogeneity in asymmetric information by comparing the settlement-survival relationship across groups of policyholders with different ψ/f. The key difficulty is that by their very nature, underlying characteristics such as preferences or bequest motive are unobservable to the LE provider.[22] One potential exception is policy face value, which enters ψ but does not directly enter the LE estimate, and which we observe in a subset of cases. The expected utility model does not deliver clear predictions for the sensitivity of ψ/f in f for small face values. However, small face values are likely associated with low wealth levels, for which the model predicts a larger ψ/f (ψ is decreasing in wealth, see Proposition A.2 in Online Appendix A.1) and hence a smaller impact of selection. For large face values, the model predicts that ψ/f increases in f, which again translates to a lower relevance of asymmetric information.

Column [L] of Table 4 presents results for our survival regression including policy face value, where we let the SaO dummy vary across face value levels. More precisely, we show separate SaO coefficients for face values less than \$500,000, for face values between \$500,000 and \$5mn, and for face values exceeding \$5mn, although the results are robust to variations in the cutoff levels or alternative functional forms describing a similar pattern. The key feature that emerges is that the negative relationship is most pronounced and significant for the medium face value range, with the coefficient being roughly 70-80% larger in absolute value than for the other ranges and more than 20% larger than when not differentiating across ranges (column [G]). The impact for the small and large face value range is still negative, although the coefficients are no longer significant. Hence, it appears that asymmetric information is most pronounced for the middle range of policy face values, arguably because these individuals are not likely to be financially constrained and for whom the policy is unlikely to present a major piece of their estates—so that they can afford to be selective in their settlement decision.

7 Conclusion

In this paper, we show that in the secondary life insurance market, policyholders choosing to settle their policy, ceteris paribus, exhibit significantly longer lifetimes—although the relationship

[22] Attempts to proxy for these unobservables using available covariates did not deliver significant results.

between settlement and mortality weakens over time. This documents the existence and relevance of hidden information regarding near-term survival prospects. Our findings are robust with respect to model specification and other sources for potential biases.

While the quantitative results are specific to our setting and particularly the population in view, we believe that our qualitative insights have broader repercussions. More precisely, in addition to complementing studies on informational asymmetries in primary insurance markets, our findings indicate that individuals in our sample are competent in assessing their *relative* survival prospects when prompted with relevant information, in a situation with significant monetary consequences. Here, by *relative* survival prospects we mean the appraisal of whether an individual expects to live longer or shorter than an average individual with a similar profile. This is in contrast to individuals' ability in predicting *absolute* life expectancies that seems to be subject to framing and other behavioral biases (Payne et al., 2013; and references therein). We believe that the former task may be more material for retirement planning given that individuals may be provided with background information or suitable default choices based on their profile.

Finally, the existence and the origin of informational frictions is also material for assessing policy-relevant questions regarding efficiency and welfare implications of life settlements in equilibrium. For instance, while arguably the existence of asymmetric information takes a toll on participants in the life settlements market since offer prices will decrease, there exists an interesting possibility that informational frictions mitigate some of the adverse effects the life settlements market has on primary insurance. To elaborate, Daily et al. (2008) and Fang and Kung (2019) show that a (perfect-information) life settlements market increases life insurance prices and hinders provision of reclassification risk insurance via front-loaded long-term contracts, which likely reduces consumer welfare. With asymmetric information, settling a life insurance policy becomes less attractive, so fewer policyholders will participate. This alleviates constraints on contracts and prices in the primary insurance market, although of course the existence of asymmetric information also has potentially adverse repercussions on provision in the primary insurance market. Assessing welfare consequences in detail will require accounting for the interactions between primary insurance, the life settlements market, and policyholders. While exploring these issues is beyond the scope of this paper, we believe our findings will inform the process of building and estimating corresponding equilibrium models.

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