Adverse Selection in Secondary Insurance Markets:
Evidence from the Life Settlement 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 settlement—market. We compare realized lifetimes for a sub-sample of settled policies relative to the entire sample, and we find a significant difference indicating the existence of informational differences between policyholders and life settlement companies. We further show that the informational advantage is temporary and wears off over approximately seven years. We argue this is in line with adverse selection on an individual’s survival prospects, which has economic consequences for the life settlement market and beyond.

JEL classification: D12; G22; J10

Keywords: Life Settlements; Life Expectancy; Asymmetric Information

Asymmetric information in insurance markets is an important and intensive area of research. This paper makes two primary contributions to the existing body of knowledge. Firstly, we provide evidence for asymmetric information in the secondary life insurance market—the market for so-called life settlements—between policyholders and life settlement companies. To the best of
our knowledge, this is the first empirical study of informational frictions in a secondary personal insurance market. Relying on the literature studying asymmetric information in primary insurance markets, we derive a test that hinges on the correlation between selling insurance coverage and ex-post risk. We argue that analyzing the presence of informational asymmetries in secondary markets complements the research from primary markets since certain *compounding factors* may be absent or may at least have a different form.

Secondly, we are able to characterize the evolution of the informational friction over time. In particular, we demonstrate that while there appears to be a significant informational advantage immediately after selling the insurance coverage, this advantage dissipates over time. We argue that such a structure points to adverse selection with regards to private information on an individual’s survival prospects as the primary source for the asymmetry, over other possible explanations such as moral hazard or an information gain due to the transaction process. Hence, we find evidence that the policyholders in our sample are competent in evaluating their own life expectancy, 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 mortality prospects.

Our results are of immediate interest and have implications for the life settlement market, for instance in view of pricing the transactions (Zhu and Bauer, 2013) and regarding equilibrium implications (Daily et al., 2008; Fang and Kung, 2010). In addition, our findings corroborate results from the primary life insurance market regarding the existence of asymmetric information (He, 2009; Finkelstein and Poterba, 2014; Wu and Gan, 2013). More broadly, our results provide insights on individuals’ ability to make financial decisions that depend on their own mortality prospects, which of course is highly relevant for retirement policy.

In what follows, we first provide background information on life settlements and the possible relevance of asymmetric information in this market. We then describe our dataset and our basic empirical approach. The next section presents our analysis of the time trend of the informational advantage. The final two sections provide robustness analyses and a discussion of the results. An online appendix collects some additional details on derivations and supplemental results.

## 1 Life Settlements and Asymmetric Information

Within a life settlement transaction, a policyholder offers her life insurance contract, typically via a broker, to a life settlement company (LS company). Based on individual life expectancy

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2Our findings are in line with a recent industry study by Granieri and Heck (2013) that postdates the first draft of our paper. More precisely, based on simple comparisons of survival curves for different populations, the authors conclude that within the life settlement market, “insureds use the proprietary knowledge of their own health to select against the investor.”
reports (LE reports, typically two) from so-called *Life Expectancy Providers* (LE providers), the company then prepares an offer. If the offer is accepted, the policy—and particularly, all life-contingent insurance benefits and premiums—will be transferred to the company, who then holds it in its own portfolio or on behalf of capital market investors. Emerging from so-called *viatical settlements* with terminally ill insureds in the 1980s, a typical life settlement transaction involves senior policyholders with a below average life expectancy. According to the research firm Conning, in 2012 the total market amounted to roughly USD 35 billion in face value, which is less than one half percent of the total US life insurance market.

Clearly, an LS company will pay more for policies with shorter life expectancies, ceteris paribus, and profits from a relatively short realized lifespan. The policyholder, on the other hand, gains from a short life expectancy estimate relative to her expected lifespan. This wedge creates the possibility for informational asymmetries 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 term-life insurance policy that pays $1 at time one in case of death before time one and nothing in case of survival thereafter. The probability for dying before time one is \( P(\tau < 1) = q \), where \( \tau \) is the time of death.

Suppose the policyholder is offered a life settlement at price \( \pi \). For simplicity, we assume she assesses her settlement decision \( \Delta = I\{\text{policyholder settles} \} \) by comparing the settlement price to the present value of her contract:

\[
\Delta = 1 \iff \pi > q - \psi,
\]

and \( \psi \) characterizes the policyholder’s proclivity for settling (the risk-free rate is set to zero).\(^3\) The latter may originate from risk-averse policyholder preferences with different bequest motives, liquidity constraints, etc. Here, we simply use \( \psi \) to capture deviations from a value-maximizing behavior, under which the market may unravel due to a *lemons problem* as in Akerlof (1970). The key assumption is that the policyholder is more likely to settle when offered a higher price.

Thus, 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 \( \psi \).\(^4\) More precisely, assume that the policyholder has private information on the mortality probability \( q \) but the LS company solely observes the expected value, \( \mathbb{E}[q] \), conditional

\(^3\)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 \( \psi \)) may hinder screening. Importantly, partial settlements are not common in the marketplace.

\(^4\)Of course, such an information asymmetry may affect the pricing of the transaction, i.e. the choice of \( \pi \). We refer to Zhu and Bauer (2013) for a corresponding analysis. Here, we focus on the implications when the settlement price is given.
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:

$$\mathbb{P}(\tau < 1 | \Delta = 1) = \mathbb{E}[q | \Delta = 1] = \mathbb{E}[q | q < (\pi + \psi)] \leq \mathbb{E}[q] = \mathbb{P}(\tau < 1).$$  \tag{2}$$

Hence, if there exists private information on $q$, we will observe a negative relationship between settling and dying.

Note that we can alternatively represent the result in (2) as:

$$\mathbb{E}[\mathbb{I}_{\{\tau<1\}} \Delta] - \mathbb{E}[\mathbb{I}_{\{\tau<1\}}] \mathbb{E}[\Delta] \leq 0 \iff \text{Corr} (\Delta, \mathbb{I}_{\{\tau<1\}}) \leq 0.$$  \tag{3}$$

Therefore, this is simply a version of the well-known correlation test for the presence of asymmetric information that examines whether (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—i.e., if she has a low probability of dying. The intuition for this result is straightforward: As indicated in (2), 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, a pool of settled policies, on average, will display relatively longer life expectancies than the entire population of policyholders, controlling for observables.

Asymmetric information with respect to $\psi$ alone, e.g. arising from heterogeneous preferences or liquidity constraints, cannot yield a negative relationship. However, it is possible that there exists an indirect relationship in case $\psi$ itself is related to the lifetime distribution. For instance, the policyholder’s wealth reflected in $\psi$ may be positively linked to her propensity to survive, although such a relationship would arguably work in the opposite direction. In any case, a negative relation between settling and dying will—directly or indirectly—originate from an information asymmetry with respect to the time of death, and hence our basic empirical approach directly analyzes this relationship.

## 2 Data and Empirical Approach

To test for the negative relationship, we analyze the impact of settling on the realized future lifetime based on individual survival data. Here, our primary dataset consists of $N = 53,947$ distinct lives underwritten by Fasano Associates (Fasano), a leading US LE provider, 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 to their lifetimes, we are given individual characteristics including sex, age, smoking status, primary impairment, as well as one or more life expectancy estimates (LE) at certain points in time. All-in-all, there are 140,257 LE evaluations, so many of the lives occur multiple times in the dataset. Here, the LE is calculated by applying an individual mortality multiplier (frailty factor)—which is the result of the underwriting process—to a given mortality table. Hence, we can use this information to derive the entire estimated lifetime distribution for each record. Since we are interested in the influence of informational frictions on the settlement decision, we focus on the earliest underwriting date for each individual. Table 1 provides summary statistics.

This dataset contains LEs for policyholders that decided to settle their policies, LEs for policyholders that walked away from a settlement offer, and LEs for individuals that were underwritten for different reasons. 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 life expectancy estimate. However, we also have access to portfolio information for five life settlement investors consisting of overall 1,055 policyholders underwritten by Fasano (and several policies not underwritten by Fasano). Hence, for this subsample of individuals, we have the additional information that they settled their policies. We will refer to this secondary dataset as the subsample of closed cases, whereas we will refer to the rest as the remaining sample. Corresponding summary statistics are also provided in Table 1.

Our empirical strategy now follows studies of asymmetric information in the primary insurance market: We regress ex-post realized risk on ex-ante coverage (Cohen and Siegelman, 2010). If, conditionally on all observed covariates, coverage has a positive and significant influence on risk, one can infer the existence of asymmetric information. In our setting, risk is given by the realized death time, whereas (elimination of) coverage is given by the settlement decision. Thus, we are analyzing the impact of settling on mortality, and a significant negative relationship is indicative of

<table>
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<th>Count (Perc.)</th>
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<td>Life Expectancy Estimate</td>
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</tr>
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<td>11.83 (4.28)</td>
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<td>681</td>
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<td>10.26 (3.24)</td>
<td>(63.36%)</td>
<td>(64.55%)</td>
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<tr>
<td>Underwriting Age</td>
<td>Male</td>
<td>Observed Deaths</td>
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<td>75.10 (7.43)</td>
<td>13,418</td>
<td>277</td>
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<td>77.85 (5.97)</td>
<td>(24.87%)</td>
<td>(26.26%)</td>
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</table>

Table 1: Summary statistics for the entire dataset (“Full”; 53,947 lives, earliest observation date) and the subsample of closed cases (“Closed”; 1,055 lives, earliest observation date).
asymmetric information (see the model in Section 1).

It is important to recall that the remaining cases include policyholders that settled their contract as well as individuals that rejected the settlement offer or were underwritten for other reasons. Thus, we actually compare settled/closed cases relative to a mix of settled and non-settled cases, and analyzing the difference in our context presents a more conservative test than when comparing closed vis-à-vis non-closed cases. In addition, our point estimate will need to be inflated to account for the mixed nature of the sample in order to present a suitable point estimate for the latter comparison. The first part of our online Appendix A.1 provides more details on this issue and derives an approximation for the appropriate inflation rate—basically, our estimate would need to be multiplied by the ratio of the remaining cases to the (unknown) truly non-settled cases.

We control for all observables in our survival regressions. In particular, we include observable characteristics such as the time of underwriting, the primary impairment, etc. as well as the mortality estimate by the LE provider ($\hat{\mu}_i(t)$) as explanatory variables. We include this estimated intensity as an (additive) covariate both to capture the basic shape of the mortality curve over time and to possibly pick up residual information from the underwriting process beyond determining primary impairments. Moreover, in order to prevent incongruences in the shape of the underlying basic mortality tables to affect our estimates, we include a non-parametric term.

Thus, we rely on the following additive semi-parametric specification of the individual force of mortality $\mu_i(t)$, $1 \leq i \leq N$:

$$\mu_i(t) = \beta_0(t) + \beta_1 \mu_i(t) + \beta_2 \text{DOU}_i + \beta_3 \text{AU}_i + \beta_4 \text{SE}_i + \sum_{j=1}^{15} \beta_{5,j} \text{PI}_{i,j} + \sum_{j=1}^{2} \beta_{6,j} \text{SM}_{i,j} + \gamma \text{SaO}_i. \quad (4)$$

Here, $\text{DOU}_i$ is the underwriting date, measured in years and normalized so that zero corresponds to January 1st, 2001. $\text{AU}_i$ is the individual’s age at underwriting, measured in years. $\text{SE}_i$ is a sex dummy, zero for female and one for male. $\text{PI}_{i,j}, j = 1, \ldots, 15$, 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” entry. We omit information that is only available for a fraction of the individuals in our basic regressions (e.g., states of residence, face amount) but discuss some of them in our robustness checks (Section 4). Finally, we include a Settled-and-observed dummy $\text{SaO}_i$ that is set to one for the subsample of closed cases and zero otherwise. Clearly, we test for asymmetric information by inferring whether $\gamma$ is negative and significant.

Models of the type as in Equation (4) are analyzed by Lin and Ying (1994), and they are

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5Chiappori and Salanié (2000) and Dionne et al. (2001) emphasize the importance of accounting for all pricing-relevant covariates. We discuss the possible impact of omitted variables and sample selection issues in Section 4.

6We do not list the primary impairments to protect proprietary information of our data supplier since they are not material to our results.
special cases of the more general semi-parametric models considered by McKeague and Sasieni (1994) and the non-parametric additive regression models by Aalen (1989). For its estimation, we rely on the generalized least-squares (GLS) approach from Lin and Ying (1994). However, we also consider a parametric (additive) specification estimated via maximum likelihood in our robustness analyses (Section 4).

Column [A] in Table 2 presents the regression results for the basic model (4). We find that the estimated force of mortality is highly significant. However, the coefficient is considerably different from one, which would correspond to a perfect fit of the estimates by the LE provider. In turn, a number of the other characteristics are statistically significant, including the underwriting date, age, sex, smoking status, and some of the primary impairments. We refer to Bauer et al. (2015) for a more detailed analysis of the LE provider’s performance.

As for the Settled-and-observed covariate that is in the focus of our analysis, the corresponding coefficient is negative and highly significant. Thus, we find a strong negative relationship between settling and dying, which as discussed above indicates the existence of asymmetric information in the life settlement market. Policyholders that settle their policy appear to have private information regarding their survival expectations and generally exhibit lower mortalities than similar policyholders (age, impairments, etc.) that do not settle.

This result complements analyses of asymmetric information in primary life insurance markets, where several papers find no 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. In contrast, the pricing of life settlements is highly individualized and the decision to settle a policy will not be subject to the same confounding factors as purchasing coverage in the primary market, or at least not to the same extent. Therefore, our results suggest that individuals possess and make use of private information on their risk—in line with He (2009) and Wu and Gan (2013) that find evidence for asymmetric information in primary life insurance when accounting for certain biases.

3 Time Evolution of the Informational Advantage

In order to analyze the pattern of the excess mortality due to settling over time, we augment the basic specification (4) by a simple linear time trend interacted with the Settled-and-observed variable. Column [B] in Table 2 presents the results. The coefficients for the covariates that are not related to the settlement decision are very similar to the basic specification in column [A]. The coefficient
<table>
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<tr>
<th></th>
<th>[A]</th>
<th>[B]</th>
<th>[C]</th>
<th>[D]</th>
<th>[E]</th>
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<td>$0.2836^{***}$</td>
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<td>(0.0006)</td>
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<td>“Aggregate” smoking status</td>
<td>$0.0115^{***}$</td>
<td>$0.0115^{***}$</td>
<td>$0.0067$</td>
<td>$0.0126^{**}$</td>
<td>$0.0135^{**}$</td>
</tr>
<tr>
<td>(0.0025)</td>
<td>(0.0025)</td>
<td>(0.4438)</td>
<td>(0.0069)</td>
<td>(0.0029)</td>
<td>(0.0029)</td>
</tr>
<tr>
<td>Settled-and-observed</td>
<td>$-0.0079^{***}$</td>
<td>$-0.0196^{***}$</td>
<td>$-0.0061^{***}$</td>
<td>$-0.0175^{**}$</td>
<td>$-0.0141^{***}$</td>
</tr>
<tr>
<td>(0.0022)</td>
<td>(0.0034)</td>
<td>(0.0007)</td>
<td>(0.0039)</td>
<td>(0.0051)</td>
<td>(0.0051)</td>
</tr>
<tr>
<td>Settled-and-observed x t</td>
<td>$0.0028^{**}$</td>
<td>$0.0008^{***}$</td>
<td>$0.0047^{***}$</td>
<td>$0.0038^{**}$</td>
<td>$0.0009$</td>
</tr>
<tr>
<td>(0.0009)</td>
<td>(0.0003)</td>
<td>(0.0011)</td>
<td>(0.0009)</td>
<td>(0.0009)</td>
<td>(0.0009)</td>
</tr>
</tbody>
</table>

Table 2: Survival regression analysis. Column [A]: GLS estimates, earliest observation date; column [B]: GLS estimates, earliest observation date, with linear time trend; column [C]: MLE estimates, earliest observation date, with linear time trend; column [D]: GLS estimates, earliest observation data, subsample with known face value; column [E]: GLS estimates, latest observation date, with linear time trend. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
for the Settled-and-observed dummy (intercept of the trend) again is negative and strongly significant but it more than doubles in its absolute value—so we find an even more pronounced negative relationship between settling and dying shortly after the settlement decision. The slope of the trend is also highly significant and positive, implying that the influence of settling becomes weaker over time. The log-likelihood value increases significantly when adding the linear trend.\footnote{We arrive at the same conclusion when including a logarithmic rather than a linear trend, although the likelihood value of the resulting model is notably lower than for the linear trend. We do not find significant results for a quadratic trend component. We refer to columns [A] and [B] in Table A.1, Appendix B for the corresponding regression results.}

To further analyze the structure of the informational advantage, we derive non-parametric estimates of the excess mortality over time since settlement (which we equate with the earliest observation date). Here, by \textit{excess} mortality, we mean the difference in mortality between an arbitrary individual in the sample of closed policies relative to an otherwise identical individual in the full sample, i.e. the effect of knowing a policyholder settled on mortality relative to not having this information. We consider \textit{multiplicative excess mortality} as a time-dependent factor multiplied on the baseline force of mortality for an arbitrary individual from the full dataset and \textit{additive excess mortality} as a time-dependent term added to the baseline force of mortality. We rely on a repeated application of the excess mortality estimators proposed by Andersen and Vaeth (1989), which in turn rely on the well-known Nelson-Aalen and Kaplan-Meier non-parametric estimators for the multiplicative and additive excess mortality, respectively. More precisely, we first adjust the mortality estimate $\hat{\mu}_t^{(i)}$ based on the mortality experience in the full sample and then derive the excess mortality to the adjusted mortality estimate based on the mortality experience in the closed subsample (see Appendix A.2 for more details on the derivation).

The left-hand panel of Figure 1 shows the non-parametric estimate for the multiplicative excess mortality over time (blue solid curve). Clearly, if this curve had the shape of a horizontal line at
one (black dotted line) or if the horizontal line at one fell within the (pointwise) 95% confidence intervals (red dashed curves), we would conclude that there is no (significant) impact of settling on an individual’s mortality pattern. The observation that this curve is overall less than one again illustrates the negative association between settling and the instantaneous mortality probability, and therefore the existence of asymmetric information. The observations for the additive excess mortality (right-hand panel) are analogous, although here of course the absence of an effect would be signified by a horizontal line at zero (black dotted line).

While with an approximately 70% reduction in mortality the impact of settling is very pronounced immediately after the settlement decision, it is decreasing in the sense that it wears off over about seven years. This, again, is in line with the regression analysis, where the trend coefficients also imply that the effect dissipates after \(\frac{\text{intercept}}{\text{slope}} = \frac{0.0196}{0.0028} = 7\) years (cf. column [B] in Table 2). Indeed, the trend line for the additive excess mortality (green dashed line) has an intercept of approximately -0.0214 and a slope of 0.0029, which closely resembles the results from the regression analysis.\(^8\) While the (point) estimate continues to increase after year eight, the confidence intervals become rather wide due to the limited data availability. In particular, they include the horizontal line at one (zero) for the multiplicative (additive) excess mortality in the last years, so that it is hardly possible to make an inference on the existence or the sign of the trend in the later years after settling. Hence, the key characteristic that emerges is a negative and receding influence over time.

\[\text{4 Robustness}\]

\[\text{Specification and Estimation Approach}\]

In addition to the semi-parametric survival regressions and the non-parametric excess mortality estimates, we consider a fully parametric specification, where the non-parametric term \(\beta_0(t)\) in (4) is replaced with a constant \(\beta_0\), estimated via Maximum Likelihood (MLE). The resulting estimates for the preferred specification with a linear time trend are presented in column [C] of Table 2 (regression results for the specification without time trend are presented in column [C] of Table A.1, Appendix B). Note that within the MLE, we need to numerically solve for the optimum, whereas within the GLS we have analytic expressions for the estimators.

The regression results generally are quite different between the GLS and the MLE approach. In particular, the MLE loads more on the estimated force of mortality. Since the estimated force of mortality differs between individuals, it is not surprising that the remaining coefficients also

\(^8\)The observation that the trend over the first year appears to be downward sloping for the additive excess mortality while the multiplicative trend is increasing can be reconciled by the observation that the force of mortality is a rapidly increasing function.
change. For instance, none of the primary impairment dummies is significant any more. This difference may be due to the absence of the non-parametric term as well as differentials in the estimation procedure. The log-likelihood value decreases considerably.

However, the results for the settlement-related variables are qualitatively analogous. Indeed, the coefficient of the basic Settled-and-observed variable is in the same range as for the specification [A] without a time trend within the GLS estimation. Although both the intercept and the slope decrease in absolute value relative to the results in [B], the relationship between intercept and slope estimate is similar in that it implies that the effect subsides after $\frac{0.0061}{0.0088} = 7.625$ years.

**Omitted Variables and Sample Selection**

In preparing the offer price, the LS company will have access to additional information. In particular, offer prices may take into account that the policy is for sale and reflect certain policy characteristics, particularly its face value. To rule out endogeneity concerns, we repeat the regression analysis when only considering cases in the remaining sample for which we have information on the policy face value (10,268 cases), since this is indicative of the policy being for sale. Column [D] of Table 2 shows the results for the specification with linear trend. Again, we find a significant negative impact of a similar magnitude as for the full sample and a positive time trend. The latter is higher than the estimate from column [B], implying that the effect wears off after $\frac{0.0175}{0.0047} = 3.72$ years, although confidence bands for the two estimates overlap.

We also run regressions incorporating the face value as a covariate. Since we only have the face value available for 236 closed cases with 40 observed deaths, the statistical power is limited and the settlement-related estimates, while still having the same signs, fail to be significant. The face value, on the other hand, has a significant negative influence—so that high face values are associated with longer life expectancies, potentially indicating a wealth effect. However, running the same regression without the face value as a covariate results in essentially the same estimates for the settlement-related coefficients, so that it does not seem that omitting the face value will lead to a bias (see columns [D] and [E] in Table A.1, Appendix B for the detailed results).

Another concern is additional pricing-relevant information the LS company possesses that is (completely) 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 the LE provider’s estimate $\hat{\mu}_t^{(i)}$ and not the LE used for pricing. To the extent that the difference is substantial, a second estimate may affect the pricing and thus the decision to settle, giving rise to possible endogeneity and a potential bias.

---

9We emphasize that the relevant perspective is that of the LS company with the winning offer for the policy. Other parties such as the broker and, of course, the policyholder may have different information sets that could also be affected by the bidding process. We discuss the origin of the informational asymmetry in the next section.
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. It is important to note that there are two relevant influences: On the one hand, a high second mortality estimate will typically lead to a higher offer price rendering settling more likely; on the other hand, a high second estimate is indicative of a higher true mortality intensity, 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. Appendix A.3 corroborates this insight by working out a version of the simple model from Section 1 with uncertainty in the offer price originating from additional information on the mortality 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 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. 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 2, we plot the proportion of policyholders within our sample of closed policies, both relative to the full sample (left) and relative to the sample of policies with known face value (right). In constructing the figures, we consider bins of multipliers of lengths 0.1 and derive the proportion as well as confidence intervals based on a binomial assumption. Since we have many outliers with relatively (very) small or large multipliers and the calculation of reliable proportions is difficult in this range, we cut the 5% of the sample with the lowest multipliers and the 15% with the highest multipliers, so that the plots are based on 80% of the sample. As is evident from the figures, we find a generally positive relationship. This suggests our analysis is robust with regards to additional estimates and that we possibly even understate the true effect.

A silent assumption for our analyses thus far is that a random sample of closed policies is a random sample of closed policies at settlement or, in other words, that being observed as one of the policies in the closed subsample is independent of survival. A potential problem with this assumption are so-called tertiary trades, that is policies that are resold at some point in time after the closing date. Clearly, a tertiary trade will only take place if the policyholder is alive, so that—assuming there exists an LE from our provider for the company that originally owned the

\[ \hat{\gamma} \]

Consider e.g. the extreme and stylized case where the company has full information (such that the true coefficient \( \gamma \) will be zero) and the correlation between \( \mu_i^{(1)} \) and SaO is 1 (-1). Then clearly the estimated \( \hat{\gamma} \) from (4) will be positive (negative).
policy—tertiary policies may be associated with longer observed lifetimes. To address this and other concerns relating to possible sample selection issues, we rerun the regression analyses using the latest observation date for each policy in the full dataset, i.e. we evaluate the impact of settling on mortality experience relative to the last time the life was underwritten by our LE provider. Regression results for the preferred specification are presented in column [E] of Table 2. The qualitative observations are analogous, although—as is to be expected given the results on the time trend from Section 3—the effect is less pronounced. In particular, the results indicate that the effect wears off after approximately $\frac{0.0141}{0.0038} = 3.71$ years (corresponding non-parametric estimates of excess mortality and supplemental results are provided in Appendix B). 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.

5 Discussion

The previous sections establish the existence of asymmetric information in the life settlement market by demonstrating that policyholders choosing to settle their policies, ceteris paribus, exhibit significantly longer lifetimes—although the impact of settling on mortality subsides over time. This effect is economically significant,\textsuperscript{11} and thus it has immediate consequences for the life settle-

\textsuperscript{11}In Appendix C.1, we provide simple example calculations for a 75-year old male policyholder’s life expectancy. We find that based on our regression point estimates, the effect of settling on life expectancy will amount to between four and eleven months relative to a life expectancy of roughly 10.5 years, depending on the (unknown) number of settled policies in our full sample.
ment market—e.g. in view of pricing (Zhu and Bauer, 2013). However, we have not yet discussed the origin of the informational friction.

The temporary and subsiding pattern illustrated in Figure 1 is akin to so-called *select-and-ultimate* life tables in actuarial studies that capture selection effects due to mandatory health examinations. More precisely, the *selection* part of the mortality table shows relatively lower mortality probabilities in the early contract years according to the health classification in the underwriting process but the difference gets smaller over time and finally the mortality probabilities approach an *ultimate* level. This analogy suggests an informational advantage regarding the initial health condition that individuals select on in their settlement decision.\textsuperscript{12}

Alternative explanations for our results include hidden actions (*moral hazard*) or a possible information gain during the settlement process. In the present context, the former may take the form of healthier lifestyle choices after relinquishing the life insurance coverage, seeking improved medical care using the proceeds from settling,\textsuperscript{13} or other changes in behavior. If this were the sole driver for the informational asymmetry, however, two identical policyholders only differing in their decision to settle should display exactly the same mortality intensity right up until settlement, whereas we would expect to see a diverging relationship thereafter. In particular, if there were differences in care or in lifestyle, we would arguably expect a persistent effect on mortality—in contrast to the subsiding pattern we identify in Section 3.

An informational asymmetry in the settlement process may arise from brokers forwarding shorter LEs to LS companies or policyholders picking the highest among several bids for their policy (*winner's curse*)—which may be submitted by the LS company that received the lowest (combination of) LEs.\textsuperscript{14} However, it is important to point out that a policy could have been settled based on any LE and, particularly, the LS companies in view may not have had access to the LE from our provider in the settlement process. Indeed, the time pattern of the excess mortality again will not support this modality as being the primary provenance of the informational asymmetry. Consider the following thought experiment: Suppose there are several identical distributed LEs 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 mortality will be constant.

\textsuperscript{12}The idea to consider dynamic relationships to characterize asymmetric information already occurs in Abbring et al. (2003) in the context of experience ratings in automobile insurance.

\textsuperscript{13}It is worth noting that policies considered for settlement usually have relatively large face values. The average face values in our sample of known face values and closed policies with known face value are 3.92 and 4.12 million USD, respectively. Thus, participants in the life settlement market are rather wealthy individuals that are likely to have access to health care.

\textsuperscript{14}While LS companies used to order LEs themselves, within current transactions typically the broker assembles several LEs and forwards them to the companies together with the policy information. While there is some discretion which estimates to forward, certain LS companies require LEs from specific providers.
over time at a level below one and the additive excess mortality will necessarily need to diverge to sustain this constant multiplicative trend (a more detailed discussion and a Monte Carlo implementation of this thought experiment are provided in Appendix C.2). Again such a pattern would be in contrast to the converging pattern depicted in Section 3.

Thus, while there are several conceivable aspects contributing to the informational asymmetry, the pattern over time suggests private information on survival prospects as one of the key drivers. While the quantitative results are specific to our setting, we believe that this qualitative insight has broader repercussions. In particular, our findings indicate that individuals—or, at least, individuals in the relevant population for our study—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 may 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.

Furthermore, the existence and the origin of the informational friction will be material for answering policy-relevant questions regarding the efficiency and welfare implications of the life settlement market. For addressing such questions, it will be necessary to consider the equilibrium implications, accounting for barriers to participate in this market (Einav et al., 2010b) and repercussions on primary insurance (Daily et al., 2008; Fang and Kung, 2010). While addressing these issues is beyond the scope of this paper, our findings will inform the process of building and estimating corresponding equilibrium models (see e.g. Einav et al. (2010a)).

References


Online Appendix to “Adverse Selection in Secondary Insurance Markets: Evidence from the Life Settlement Market”

Daniel Bauer, Jochen Russ, Nan Zhu

October 2015

This online appendix collects supplemental material for the paper “Adverse Selection in Secondary Insurance Markets: Evidence from the Life Settlement Market.” Part A provides relevant technical details, particularly a discussion of the impact of the mixed nature of the dataset discussed in Section 2 in the main text (Appendix A.1), the derivation of the non-parametric estimate of excess mortality used in Section 3 in the main text (Appendix A.2), and an extension of the model from Section 1 with price uncertainty that is relevant for robustness analyses with regards to omitted variables in Section 4 in the main text (Appendix A.3). Part B presents additional results for the analyses in Sections 2, 3, and 4 in the main text. Finally, the last part presents additional analyses, particularly a brief discussion of the quantitative impact of the settlement decision on estimated life expectancy based on example calculations (Appendix C.1) and a Monte Carlo experiment of the informational pattern over time when brokers or policyholders “cherry-pick” among LEs or policy offers (Appendix C.2). We refer to both in the last section of the main text.
A Technical Appendix

A.1 Impact of the Mixed Nature of the Remaining Cases

As discussed in the main text, the estimate for the regression coefficient $\gamma$ of the Settled-and-observed variable generally does not provide a consistent estimate for the difference between closed and non-closed cases due to the mixed nature of the sample of remaining policies. Put differently, since the remaining cases include non-closed and closed cases, $\gamma$ will not constitute a suitable adjustment for closed cases relative to individuals that did not settle their policies but will only amount to a fraction of the “true” difference, and therefore needs to be inflated.

To illustrate and to derive an appropriate inflation rate, consider the following simplified version of our additive hazard model (4):

$$\mu_i(t) = \beta_0(t) + \gamma \text{SaO}_i.$$  (5)

Denote by $N_t$ all remaining observations at time $t$, by $N_t^{(1)}$ all remaining settled/closed cases at time $t$ (unobserved), $p_t = N_t^{(1)}/N_t$, and by $N_t^{(2)}$ all remaining Settled-and-observed cases at time $t$, $q_t = N_t^{(2)}/N_t$. Furthermore, denote by $\gamma^{\text{act}}$ the unknown actual regression coefficient for the model in which the econometrician observes all settlement decisions (effectively replacing the Settled-and-observed variable by a corresponding Settled variable in (5)), and by $\gamma^{\text{our}}$ our coefficient based on Settled-and-observed cases only. For simplicity, assume further that at any time $t$, the probability that a settlement decision is observed is constant. Therefore, we have based on the estimates in Lin and Ying (1994, Eq. 2.8):

$$\frac{\hat{\gamma}^{\text{act}}}{\hat{\gamma}^{\text{our}}} \approx \frac{1 - q_t}{1 - p_t},$$

which suggests that

$$\frac{\hat{\gamma}^{\text{act}}}{\hat{\gamma}^{\text{our}}} \approx \frac{1 - q}{1 - p}.$$  (6)

Here $p$ is the overall (unknown) proportion of settled cases and $q$ is the (known) overall proportion of Settled-and-observed cases in the portfolio, which for simplicity we assume are constant. Thus, under the assumptions above, a suitable estimator for the actual difference between closed and non-closed cases is:

$$\hat{\gamma}^{\text{act}} \approx \hat{\gamma}^{\text{our}} \times \frac{1 - q}{1 - p},$$

where of course $\hat{\gamma}^{\text{our}}$ corresponds to the estimate from specification (4). In particular, since the ratio $(1 - q)/(1 - p)$ is always greater than one, the inflated coefficient will clearly be greater than...
the one estimated from the mixed sample.

A.2 Development of the non-parametric estimators

Following the description in the main text, we derive non-parametric estimates for the excess mortality for policyholders that settled their policies as a function of time. To formalize our notions of excess mortality, assume we are given two individuals $S$ and $R$ with forces of mortality $\{\mu^S_t\}_{t \geq 0}$ and $\{\mu^R_t\}_{t \geq 0}$, respectively, that differ only in the information regarding their settlement decision but are otherwise identical. More precisely, assume that we know $S$ settled her policy whereas the settlement decision for $R$ is not known. Then we can define the multiplicative excess mortality $\{\alpha(t)\}_{t \geq 0}$ and the additive excess mortality $\{\beta(t)\}_{t \geq 0}$ via the following relationships:

$$\mu^S_t = \alpha(t) \times \mu^R_t \quad \text{and} \quad \mu^S_t = \beta(t) + \mu^R_t.$$ 

Andersen and Vaeth (1989) provide non-parametric estimators for the multiplicative and additive excess mortality by relying on the Nelson-Aalen (N-A) estimator for $\int_0^t \alpha(s) \, ds$ and the Kaplan-Meier (K-M) estimator for $\int_0^t \beta(s) \, ds$, respectively. However, their approach relies on the assumption that the baseline mortality ($\mu^R_t$ in our specification) is known, whereas we only have available estimates $\{\hat{\mu}^R_t\}_{t \geq 0}$, $1 \leq i \leq N$, given by the LE provider. Therefore, for the estimation of the multiplicative excess mortality, we instead use the following three-step procedure that relies on a repeated application of the Andersen and Vaeth (1989) estimator:

1. We start with the specification:

$$\mu_t^{(i)} = A(t) \times \hat{\mu}^{(i)}_t, \quad 1 \leq i \leq N, \quad (7)$$

and use the Andersen and Vaeth (1989) excess mortality estimator to obtain an estimate for $A$, say $\hat{A}$, based on the full dataset. Hence, $\hat{A}$ corrects systematic deviations of the given estimates based on the observed times of death (in sample). We set:

$$\bar{\mu}_t^{(i)} = \hat{A}(t) \times \hat{\mu}^{(i)}_t, \quad 1 \leq i \leq N,$$

for the corrected individual baseline force of mortality.

2. We then use the specification:

$$\mu_t^{(i)} = \alpha(t) \times \hat{\mu}^{(i)}_t$$

for individual $i$ in the closed subsample. Note that if we used the full dataset to estimate $\alpha$, we would obtain $\alpha(t) \equiv 1$ and $\int_0^t \alpha(s) \, ds$ would be a straight line with slope one. However,
when applying (8) to the subsample of closed policies, the resulting estimate for \( \alpha \)—or rather \( \int_0^t \alpha(s) \, ds \)—picks up the residual mortality information due to the settlement decision.

3. Finally, we derive an estimate for \( \alpha \) from the cumulative estimate using a suitable kernel function as in Wang (2005).

For the additive excess mortality, we proceed analogously replacing Equations (7) and (8) by:

\[
\mu_t^{(i)} = B(t) + \hat{\mu}_t^{(i)} \quad \text{and} \quad \mu_t^{(i)} = \beta(t) + \left[ \hat{B}(t) + \hat{\mu}_t^{(i)} \right],
\]

respectively.

In the context of Figures 1 and A.1, for the derivation of the derivatives in step 3, we use the Epanechnikov kernel with a fixed bandwidth of one.

A.3 A Version of the Model from Section 1 with Price Uncertainty

Assume the LS company has access to an additional estimate for \( q \) that is not known to the econometrist, say \( \theta \). Here, we assume that the underlying probability measure \( \mathbb{P} \) reflects all available information and, to simplify the presentation, we ignore uncertainty in \( \psi \). Since we interpret \( \theta \) as a signal for \( q \), we assume (i) that a higher \( \theta \) will result in a higher offer price, i.e. \( \pi(\theta) \) is increasing, and (ii) that \( q \) is stochastically increasing in \( \theta \). Then it is easy to see that:

\[
\mathbb{E} [q | q < \pi(\theta) + \psi, \theta] \text{ is increasing as a function of } \theta.
\]

(9)

Indeed, it is sufficient to assume the weaker condition (9) holds, which solely indicates that the estimate for \( q \) conditional on a policyholder settling her policy is increasing in \( \theta \).

Now if the econometrist finds a negative correlation between settling and dying, in the context of this extended model this means:

\[
\mathbb{E} [q | q < \pi(\theta) + \psi] < \mathbb{E} [q],
\]

(10)

where the conditional expectation on the left-hand side incorporates all the information available to the econometrist (reflected in \( \mathbb{P} \)) and the observation that the policyholder settled. However, the question from the point of view of the LS company—which, as indicated in Footnote 9, is the relevant perspective—is whether there exists asymmetric information, indicated by a negative correlation, when incorporating all pricing-relevant information, particularly \( \theta \):

\[
\mathbb{E} [q | q < \pi(\theta) + \psi, \theta] \overset{?}{<} \mathbb{E} [q|\theta]
\]
for at least some choices of \( \theta \). When aggregating over all policyholders:

\[
\mathbb{E} \left[ \mathbb{E} \left[ q | q < \pi(\theta) + \psi, \theta \right] \right] < \mathbb{E} \left[ \mathbb{E} \left[ q | \theta \right] \right] = \mathbb{E} [q]. \tag{11}
\]

Therefore, the question of whether the observed relationship (10) provides definite evidence for the relevant relationship (11) depends on the relationship between the expectations on the left-hand sides of (10) and (11). In particular, the implication will hold if:

\[
\mathbb{E} \left[ \mathbb{E} \left[ q | q < \pi(\theta) + \psi, \theta \right] \right] \leq \mathbb{E} [q | q < \pi(\theta) + \psi]. \tag{12}
\]

We need the following lemma:

**Lemma A.1.** Let \( X \) be a real random variable, \( g \) be an increasing function such that \( \mathbb{E} [g(X)] = 0 \), and \( h \) be an increasing and positive function. Then \( \mathbb{E} [g(X) h(X)] \geq 0 \).

**Proof.** Let \( K = \text{argmax}_x \{ g(x) \leq 0 \} \). Then:

\[
0 = \mathbb{E}[g(X)] = \mathbb{E}[g(X) | X \leq K] \mathbb{P}(X \leq K) + \mathbb{E}[g(X) | X > K] \mathbb{P}(X > K).
\]

Now clearly \( g(X) h(K) \leq g(X) h(X) \) on \( \{ X \leq K \} \), so that

\[
\mathbb{E} [g(X) h(K) | X \leq K] \leq \mathbb{E} [g(X) h(X) | X \leq K].
\]

Similarly,

\[
\mathbb{E} [g(X) h(K) | X > K] \leq \mathbb{E} [g(X) h(X) | X > K].
\]

Thus,

\[
0 = \mathbb{E} [g(X) h(K) | X \leq K] \mathbb{P}(X \leq K) + \mathbb{E} [g(X) h(K) | X > K] \mathbb{P}(X > K)
\]

\[
\leq \mathbb{E} [g(X) h(X) | X \leq K] \mathbb{P}(X \leq K) + \mathbb{E} [g(X) h(X) | X > K] \mathbb{P}(X > K)
\]

\[
= \mathbb{E} [g(X) h(X)].
\]

Now, by the tower property of conditional expectations, (12) is equivalent to:

\[
\frac{\mathbb{E} \left[ \mathbb{E} \left[ q \mathbf{1}_{q < \pi(\theta) + \psi} | \theta \right] \right]}{\mathbb{P}(q < \pi(\theta) + \psi)} - \mathbb{E} \left[ q | q < \pi(\theta) + \psi, \theta \right] \geq 0
\]

\[
\iff \mathbb{E} \left[ q | q < \pi(\theta) + \psi, \theta \right] \left( \frac{\mathbb{P}(q < \pi(\theta) + \psi)}{\mathbb{P}(q < \pi(\theta) + \psi)} - 1 \right) \geq 0.
\]
Since \( \mathbb{E}[q|q < \pi(\theta) + \psi, \theta] \) is increasing as a function of \( \theta \) by our assumption and since \( \mathbb{E}[g(\theta)] = 0 \), with the lemma relationship (11) will hold if \( g \) is increasing. Note that \( g \) is an affine transformation of the proportion of policyholders deciding to settle given the estimate \( \theta \), so that the pivotal relationship is the increasingness of this proportion in \( \theta \). Conversely, the implication will go in the other direction, so that the econometrist’s analysis will potentially overstate the effect, if the proportion of policyholders settling their policy is decreasing in the estimate.

B Supplemental Estimation Results

Table A.1 presents supplemental results. Columns [A] and [B] show GLS regression results for the earliest observation date with alternative trend specifications. In particular, we consider a quadratic trend \( \text{SaO} \times (\gamma_1 + t\gamma_2 + t^2\gamma_3) \) and a logarithmic specification \( \text{SaO} \times (\gamma_1 + \log(t+1)\gamma_2) \). As is evident from the table, the quadratic trend components fail to be significant whereas we obtain similar observations for the logarithmic version as for the basic linear trend (column [B] in Table 2 in the main text). However, the likelihood value decreases.

Column [C] presents the regression results for the fully parametric specification estimated via MLE discussed in Section 4 of the main text, albeit without the linear trend. Comparing the GLS (column [A] in Table 2 in the main text) and MLE results, we find an analogous relationship as for the GLS and MLE results with a linear time trend (column [B] and [C] in Table 2 in the main text). In particular, the impact of the Settled-and-observed variable is still negative and highly significant but it decreases in absolute value (-0.0041 (0.0007) relative to -0.0079 (0.0022)).

Columns [D] and [E] present regression results when limiting the full sample to those cases with observed face values (also for the Settled-and-observed cases). The difference is that for the results in column [D], we include the face value as a covariate. As indicated in the main text, the resulting sample contains 10,268 records for the remaining cases and merely 236 observations (with only 40 deaths) for the closed cases. As a consequence of the limited data availability and the associated loss in statistical power, the settlement-related variables fail to be statistically significant although they still carry the same signs and at least the trend coefficient is of a similar magnitude. The face value, on the other hand, is negative and highly statistically significant, and the likelihood value increases markedly. This means that policyholders with a high face value ceteris paribus tend to live longer, indicating a possible wealth effect. However, whether or not the face value is included as a covariate has virtually no impact on the settlement-related coefficients.

Finally, column [F] presents GLS regression results for the latest observation date without a trend component. While the coefficient for the Settled-and-observed variable still carries a negative sign, it fails to be statistically significant—even though the likelihood value is considerably lower than for the specification with trend (column [E] in Table 2 in the main text). Figure A.1 provides
Table A.1: Survival regression analysis. Column [A]: GLS estimates, earliest observation date, with quadratic trend; column [B]: GLS estimates, earliest observation date, with logarithmic trend; column [C]: MLE estimates, earliest observation date, without trend; column [D]: GLS estimates, earliest observation data, subsample with known face value (also for closed subsample), face value as covariate; column [E]: same as [D], without face value as covariate; column [F]: GLS estimates, latest observation date, without trend. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
more insights on the impact over time by plotting the multiplicative (left) and additive (right) excess mortality for settling policyholders based on the latest observation date. Again, we find an overall negative and receding relationship in the sense that the multiplicative excess mortality overall tends to be less than one and the additive excess mortality tends to be less than zero but the trend lines for both are positively sloped. However, the differences are only significant over some time intervals (that notably differ between the two), providing an explanation for the lack of significance in the regression.

C Supplemental Analyses

C.1 Quantitative Impact of Settling on Life Expectancy

To appraise whether the impact of settling on life expectancies is economically significant, we provide some example calculations relying on our regression results. More precisely, we use Equation (6) from Appendix A.1 to adjust the coefficient of the Settled-and-observed variable. Here, while $q$ is given by the size of our closed subsample, we need to make an assumption on the proportion of closed policies on the full sample. We consider choices between 30% and 70%, according to a rough guess by our data supplier. Moreover, we adjust the coefficient associated with the linear trend component such that the intersection with the time-axis remains the same, i.e. we assume the effect wears off over the same time period. Based on the adjusted estimates, we then derive life expectancies for a 75-year old US male policyholder, in line with Table 1.  

15The 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 proba-
Table A.2: Difference in average life expectancies between settled and non-settled policyholders.

<table>
<thead>
<tr>
<th></th>
<th>30%</th>
<th>40%</th>
<th>50%</th>
<th>60%</th>
<th>70%</th>
</tr>
</thead>
<tbody>
<tr>
<td>average LE for settled subset</td>
<td>10.84</td>
<td>10.90</td>
<td>11.00</td>
<td>11.15</td>
<td>11.42</td>
</tr>
<tr>
<td>LE difference</td>
<td>0.36</td>
<td>0.43</td>
<td>0.52</td>
<td>0.67</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Table A.2 presents the results, where for comparison the non-adjusted life expectancy is 10.48 years. We obtain differences between 0.36 and 0.94 years, which correspond to between roughly 3.5% and 9% of the life expectancy. Of course, these results are based on rather ad-hoc assumptions and, as we discuss in the main text, there are aspects that may cause deviations in either direction. For instance, we find a smaller effect for the MLE estimates but additional information on the LE may boost the impact (cf. Section 4 in the main text). Nevertheless, these magnitudes suggest that adverse selection may have a considerable impact on the life settlement market, and that asymmetric information should be accounted for in market operations and assessments, such as pricing and valuation.

C.2 Monte Carlo Experiment on Excess Mortality

To implement a Monte Carlo version of the thought experiment in Section 5, we first run a least-square regression of the logarithm of the available LEs on the observable characteristics excluding the multiplier estimate and the settlement-related variables. We also include significant interactions of the terms so that we have 41 covariates in total. Based on the regression model, we then derive projected life expectancies as well as the standard deviation of the error term. The projected life expectancies will then be used as the benchmark of the assessment in the Monte Carlo experiment, i.e. we assume these present the true life expectancies.

Now, following the logic from Section 5, assume that a fraction of all cases enter into a life settlement transaction and the brokers commissioned with the sale “cherry-pick” among the available LEs. More precisely, assume that for these transactions, several LEs from various LE providers will be obtained but only the shortest LE is submitted. Alternatively, we may assume that there are several offers from various LS companies that base their pricing on different LEs, and the one with the highest bidding price (corresponding to the lowest LE) will make the trade. Importantly, while in the context of this experiment we assume the policyholder does not have private possibilities, where we use the Lee and Carter (1992) method to produce forecasts.
information on her survival prospects, note that there still exists an informational asymmetry—the broker and/or policyholder will have more information than the winning LS company—but this asymmetry emerges in the transaction process.

Assume that each provider’s LE is based on the same projected life expectancy plus a varying error term (with mean of zero), according to our regression estimates. For simplicity, we assume that the submitted (shortest) LE corresponds to the 25th percentile. Based on this logic, closed cases are systematically assessed with shorter life expectancies, whereas the remaining cases have no systematic deviation. We use the resulting LEs to generate a hypothetical set of forecasts \( \hat{\mu}_t^{(i)} \), \( 1 \leq i \leq N \), where we use the skewed LE for the (randomly sampled) closed cases and the projected LE for the remaining cases. Based on the simulated sample, we derive non-parametric estimators similarly as in Section 3.

Figure A.2 presents the results for five different simulated datasets, where as for our actual dataset we assume 1055 out of the 53947 policyholders are Settled-and-observed. While the shapes and magnitudes differ between the simulated datasets, we observe that the multiplicative excess mortality roughly evolves according to a straight line below one, whereas the additive excess mortality diverges. This is consistent with the assertions in Section 5. While it is possible that there are systematic differences in the underwriting process between the LE providers, it is difficult to construct a situation that yields the observed patterns from Section 3 based on this selection process.

References


Figure A.2: Monte-Carlo experiment of non-parametric estimates of excess mortality; earliest observation date.