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Hedging Longevity Risk in Life Settlements Using Biomedical Research-Backed Obligations

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Abstract

In the life settlement market, mortality risk is transferred from life insurance policyholders to third-party life settlement firms. This risk transfer occurs in conjunction with an information transfer that is relevant not only for pricing, but also for risk management. In this analysis, we compare the efficiency of two different hedging instruments in managing the mortality risk of the life settlement firm. First, we claim and then demonstrate that conventional longevity-linked securities do not perform as effectively in the secondary life market, that is, life settlement market, as in the annuity and pension markets due to the basis risk that exists between the general population and the life settlement subgroup. Second, we show that the unique risk exposure of the life settlement firm can be specifically targeted using a new instrument—the biomedical research-backed obligations. Our finding connects two seemingly independent markets and can promote the healthy development of both.

Introduction

Life settlements are transactions in a secondary life insurance market. In a life settlement, the owner of a life insurance policy transfers the stream of future premium payments and, upon the death of the original insured, the death benefit to the life settlement firm in exchange for a lump sum payment from the life settlement firm. The lump sum payment is larger than the policy's surrender value and this creates the incentive for life policyholders to participate in this secondary market. The life settlement market is the successor to the viatical settlement market that grew in the late 1980s due to the AIDS epidemic.

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The profitability and sustainability of the life settlement market depend on the ability of market participants, that is, life settlement companies, to generate accurate forecasts of the insureds' life expectancies. While mortality forecasts can be improved with the employment of state-of-the-art stochastic mortality forecasting models (Hunt and Blake, 2014), not all of them allow for longevity jumps. The possibility of a biomedical breakthrough that dramatically changes life expectancy (LE) is crucial to the cash flows and solvency of life settlement firms; this is a risk that must be managed. The failure of the viatical settlement market has been attributed to the medical research that yielded the drug/therapy for AIDS patients; that drug and therapy prolonged the lives of AIDS patients and resulted in losses and bankruptcies in the viatical settlement market (Stone and Zissu, 2006). Successful invention of new drugs and treatments for other (chronic) diseases will also increase the life expectancies of the impacted patients and so impose an (adverse) *longevity shock* on the life settlement market.

The current life settlement market deals with this issue by hiring professional LE companies to provide tailored assessment for each individual transaction. In particular, the LE companies employ physicians and medical experts when furnishing an estimation to make sure that the estimation not only covers best estimate from the individual's current medical profile, but also contains professional insights on how the forecast would be impacted by potential advancements that are disease specific. In a recent contribution, Brockett et al. (2013) also illustrate how to price life settlements by generating a mortality table that reflects the underwriter's medical information and using a double exponential jump diffusion mortality model first developed by Deng, Brockett, and MacMinn (2012). As this can be used to price contracts for unhedged life settlement firms, the question of how a life settlement company can effectively manage its longevity risk remains open, interesting, and important.

The capital market solutions for longevity risk have steadily evolved over the years; for example, see Blake et al. (2014) and Tan, Blake, and MacMinn (2015) for recent updates.[1] As existing longevity-linked securities differ among each other in their explicit forms, they are in general designed with payments dependent upon the longevity prospect of certain *underlying populations* or, equivalently, large demographic cohorts. This reduces asymmetric information and promotes such securities in the capital market and is overall well received by market participants like insurance companies and pension funds as their tools to manage longevity exposures. However, we argue that these conventional products might not be equally effective as hedging tools in the life settlement market, due to the considerable basis risk that exists between the general population and the smaller group of settled insureds. In particular, it is unlikely that a longevity shock that impacts the life settlement market, for example, the potential biomedical breakthrough in certain diseases, will be systematically picked up by a population longevity index.

[1]In what follows, we will use the terms *longevity risk* and *mortality risk* interchangeably to denote *uncertainty* in future mortality experience, although frequently researchers separate the concepts with respect to the direction of the shock.

New hedging instruments for the life settlement firms are possible. In another vein of the finance literature, new financing methods have been suggested for the biopharma industry; for example, see Fernandez, Stein, and Lo (2012), Fagnan et al. (2013), Lo and Naraharisetti (2014), and Lo (2015). Lo and Naraharisetti (2014) note that "new alternative investment companies have emerged to bridge the biopharma funding gap by purchasing economic interests in drug royalty streams. Such purchases allow universities and biopharma companies to monetize their intellectual property, creating greater financial flexibility for them while giving investors an opportunity to participate in the life sciences industry at lower risk." By combining a large number of the economic interests in drug-development projects into a single portfolio or megafund the future cash flows of the projects can be pledged as collateral: the megafund is subsequently referred to as biomedical research-backed obligations, or biomedical RBOs. These biomedical RBOs provide the necessary diversification to reduce risk in associated research, while at the same time represent an investment that is uncorrelated or has low correlation with other financial market instruments. The RBOs can then be securitized and placed primarily in the deeper pockets of the debt markets. The RBO senior debt instruments as well as instruments from other tranches can be traded in secondary markets and so provide investors with liquid instruments. RBOs have been discussed but not yet created.[2]

The value of the megafund lies in its effective diversification, risk reduction, and potential for securitization. Securitization with credit guarantees would allow the senior, that is, the safest, tranche to be rated and sold in the debt markets to institutional investors, for example, pension funds and insurance companies, with sufficient capital to solve the underfunding problem of the biopharma industry. Nevertheless, to date the question of the placement of the riskiest tranche, that is, the equity tranche, of a biomedical RBO has not been specifically addressed in the literature. The question is whether there is a natural class or group of investors who would prefer the equity tranche of a biomedical RBO to the debt tranche of the same RBO, or any other financial instruments. The analysis here contributes to the literature by providing a definite answer to this question.

In this analysis, we connect the two strands of seemingly unrelated literature and show that life settlement firms can use biomedical RBOs to effectively manage their longevity risk. We start by explicitly modeling mortality improvement from successful biomedical research. In a stylized framework, we show that the returns of biomedical RBOs, especially of the equity tranche, provide an effective hedge for longevity shocks due to medical advancements. In fact, the equity tranche of the RBO alone provides a better match to the risk faced by the life settlement firm than hedging the risk with other longevity-linked instruments such as longevity bonds or q-forwards.[3] Hence,

[2] Although biomedical RBOs are not available in capital markets, Lo and Naraharisetti (2014) provide empirical "proof of concept" for certain key characteristics of the megafund model via a case study of Royalty Pharma Inc. They conclude that the success of the firm's business model "provides compelling proof that new financial methods and models can play a pivotal role" in addressing both short- and long-term issues in the biopharma industry.

[3] We refer to Deng, Brockett, and MacMinn (2012) and Tan, Blake, and MacMinn (2015) for an introduction of the q-forward.

the analysis here shows that life settlement companies are natural buyers of the equity tranche of the RBO; such purchases would promote the development and securitization of biomedical megafunds and so further promote investment in the biopharma industry.

The analysis in the article is conducted in two stages. First, we use a stylized three-period model to illustrate the benefit of biomedical RBOs to the life settlement industry and to compare the hedging effectiveness of the RBO with the cases of no hedging and hedging with conventional longevity products. Here, we model the life settlement company's attitude toward longevity risk with an ambiguity aversion function. Second, we perform in-depth numerical analysis on the optimal hedging performance coupled with robustness tests, using cancer as an example. Our goal is not so much providing realistic and quantitative implications as it is on raising awareness to the qualitative longevity hedging advantages of biomedical RBOs to the life settlement industry.

The article is structured as follows. In "The Model" section, we investigate a representative ambiguity-averse life settlement firm and the effectiveness of two hedging instruments. In the "Numerical Analysis" section, we extend the model and compare hedges in more complex scenarios. The "Conclusion and Discussion" section concludes and discusses several unmodeled aspects.

THE MODEL

Consider a stylized three-period model. Assume that the life settlement market is composed of companies run by homogeneous managers. We focus on a representative life settlement firm. At date $t = 0$, the life settlement company purchases a whole-life insurance policy from a policyholder; the face value of the representative contract is 1 and the owner is assumed to have a particular disease A such as cancer. Assume that based on the current medical technology, the policyholder has a single-period survival probability p for the first and second periods, and that the survival probability for the final period is zero. The policyholder may die due to this disease or another cause. Further, assume that a biomedical research project on the disease is currently being conducted, and has probability π_A of being successful at $t = 1$ and $1 - \pi_A$ of failing. When the research succeeds, a longevity shock is realized and the estimated survival probability of the policyholder in the second period will be increased from p to $p + \Delta_A$. For simplicity, assume that all premiums of the policy have been paid in full and that the interest rate is a constant r for each period.

Under such a model framework, without the longevity shock, the *intrinsic value* of the policy at the time of purchase is V^n where:

$$V^n = \frac{1-p}{1+r} + \frac{p(1-p)}{(1+r)^2} + \frac{p^2}{(1+r)^3}. \tag{1}$$

With the longevity shock the intrinsic value of the policy at the time of purchase is V^s where:

$$V^s = \frac{1-p}{1+r} + \frac{p(1-p-\Delta_A)}{(1+r)^2} + \frac{p(p+\Delta_A)}{(1+r)^3}$$
$$= V^n - \frac{rp\Delta_A}{(1+r)^3}. \quad (2)$$

The *ex ante* value of the policy is therefore $\pi_A \times V^s + (1-\pi_A) \times V^n$. This is sometimes referred to as the *actuarially fair price* under competitive market assumptions denoted by P^a.

In the following subsections, we construct a stylized model of a life settlement firm that is averse to ambiguity.[4] We further explore how the company can improve its value by using different hedging tools such as conventional longevity securities versus a biomedical RBO.

The Ambiguity-Averse Life Settlement Company

When all future survival probabilities are fixed and known to the life settlement company, the idiosyncratic times of death of individuals can be treated as unsystematic risk and so diversified or, equivalently, reduced under the law of large numbers when grouping a large number of identical policies. In such a setting, the life settlement company may be assumed to be *risk neutral* with respect to the individual's random time of death. As it is common, in the life insurance and actuarial science literature, to assume risk neutrality with respect to unsystematic mortality risk of life market participants, one key factor is neglected. The market participants can still be affected by systematic mortality risk that cannot be diversified. We model such a case here. In the secondary market for life insurance, the settlement company faces different sets of survival probabilities contingent on the outcome of the biomedical research, an event that is unobservable when the policy is purchased and will impact all individuals with the same disease simultaneously. Hence, the biomedical research outcome represents a systematic risk for the life settlement company. The ways and means of managing this systematic risk are considered here.[5]

Ellsberg (1961) questions subjective expected utility models (Savage, 1954) and shows that decision makers typically prefer betting on events with known probabilities, for example, drawing from an urn containing 50 red balls and 50 black balls, to betting on events whose probabilities are ambiguous, for example, drawing from an urn containing 100 red and black balls in unknown proportions. Therefore, in addition to attitude toward risk (randomized events), decision makers also have in mind a

[4] Ambiguity aversion is also called uncertainty aversion in the economic literature.

[5] For the life settlement firm, systematic risk may also include longevity shocks due to other causes. While in "The Model" section, we consider the biomedical research outcome as the sole source of systematic risk, we introduce an additional background longevity shock in the following "Numerical Analysis" section.

second-order attitude toward a set of probability measures (states of nature). The final evaluation function depends jointly on both first-order risk preference and second-order ambiguity preference. In our model setup, ambiguity connects to systematic mortality risk and originates from the outcome of the biomedical research, as it leads to different states of nature (sets of future survival probabilities), whereas risk connects to unsystematic risk and originates from the random time of death of the individual. As diversification works for the latter but not the prior, we assume the life settlement company is risk neutral but ambiguity averse.

Our analysis is based on a special case of the model of partially separate preferences (i.e., see Nau, 2006).[6] The model consists of a state space with two logically independent partitions. The first partition is based on the success or failure of the biomedical research project, whereas the second partition is based on the payoffs of the representative life insurance contract. With state-independent preferences, Nau (2006) shows that a decision maker's utility can be represented in the two-stage functional form[7]

$$\mathbb{U}(\mathbf{w}) = \sum_{i=0}^{I} \pi_i \times \phi \left(\sum_{t=0}^{T} \sum_{j=0}^{J} \delta^t \, p_{ijt} \, u(w_{ijt}) \right), \tag{3}$$

where $i \in \{0, \ldots, I\}$ represents state in the first partition $\mathfrak{I}$ and π_i is the probability on state i, $j \in \{0, \ldots, J\}$ represents state in the second partition $\mathfrak{J}$ and p_{ijt} is the probability on state j at time t, conditional on i. $\delta = 1/(1+r)$ is the discount factor given the rate of interest r and w_{ijt} is the state (i, j) payoff at t. $u(\cdot)$ is the first-order utility function measuring risk preference and $\phi(\cdot)$ is the second-order utility function measuring ambiguity preference. The decision maker then bets on the events measurable in the first partition as if the utility is $\phi(\mathbb{E}(u(w_i)))$. Both u and ϕ are increasing and concave. The concavity of ϕ makes the decision maker averse to uncertainty due to the unknown probability measure.

With only one biomedical research project undergoing and insurance payoff depending solely on the survival status of the policyholder, $I = 1$ and $J = 1$. Let $w_{ij0} = -P^m$, where P^m is the market price of a normalized life settlement contract; $w_{i0t} = 0$ and $w_{i1t} = 1$ for $t = 1, \ldots, T$, where $T = 3$ in our model setup. Similarly, let

$$p_{0j0} = 1,\ p_{0j1} = \begin{cases} p & j = 0 \\ 1-p & j = 1 \end{cases},\ p_{0j2} = \begin{cases} p^2 & j = 0 \\ p(1-p) & j = 1 \end{cases},\ p_{0j3} = \begin{cases} 0 & j = 0 \\ p^2 & j = 1 \end{cases},$$

and

$$p_{1j0} = 1,\ p_{1j1} = \begin{cases} p & j = 0 \\ 1-p & j = 1 \end{cases},\ p_{1j2} = \begin{cases} p(p+\Delta_A) & j = 0 \\ p(1-p-\Delta_A) & j = 1 \end{cases},\ p_{1j3} = \begin{cases} 0 & j = 0 \\ p(p+\Delta_A) & j = 1 \end{cases},$$

[6] Klibanoff, Marinacci, and Mukerji (2005) propose an analogous two-stage preference model based on both risk and ambiguity aversions.

[7] Here, we change some notations in the original model of Nau (2006) for better consistency with the rest of the article. We also include the time horizon.

where again Δ_A is the positive increment added to the survival probability if the biomedical project is successful. Here, $\pi_0 \equiv 1 - \pi_A$ is the probability that the biomedical project fails, whereas $\pi_1 \equiv \pi_A$ is the probability that the project succeeds. Now letting the life settlement firm be indifferent to the diversifiable risk, that is, $u(w) = w$, (3) may be rewritten as

$$\mathbb{U}^U \equiv \mathbb{U}(P^m) = (1 - \pi_A)\phi(V^n - P^m) + \pi_A\phi(V^s - P^m). \tag{4}$$

Note that some aversion remains but it is the aversion to the uncertain success of the biomedical project and that is the systematic risk.

Hedging Longevity Risk With Longevity Forwards

For an ambiguity-averse life settlement company as modeled above, its utility is directly impacted by the existence and the degree of systematic longevity risk. Equivalently, any efforts in alleviating, or hedging, such risk will potentially increase the firm's utility. A number of hedging instruments exist in the nascent mortality-linked securities market, (e.g., see Blake et al., 2014), including longevity bonds, swaps, and forwards. As the structure of the instruments varies, most of them are designed to hedge longevity risk by generating payoffs that are based on the realization of a population mortality index. The instruments can therefore effectively hedge longevity risk in pension and annuity markets subject to some basis risk. The claim here, however, is that the current instruments are not *as effective* in the life settlement market. To set the stage for considering this claim, we allow the life settlement firm to hedge its longevity risk with a longevity forward contract. We will suppose the hedge is for the possible cash flows at date $t = 2$ when the information about the success or failure of the biomedical research project is realized.

Consider a forward contract with a date $t = 2$ payoff. As forward contracts are structured using a population index, we extend the model as follows. Assume that the population is equally composed of two groups $k = A,\ B$: group k is subject to disease k and biomedical research is being conducted for each group. Similar to group A, successful completion of research for group B would change its second-period survival probability from p to $p + \Delta_B$ with probability π_B. Now, if we let M_2 be the death probability in the second period for the population, then its value depends on the realization of one of the four states of nature, characterized by the outcomes of research on both groups:

$$M_2 = \begin{cases} m_{20} = p\left(1 - \left(p + \frac{1}{2}\Delta_A + \frac{1}{2}\Delta_B\right)\right), & \pi_A\pi_B \\ m_{21} = p\left(1 - \left(p + \frac{1}{2}\Delta_A\right)\right), & \pi_A(1 - \pi_B) \\ m_{22} = p\left(1 - \left(p + \frac{1}{2}\Delta_B\right)\right), & (1 - \pi_A)\pi_B \\ m_{23} = p\,(1 - p)\,. & (1 - \pi_A)(1 - \pi_B) \end{cases}$$

The forward contract payoff would be $\mathbb{E}M_2 - m_{2i}$, $i = 0,\ 1,\ 2,\ 3$.[8]

[8]The factor $\frac{1}{2}$ appears in m_{2i}, $j = 0,\ 1,\ 2$, as we assume equal proportion of groups A and B in the population. Therefore, successful completion of research for disease k will only increase the second-period *population* survival probability by $\frac{1}{2}\Delta_k$, $k = A,\ B$.

If the realized mortalities m_{2i} matched those of the firm, then we would have a full hedge that eliminated the ambiguity. A firm in a pension or annuity market would not generally be able to match the realized population mortalities due to selection effect as well as possibly not having books of business equally representing groups A and B. This leaves such firms with some basis risk. In the case of a life settlement firm specializing in group A, the basis risk can be even more of a concern. We consider its value.

Consider a partial equilibrium result by allowing the life settlement firm to hedge its longevity risk with the forward contract described here. Suppose the manager selects an optimal position in forwards. Let $n \in [0,1]$: $n = 0$ is no hedge, whereas $n = 1$ is a full hedge. The utility of the firm is

$$\begin{aligned}\mathbb{U}^F(n^*) = \max_n \Big\{ & \pi_A \pi_B \times \phi\left(V^s - P^m + \delta^2 n\left(\mathbb{E}M_2 - m_{20}\right)\right) \\ & + \pi_A(1-\pi_B) \times \phi\left(V^s - P^m + \delta^2 n\left(\mathbb{E}M_2 - m_{21}\right)\right) \\ & + (1-\pi_A)\pi_B \times \phi\left(V^n - P^m + \delta^2 n\left(\mathbb{E}M_2 - m_{22}\right)\right) \\ & + (1-\pi_A)(1-\pi_B) \times \phi\left(V^n - P^m + \delta^2 n\left(\mathbb{E}M_2 - m_{23}\right)\right)\Big\}. \end{aligned} \tag{5}$$

As analytically solving for the Optimal position n^* is cumbersome, Online Appendix A.1 (Macminn and Zhu, 2017) shows that

$$\frac{d\mathbb{U}^F(\cdot)}{dn}|_{n=0} = \frac{1}{2}\pi_A(1-\pi_A)\Delta_A\delta^2 p \times \left[\phi'(V^s - P^m) - \phi'(V^n - P^m)\right].$$

As $V^s < V^n \Leftrightarrow V^s - P^m < V^n - P^m$, it immediately follows that for any strictly increasing and concave function $\phi(\cdot)$, $\phi'(V^s - P^m) > \phi'(V^n - P^m)$. Therefore, the derivative of $\mathbb{U}^F$ evaluated at $n = 0$ is positive; that is, the life settlement firm will choose a positive hedging in the forward market despite the basis risk that is introduced.

Hedging Longevity Risk With Biomedical RBOs

As we have noted the conventional longevity-linked securities such as q-forwards, swaps, and longevity bonds could alleviate the longevity risk exposure faced by the life settlement firm. The firm, however, specializes in a particular disease and this limits the effectiveness of the conventional instruments. The risk analyzed here stems directly from potential medical improvement in the treatment of disease A; a more effective hedging tool with a minimal basis risk would come from an investment in a security with payments directly linked to the research and subsequent payoff given the specific disease A. Investment in biomedical research is, however, rather exclusive. Aside from pharmaceutical firms, certain venture capitals and hedge funds there is little access to such investment opportunities.

In recent years, there has been considerable underfunding of bioresearch projects (Pisano, 2006). To address this issue, a recent work by Fagnan et al. (2013) proposes an alternative funding solution in the form of a megafund that targets the general investors, so that more resources would become available to fund medical research.

The megafund is composed of numerous research projects that are being conducted simultaneously on the same disease, so that the risk is controlled with effective diversification. While in Fagnan et al. (2013) the megafund was designed to attract general institutional investors in debt markets, we argue that it provides the life settlement company an excellent opportunity to hedge the specific disease-related risk.

Consider a biomedical RBO in its simplest form. Specifically, for one unit of initial investment, let the present value of the payoff streams when the research is successful be $1 + R$ (with probability π_A) and $1 - R\pi_A/(1 - \pi_A)$ when the research fails (with probability $1 - \pi_A$).[9] Similarly, the company will choose the optimal amount of capital K^* invested in the biomedical RBO in order to maximize its utility:

$$\mathbb{U}^R(K^*) = \max_K \left\{ \pi_A \times \phi\left(V^s - P^m + KR\right) + (1 - \pi_A) \times \phi\left(V^n - P^m - K\frac{R\pi_A}{1 - \pi_A}\right) \right\}.$$

It follows by direct calculation that the optimum is achieved when $K^* = \frac{\delta^3 p(1-\pi_A)\Delta_A}{R}$. In this case, the company receives the same payoff, $V^s - P^m + \delta^3 p(1 - \pi_A)\Delta_A = P^a - P^m$, independent of the research outcome. The following proposition compares the three alternatives to the company for dealing with the longevity risk. A proof is provided in Online Appendix A.2 (Macminn and Zhu, 2017).

Proposition 1: *The risk-neutral ambiguity-averse life settlement company achieves the highest expected utility by using biomedical RBOs to hedge longevity risk, rather than no hedge or a forward hedge, that is,* $\mathbb{U}^R(K^*) > \mathbb{U}^F(n^*) > \mathbb{U}^U$.

As suggested in the proposition, in our stylized model investing in biomedical RBOs works like obtaining full insurance for the longevity shock as there is no basis risk. The company is completely protected from the adverse shock and can therefore achieve the highest utility compared to the other two cases. In reality, basis risk inevitably exists in biomedical RBO investment, and the effectiveness of various hedging tools depends on their relative exposure to basis risk. This is studied in the following "Numerical Analysis" section. Furthermore, we discuss some unmodeled features of biomedical RBOs in the final section.

NUMERICAL ANALYSIS

In this section, we conduct exemplifying numerical tests. Using cancer as an example, we first introduce two independent sources of systematic longevity shocks, and derive the settlement price of a whole-life insurance policy currently owned by a representative cancer patient. We then show how the firm can subsequently increase its

[9] This implies the risk premium of the investment is zero, as the expected present value of the payoff is one unit, same as the initial investment. With positive risk premia, it can be easily verified that the life settlement company can even attain higher utility, as the expected present value will have to be greater than one. We therefore use the zero risk premium case as the base case here. The numerical analysis in the following section considers the case of positive risk premium of the RBO investment.

utility by using either longevity forwards or biomedical RBOs. Last, we compare the hedging results, followed by robustness checks.

Longevity Shocks and Market Price

Consider the case in which a life settlement company is acquiring a whole-life insurance policy from a 75-year-old female policyholder with general cancer at the beginning of year 2004.[10] The policy was initially purchased when the policyholder was 40 years old and with no disease at the beginning of year 1969, with a face amount of $500,000 and level annual premiums payable at the beginning of each year, contingent on the survival of the policyholder. We assume the initial insurer was both risk and ambiguity neutral. Using a constant 4 percent annual interest rate and U.S. mortality data as available from the Human Mortality Database (HMD),[11] we first calculate the actuarially fair annual premium at $6,809 from standard period life table at year 1969. We further derive the generation life table—the table that incorporates projection on future mortality trend—for the 75-year-old at year 2004, using the Lee and Carter (1992) methodology and HMD mortality data from 1974 to 2003 (we refer to Zhu and Bauer, 2013, for a detailed explanation).[12] This table provides baseline future mortality rates for our representative policyholder.

The systematic longevity risk is further introduced from two independent sources. The first is a background longevity shock ($b \in \mathfrak{I}_B$) that impacts the future mortality rates of every individual in the population simultaneously. For simplicity without loss of generality, we assume that 1-year mortality rates for all ages in the future are either decreased with a multiplier at 99.5 percent (positive longevity shock; $b = 0$), kept unchanged (neutral longevity shock; $b = 1$), or increased with a multiplier at 100.5 percent (negative longevity shock; $b = 2$) with same probabilities. This background shock, which can be perfectly hedged by population-based conventional longevity products, reduces hedge effectiveness of biomedical RBOs by generating an extra layer of shock to cancer patients that is uncorrelated to biomedical research and the resulting financial returns. The inclusion of the background risk thus allows a more practical and balanced comparison between various hedging tools.

The second longevity risk is the one specifically related to cancer research development. In order to quantify that we first consider the impact of cancer on a standard mortality table, that is, other things being equal, how will the mortality rates increase

[10] We use year 2004 as this is the latest year with age-specific mortality rates available for cancer patients.

[11] Human Mortality Database. University of California, Berkeley (United States), and Max Planck Institute for Demographic Research (Germany). Available at www.mortality.org or www.humanmortality.de.

[12] Theoretically, a more consistent approach to calculating the annual premium would be to also use the generation life table derived at year 1969. Here, we use period life table as this was the approach used by life insurers back in the 1960s. Nevertheless, we do repeat our entire analysis by obtaining an actuarially fair annual premium based on the generation life table and find qualitatively analogous results and the same conclusion regarding hedging comparisons.

TABLE 1
Probability and Associated Intrinsic Life Settlement Contract Value for Each State of Nature on Future Mortality Rates

Probability/Intrinsic Value $(\pi_{bc})/(V^{bc})$	Background Longevity Shock (b)		
	Positive	Neutral	Negative
Cancer research success (c)			
0	1.61%/$218,769	1.61%/$219,290	1.61%/$219,809
1	4.93%/$216,629	4.93%/$217,147	4.93%/$217,662
2–3	15.04%/$215,541	15.04%/$216,059	15.04%/$216,574
>3	11.76%/$214,443	11.76%/$214,961	11.76%/$215,476

Note: The intrinsic value is defined as the present value of the expected death benefits minus the present value of future contingent premiums. The columns are for the background longevity shock ($b \in \mathfrak{I}_B$) that can be either positive, neutral, or negative. The rows are for the cancer-specific longevity shock ($c \in \mathfrak{I}_C$) represented by the number of successful cancer research.

for an individual with cancer compared to one without. As specific mortality tables for cancer patients are generally unavailable in public, we rely on statistics from the National Cancer Institute to obtain approximated mortality prospects for cancer patients.[13] In particular, for a 75-year-old female in year 2004 with a standard 1-year mortality rate of 2.91 percent, the average (absolute) mortality rate increase from cancer is estimated at 0.75 percent.[14] This is converted to a mortality-rate multiplier at 125.8 percent, which is further used to scale the standard mortality rates of other ages for the cancer patient.[15]

We then introduce the cancer-specific longevity shock ($c \in \mathfrak{I}_C$) by assuming that there are 150 independent cancer-related medical research projects currently underway, with each having a 2 percent chance of being successful before the respective research cycle—assumed as 1 year—ends. The impact of cancer on mortality rates, that is, the 125.8 percent mortality multiplier, would be immediately reduced by 0, 10, 15, and 20 percent; with zero ($c = 0$), one ($c = 1$), two to three ($c = 2$), or more than three ($c = 3$) successful research projects at the end of year 2004, respectively. By assuming independence between the background and cancer-specific longevity shocks, in our setup there are a total of $3 \times 4 = 12$ states of nature in the first partition ($\mathfrak{I} = \mathfrak{I}_B \times \mathfrak{I}_C$). Table 1 shows the probability (π_{bc}) and the associated intrinsic life settlement contract value (V^{bc}) with a 6 percent hurdle rate assumption[16] for each realized state of nature on future mortality rates, $b = 0, 1, 2$, $c = 0, 1, 2, 3$. Table A.1 in Online Appendix B (Macminn and Zhu, 2017) further shows the realized 1-year mortality rates for a representative 75-year-old female with cancer at the end of year 2004 in each state of

[13]Cancer mortality maps available at http://ratecalc.cancer.gov.
[14]We note that the National Cancer Institute interprets the 0.75 percent as the *extra* rate of mortality added to the standard age 75 female mortality rate.
[15]The mortality-rate multiplier is also referred to as the frailty factor in the actuarial literature.
[16]Here, the hurdle rate is defined as the rate required by the firm to undertake such investment.

nature as an example. Similar to the previous section, the actuarially fair offer price is calculated as the expectation of intrinsic values from Table 1: P^a =\$215,988.

We assume a competitive life settlement market where the expected utility of the life settlement company without hedging is 0 at the market price, that is, the market price P^m is the price such that the company is *indifferent* between remaining in the market or leaving it.[17] If the market price was greater then firms would exit the market, whereas if it was less then firms would enter the market. This implies that P^m satisfies

$$\mathbb{U}^U = \mathbb{U}(P^m) = \sum_{b=0}^{2} \sum_{c=0}^{3} \pi_{bc} \times \phi \left(V^{bc} - P^m \right) = 0. \tag{6}$$

In particular, we consider a second-order utility function $\phi(x) = 1 - \exp(-ax)$ based on the firm's time 0 expected profit x, with $a = 0.002$.[18] The market price is then calculated at $P^m = \$215,248$, which is \$740 lower than the actuarially fair price. Table A.2 in Online Appendix B (Macminn and Zhu, 2017) further shows the expected net present value of the unhedged life settlement transaction in each state of nature. This price will be further used as the benchmark price in the subsequent discussions.

Longevity Hedging

After obtaining the benchmark price P^m, we further study whether and to what extent the life settlement company can improve upon its utility with various longevity hedging tools. We first evaluate the use of longevity forwards as an example of conventional longevity products, followed by the analysis of the biomedical RBOs.

Longevity Forwards. Assume a longevity forward maturing at the end of year 2004 with payments dependent on the population-level 1-year mortality rate of a 75-year-old female, where we further assume that cancer patients take 5 percent of the entire population, and that the remaining 95 percent individuals are in the homogeneous cancer-free cohort. Naturally, for the latter group, their mortality movements are

[17] If there is an initial wealth to the firm, then the zero would be replaced by the expected utility of that initial wealth. Furthermore, in this research we leave out discussions on the policyholder's decision making and simply assume that the market price will always be accepted. We argue that this should not be an issue, as in our model framework the policyholder possesses no hidden information with respect to her health state and is therefore unable to extract any additional information rent from the life settlement transaction.

[18] Here, we use constant absolute risk (ambiguity) preference rather than constant relative risk (ambiguity) preference as our utility function is defined on both positive and negative time 0 profits. Simple CRRA assumptions such as power functions are hence not directly applicable in our model framework. While under CARA utility wealth effects (aggregate volume of all life settlement contracts) could potentially affect the life settlement firm's optimal hedging behavior, we note this is at least partly controlled by the homogeneity assumption of the underlying insurance policyholders and the value of the parameter a. We provide a detailed discussion on this in Online Appendix A.3 (Macminn and Zhu, 2017). Numerical test on the degree of ambiguity aversion is further conducted as one robustness check in the "Comparisons and Robustness Tests" section.

TABLE 2
Payoffs From the 1-Year Longevity Forward in Associated States of Nature as in Table 1

Forward Payoff (F^{bc})	Background Longevity Shock (b)		
	Positive	Neutral	Negative
Cancer research success (c)			
0	\$0.0883	−\$0.0574	−\$0.2030
1	\$0.1256	−\$0.0199	−\$0.1653
2-3	\$0.1443	−\$0.0011	−\$0.1465
>3	\$0.1629	\$0.0176	−\$0.1277

Note: The payoff is defined as the difference between the expected and realized population-level 1-year mortality rate of age 75 female at the end of year 2004, further scaled by \$1,000.

independent of cancer-related medical research and are only affected by the background longevity shock.[19] Similarly, for the longevity forward there are in total 12 different payoff scenarios that depend on the realized states of nature. Table 2 shows the payoff from this 1-year longevity forward, F^{bc}, with payment in each scenario as the difference between *expected population-level 1-year mortality rate* and *realized population-level 1-year mortality rate* of age 75 females at the end of year 2004, scaled by \$1,000. This is further defined as one position in the longevity forward.

The life settlement company chooses the optimal position in the longevity forward, n^*, to maximize its utility

$$\mathbb{U}^F(n^*) = \max_n \sum_{b=0}^{2} \sum_{c=0}^{3} \pi_{bc} \times \phi \left(V^{bc} - P^m + \delta n \times F^{bc} \right).$$

We calculate n^* at 4,324, which further increases the company's utility from 0 to 0.3573. This corresponds to our previous claim; namely, the life settlement company generally benefits from conventional longevity securities, despite the considerable basis risk. Table A.4 in Online Appendix B (Macminn and Zhu, 2017) further shows the expected net present value of the life settlement transaction with optimal longevity forward hedging in each state of nature.

Biomedical RBOs. Without loss of generality, we assume that each of the aforementioned 150 medical research projects requires an up-front investment of \$1,000,000 and, once successful, generates a stream of payoffs with present value at \$60,000,000.[20] We

[19] Table A.3 in Online Appendix B (Macminn and Zhu, 2017) shows the realized 1-year mortality rates for a representative 75-year-old female without cancer at the end of year 2004 in each state of nature as an example.

[20] The expected present value of each investment return is $\$60,000,000 \times 0.02 = \$1,200,000 > \$1,000,000$; that is, the investment has a positive risk premium. As this is practically necessary in order to construct different securitization tranches of the pooled megafund associated with different pairings of risk and return, we study the extreme case of zero risk premium in the following robustness tests.

TABLE 3
Summary of the Biomedical RBO Debt and Equity Tranches

	Tranche	
	Debt	Equity
Volume	$55,000,000	$95,000,000
Ruin probability	4.83%	19.61%
Expected return	$57,102,239	$122,897,761

Note: The volume indicates the initial investment allocated in each tranche. Ruin probability gives the probability that the return does not exceed initial investment, that is, no success for the debt tranche or fewer than two successes for the equity tranche. Expected return is the expected present value of payoff streams in each tranche.

follow the idea in Fernandez, Stein, and Lo (2012) to construct a megafund funding all 150 research projects, which is further securitized with different tranches into the general investment market. For simplicity, here we use only two instead of the typically assumed three tranches, namely, the debt tranche and the equity tranche.[21] The debt tranche represents a relatively safe investment, whereas investment in the equity tranche is much riskier, and therefore has higher expected return. In particular, we assume that out of the total $150,000,000 initial investment raised in the megafund, $55,000,000 is funded through the debt tranche, with the remaining through the equity tranche. In the unlucky event of 0 success out of 150, both tranches return no payment streams. Otherwise, the revenue from the first successful research goes to the debt holder, and any additional revenues that are generated from the second successful research and beyond will go to the equity holder. Table 3 provides a brief summary of the two tranches.

We assume that the life settlement company is free to invest in both debt and equity tranches (K_D and K_E, respectively), and chooses the optimal allocation to maximize its utility:

$$\mathbb{U}^R(K_D^*, K_E^*) = \max_{K_D, K_E} \sum_{b=0}^{2} \sum_{c=0}^{3} \pi_{bc} \times \phi \left(V^{bc} - P^m + R_D^c \times K_D + R_E^c \times K_E \right),$$

where R_D^c and R_E^c represent the net (average) returns from the debt and equity tranches in state $c \in \mathfrak{I}_C$. For example, $R_D^0 = -1$, and $R_D^1 = R_D^2 = R_D^3 = (\$60,000,000 - \$55,000,000)/\$55,000,000 = 9.09$ percent. We obtain the optimal amount of investments K_D^* at $2,197 and K_E^* at $1,032. The realized utility of the life settlement company is further calculated at 0.8407 in this case. Table A.5 in Online Appendix B further shows the expected net present value of the life settlement transaction with optimal biomedical RBO hedging in each state of nature.

[21]The tranche neglected here is the intermediary mezzanine tranche.

Comparisons and Robustness Tests

In what follows, we first compare the two hedging instruments as discussed above. As our numerical finding depends on the specific parameter assumptions, we further conduct several robustness tests to check how the results change when the assumptions vary in the base case.

Comparing Hedging Tools. As the utility is considerably improved when using longevity forwards (from 0 to 0.3573), the improvement is even more pronounced with the use of biomedical RBOs (from 0 to 0.8407). Again, this can be attributed to the existence and the degree of basis risk: as conventional longevity products such as longevity forwards are based on the mortality movements of the entire population, it cannot accurately reflect the shift of mortality for a certain subgroup. In our assumption, while the cancer cohort is affected by both background and cancer-specific longevity shocks, the latter dominates in the relative size, but at the same time fails to be fully captured by the longevity forwards. On the other hand, biomedical RBOs are specifically correlated with the underlying disease and hence the disease-specific longevity shock. Even if the mortality improvements and the investment returns are assumed to be not completely correlated, and the RBOs cannot hedge the background risk, our numerical results suggest the advantage of hedging with RBOs when the magnitude of the embedded basis risk is at relatively lower level.

The difference in the hedging effectiveness can be further shown using the concept of *cash equivalent*. Here, we define the cash equivalent as a hypothetical offer price P^{CE} from the life settlement firm in conjunction with no hedging (cf. Equation (6)), yet gives the same positive utility as when hedging instruments are utilized, that is, $\mathbb{U}(P^{CE}_{Forward}) = 0.3573$ in the longevity forward case and $\mathbb{U}(P^{CE}_{RBO}) = 0.8407$ in the biomedical RBO case. The difference between the market price and cash equivalent can, thus, be seen as the *saving* from longevity risk management and serves as a more direct monetary metric compared to utility values. For longevity forwards and biomedical RBOs, the cash equivalents are calculated at $P^{CE}_{Forward} = \$215{,}027$ and $P^{CE}_{RBO} = \$214{,}330$, respectively. Therefore, as longevity forwards provide a saving at \$221, a higher saving of \$918 can be achieved from the use of biomedical RBOs.

Demographic Composition. For robustness tests, we first revisit the payment structure of longevity forwards under different demographic compositions. Similar to the base case, here we assume that the entire population is composed of both cancer patients and a cancer-free cohort, and that the behavior of longevity shocks within each subgroup remains the same. We then adjust the assumption on the percentage of cancer patients in the entire population. Table 4 shows the optimal position in longevity forwards, n^*, the utility value when using longevity forwards, $\mathbb{U}^F$, as well as the associated cash equivalent, $P^{CE}_{Forward}$, for the cancer ratio varying between 5 and 80 percent. From the table, it is apparent that the longevity forward hedging becomes more effective as the ratio increases, that is, when the residual basis risk becomes less pronounced. However, we also observe that longevity forwards still perform inferior to biomedical RBOs, even in the case where the cancer patients take 80 percent of the entire population.

TABLE 4
Robustness Test With the Percentage of Cancer Patients in the Entire Population Varying from 5 to 80 Percent

	Percentage of Cancer Patients in the Population					
	5%	20%	35%	50%	65%	80%
n^*	4,323	5,729	6,053	5,363	4,524	3,828
$\mathbb{U}^F$	0.3573	0.5665	0.6951	0.7496	0.7680	0.7721
$P^{CE}_{Forward}$	\$215,027	\$214,830	\$214,654	\$214,556	\$214,518	\$214,509

Note: Here, n^* denotes the optimal position in the 1-year longevity forwards, $\mathbb{U}^F$ is the associated utility of the life settlement firm when using longevity forwards, and $P^{CE}_{Forward}$ is the associated cash equivalent.

Degree of Ambiguity Aversion. We test the hedging effectiveness with alternative values of ambiguity aversion parameter (a) ranging from 0.0005 to 0.01. As directly comparing utilities across different values of a does not provide much information, Table 5 summarizes the market price (P^m) solved from Equation (6), as well as the cash equivalents ($P^{CE}_{Forward}$ and P^{CE}_{RBO}) for each value of a. From the table, we notice a weaker hedging performance ($P^m - P^{CE}_{Forward}$) using longevity forwards when the firm is less ambiguity averse (lower a). Biomedical RBOs, on the other hand, always provide a high saving from the perspective of longevity risk management ($P^m - P^{CE}_{RBO}$) that is relatively consistent across all values of a.

Restriction on Biomedical RBO Investment. It is possible that the life settlement company does not have full access to both debt and equity tranches simultaneously, but can only choose to invest in one. To analyze the sensitivity to such restriction on investment, we modify the associated optimization problem by restricting the life settlement firm to only invest in either the debt or equity tranche. The results are summarized in Table 6. From the table, we observe that as investing in either tranche can still improve the firm's utility considerably, the riskier equity tranche outperforms the debt tranche in terms of both hedging effectiveness ($\mathbb{U}^R$) and the reduction of up-front investment cost (K^*). The equity tranche alone also outperforms longevity forwards. This should not be surprising, as the equity tranche provides compensation when the longevity

TABLE 5
Robustness Test With the Parameter Value of the Ambiguity Aversion (a) Varying From 0.0005 to 0.01

	Parameter of Ambiguity Aversion (a)				
	0.0005	0.001	0.002	0.005	0.01
P^m	\$215,724	\$215,526	\$215,248	\$214,854	\$214,657
$P^{CE}_{Forward}$	\$215,653	\$215,397	\$215,027	\$214,478	\$214,186
P^{CE}_{RBO}	\$215,071	\$214,776	\$214,330	\$213,724	\$213,448

Note: Here, P^m is the market price; $P^{CE}_{Forward}$ and P^{CE}_{RBO} are the cash equivalents when using longevity forwards and biomedical RBOs, respectively.

TABLE 6
Robustness Test With Restriction on Biomedical RBO Investment in Only One Tranche

	Restriction on RBO Investment	
	Debt Only	Equity Only
K^*	\$3,842	\$1,112
$\mathbb{U}^R$	0.4574	0.7836
P^{CE}_{RBO}	\$214,942	\$214,483

Note: Here, K^* denotes the optimal investment in either tranche, $\mathbb{U}^R$ is the associated utility of the life settlement firm when using biomedical RBOs, and P^{CE}_{RBO} is the associated cash equivalent.

risk is excessive, whereas the debt tranche provides a much gentler protection to the longevity shock. The life settlement firm therefore serves as a natural buyer of the equity tranche in the market.

Assumption on Risk Premia. One extreme case that is worth testing is when we assume zero risk premium for the biomedical RBOs, that is, when the present value of the payoff streams equates initial investment within each tranche, regardless of the risk level of the investment. As this is highly unlikely in practice, it can be seen as the worst-case scenario of the hedging effectiveness when using biomedical RBOs, similar to the assumptions in "The Model" section.

For the same 150 independent medical research projects, the up-front cost of each project needs to increase to \$1,200,000 under the zero risk premium assumption.[22] From the total \$180,000,000 raised in the megafund, we further readjust the fair proportion invested in the debt and the equity tranches, so that the initial volume matches the expected return in each tranche. The updated summary of the biomedical RBOs is displayed in Table 7. Table 8 further shows the results from the optimization as well as the associated cash equivalents in different cases regarding restrictions on biomedical RBO investment. From the table, we observe similar results as in the positive risk premium case. In particular, biomedical RBOs still perform rather well in terms of longevity hedging, and the majority of the improvement in the utility stems from the risky equity tranche.

Last, a related case that is worth discussing is the potential risk premium on the longevity forwards, which is implicitly chosen at zero in above analysis as we directly use the expectation of future mortality rates in calculating the payoffs. As in practice longevity forwards may also entail positive risk premia, we argue that this will only make longevity forwards less preferable to the life settlement firms as they are the ones who seek to hedge systematic mortality risk, and are hence the ones who need to absorb positive risk premia as additional costs. Specifically, in the case of positive risk premium, the forward payoff F^{bc} has to be *lowered* by a fixed amount in each

[22]The expected present value of the investment return is \$60,000,000 × 0.02 = \$1,200,000, the same as the adjusted initial investment.

TABLE 7
Summary of The Modified Biomedical RBO Tranches When Assuming Zero Risk Premium

	Tranche	
	Debt	Equity
Volume	$57,102,239	$122,897,761
Ruin probability	4.83%	19.61%
Expected return	$57,102,239	$122,897,761

Note: The volume indicates the initial investment allocated in each of the two tranches. Ruin probability gives the probability that the return does not exceed initial investment, that is, no success for the debt tranche or fewer than two successes for the equity tranche. Expected return is the expected present value of payoff streams in each tranche, which is equal to the respective initial investment volume under the zero risk premium assumption.

realized state of nature, resulting in a *reduced* utility from longevity forward hedging. Therefore, our base case represents the best-case scenario of the hedging effectiveness when using conventional longevity products, and this reinforces or even strengthens our previous claim on the advantage of biomedical RBOs.

We note that the contracting effects of risk premia on hedging effectiveness when using conventional longevity products versus biomedical RBOs could potentially serve as an additional reason—other than the basis risk argument—why the latter should be considered by the life settlement companies.

CONCLUSION AND DISCUSSION

In this article, we investigate longevity risk management of an ambiguity-averse life settlement company by comparing two hedging instruments: conventional longevity forwards and biomedical RBOs. Our numerical analysis shows that the prior exhibit relatively inferior performance in terms of hedging due to the nonnegligible basis risk between the general population and the settled subgroup, whereas the latter overcome this issue by providing returns that are strongly positively correlated with the specific longevity shock. The life settlement industry therefore becomes the natural buyer of

TABLE 8
Robustness Test With Zero Risk Premium Assumption For Biomedical RBOs

	Zero Risk Premium for Biomedical RBOs		
	Debt Only	Equity Only	Both
K_D^*	$3,711	·	$2,249
K_E^*	·	$1,124	$1,062
$\mathbb{U}^R$	0.2790	0.6137	0.6761
P_{RBO}^{CE}	$215,085	$214,772	$214,684

Note: We consider cases without and with restriction on investment in either debt or equity tranche. Here, $K_\cdot^*$ denotes the optimal investment in either tranche (when not restricted), $\mathbb{U}^R$ is the associated utility of the life settlement firm when using biomedical RBOs, and P_{RBO}^{CE} is the associated cash equivalent.

this novel security and this would in turn promote the healthy development of both life settlement and biopharma markets.

With our numerical results strongly in favor of RBOs, below we discuss several unmodeled aspects for a more objective and balanced viewpoint. We note that some of them may serve as drawbacks, or at least cautions for biomedical RBOs in reality. We call for future numerical and empirical studies for a more comprehensive assessment.

In the article, we assume that the life settlement firm only focuses on patients with a certain disease and the rest are hence treated as basis risk to the firm. In reality, life settlement companies deal with different types of clients and it shall be of interest to test whether traditional longevity products fare better when the firm buys policies from a variety of policyholders who resemble closer to the general population. We leave a short note here that the firm can also simultaneously invest in different biomedical RBOs targeting different diseases and extract positive risk premia from such investments compared to conventional longevity securities.

With only one age/gender combination considered in the analysis, in reality a life settlement company deals with both male and female policyholders at various ages. In this case, holding a portfolio of longevity forwards targeting mortality rates at different age/gender combinations could practically increase the hedging performance, especially in the case of discrepancies in mortality improvements among these factors. On the other hand, the embedded basis risk in biomedical RBOs is amplified due to different sensitivities to medical improvements for different age/gender groups.

Biomedical research projects are by nature risky endeavors with no guarantee of success. Even with grouping a large set of projects, it is not clear whether or, more importantly, *when* the medical breakthrough will occur. This is crucial to the popularity of biomedical RBOs as payments can only be delivered after success, and the uncertainty in timing can result in a mismatch of payments from RBOs and of the cash flows from the life settlement contract itself, which further brings in issues regarding the company's funding ratios. Longevity forwards, on the other hand, prescribe fixed payment time at the inception of the contract. As timing is not explicitly modeled in our framework as utility is based on time 0 expected profits, we note that the issue is closely related to the liquidity of these longevity products. As the biomedical RBOs only exist as a conception in theory for now, as pointed out in Lo and Naraharisetti (2014), the depth and liquidity of this market should be highly correlated with asset growth, and "if tens of billions of dollars flow into biomedical megafunds, that alone is likely to enhance secondary market activity substantially." Nevertheless, even with a liquid secondary market, the market value of RBOs can still be highly volatile, which has an adverse impact on the asset side of the life settlement firm's balance sheet.

Last but not the least, as biomedical RBOs provide a direct route for the life settlement industry to receive returns that are positively related with medical research, one topic that might be interesting in practice is what other alternatives are available in generating similar patterns of return. One candidate would be to purchase stocks of biomedical firms. However, we argue that this too might not work as effectively as biomedical RBOs: the stock prices are usually confounded by many other factors uncorrelated with the medical research and so with any longevity shock. Further,

frontline research projects are often conducted by labs and firms that are not publicly traded and so are not available as potential hedging instruments.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendices