Longevity Shocks and Debt Market Transmission*

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Abstract

This paper examines how longevity shocks influence corporate debt markets. We show that unexpected changes in life expectancy affect corporate debt demand via life insurers, who adjust the duration of their corporate bond portfolios in response to mortality-driven shifts in liability duration. These shifts alter insurers' demand for short-term and long-term bonds, affecting corporate bond prices and term spread. In turn, firms, especially those reliant on insurers and with investment-grade ratings, respond by altering the maturities of newly issued debts.

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1 Introduction

While human life expectancy has generally trended upward, it also exhibits significant year-to-year fluctuations. In the US, for example, life expectancy increased by an average of roughly 0.15 years annually between 1974 and 2018, yet some years saw minimal gains or even declines, with annual variations around 0.14 years, which is larger than the threshold of regulations over duration mismatch.[1] These "longevity shocks" are often driven by a complex mix of environmental, healthcare, lifestyle, biological, institutional, and socioeconomic factors (Fuchs, 2004; Shaw, Horrace, and Vogel, 2005; Cutler, Deaton, and Lleras-Muney, 2006; OECD, 2010; Moreno-Serra and Smith, 2015; Chiu and Pain, 2018; Woolf and Schoomaker, 2019).

Longevity shocks have wide-ranging implications for aggregate consumption, savings, labor supply, education incentives, human capital, and productivity. Yet, their impact on financial markets, particularly corporate debt, remains less understood. This paper examines how these shocks affect life insurers and, through them, corporate debt markets. Changes in life expectancy alter the duration of life insurers' liabilities, primarily annuities and whole life insurance, requiring adjustments to their asset portfolios due to regulatory mandates and risk management purposes. Positive longevity shocks extend liability duration, prompting insurers to seek longer-duration assets to hedge increased duration risk. Conversely, negative shocks shorten liability duration, shifting demand toward shorter-term assets. Given that corporate bonds comprise 38% of life insurers' financial assets and 59% of their transactions, they are the primary asset class affected by these duration adjustments.

The paper addresses two key questions: (1) How do longevity shocks affect life insurers' duration adjustments and trading of corporate bonds? (2) What are the broader effects on bond prices, term spreads, bond market dynamics, and firms' long-term financing and debt maturity decisions? By linking longevity risk to insurer behavior, this research highlights its significant impact on corporate debt markets. Understanding these relationships is essential for assessing how demographic shifts, particularly changes in

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[1] See Internet Appendix Figure A.1, which illustrates U.S. life expectancy trends and yearly variations from 1950 to 2018.

life expectancy, shape firms' maturity choices.

We find that life insurers actively adjust the duration of their corporate bond portfolios in response to longevity shocks, with changes ranging from 0.7 to 0.8 years for every one-year shift in life expectancy. When life expectancy rises, insurers increase purchases of long-term, investment-grade bonds and reduce holdings of short-term bonds. In contrast, when life expectancy decreases, they shift toward shorter-term bonds.

Using state-level longevity shocks, we conduct several tests to validate that insurers' portfolio adjustments are driven by changes in life expectancy rather than unobserved economic factors. Specifically, we examine two exogenous sources of local longevity variation: state-level opioid overdose rates and the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) with a must-access provision. Opioid overdoses, a leading cause of injury-related deaths in the U.S., reduce life expectancy, while PDMPs aim to curb opioid abuse. Focusing on "local" insurers, defined as those deriving at least 80% of their revenue from their home state, we find that variation in opioid-related deaths strongly predicts duration adjustments in their bond portfolios. Furthermore, we show that local insurers in states adopting opioid-limiting legislation (PDMPs with a must-access provision) extend the duration of their corporate bond holdings relative to those in states without such regulation. More importantly, our tests show that local insurers in states experiencing opposite local longevity shocks often trade the *same bond* in opposite directions. This pattern highlights that their trades are driven by efforts to hedge duration mismatches caused by local longevity shocks, rather than by local macroeconomic or credit market conditions.

We next examine whether shifts in life insurers' demand for specific bond maturities impact bond yields and debt supply. Consistent with preferred habitat models (Greenwood and Vayanos, 2010; Greenwood, Hanson, and Stein, 2010; Vayanos and Vila, 2021), changes in maturity-specific demand can cause yields to deviate from those predicted by the expectation hypothesis. Life insurers, managing long-dated liabilities, respond to unexpected increases in longevity by purchasing more long-term bonds. Due to the high arbitrage costs at the long end of the market (Badoer and James, 2016), this increased demand lowers long-term bond yields and flattens the corporate term structure.

Corporate issuers respond to these yield changes by adjusting debt maturities. While firms aim for balanced maturity profiles, avoiding excessive concentration (Servaes and Tufano, 2006; Choi, Hackbarth, and Zechner, 2018; Chaderina, Weiss, and Zechner, 2022), they also consider financing costs, often issuing longer-term debt when long-term yields decline (Guedes and Opler, 1996; Barclay and Smith, 1995; Stohs and Mauer, 1996; Baker, Greenwood, and Wurgler, 2003). When deviations from target maturity profiles entail low costs, firms flexibly issue longer-term debt to meet insurers' increased demand during longevity shocks.

We find that the maturities of corporate bonds lengthen after increases in life expectancy. Firm-level data show a clear shift toward increased long-term debt issuance and reduced short-term debt issuance after longevity gains. Importantly, these effects persist even in nondemographic-sensitive industries, suggesting the broad impacts of longevity shocks on the economy, beyond the consumption channel in demographic-sensitive industries (DellaVigna and Pollet, 2007).

Additional cross-sectional tests confirm that companies adjust debt maturities primarily in response to insurers' hedging needs rather than changes in their own fundamentals. First, "insurer-dependent" firms, i.e., those whose bonds are already held by insurers, significantly increase long-term issuance during positive longevity shocks, while other firms do not (Barbosa and Ozdagli, 2023). Second, consistent with insurers' preference for investment-grade securities, the effect is concentrated among highly rated issuers. Investment-grade issuers respond strongly to longevity shocks by extending debt maturities, while non-investment-grade firms show minimal responsiveness. In summary, longevity shocks influence credit availability for firms that can efficiently supply macro liquidity to the corporate debt market, particularly investment-grade and insurer-dependent firms. These findings highlight the role of life insurers as a key transmission channel through which demographic shifts affect corporate financing decisions.

This paper makes three key contributions. First, we extend research on how demographics shape the real economy and financial markets. While prior work links changes in life expectancy to aggregate consumption, savings, labor supply, education, human capital, productivity (Bloom and Canning, 2000; Murphy and Topel, 2006; Acemoglu and

Johnson, 2007), and to asset demand, interest rates, and household portfolio choices (Bakshi and Chen, 1994; Goyal, 2004; Chen and Yang, 2019), we focus on whether longevity shocks influence corporate financing by shifting demand for corporate debt of specific maturities. Unlike studies that relate demographic changes to age-sensitive industries (DellaVigna and Pollet, 2007, 2013; Cunha and Pollet, 2020), we highlight the broader effects of longevity shocks on the corporate bond market, demonstrating their impacts on debt financing costs and maturity structures across industries.

Second, we contribute to the literature on how regulatory constraints affect insurers' asset holdings and product strategies. Prior studies document how capital requirements influence insurers' investment demand and corporate bond prices (Murray and Nikolova, 2022), how regulatory frictions trigger fire sales of downgraded bonds (Ellul, Jotikasthira, and Lundblad, 2011), how insurers shift toward safe bonds after losses (Ge and Weisbach, 2021), and how regulations affect demand for specific maturities, risk management, and holdings of asset-backed and mortgage-backed securities (Ellul et al., 2015; Becker, Opp, and Saidi, 2022; Jansen, 2023; Sen, 2023), as well as insurance product pricing (Koijen and Yogo, 2015). We extend this literature by showing how regulatory mandates that require insurers to minimize asset-liability duration mismatches in response to longevity shocks drive demand for long-term corporate debt. We provide novel evidence that changes in life expectancy prompt insurers to trade bonds of specific maturities, influencing corporate term spreads and firms' debt issuance decisions.

Third, we contribute to the demand-based asset pricing literature, which studies how investor demand influences asset prices (Koijen and Yogo, 2019; Koijen, Richmond, and Yogo, 2023; Bretscher et al., 2024). Prior studies analyze demand for illiquid bonds (Sen and Sharma, 2020; Bretscher et al., 2024), credit risk (Ellul et al., 2022), duration (Domanski, Shin, and Sushko, 2017; Ozdagli and Wang, 2020; Yu, 2020), and "reach-for-yield" behavior (Becker and Ivashina, 2015). In contrast, we examine longevity shocks as a novel driver of duration adjustments which affect life insurers' demand for corporate bonds. Our results support the preferred habitat theory (Greenwood and Vayanos, 2010; Greenwood and Vissing-Jorgensen, 2018; Vayanos and Vila, 2021), indicating that life insurers — key investors in corporate bond markets — respond to longevity shocks in ways that influence bond yields and corporate term spreads. We provide direct evidence that insurers actively trade bonds of specific maturities in segmented markets (Greenwood, Hanson, and Stein, 2010; Badoer and James, 2016), revealing a demand-driven mechanism affecting term spread and corporate financing.

2 Background

Two features of U.S. life insurers shape their responses to longevity shocks and influence corporate bond markets. First, regulations require them to minimize the duration gaps between assets and liabilities. Thus, when changes in life expectancy alter liability duration, insurers must adjust asset duration. Second, because they invest mainly in corporate bonds, they manage duration mismatches mainly by rebalancing their bond portfolios. As the largest holders of corporate bonds, their trades, especially in certain maturities, can significantly affect bond prices and term spread.

2.1 Insurance regulations

We first turn to the regulatory constraints that compel U.S. life insurers to adjust asset durations when mortality-driven shifts alter liability duration. Regulations require close alignment between assets and liabilities, enforced through the NAIC's asset adequacy analysis, cash flow testing under multiple scenarios, and annual solvency reports. Mortality assumptions are central to these assessments. Actuarial Standards of Practice Nos. 7 and 22 further require insurers to maintain reserves sufficient to cover longevity risk with 99% confidence and report these annually (Actuarial Standards Board, 2002, 2001). In addition, the NAIC's Risk Management and Own Risk and Solvency Assessment Model Act (RMORSA) requires insurers to file ORSA reports detailing risk models, exposure horizons, and strategies for underwriting and investment.[2] Together, these requirements, reinforced by frequent oversight, force insurers to adjust asset durations when liability durations shift.

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[2] Available at: `https://content.naic.org/sites/default/files/model-law-505.pdf`.

Risk-based capital (RBC) rules strengthen this alignment by tying capital charges to duration mismatch. Gaps under 0.125 years are classified as "Low-Risk," but larger mismatches raise both capital requirements and risk classifications.[3] Insurers that fail to manage mismatches face higher capital costs, regulatory scrutiny, and potential credit rating downgrades.[4] Because the RBC framework requires continuous monitoring and adjustments, insurers cannot afford to wait for longevity shocks to reverse. Even temporary gaps would trigger higher capital requirements.

2.2 Life insurer holdings of corporate bonds

We next highlight the central role of corporate bonds in U.S. life insurer balance sheets using data from the U.S. national accounts (L.116, Z.1 Financial Accounts, March 2023 release). Table 1 reports asset allocations and purchases across the major asset classes as shares of total financial assets. Life insurers hold a range of instruments, including corporate bonds, Treasuries, other debt instruments, and equities. They can, in principle, adjust portfolio duration through any of them. However, corporate bonds dominate: Panel A shows that they account for 38.3% of holdings from 1990 to 2019. Other debt instruments (e.g., open market paper, Treasury securities, agency and GSE-backed securities, and municipal securities) comprise 14.1%, while equities account for just 7.9%.[5]

— Table 1 about here —

Panel B of Table 1 presents the flow data from Table F.116, showing asset purchases as a share of total net financial asset acquisitions, averaged over years. Corporate bonds again dominate, accounting for 59.8% of purchases, ranging from 40.2% in 1990-1994 to 80.7% in 2015-2019. Other debt and loans averaged 27%, while equities accounted for just 7.5%. Most bond holdings are investment-grade. Together, the stock and flow data underscore the central role of corporate bonds, particularly investment-grade securities, as insurers' primary instrument for managing duration mismatch.

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[3] In 2021, the NAIC added explicit longevity risk charges (Proposal 2021-13-L) to the RBC framework, increasing capital costs of insurers and amplifying sensitivity to mortality.

[4] Rating agencies such as S&P and Moody's incorporate duration risk into their assessments.

[5] High capital charges on equities likely limit insurers' equity exposure.

Another reason for life insurers' central role in U.S. corporate bond markets lies in market structure: life insurers are the largest investors. Two facts illustrate this dominance. First, from 1990 to 2019, life insurers held an average of 24% of outstanding corporate and foreign bonds (Table 1, Panel C). Although their share declined from 30.5% in the early 1990s to 22.3% in the late 2010s, they remain the largest domestic holders. Second, NAIC Schedule D filings and TRACE data show that between 2002 and 2018, life insurers accounted for roughly 14% of investment-grade corporate bond trading and 6% of non-investment grade trading (see Figure 1).

— Figure 1 about here —

In sum, life insurers naturally favor long-term, high-quality corporate bonds given their long-duration liabilities and regulatory capital constraints. Their dominance in U.S. corporate bond markets implies that shifts in their demand for bonds of specific maturities can move bond returns, since arbitrageurs (e.g., broker-dealers and hedge funds) face high costs and limited risk capacity to arbitrage across maturities (Greenwood, Hanson, and Stein, 2010). Unlike arbitrageurs, corporate issuers can respond to these demand shocks by adjusting the maturity structure of newly issued debt.

3 Data and variables

We estimate U.S. population-level longevity shocks from 1974 to 2018 using mortality and population data from the Human Mortality Database.[6] For each year t, we compute the weighted-average period life expectancy E_t as:

$$E_t = \frac{\sum_{x=0}^{99}(x + e_{x,t})E_{x,t}}{\sum_{x=0}^{99} E_{x,t}}, \tag{1}$$

where $e_{x,t}$ is the remaining period life expectancy at age x, and $E_{x,t}$ is the exposure for that age group.[7] We define longevity shocks (*LongevityShocks*) as the year-over-year change

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[6] Available at `mortality.org`.

[7] Ages above 99 are excluded due to data limitations. Younger cohorts are included because some life insurance products target this group (e.g., policies purchased by parents or guardians). Results are robust to restricting the sample to ages 20–65.

in E_t (i.e., E_t - E_{t-1}). This model-free measure provides a straightforward indicator of changes in life expectancy.[8]

Panel A of Table 2 shows that national longevity shocks averaged 0.15 years annually from 1974 to 2018. Internet Appendix Figure A.1 illustrates both the long-term trend and year-over-year fluctuations in period life expectancy. While life expectancy has generally increased, the data reveal substantial annual variation, with a standard deviation of 0.14 years. These fluctuations can affect the duration of life insurer liabilities, potentially leading to asset-liability mismatches. For certain analyses, we use state-level longevity shocks (*LocalLongevityShocks*), constructed analogously using state-level mortality data from 1989 to 2018, sourced from the U.S. Mortality Database.[9] On average, state-level shocks were smaller (a mean of 0.10 years) but more volatile (a standard deviation of 0.21 years).

— Table 2 about here —

Panel B of Table 2 summarizes key bond market variables from 1990 to 2019, based on data from the Federal Reserve Economic Data (FRED). Changes in one-year Treasury yield ($\triangle$*Treasury1Y*), which capture monetary policies, averaged -0.21%. The credit spread (*CreditSpread*)–defined as the yield difference between Moody's Baa Corporate Bond Index and 20-year Treasury securities–averaged 2.07%. The term spread (*TermSpread*), measured as the yield difference between 10- and 1-year Treasuries, averaged 1.42%, while the orthogonalized term spread (*Term spread*$^{\perp}$), which is net of longevity shocks, averaged 0.57%. The excess bond premium (*EBP*)–a sentiment driven premium (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017)–averaged 0.11%.[10]

Data on corporate bond issuance by U.S. non-financial firms are sourced from the Mergent Fixed Income Securities Database (FISD). Annual changes in the corporate term spread ($\triangle$*CorpTermSpread*), defined as the yield spread between long-term (maturity >10 years) and short-term (maturity ≤ 3 years) bonds, averaged 0.03%. The ratio of long-term

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[8] An alternative measure is the latent mortality index of Lee and Carter (1992), which is highly correlated with our measure (correlation: -0.99) and produces similar results.

[9] Available at `usa.mortality.org`. See Mila (2019).

[10] Available at `www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv`.

to short-term issuance averaged 5.1. The weighted average duration of newly issued bonds (Δ *NewBondDuration*), adjusted for issue size, changed by 0.01 years annually.[11]

Panel C of Table 2 summarizes the characteristics of life insurers from 1995 to 2019, based on NAIC filings. Life insurers are large (mean assets, *InsAsssets*: 0.73): $6.66 billion; median: $338 million), highly leveraged (mean leverage, *InsLeverage*: 0.73), and profitable (mean return on assets, *InsROA*: 2%). The average risk-based capital ratio (*RBC*) is 17.57. The average growth rate of net premium written (*NPWGrowth*) is 11%. There are different capital requirements tied to bond ratings (NAIC 1 being the lowest risk and NAIC 6 the highest).[12] Most holdings are investment-grade corporate bonds: 55% are NAIC 1 (highest quality), 27% NAIC 2, and the remainder NAIC 3 or higher. Transaction-level data from NAIC's Schedule D filings include information on holdings, issuers, bond features, and trades. The average annual change in the duration of the corporate bond portfolio (Δ*InsDuration*) is 0.04 years.

Panel D reports the characteristics of corporate bond issuers from 1975 to 2019, using Compustat data. Issuers average 17 years of public listing and $6.67 billion in assets (median: $906 million). Key financial metrics include a 16% ROA, Tobin's q of 1.63, an 8% cash-to-asset ratio, and 46% asset tangibility.

4 Life insurers' corporate bond duration adjustments

We start by examining whether life insurers adjust the duration of their corporate bond holdings in response to life expectancy shocks. Such shocks change the duration of insurers' long-term liabilities, requiring changes in bond portfolio maturity to minimize asset-liability duration gaps. To assess insurers' responsiveness, we test whether lagged longevity shocks affect changes in bond portfolio duration, controlling for credit market conditions, macroeconomic conditions, and insurer-specific factors. We also analyze corporate bond trades to see if insurers actively shift maturities in response to these shocks.

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[11] Our Macaulay duration estimates do not adjust for callable and convertible features, which introduces noise and likely biases results toward zero.

[12] See Internet Appendix IB for additional details.

4.1 Duration adjustments

A plot of average changes in insurers' corporate bond portfolio duration and lagged longevity shocks shows strong co-movement (Figure 2, correlation $\rho = 0.32$). We assess this relationship by estimating regressions of the following form:

$$\Delta InsDuration_{i,t} = \beta \cdot LongevityShocks_{t-1} + \mathbf{Z}_t^{'} \cdot \gamma + \mathbf{X}_{i,t} + \zeta_i + \epsilon_{i,t}, \tag{2}$$

where Δ*InsDuration* is the annual change in the duration of corporate bond portfolio for insurer i, and *LongevityShocks*$_{t-1}$ is the lagged change in national life expectancy. $\mathbf{Z}_t$ includes credit market and macroeconomic controls, including changes in the one-year Treasury yield (Δ*Treasury1Y*), term spread (*TermSpread*), credit spread (*CreditSpread*), inflation rate (*CPIGrowth*) and GDP growth rate (*GDPGrowth*). Insurer-level controls $\mathbf{X}_{i,t}$ include total assets (*ln(InsAssets)*), leverage (*InsLeverage*), risk-based capital ratio (*RBC*), ROA (*InsROA*), and the growth rate of net premium written (*NPWGrowth*). Insurer fixed effects (ζ_i) absorb time-invariant heterogeneity. The coefficient β measures the average change in portfolio duration resulting from a one-year increase in life expectancy. Standard errors are clustered at the insurer level.

— Figure 2 about here —

Table 3 reports the estimates. Column (1) shows estimates from the least-restrictive specification without controls or fixed effects. The results indicate that a one-year increase in life expectancy raises bond portfolio duration by approximately 0.80 years ($p <$ 0.01).[13]

— Table 3 about here —

Column (2) adds credit market controls and insurer fixed effects. Demographic changes can influence real interest rates through aggregate savings behavior (Carvalho, Ferrero, and Nechio, 2016). Declining rates lengthen liability duration more than asset

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[13] In contrast, Ozdagli and Wang (2020) find that the duration adjusts slowly in response to interest rate shocks.

duration, given negative convexity, prompting purchases of longer-duration bonds (Domanski, Shin, and Sushko, 2017). Lower rates can also reduce contract surrenders and increase paid-up additions, both of which extend liability duration and necessitate corresponding adjustments in asset duration (Ozdagli and Wang, 2020). While long-term demographic trends affect savings behavior and interest rates, transitory longevity shocks should have little direct effect. Still, we control for concurrent interest rate movements by including changes in the one-year Treasury yield, term spread, and credit spread.

Credit market variables enter with expected signs. Changes in the one-year Treasury yield have a negative coefficient, indicating that portfolio duration increases when rates fall, but is less significant. We also use changes in 10-year Treasury yield as an alternative, and find a negative and significant coefficient. It is consistent with prior findings (Domanski, Shin, and Sushko, 2017; Ozdagli and Wang, 2020). That is, insurers tend to invest more in long-duration assets when interest rates are low. Term spread is positively associated with duration changes, while credit spread has a negative effect. Importantly, the coefficient on *LongevityShocks* remains significant at 0.82 ($p < 0.01$), nearly identical to the estimate in Column (1).

Column (3) adds CPI and GDP growth to further disentangle longevity shocks from broader economic conditions. Although prior research attributes changes in U.S. life expectancy to medical and behavioral improvements rather than macroeconomic conditions (Cutler, Deaton, and Lleras-Muney, 2006; Acemoglu and Johnson, 2007), we include these controls for completeness, as they might affect credit markets. The specification also incorporates insurer characteristics that vary over time. With these additional controls and insurer fixed effects, we estimate that a one-year increase in life expectancy leads to a 0.72-year increase in corporate bond portfolio duration ($p < 0.01$), consistent with earlier results.[14] In particular, we see that changes in one-year Treasury yield have a significantly negative coefficient in Column (3). In general, evidence indicates that insurers actively adjust bond durations in response to longevity shocks, regardless of interest rates, macroeconomic conditions, or insurer-specific factors.

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[14] This finding is robust to using longevity shocks orthogonalized to the business cycle (LongevityShocks$^{\perp}$), defined as residuals from regressing longevity shocks on the cyclical component of industrial production growth.

Robustness checks in the Internet Appendix IC show that longevity shocks continue to significantly drive duration adjustments after accounting for market-wide corporate bond illiquidity (e.g., Amihud illiquidity) or ownerships of other institutional investors such as mutual funds and pensions.

A natural concern is whether the duration response documented above reflects insurers' yield-seeking behavior. If longevity shocks increase liabilities and create funding gaps, they can prompt insurers to "reach for yield" by purchasing longer, higher-yielding maturity bonds (Ozdagli and Wang, 2020). We test this by examining duration responses across insurers with varying incentives to reach for yield (RFY). If yield-seeking drives duration adjustments, insurers with stronger RFY incentives should exhibit greater sensitivity of duration response to longevity shocks. We measure each insurer's RFY incentive as the value-weighted average deviation of yields on its corporate bond holdings from rating-and-maturity-matched benchmarks (Choi and Kronlund, 2018).[15] Insurers with RFY above the sample median are classified as those with strong reach for yield incentives (*RFYInsurer*). We then augment Equation (1) with *RFYInsurer* and its interaction with lagged *LongevityShocks*.

Contrary to predictions that insurers reach for yield when they adjust bond duration in response to longevity shocks, Column (4) shows that insurers with weaker RFY incentives exhibit a stronger duration response to longevity shocks–adjusting by 0.81 years ($p < 0.01$) for a one-year increase in longevity. Insurers with stronger RFY incentives are less responsive, although the difference between the two groups is not statistically significant. Thus, it is unlikely that our results can be explained by the yield-seeking behavior of insurers.

We next examine whether insurers use interest rate derivatives as substitutes for duration adjustment in response to longevity shocks. If derivatives effectively hedge the duration mismatch, derivative users should exhibit weaker duration responses. Using NAIC Schedule DB filings (2006-2019), we identify insurers with interest-rate derivative positions and calculate exposures using Bloomberg forward swap rates. Following Sen

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[15] On average, life insurers do not reach for yield relative to benchmarks: mean and median RFY are both -79 basis points annually.

(2023), we measure each insurer's net interest rate risk exposure by aggregating across all positions, accounting for maturity and direction. Insurers with non-zero exposure are classified as "*DerivativeUser*." Derivative use for interest-rate hedging is relatively uncommon, appearing in only about 10.6% of insurer-year observations.[16]

We extend equation (1) to include *DerivativeUser* and its interaction with *LongevityShocks*. Column (5) of Table 3 shows that the interaction is statistically insignificant, indicating no meaningful difference in responsiveness between derivative users and non-users. Both groups significantly adjust bond portfolio duration in response to longevity shocks. These findings are consistent with previous research showing that derivatives are primarily used to hedge complex guarantees in variable annuities, where cash flows are more amenable to derivative-based hedging (Sen, 2023). In contrast, duration mismatches from longevity shocks are more effectively addressed through adjustments in corporate bond portfolios. Unreported tests show that insurers' derivative exposures increase with longevity shocks, suggesting that derivatives and duration adjustments are complementary rather than substitute strategies.

Placebo test using P&C insurers To confirm that our results reflect responses to longevity shocks rather than broader economic conditions or market movements, we performed a placebo test using property and casualty (P&C) insurers, whose liabilities are not related to life expectancy. If longevity shocks drive duration adjustments for insurers' balance sheets, they should not affect P&C insurers. We re-estimate Equation (2) using changes in P&C insurers' bond portfolio duration as the dependent variable. As shown in Column (6), the coefficient on *LongevityShocks* for P&C insurers is statistically indistinguishable from zero, confirming that these shocks do not influence the duration choices of P & C insurers.

In summary, these findings reinforce that life insurers actively and significantly adjust the duration of their corporate bond portfolios in response to longevity shocks, consistent with regulatory incentives to manage duration mismatches.

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[16] Berends and King (2015) note that many life insurers face regulatory constraints, including the requirement to maintain a formal "derivatives use plan."

4.2 Cross-sectional heterogeneity

We next examine how life insurers' responses to longevity shocks vary along three dimensions: financial constraints, exposure to longevity shocks, and the tightness of regulatory constraints.

4.2.1 Financial constraints

Ge and Weisbach (2021) argue that financially constrained institutions prefer more liquid portfolios, such as cash and Treasury securities, due to the challenges that illiquidity poses for firms facing high external financing costs. In contrast, less constrained insurers can hold riskier and less liquid assets, such as corporate bonds and mortgage-backed securities. Firm size is found to be a more effective proxy of financial flexibility among life insurers than traditional metrics such as leverage or RBC ratios.

We classify insurers as small or large based on annual asset rankings and hypothesize that large insurers will exhibit a stronger duration response to longevity shocks via their corporate bond holdings. Smaller insurers, with greater liquidity needs and higher Treasury allocations, are expected to adjust duration through both Treasuries and corporate bonds, relying more heavily on the former. Consistent with this hypothesis, Columns (1)-(2) of Table 4 show that small insurers adjust bond duration by 0.55 years per one-year increase in longevity, while large insurers adjust by 0.90 years–a statistically significant difference at the 1% level.

— Table 4 about here —

4.2.2 Exposure to Longevity Risk

Life insurance and annuity liabilities respond in opposite directions to changes in mortality. When mortality improves, annuity liabilities increase due to longer benefit payout periods, while life insurance liabilities fall as death benefits are reduced or delayed. The reverse occurs when mortality worsens: life insurances incur more losses, while annuity writers benefit.

Insurers could mitigate exposure by balancing life insurance and annuity products to minimize the variance of liability from longevity shocks (Cox and Lin, 2007). However, few achieve this balance. Simulations in the Internet Appendix ID suggest that an optimal mix includes 81.9% life insurance premiums, compared to an average of just 31.6% in NAIC data. This indicates that most insurers are under-hedged.

We measure insurers' exposure to longevity shocks as the absolute deviation between an insurer's life insurance premium share and the simulated optimal share (*Deviation*). Insurers with *Deviation* above the median are classified as more exposed. Columns (3)-(4) show that more exposed insurers adjust bond duration by 0.92 years for a one-year increase in life expectancy, while less exposed insurers adjust by only 0.47 years–a statistically significant difference at the 1% level.

4.2.3 Regulatory strictness

Insurance regulation in the U.S. follows a state-based system coordinated by the NAIC. While NAIC develops model laws and facilitates interstate coordination, enforcement is handled by individual state insurance departments. This decentralized structure leads to substantial variation in the regulatory stringency, capacity, and timing of regulatory enforcement between states and over time (Grace, 2015; Alexander, Grace, and Luo, 2024). Such heterogeneity offers a useful setting for empirical analysis. As discussed in the background section, if insurers adjust portfolio durations in response to regulatory pressures, we expect stronger reactions to longevity shocks in states with stricter enforcement and weaker responses in states with less oversight.

To measure regulatory capacity, we use data from the "Examination and Oversight" section of NAIC's annual Insurance Department Resources Report (IDRR), focusing on the number of financial and market conduct examinations conducted by each state insurance department. We scale this number by the number of domiciled life insurers to construct our enforcement variable *ExaminationIntensity*.

We classify each state-year observation into high- or low-enforcement groups based on the annual median of *ExaminationIntensity*. We then estimate our main regression model separately for each group to assess how enforcement intensity affects insurers' responses to longevity risk. The results are shown in Columns (5) and (6) of Table 4. The coefficient on *LongevityShocks* is significantly larger in the strong-enforcement group, indicating that insurers under greater scrutiny respond more strongly to changes in life expectancy. A two-sample Chow test confirms the statistical significance of this difference, supporting our argument that regulatory enforcement shapes insurer behavior.

5 Local longevity shocks and insurers' bond portfolio adjustments

To address remaining concerns that unobserved macroeconomic factors may drive insurers' portfolio adjustments, we exploit state-level disparities in longevity shocks. These shocks are largely driven by regional differences in health and environmental factors–such as smoking rates, obesity, drug abuse, physician density, and air pollution ($PM_{2.5}$).[17]

We estimate state-level longevity shocks (*LocalLongevityShocks*) using data from the U.S. Mortality Database, revealing substantial geographic disparities in life expectancy trends. Figure 3 maps these decade-end shocks across U.S. states, with darker shades indicating larger increases. The figure highlights significant regional heterogeneity, including both gains and declines in longevity over time.

— Figure 3 about here —

We focus on "local" life insurers–defined as those deriving at least 80% of their revenues from a single state. If duration adjustments reflect changes in local life expectancy, then these local insurers should respond to state-specific longevity shocks. Because insurers typically invest in national bond markets and often hold bonds issued by firms outside their home state (Liu and Xiong, 2023), we are particularly interested in examining local insurers' trades in *non-local* corporate bonds. This setting isolates the effect of local longevity shocks from local credit market conditions. By analyzing duration adjust-

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[17] See, for example, Chetty et al. (2016), Dwyer-Lindgren et al. (2017), Couillard et al. (2021), Deryugina and Molitor (2020), and Deryugina and Molitor (2021).

ments in non-local bond trades, we rule out the possibility that unmeasured state-level factors are driving the observed changes in insurers' bond portfolios.

5.1 Duration adjustments in response to longevity shocks

Using state-level data, we first test whether local insurers in states with rising (falling) longevity extend (shorten) the duration of their corporate bond portfolios. Column (1) of Table 5 presents regression results examining the effect of local longevity shocks on portfolio duration. The models control for macroeconomic conditions (CPI growth, U.S. GDP growth, state-level GDP, and state-level population growth), credit market variables (changes in Treasury yields, term spread, and credit spread), insurer characteristics (size, leverage, risk-based capital, profitability, and net premium written growth), and insurer fixed effects.

— Table 5 about here —

Panel A, Column (1) reports duration adjustments of insurers through both local and non-local bonds. We find a strong positive relationship: a one-year increase in state-level life expectancy leads to a 0.46-year increase in bond portfolio duration ($p < 0.01$).[18] To further isolate the effect from local economic conditions, we re-estimate the model excluding bonds issued by firms headquartered in the same state as the insurer. Column (1), Panel B of the table shows that focusing solely on trades of non-local corporate bonds yields qualitatively similar results. This confirms that local insurers adjust bond portfolio duration in response to local longevity shocks–even when trading in national bond markets. These adjustments, made through non-local bond trades, underscore that the observed behavior is driven by longevity risk management rather than local credit market conditions or unmeasured macroeconomic factors.

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[18] In unreported tests, we separately analyze states with rising and falling longevity. In both cases, the coefficient on *LocalLongevityShocks* remains significantly positive, indicating that insurers lengthen duration when longevity rises and shorten it when longevity falls.

5.2 Trading behavior in response to longevity shocks

Life insurers adjust the duration of their bond portfolio by actively trading bonds of various maturities. If they respond to longevity shocks, we expect them to buy long-term bonds and sell short-term bonds when life expectancy rises, and do the opposite when it falls. Using corporate bond transaction data from NAIC Schedule D filings, we construct two measures: *NetBuyLTBonds*, which captures net purchase of long-term bonds (maturity $\geq$10 years), and *NetBuySTBonds*, which captures net purchase of short-term bonds (maturity $\leq$3 years). Both measures are scaled by the insurer's total bond portfolio market value.

The remaining columns of Table 5 examine how lagged longevity shocks affect these trades, controlling for credit market factors, macroeconomic conditions, and insurer characteristics. Panel A reports results for trades of both local and non-local bonds. Columns (2) through (4) focus on *NetBuyLTBonds*. A one-year increase in life expectancy leads to a 6.9% increase in long-term bond purchases, significant at the 5% level. Breaking this down by bond ratings, investment-grade purchases increase by 3.9% per ($p < 0.10$), while long-term speculative-grade bonds increase by just 0.3%, which is not statistically significant.

Columns (5) through (7) analyze *NetBuySTBonds*. As expected, rising life expectancy leads to a 2.8% decline in short-term bond purchases (Column (5)), significant at the 10% level. This effect is concentrated in investment-grade short-term bonds (Column (6)), with no significant change in speculative-grade purchases (Column (7)). Overall, insurers primarily hedge longevity increases by increasing their holdings of long-term, investment-grade bonds and reducing holdings of high-quality short-term bonds, with minimal adjustments to speculative-grade bonds.

Panel B focuses on trades in non-local bonds–those issued by firms headquartered in a state different from that of the insurer. This isolates the effect of local longevity shocks from local credit market conditions. The results mirror those in Panel A: local insurers significantly increase purchases of long-term non-local bonds when life expectancy rises. These findings confirm that duration adjustments are driven by longevity risk rather than the dynamics of the local bond market.

6 Identifications: Opioid mortality as a source of longevity shocks

Opioid-related mortality has become a leading cause of injury death (Cornaggia et al., 2022). In 2019, over 70,000 people in the U.S. died from drug overdose, corresponding to an age-adjusted rate of 21.6 per 100,000 population. Most of these deaths involved opioids, with overdose rates more than seven times higher than two decades earlier. Without opioid-related mortality, the US life expectancy would have continued to increase after 2013 rather than declining (Currie and Schwandt, 2021; Dyer, 2018).

Two key features of the opioid crisis are central to our analysis. First, supply-side factors explain much of the variation in opioid abuse. The surge in opioid prescriptions followed the introduction and aggressive marketing of new opioids, most notably OxyContin, in the late 1990s (Alpert et al., 2022). Until 2015, prescription opioids caused more deaths than any other drug category. The variation in prescribing rates reflects local physician practices and pharmaceutical marketing strategies, rather than patient-level characteristics such as economic hardship or health status (Paulozzi et al., 2011; Paulozzi, Mack, and Hockenberry, 2014; Finkelstein et al., 2022). Supporting this supply-driven view, Currie, Jin, and Schnell (2019) and Currie and Schwandt (2021) find no significant link between economic conditions and opioid abuse, while Ruhm (2018) estimates that economic factors explain less than one-tenth of the rise in opioid mortality.

Second, opioid-related deaths exhibit stark geographic variation. In 1999, state-level death rates ranged from 0.7 per 100,000 in Louisiana to 10.2 in New Mexico; by 2019, the range had increased from 3.5 in Hawaii to 43 in Delaware. This variation is partly driven by supply-side factors, including differences in prescribing practices (Schnell and Currie, 2018) and pharmaceutical marketing intensity across states (Fernandez and Zejcirovic, 2019; Hadland et al., 2019).[19] State policies also shaped access to opioids and

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[19] For example, Fernandez and Zejcirovic (2019) show that pharmaceutical marketing significantly contributes to geographical variation: states with more physician outreach have higher opioid overdose mortal-

mortality through clinical guidelines, relaxed restrictions on treating chronic noncancer pain, and variation in nurse practitioner authority and density (Griffith et al., 2021). Medical insurance policies (Powell, Pacula, and Taylor, 2020) and targeted legislation further influenced outcomes. For instance, Florida's 2010 pain clinic legislation and 2011 ban on prescriber dispensing significantly reduced drug diversion and cut oxycodone overdose deaths by 52%. A key policy instrument that we will exploit in our analysis is the prescription drug monitoring programs (PDMPs) in some states, especially the *must-access* provisions, which require physicians to consult them before prescribing opioids. These must-access PDMPs have proven effective (Buchmueller and Carey, 2018). For example, after implementing the must-access provisions in 2012, New York and Tennessee saw inappropriate multiple prescriptions drop by 75% and 36%, respectively. Taken together, these supply-side differences strongly predict state-level opioid mortality, while local economic conditions are largely unrelated to variation in overdose deaths. This allows us to exploit geographic variation in opioid abuse as a source of exogenous shocks to local longevity.

6.1 Instrumenting local longevity shocks by opioid mortality

We use annual state-level drug-related mortality rates as our primary measure of local opioid severity. To identify causal effects, we instrument state-level longevity shocks with opioid-related deaths per 100,000 population. Opioid abuse disproportionately affects the working-age population, including insured individuals, reducing life expectancy and directly altering the duration of insurers' liabilities (Currie and Schwandt, 2021; Ouimet, Siminitze, and Ye, 2024). Mortality data are from the National Vital Statistics System's multiple-cause-of-death files. Drug overdose deaths are defined as those with an underlying cause classified under the ICD-10 codes X40–X44 (accidental drug poisoning), X85 (assault by drug poisoning) and Y10–Y14 (drug poisoning with undetermined intent).[20]

— Table 6 about here —

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ity, and physicians targeted by promotions prescribe more opioids. Proximity to pharmaceutical headquarters increases promotional activity, although some states have responded with bans on physician-targeted marketing.

[20] Vital statistics likely underestimate prescription and illicit drug deaths because many death certificates do not specify the drug involved.

Table 6 reports IV regression results that examine the impact of local longevity shocks on duration adjustments by local life insurers, which derive at least 80% of their revenues from a single state. State-level opioid mortality (per 100,000 population) serves as the instrument for local longevity risk. Column (1) shows the first-stage regression results, which confirms that opioid-related mortality is a strong and statistically significant predictor of local longevity shocks, with a coefficient indicating that higher opioid-related mortality reduces local longevity. Column (2) presents the second-stage regression results, showing that insurers' bond portfolio duration adjustments respond significantly to predicted longevity from the first-stage regression ($p<0.05$). These findings suggest that life insurers actively adjust the maturity structure of their corporate bond holdings in response to exogenous demographic shocks, including those driven by opioid abuse.

6.2 Difference-in-differences analysis with must-access PDMPs

In this subsection, we examine how the staggered rollout of *must-access* prescription drug monitoring programs (PDMPs) influenced the way life insurers manage the duration of their corporate bond portfolios. Nearly all states, except Missouri, implemented PDMPs to help physicians and pharmacists track patients' prescription histories. However, early versions of these programs were voluntary, saw limited participation, and had minimal impact on prescribing behavior (Paulozzi, Kilbourne, and Desai, 2011; Reifler et al., 2012; Li et al., 2014; Meara et al., 2016). Only when states mandated the use of PDMPs by physicians (i.e., must-access PDMPs) did the programs become effective, significantly reducing doctor shopping and overprescribing (Dowell et al., 2016; Buchmueller and Carey, 2018). States that adopted must-access PDMPs experienced a 9% decrease in fatal overdoses, a shift that improved local life expectancy.

We study how insurers responded to these changes in mortality risk using a difference-in-differences (DiD) design. Specifically, we compare the duration adjustments of local life insurers in 21 states that adopted must-access PDMPs during our sample period with those in states that either never adopted PDMPs or kept them voluntary. We define treatment (*PDMPState* = 1) if a state implemented a must-access PDMP during the sample period. *Post* indicates the years in which a must-access PDMP is in effect. The State-level implementation dates are drawn from the Prescription Drug Abuse Policy System. Our focus is on the duration adjustment of insurers' corporate bond portfolios, which reflects how insurers manage asset-liability duration matching in response to exogeneous changes in local longevity.

One challenge is that the adoption of must-access PDMPs was not random. Ouimet, Siminitze, and Ye (2024) show that it was driven almost entirely by the age-adjusted opioid overdose death rates of the states. That is, states that adopted must-access PDMPs earlier typically exhibited worse pre-policy opioid abuse and faster-rising opioid-related mortality. As a result, the treated and control groups would have different trajectories, leading to bias in the DiD estimation. To address this treatment selection issue, we follow the methodology of Moser and Voena (2012), which augments the DiD estimation in two ways. First, it adds the interactions of treatment and year, allowing the treated and control groups to have different baseline slopes so that we can compare the deviation from each group's own baseline trend and measure the treatment effects caused by must-access PDMPs. Second, it considers pre-policy selection variables at the state level which predict the treatment so that the identifying assumption becomes conditional parallel trends. In our data, we further verify that there is no statistically significant differences in pre-policy trends between treated and control states. Column (3) of Table 6 reports the DID estimates: the coefficient on *PDMPState* × *Post* is significantly positive ($p < 0.05$), indicating that local insurers in treated states adjust duration upward after the adoption of must-access PDMPs (see more details in Internet Appendix IE).

Alternatively, as suggested in Baker, Larcker, and Wang (2022), we also use stacked DiD to study the staggered rollout of must-access PDMP. We repeat the main analysis use the stacked DiD methods proposed by Callaway and Sant'Anna (2021) or Sun and Abraham (2021). Again, We find that local insurers significantly increase their bond portfolio duration after the adoption of must-access PDMPs.

Overall, the results highlight opioid-related mortality as a natural experiment in longevity risk, showing how insurers adjust bond maturities in response to local longevity changes.

6.3 Opposing trades in response to divergent longevity shocks

To provide further evidence of causality, we examine bond trades of local life insurers in states with correlated state-level longevity shocks. As discussed earlier, changes in life expectancy vary significantly across regions and over time. In any given year, longevity shocks in a pair of two states could be positively or negatively correlated. For example, life expectancy changes in Florida and Georgia are highly positively correlated (ρ = 0.88), whereas those in Massachusetts and Alaska are negatively correlated (ρ = -0.27).

We investigate whether local insurers adjust their bond portfolios in opposite directions when located in states with negatively correlated longevity changes. If trading behavior is driven by *local* life expectancy changes, insurers in negatively correlated states should make opposite trades in the same bonds. To focus on meaningful positions, we restrict the analysis to bonds that fall above the 70th percentile of each insurer's portfolio weight distribution.

— Table 7 about here —

Table 7 presents instrumental variable (IV) regression results examining how the correlation in longevity shocks between states i and j affects the direction of bond trades by local insurers in these two states. We use the correlation of opioid-related mortality in two states as the instrument variable. Column (1) reports the first stage regression, where the correlation of local longevity shocks ($LongevityCorr_{i,j}$) is regressed on the correlation of opioid mortality across the same states. The results confirm that the correlation of opioid mortality significantly and positively predicts the correlation of changes in life expectancy.

Column (2) presents the second stage regression, where the dependent variable is an indicator equal to one if the two local insurers trade the same bond in opposite directions, and zero otherwise. Standard errors are clustered by states i and j. The coefficient on $LongevityCorr_{i,j}$ is negative and statistically significant (p<0.01), indicating that insurers facing negatively correlated longevity shocks are more likely to trade the same bond in opposite directions. Columns (3)–(4) repeat the analysis using non-local bonds, excluding those issued by firms headquartered in the same state as either local insurer. The results remain qualitatively similar, reinforcing the conclusion that insurers respond to local longevity shocks by adjusting their holdings of nationally traded corporate bonds in opposite directions.

7 Impacts of longevity shocks on corporate bond markets

Preferred habitat models suggest that in segmented markets, shifts in demand for bonds of specific maturities expose arbitrageurs to interest rate risk, resulting in price deviations (Greenwood, Hanson, and Stein, 2010; Krishnamurthy and Vissing-Jorgensen, 2011; Vayanos and Vila, 2021). Consequently, life insurers' trades of short-term or long-term bonds can influence bond prices and yields. For example, rising life expectancy increases their demand for long-term bonds, which increases long-term bond prices in segmented markets. Similar effects occur to short-term bonds. This implies that the corporate term spread decreases with longevity.

— Figure 4 about here —

We measure annual corporate term spreads as the average yield difference between long-term ($>$ 10 years) and short-term ($\leq$3 years) corporate bonds. Figure 4 plots corporate term spread against longevity shocks and confirms the predicted inverse relationship between the two series (correlation $\rho = -0.32$).

— Table 8 about here —

Column (1) of Table 8 runs a regression to support this finding, showing a significantly negative relationship ($p < 0.01$) between longevity shocks and corporate term spreads, controlling for inflation (*CPIGrowth*), GDP growth (*GDPGrowth*), changes in short-term Treasury yields (Δ*Treasury1Y*), and other credit market variables. We see that a one-standard deviation increase in longevity leads to a decrease of 80 bps in corporate term spread. As expected, we see that the Treasury term spreads (Δ*TermSpread*) are positively associated with the corporate term spreads, while the excess bond premium (*EBP*) is negatively related to the corporate term spreads, but other controls are less significant.

Do these price effects have real consequences for bond issuances? If firms respond to pricing shifts over the term structure, we should observe changes in debt maturity to meet insurers' demand. To test this, we examine whether firms issue more longer-maturity debts as life expectancy rises. Using FISD data on new domestic bond issuance, we calculate the average duration of newly issued bonds (weighted by issue size) and plot it against lagged *LongevityShocks* in Figure 5. The strong positive correlation ($\rho = 0.47$) indicates that firms issue longer-dated bonds in response to the increase in life expectancy.

— Figure 5 about here —

Regression results in Column (2) of Table 8 confirm this finding: the coefficient on *LongevityShocks* is positive and significant ($p < 0.05$). The negative coefficient on Δ*Treasury1Y* suggests that firms issue more long-term bonds due to stronger demand, when short-term rates are low. Similarly, the negative relationship between Treasury term spreads (Δ*TermSpread*) and bond duration ($p < 0.01$) aligns with Baker, Greenwood, and Wurgler (2003), which show that firms adjust debt maturity based on expected long-term bond returns.

Last, we run a regression in Column (3) of Table 8 to examine changes in the relative size of long-term vs. short-term bond issuances, using the first difference of the log ratio of long-term to short-term issuance as the dependent variable. The positive and significant coefficient on *LongevityShocks* ($p < 0.05$) confirms that firms increase the issuance of relatively long-term bonds as the life expectancy increases. Consistent with Column (2), both Δ*Treasury1Y* and Δ*TermSpread* are negatively associated with the relative size of the issuances. In summary, rising longevity decreases corporate term spreads and prompts firms to issue more longer-maturity debts, accommodating increased demand from life insurers.

8 Corporate debt responses: Firm-level evidence

This section presents firm-level evidence on how companies adjust debt maturity in response to longevity shocks. We focus on the maturity structure of newly issued corporate bonds. Bond issuance data from Mergent FISD are matched to firm-level financial data from Compustat using CUSIPs (via Capital IQ). Unmatched bonds are manually linked using issuer names. More than 80% of the FISD bond issuances are successfully matched.

We categorize the maturity of newly issued debt into four buckets: short-term (0-3 years), medium-term (3-10 years), long-term (10-20 years), and very long-term (20+ years). To examine how longevity shocks influence the likelihood of issuing bonds in each maturity category, we estimate a multinomial logit model using the [3,10) year range as the base category:

$$Issue^{j}_{i,t} = \beta \cdot LongevityShocks_{t-1} + \mathbf{X}'_{i,t-1} \cdot \lambda + \gamma_{Issuer} + \nu_{Period} + \epsilon_{i,t}, \tag{3}$$

Control variables include macroeconomic factors and credit market conditions (CPI growth, GDP growth, credit spread, changes in one-year Treasury yield, and term spread), along with firm-specific characteristics (including ROA, total assets, Tobin's *Q*, leverage, age, cash holdings, equity issuance, net income growth, and asset tangibility). The model also includes time interval indicators and firm fixed effects. Standard errors are clustered at the firm level.

— Table 9 about here —

Table 9 reports the results. Column (1) shows that firms significantly increase long-term and very long-term debt issuance in response to longevity increase, while reducing short-term debt issuance–indicating a clear shift toward longer maturities. For example, a one-standard-deviation increase in longevity shocks increases the likelihood of issuing very long-term bonds (relative to the medium-term) by 60%. This pattern suggests that firms respond to rising life expectancy by supplying longer-duration debt, acting as macro-liquidity providers.

8.1 Nondemographic-Sensitive Industries

A potential concern is that our findings may reflect industry-specific demand shifts driven by demographic changes. As demographics evolve, demand for certain goods and services may increase, improving the growth prospects of firms in the affected sectors. Prior research shows that demographic trends can generate abnormal industry-level returns and influence firm behavior, such as innovation, equity issuance, and cash holdings, particularly in sectors with predictable demand growth (Acemoglu and Linn, 2004; DellaVigna and Pollet, 2007, 2013; Cunha and Pollet, 2020).

Although our analysis focuses on the aggregate effects of longevity shocks, it is plausible that firms in age-sensitive sectors, such as healthcare, pharmaceuticals, travel, and leisure, respond differently due to anticipated changes in consumption demand. This raises the question: are our results primarily driven by firms in industries most exposed to demographic shocks?

To address this concern, we exclude the 20 industries identified by DellaVigna and Pollet (2007) as the most sensitive to demographic-driven consumption shifts. These include sectors such as childcare, children's books and clothing, educational materials, pharmaceuticals, health and life insurance, funeral services, nursing care, residential construction, housewares, adult apparel, and leisure-related goods such as golf, jewelry, and motorcycles. By removing these industries, we construct a sample of firms operating in nondemographic-sensitive sectors, those less likely to be directly affected by changes in demographic structure.

Column (2) of Table 9 shows that firms in nondemographic-sensitive industries also respond to longevity shocks by increasing long-term debt issuance as life expectancy increases. These findings demonstrate that the impact of longevity shocks on corporate debt markets is not limited to demographic-sensitive sectors. Instead, longevity shocks appear to influence corporate financing choices broadly across industries because longevity shocks affect bond pricing. This extends beyond the industry-specific consumption channel emphasized in prior literature.

8.2 Testing the insurer channel

We now test whether demand from life insurers drives the observed shift toward debts with specific maturities. Life insurers exhibit investment stickiness, often purchasing new bonds from issuers they already hold, similar to mutual fund behavior (Zhu, 2021; Barbosa and Ozdagli, 2023)). This preference helps to reduce screening and monitoring costs. We classify a firm as “insurer dependent” if life insurers hold more than the sample median share of its outstanding bonds. We then estimate the multinomial logit model separately for insurer-dependent and non-insurer-dependent firms.

Consistent with the insurer channel, Column (3) of Table 9 shows that insurer-dependent firms significantly increase long-term and decrease short-term bond issuance in response to the increase in life expectancy. In contrast, Column (4) shows no statistically significant response among non-insurer-dependent firms. This suggests that the maturity shift is concentrated among firms with stronger ties to life insurers.

Because life insurers invest primarily in investment-grade bonds (see Table 5), we also expect investment-grade firms to be more responsive to longevity shocks. Columns (5) and (6) confirm this: when longevity increases, investment-grade firms (Column (5)) significantly increase long-term and reduce short-term issuance, while speculative-grade firms (Column (6)) show no significant response. Together, these results support the view that life insurers are a key transmission channel through which longevity shocks influence corporate debt markets.

9 Conclusions

This paper examines how longevity shocks influence life insurers’ duration adjustments and the resulting impact on corporate debt markets and firms’ debt maturity choices. As life expectancy increases, insurers extend the duration of their corporate bond portfolios to better align assets with longer liabilities. These adjustments are substantial and relatively rapid; a one-year increase in life expectancy leads to a 0.8-year increase in bond portfolio duration within the following year.

Given insurers’ large holdings of corporate bonds, their shift in demand alters the corporate term structure, lowering long-term yields relative to short-term yields and compressing corporate term spread when longevity increases. Corporate issuers respond strategically, increasing long-term debt issuance to take advantage of cheaper long-term financing. This effect is especially pronounced for investment-grade firms and those already held by insurers.

Our findings matter for three key reasons. First, they reveal that longevity shocks have a significant impact on corporate bond markets, extending their effects beyond traditionally demographic-sensitive sectors. Second, they identify a transmission channel into the real economy: the cost of debt financing via insurers and bond markets. Finally, they show that increasing life expectancy lowers long-term financing costs and encourages long-term debt issuance among firms predisposed to such financing.

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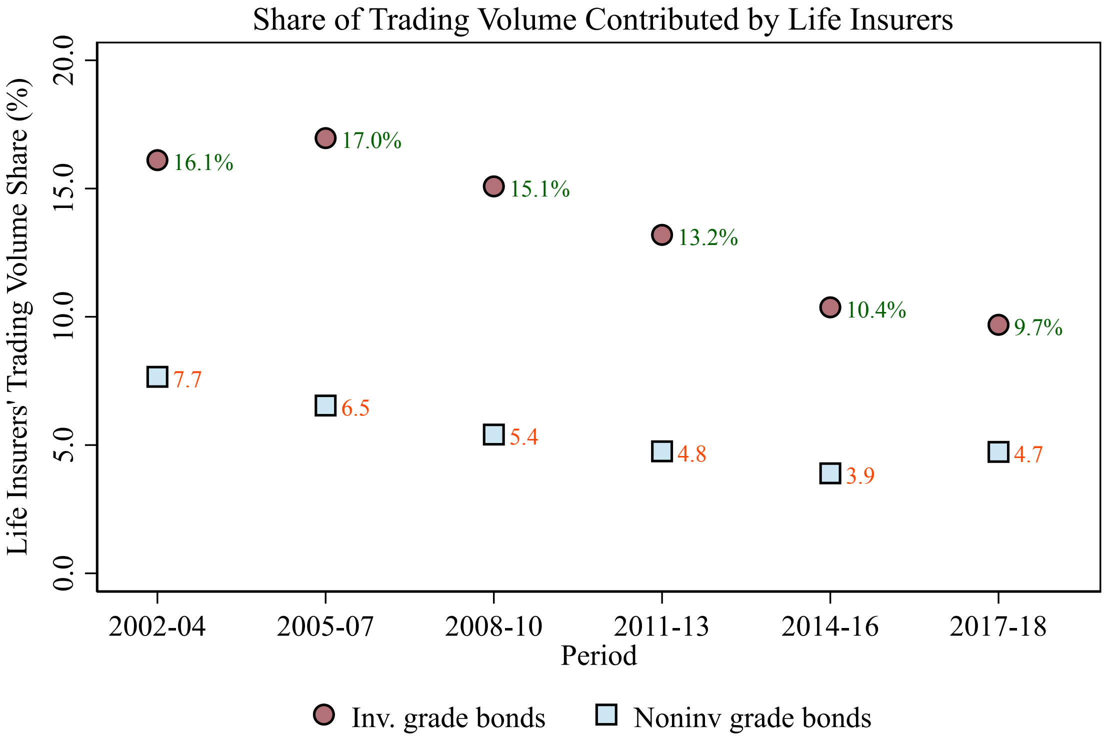


Figure 1: Life insurer trading share of corporate bonds

The figure plots life insurers' share of annual corporate bond trading volume from 2002 to 2018, including investment-grade bonds (in red) and noninvestment-grade bonds (in blue). Data are from NAIC Schedule D filings and TRACE.

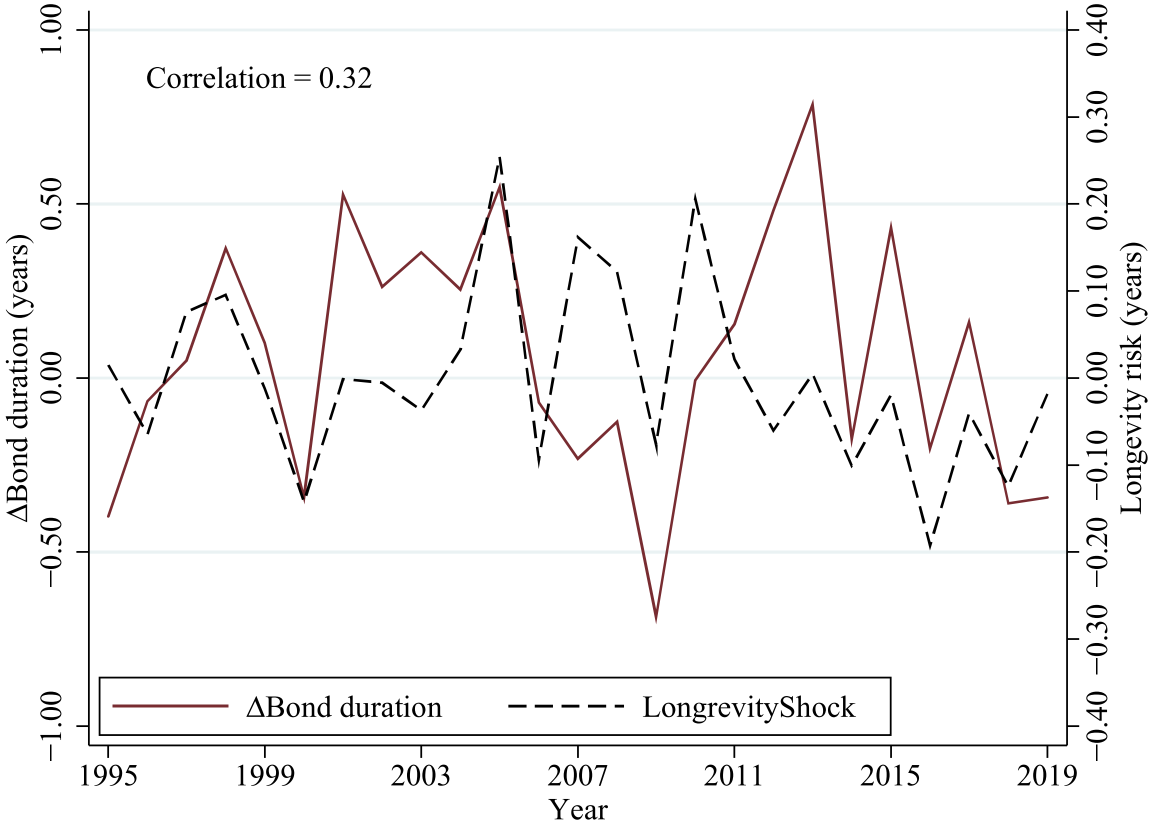
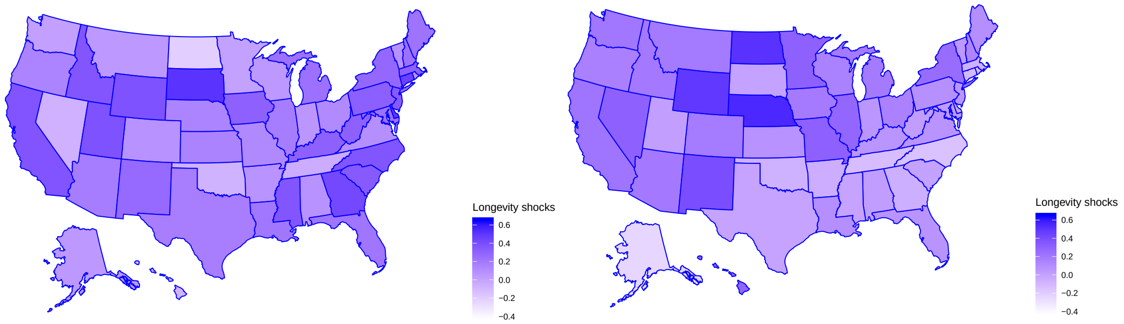
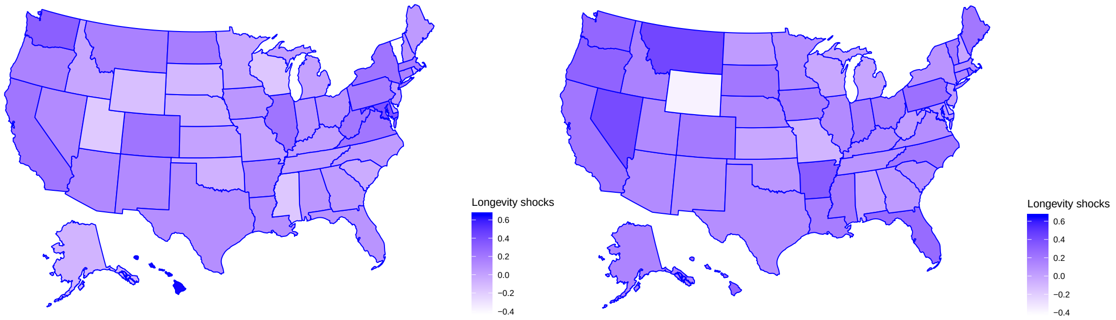


Figure 2: Changes in bond portfolio duration of life insurers and longevity shocks

The figure shows the average yearly changes in the duration of corporate bond portfolios held by U.S. life insurers (red line) from 1995 to 2019, alongside the previous year's longevity shocks (blue dashed line), measured by changes in weighted average life expectancy. Bond holdings data are sourced from the NAIC, and life expectancy data from the Human Mortality Database.



(a) State-level longevity shocks (1990) **(b)** State-level longevity shocks (2000)



(c) State-level longevity shocks (2010) **(d)** State-level longevity shocks (2018)

Figure 3: State-level longevity shocks across years

These figures show state-level longevity shocks (changes in weighted average life expectancy) for 1990, 2000, 2010, and 2018, calculated from U.S. Mortality Database.

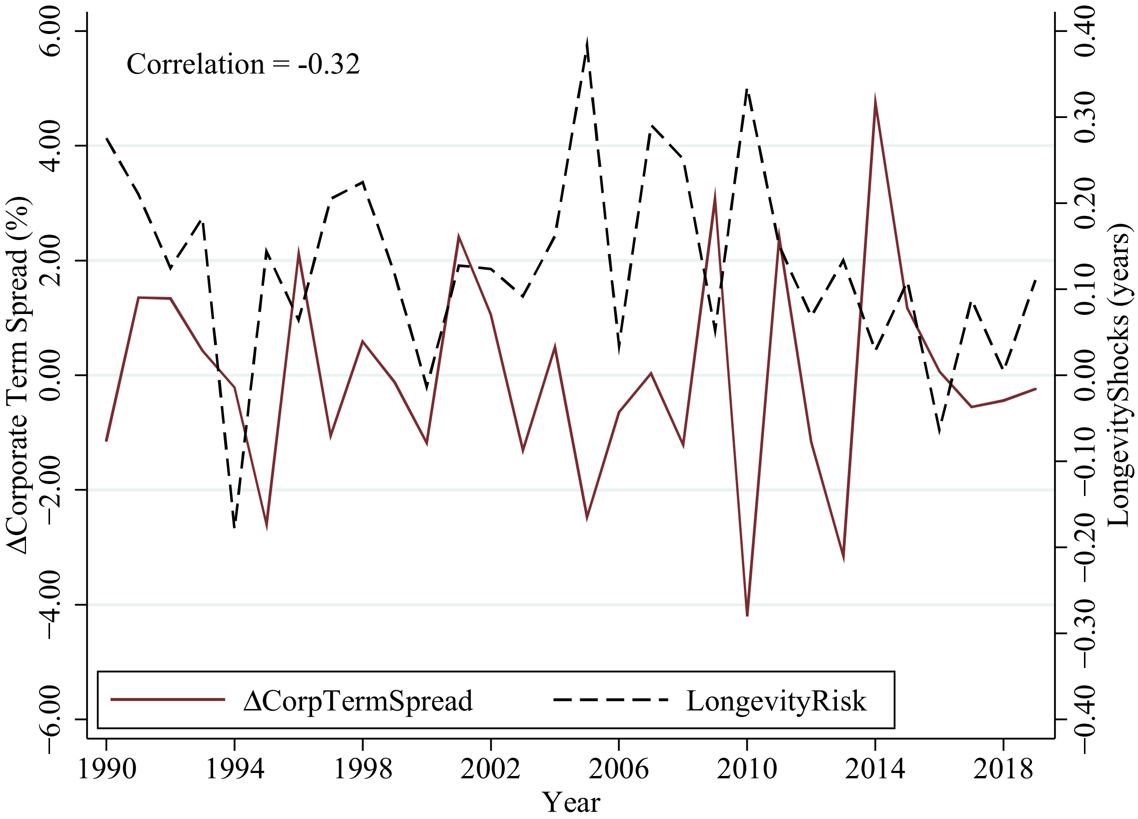


Figure 4: Changes in corporate bond term spreads and longevity shocks

The figure displays annual changes in corporate bond term spreads (red line), defined as the yield difference between long-term and short-term bonds, from 1990 to 2019, alongside the previous year's longevity shock (blue dashed line).

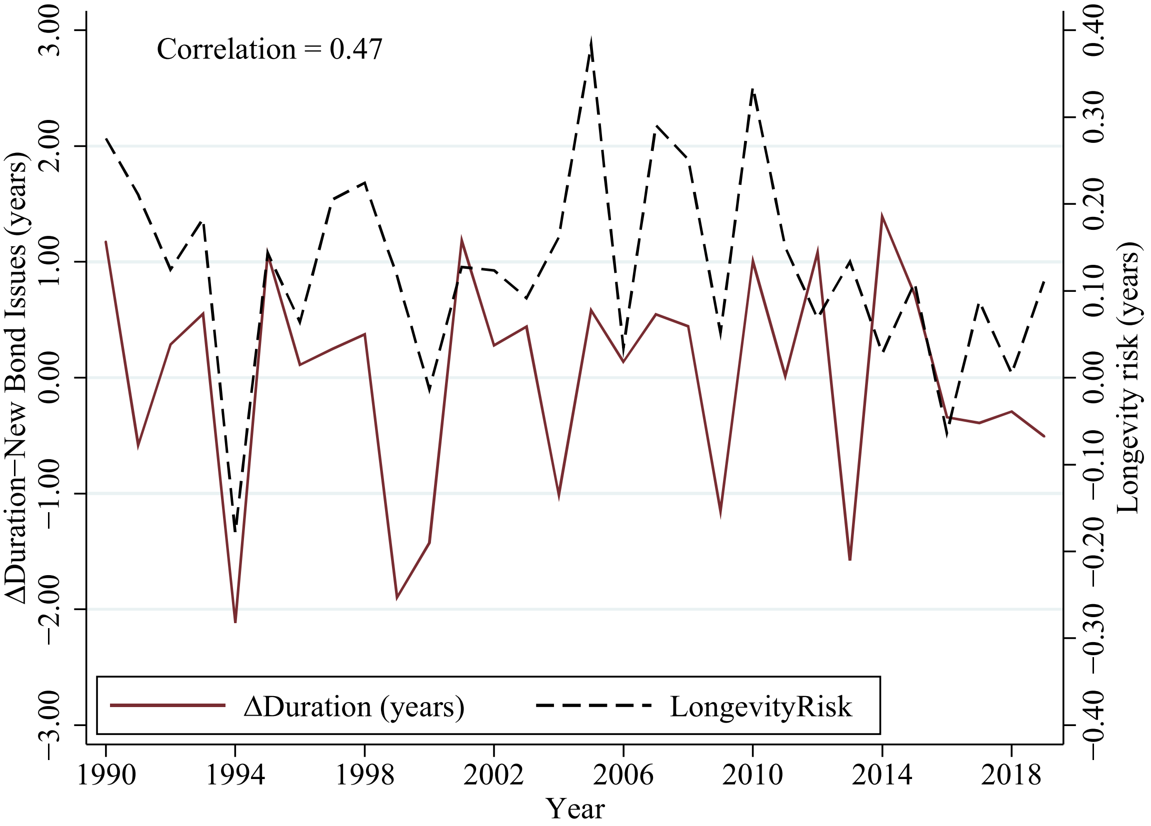


Figure 5: Changes in the average duration of new bond issues and longevity shocks

This figure compares changes in the average duration of new corporate bond issues, weighted by size (red line), from 1990 to 2019, alongside the previous year's longevity shock (blue dashed line). Duration is computed from FISD.

Table 1:
Life insurers' Financial Assets and Corporate Bond Holdings

The table summarizes life insurers' financial asset holdings and acquisitions, as well as corporate bond holdings across major U.S. sectors, using data from the U.S. national accounts from 1990 to 2019 (Z.1 Financial Accounts, March 9, 2023 release). Panel A (based on L.116) reports the average composition of life insurers' financial assets from 1990-2019. Asset shares are expressed as a percentage of total financial assets. Row numbers used from national accounts are shown in parentheses. Panel B (based on F.116) presents average net acquisitions of financial assets over the same period. Each item is shown as a share of total net financial asset acquisitions (corresponding to row 3 of F.116). Row numbers used in the construction are also indicated. Panel C shows the average holdings of corporate and foreign bonds by major U.S. sectors from 1990-2019, using data from Table L.213. Sector holdings (row numbers in parentheses) are expressed as a percentage of total outstanding bonds (L.213, row 1).

	All years	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019
Panel A: Composition of financial assets (%)							
Deposits and liquid assets (2 to 4)	1.9	1.3	1.2	2.3	2.7	2.1	1.8
Corporate bonds (10)	**38.3**	**40.9**	**40.8**	**39.5**	**36.5**	**36.5**	**35.7**
Other debt (6 to 9)	14.1	20.4	17.0	12.5	11.5	12.4	11.0
Loans (11)	11.7	20.7	13.1	10.0	9.3	8.1	8.8
Corporate equities (14)	7.9	6.7	9.2	8.6	7.7	7.4	7.7
Mutual fund shares (15)	15.3	3.7	12.7	16.8	19.2	19.8	19.8
Other financial assets (16 to 20)	10.9	6.4	6.1	10.4	13.2	13.9	15.2
Panel B: Acquisitions of financial assets (%)							
Additions to liquid assets (4 to 6)	-8.7	0.8	4.1	1.4	-37.8	-20.7	0.1
Purchase of corporate bonds (12)	**59.8**	**40.2**	**54.0**	**53.5**	**45.3**	**84.9**	**80.7**
Purchase of loans (13)	6.4	-16.1	6.2	5.4	-1.8	8.5	36.2
Purchase of other debt (8 to 11)	20.6	48.7	-4.7	5.2	50.7	21.4	2.2
Purchase of equity (16)	7.5	15.3	6.0	-3.0	9.8	14.1	2.8
Purchase of mutual fund shares (16)	15.3	15.2	34.2	19.7	47.1	-0.6	-23.7
Purchase of other fin. assets (18 to 22)	-0.9	-4.2	0.1	17.7	-13.4	-7.6	1.7

Table 1: Continued

	All years	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019
Panel C: Holdings of Corporate and Foreign Bonds: Major Sectors (%)							
All sectors	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*
Household sector (13)	10.6	14.3	16.5	10.3	8.5	10.9	3.1
Federal/state government (14 and 15)	1.5	1.0	1.4	1.8	1.6	1.7	1.7
Banks (16, 19 to 21)	7.8	9.0	6.2	8.3	10.3	7.5	5.7
Property-casualty insurance (24)	3.9	4.7	4.1	3.7	2.9	3.7	4.1
Life insurance companies (27)	**24.1**	**30.5**	**27.3**	**24.4**	**18.9**	**21.1**	**22.3**
Private pension funds (30)	6.0	9.2	7.4	4.7	3.5	5.1	6.4
Government retirement funds (31 and 32)	5.2	7.6	6.5	4.7	3.8	4.5	4.4
Mutual funds (33 and 34)	11.1	5.7	9.0	11.1	10.2	14.2	16.2
Closed-end funds and ETF (35 and 36)	1.4	0.9	0.8	0.7	0.9	1.9	3.5
Other institutions (37, 40 to 44)	7.3	5.7	8.0	10.7	11.2	5.3	2.7
Rest of the world (45)	20.2	11.6	12.9	18.8	23.9	24.7	29.4
Discrepancy (48)	0.8	-0.2	-0.2	0.8	4.3	-0.7	0.5

Table 2:
Summary statistics

This table summarizes key data. Panel A reports national and state-level longevity shock statistics. Panel B covers credit market conditions. Panel C describes the sample of life insurance companies, and Panel D summarizes bond issuer characteristics (1975–2019). See Appendix A for variable definitions.

				Distribution		
	N	Mean	SD	$P10$	Median	$P90$
Panel A: Longevity shocks						
LongevityShocks (years)	45	0.15	0.14	-0.01	0.12	0.33
LocalLongevityShocks (years)	1,530	0.10	0.21	-0.16	0.10	0.36
Panel B: Bond market characteristics						
ΔTreasury1Y (%)	30	-0.21	1.39	-2.25	-0.09	1.34
TermSpread (%)	30	1.42	1.13	0.12	1.56	2.98
CreditSpread (%)	30	2.07	0.86	1.26	1.95	2.86
EBP (%)	30	0.11	0.74	-0.54	-0.10	0.74
ΔCorpTermSpread (%)	30	0.03	1.91	-2.56	-0.24	2.38
LTtoSTDebt	30	5.07	3.86	0.93	4.25	10.48
ΔNewBondDuration (years)	30	0.01	0.95	-1.50	0.26	1.13
Panel C: Life insurer characteristics						
InsAssets (MM$)	15,523	6,663	23,996	13	338	12,363
InsLeverage	15,523	0.73	0.25	0.34	0.83	0.95
RBC	15,523	17.57	30.62	4.42	8.89	32.61
InsROA	15,523	0.02	0.05	-0.02	0.01	0.06
NPWGrowth	15,523	0.11	1.24	-0.44	-0.01	0.44
NAIC1	10,250	0.55	0.11	0.42	0.54	0.68
NAIC2	10,250	0.27	0.10	0.16	0.26	0.41
NAIC3	10,250	0.07	0.04	0.02	0.06	0.10
NAIC4	10,250	0.07	0.04	0.02	0.07	0.12
NAIC5	10,250	0.02	0.02	0.00	0.02	0.05
NAIC6	10,250	0.02	0.02	0.00	0.01	0.04
DerivativeHedging	8,391	-0.02	0.10	0.00	0.00	0.00
BondDurationIns (years)	15,523	6.96	2.51	3.78	6.90	10.21
ΔBondDurationIns (years)	15,523	0.04	1.12	-0.93	-0.04	1.14

Table 2: Continued

				Distribution		
	N	Mean	SD	$P10$	Median	$P90$
Panel D: Firm characteristics						
Assets (MM$)	48,131	6,669	24,314	70	906	14,136
LTDebtGrowth	48,131	0.08	0.50	-0.21	-0.02	0.43
R&DIntensity	48,131	0.02	0.03	0.00	0.00	0.05
PPEGrowth	48,131	0.03	0.09	-0.03	0.01	0.12
Capex	48,131	0.09	0.08	0.02	0.06	0.17
AssetMat	48,131	7.24	7.60	1.58	4.24	17.89
ROA	48,131	0.16	0.07	0.08	0.15	0.25
TobinsQ	48,131	1.63	1.07	0.83	1.29	2.77
Leverage	48,131	0.28	0.15	0.08	0.28	0.48
Age	48,131	17.14	12.54	3.00	15.00	36.00
Cash	48,131	0.08	0.10	0.01	0.05	0.21
EquityIssue	48,131	0.01	0.07	-0.03	0.00	0.03
NIGrowth	48,131	0.06	0.72	-0.65	0.08	0.72
Tangibility	48,131	0.46	0.28	0.13	0.40	0.86
LTDebtDep	48,131	0.52	0.28	0.13	0.52	0.92

Table 3:
Effect of longevity shocks on insurers' bond portfolio duration

The table reports regressions of changes in insurers' corporate-bond portfolio duration ($\Delta InsDuration_{i,t}$) to lagged longevity shocks ($LongevityShocks_{t-1}$). Columns (1) to (5) examine life insurers. Column (6) focuses on property and casualty (P&C) insurers, as a placebo test. Column (2) controls for credit market conditions. Column (3) controls for credit market conditions, macroeconomic conditions, and insurer characteristics. Columns (4)–(5) further control for the reaching for yield incentive and interest rate derivative hedging, respectively. See Appendix A for variable descriptions. Standard errors, clustered by insurers, are reported in parentheses. The sample period is from 1995 to 2019. $^{*}p$ <0.10, $^{**}p$ <0.05, and $^{***}p$ <0.01.

	Dependent Variable: $\Delta InsDuration_{i,t}$					
	Life Insurers					P&C Insurers
	(1)	(2)	(3)	(4)	(5)	(6)
LongevityShocks	0.801^{***} (0.088)	0.815^{***} (0.089)	0.716^{***} (0.090)	0.805^{***} (0.141)	0.779^{***} (0.185)	0.092 (0.088)
LongevityShocks × RFYInsurer				-0.287 (0.195)		
RFYInsurer				0.250^{***} (0.034)		
LongevityShocks × IRDerivUser					0.113 (0.347)	
IRDerivUser					-0.330^{***} (0.075)	
Δ Treasury1Y		-0.004 (0.009)	-0.027^{***} (0.010)	-0.035^{***} (0.010)	-0.004 (0.026)	-0.151^{***} (0.013)
TermSpread		0.053^{***} (0.008)	0.080^{***} (0.009)	0.065^{***} (0.010)	-0.004 (0.015)	0.012 (0.009)
CreditSpread		-0.041^{***} (0.014)	0.093^{***} (0.022)	0.088^{***} (0.022)	0.251^{***} (0.042)	0.036 (0.028)
CPIGrowth			-0.037^{***} (0.012)	-0.014 (0.012)	-0.041^{**} (0.020)	-0.046^{***} (0.013)
GDPGrowth			0.112^{***} (0.010)	0.087^{***} (0.011)	0.210^{***} (0.023)	0.101^{***} (0.014)
Ln(InsAssets)			-0.006 (0.019)	-0.036^{*} (0.020)	-0.133^{***} (0.041)	-0.063^{**} (0.028)
InsLeverage			0.112 (0.123)	0.122 (0.123)	0.175 (0.256)	0.084 (0.131)

Table 3: Continued

	Dependent Variable: $\Delta InsDuration_{i,t}$					
	Life Insurers					P&C Insurers
	(1)	(2)	(3)	(4)	(5)	(6)
RBCRatio			-0.001	-0.001	-0.002	-0.000
			(0.001)	(0.001)	(0.002)	(0.002)
InsROA			0.015	0.027	0.230	-0.214
			(0.302)	(0.302)	(0.487)	(0.256)
NPWGrowth			0.019^{*}	0.021^{**}	0.034^{**}	0.030
			(0.010)	(0.010)	(0.016)	(0.023)
Observations	15,242	15,242	15,242	15,242	8,077	26,094
R-squared	0.01	0.06	0.07	0.08	0.10	0.06
Insurer FE	No	Yes	Yes	Yes	Yes	Yes

Table 4:
Heterogeneity in Life Insurers' Response to Longevity Shocks

The table shows how longevity shocks ($LongevityShocks_{t-1}$) affect changes in insurers' corporate bonds portfolio duration ($\Delta InsDuration_{i,t}$). Columns (1)–(2), (3)–(4), and (5)–(6) group insurers by size, longevity shock exposure, and regulatory strictness, respectively. All regressions include controls for credit markets, macroeconomic conditions, insurer characteristics, and insurer fixed effects (see variables in Table 3, Column (3)). Variable definitions are collected in Appendix A. Standard errors, clustered by insurers, are reported in parentheses. The sample period is 1995-2019. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Insurer size		Longevity exposure		Regulatory Strictness	
	Small (1)	Large (2)	Low (3)	High (4)	Weak (5)	Strong (6)
LongevityShocks	0.550***	0.904***	0.469***	0.918***	0.595***	0.970***
	(0.147)	(0.103)	(0.116)	(0.162)	(0.108)	(0.185)
Observations	7,598	7,606	9,535	3,965	11,203	4,295
R-squared	0.08	0.09	0.08	0.11	0.08	0.13
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit market controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurer controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 5:
Corporate bond adjustments by local life insurers

This table examines local life insurers' corporate bond adjustments in response to local longevity shocks. Local life insurers derive at least 80% of their revenues from their respective states. Column (1) examines the impacts of local longevity shocks on bond portfolio duration. Columns (2) to (4) examine net purchases of long-term bonds (with a duration of 10 years or more) by insurers in response to changes in life expectancy. Columns (5) to (7) examine net purchases of short-term bonds (with a duration of 3 years or less) in response to longevity shocks. Net purchases are scaled by the market value of an insurer's bond portfolio. We consider net purchases of all bonds, investment-grade or speculative-grade bonds. We control for credit markets, macroeconomic conditions, and insurer characteristics (see variables in Table 3, Column (3)). Variable definitions are collected in Appendix A. Standard errors are clustered by insurers and reported in parentheses. The sample period is from 1995 to 2019. $^{*}p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$.

Dependent Variable	ΔInsDuration	Life insurers' net corporate bond purchases					
		Long-term bonds			Short-term bonds		
	(1)	All bonds (2)	Investment grade (3)	Speculative grade (4)	All bonds (5)	Investment grade (6)	Speculative grade (7)
Panel A: Duration adjustments through both local and non-local bonds							
LocalLongevityShocks	0.462***	0.069**	0.039*	0.003	-0.028*	-0.022**	-0.001
	(0.087)	(0.033)	(0.021)	(0.004)	(0.015)	(0.010)	(0.003)
Observations	5437	5183	5183	5183	5183	5183	5183
R^2	0.07	0.05	0.04	0.04	0.02	0.02	0.02
Panel B: Duration adjustment through non-local corporate bonds							
LocalLongevityShocks	0.295***	0.043*	0.038*	0.006***	-0.011	-0.015*	0.000
	(0.059)	(0.024)	(0.021)	(0.002)	(0.010)	(0.009)	(0.002)
Observations	5437	5183	5183	5183	5183	5183	5183
R^2	0.08	0.03	0.03	0.03	0.03	0.03	0.01
Credit market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6:
Local longevity shocks and duration adjustments: Identifications

Columns (1) and (2) present instrumental variable (IV) regression results, examining the impact of local longevity shocks on the duration adjustment of local life insurers. Local longevity shocks are state-level. Local life insurers derive at least 80% of their revenues from their respective states. State-level opioid related mortality (per 100,000 population) is the instrument for local longevity risk. Column (3) shows difference-in-differences results around the implementation of state-level Prescription Drug Monitoring Programs (PDMPs), using the DiD methodology of Moser and Voena (2012). A state is "treated" (a dummy *PDMPState* = 1) after implementing a PDMP with a must-access provision. The control group comprises states without PDMPs or without a must-access provision. *Post* indicates the first year after adopting PDMPs with a must-access provision or later years. Control variables (credit market, macroeconomic, and insurer characteristics) and insurer fixed effects are the same as in Column (3) of Table 3. See Appendix A for variable definitions. Standard errors, clustered by state, are in parentheses. The sample period is from 1999 to 2019. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Instrumental Variable		
	First Stage Regression	Second Stage Regression	Difference-in-Differences
Dependent Variable	Local LongevityShock (1)	ΔDuration (2)	ΔDuration (3)
IV=OpioidMortality	-8.494***		
	(2.012)		
LocalLongevityShocks		1.255**	
		(0.639)	
PDMPState × Post			0.214**
			(0.094)
Credit market controls	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes
Insurer characteristics	Yes	Yes	Yes
Insurer fixed effects	Yes	Yes	Yes
R^2	0.179	0.009	0.074
Observations	5429	5429	5378

Table 7:
Corporate bond trades: IV regressions

This table presents instrumental variable (IV) regression results examining how longevity shock correlations affect the trading directions of two local life insurers in states i and j. Columns (1) and (3) show the first stage regression: the correlation of local longevity shocks (*LongevityCorr*$_{i,j}$) regressed on the correlation of opioid related mortality in states i and j. Columns (2) and (4) show the second stage regression: the dependent variable is a dummy equal to one if insurers i and j trade the same bond in opposite directions, and zero otherwise. Local insurers drive at least 80% of their revenue from their respective states. Local longevity shocks are state-level. Columns (3) and (4) exclude bonds of firms headquartered in states i and j, focusing on trades of non-local bonds. Control variables (credit market, macroeconomic, and insurer characteristics) and insurer fixed effects are the same as in Column (3) of Table 3. We also control for state-level macroeconomic conditions, including local GDP grwoth rate and population growth rate. Variable definitions are in Appendix A. Standard errors, clustered by state of insurer$_i$ and insurer$_j$, are shown in parentheses. The sample period is from 1995 to 2019. $^{*}p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$.

	All bonds		Non-local bonds (Excl. bonds in i and j)	
	First Stage	Second Stage	First Stage	Second Stage
Dependent Variable	Longevity Corr$_{i,j}$ (1)	Opposite Trades (2)	Longevity Corr$_{i,j}$ (3)	Opposite Trades (4)
OpioidMortalityCorr_i, j	0.250***		0.243***	
	(0.077)		(0.070)	
LongevityCorr_i, j		-0.064***		-0.069**
		(0.023)		(0.028)
Credit market controls	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
State macroeconomic controls	Yes	Yes	Yes	Yes
Insurer controls	Yes	Yes	Yes	Yes
R^2	0.174	0.001	0.171	0.001
Observations	173376	173376	123516	123516

Table 8:
Longevity shock, yields and bond issues

This table presents regression results examining the impact of longevity shocks on bond yields, maturities, and issue size. Column (1) analyzes changes in term spreads (long-term minus short-term corporate bond yields). Column (2) examines changes in the average duration of new bond issuances, weighted by issue size. Column (3) studies changes in the relative issue size of long-term versus short-term bonds. Variable definitions are in Appendix A. Standard errors (in parentheses) are calculated using Newey-West standard errors with two lags. The sample period is from 1990 to 2019. $^{*}p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$.

	Dependent Variable:		
	ΔCorporate term spread	ΔNewBondDuration	Δln(Long term /Short term)
	(1)	(2)	(3)
LongevityShocks	-5.653***	2.477**	1.714**
	(1.959)	(0.909)	(0.685)
CPIGrowth	0.041	-0.094	-0.060
	(0.311)	(0.170)	(0.086)
GDPGrowth	0.187	-0.083	-0.109
	(0.174)	(0.117)	(0.081)
ΔTreasury1Y	-0.100	-0.331***	-0.294***
	(0.209)	(0.107)	(0.079)
ΔCreditSpread	0.334	-0.266	-0.122
	(0.544)	(0.376)	(0.225)
ΔTermSpread	1.198***	-0.416**	-0.236**
	(0.299)	(0.155)	(0.085)
ΔEBP	-0.685***	-0.037	0.051
	(0.233)	(0.092)	(0.048)
$Constant$	0.123	0.054	0.134
	(1.035)	(0.483)	(0.271)
R^2	0.484	0.455	0.654
Observations	30	30	30

Table 9:
Corporate response to longevity shocks: Bond maturity choices

This table reports results from multinomial logit regressions examining the impact of longevity shocks on corporate bond maturity choice. Maturities are classified as short-term (< 3 years), medium (3-10 years), long (10-20 years), and extra-long (>20 years), with medium-term bonds as the base category. Column (1) includes all firms. Column (2) excludes firms in demographic-sensitive industries (DellaVigna and Pollet, 2007). Columns (3) and (4) split firms by life insurers' holdings: firms above the median share are classified as insurer-dependent. Columns (5) and (6) distinguish firms by credit rating. Control variables (credit market, macroeconomic, and insurer characteristics) and insurer fixed effects are the same as in Column (3) of Table 3. We also control for firm-level characteristics, including ROA, total assets, Tobin's *Q*, leverage, age, cash holdings, equity issuance, net income growth, and asset tangibility. Variable definitions are provided in Appendix A. Standard errors clustered at the firm-level are reported in parentheses. The sample covers 1990-2019. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	All firms	Non-demographic industries	Insurer-dependent firms?		Investment-grade firms?	
			Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Maturity < 3 *years*						
LongevityShocks	-3.516***	-3.403*	-3.339***	5.514	-4.734*	-4.330
	(1.26)	(1.83)	(1.29)	(9.64)	(2.73)	(3.19)
Panel B: Maturity $[10, 20)$ *years*						
LongevityShocks	0.692*	1.478***	1.451***	-0.189	1.559**	0.709
	(0.35)	(0.53)	(0.50)	(0.51)	(0.76)	(0.57)
Panel C: Maturity ≥ 20 *years*						
LongevityShocks	2.658***	2.999***	3.377***	1.758	2.779***	0.791
	(0.42)	(0.58)	(0.50)	(1.18)	(0.77)	(0.78)
Credit market controls	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic conditions	Yes	Yes	Yes	Yes	Yes	Yes
Insurer controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Period indicators	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.122	0.103	0.068	0.106	0.110	0.133
Observations	6806	3296	4415	2391	2932	3067

Appendix

A Variable Definitions, Data Sources, and Sample Period

This appendix defines the variables used in the study, along with their data sources and sample periods.

Panel A: Longevity and Mortality Data

LongevityShocks Annual change in average U.S. life expectancy, based on period life expectancy and exposure data from the Human Mortality Database (HMD, `https://mortality.org`, Mila (2019), 1974–2018).

LocalLongevityShocks State-level longevity shocks, derived from the U.S. Mortality Database (`https://usa.mortality.org`), 1989-2018.

LongevityCorr$_{i,j}$ Time-series correlation of longevity shocks between insurer states i and j.

OpioidMortality State-level opioid mortality per 100,000 population, based on CDC's WONDER database (ICD 10 codes X40–X44 for unintentional abuse and Y10–Y14 for undetermined intent), 1999-2019.

PDMPState Indicator variable equal to one if the state has a prescription drug monitoring program (PDMP) with a must-access provision, and zero otherwise (Buchmueller and Carey (2018); Prescription Drug Abuse Policy System website, 1999-2019).

MMEBase Per-capita morphine-milligram-equivalent opioids dispensed through retail pharmacies one year before the must-access PDMP.

Panel B: Macroeconomic and Credit Market Data

CPIGrowth U.S. Consumer Price Index growth rate. Source: FRED (item CPIAUCSL), 1990–2019.

GDPGrowth U.S. GDP growth rate. Source: FRED (item GDPC1), 1990–2019.

StateGDPGrowth State-level GDP growth rate. Source: U.S. Bureau of Economic Analysis (item SAGDP1), 1990–2019.

StatePopGrowth State-level population growth rate. Source: U.S. Bureau of Economic Analysis (item SAINC51), 1990–2019.

IndProdGrowth U.S. industrial production growth rate. Source: FRED (item INDPRO), 1990–2019.

CreditSpread Yield difference between Moody's Baa-rated bonds and 20-year Treasury bonds. Source: FRED (item GS20), 1990–2019.

$\triangle$Treasury1Y Annual change in the 1-year Treasury yield. Source: FRED (item GS1), 1990–2019.

TermSpread Yield difference between 10-year and 1-year Treasuries. Source: FRED (items GS10 and GS1), 1990–2019.

TermSpread$^{\perp}$ Orthogonalized term spread, defined as residuals from regressing term spread on longevity shocks. Source: FRED (items GS10 and GS1), 1990–2019.

Amihud Maket-wide bond illiquidity, computed from TRACE data. We first compute the daily Amihud illiquidity of individual bonds based on the transaction data in TRACE. Second, we computed each bond's annual average Amihud illiquidity using its daily Amihud illiquidity estimates. Third, we take a simple average of bond-level Amihud illiquidity as the bond market Amihud illiquidity measure.
Source: Trade Reporting and Compliance Engine (TRACE) data, 2002–2019.

$\triangle$PensionShare Changes in the market share of corporate bonds held by pensions. Source: Federal Reserve Economic Data (item BOGZ1FL593063045Q), 1995–2019.

$\triangle$MutualFundShare Changes in the market share of corporate bonds held by mutual funds. Source: Federal Reserve Economic Data (item BOGZ1FL653063043Q), 1995–2019.

Panel C: Bond Characteristics

$\triangle$CorpTermSpread Change in the yield spread between long-term (>10 years) and short-term (<3) corporate bonds. Source: Mergent FISD, 1990–2019.

$\triangle$ln(Long term/Short term) Annual change in log ratio of long-term to short-term corporate bond issuance. Source: Mergent FISD, 1990–2019.

$\triangle$NewBondDuration Annual change in the Macaulay duration of newly issued corporate bonds. Source: Mergent FISD, 1990–2019.

$\triangle$Yield Annual change in corporate bond yields. Source: Mergent FISD, 1990–2019.

$\triangle$IssueSize Annual change in the log ratio of long-term to short-term bond issue size. Source: Mergent FISD, 1990–2019.

Panel D: Life Insurer Characteristics

$\triangle$InsDuration Annual change in the Macaulay duration of life insurers' corporate bond portfolios. Source: NAIC, 1995–2019.

NetBuyLTBond Net purchase of long-term corporate bonds (duration $\geq$10 years), scaled by the market value of the bond portfolio. Source: NAIC, 1995–2019.

NetBuySTBond Net purchase of short-term corporate bonds (duration $\leq$3 years), scaled by market value of the bond portfolio. Source: NAIC, 1995–2019.

RBC Risk-based capital ratio, defined as adjusted total capital divided by required risk-based capital. Lower values indicate lower capital adequacy. Source: NAIC, 1995–2019.

NPWGrowth Growth rate of net premiums written. Source: NAIC, 1995–2019.

InsROA Insurer profitability, measured as net income divided by average total assets. Source: NAIC, 1995–2019.

ln(InsAssets) Natural logarithm of total assets (insurer size). Source: NAIC, 1995–2019.

InsLeverage Ratio of total liabilities to total assets. Source: NAIC, 1995–2019.

Deviation Absolute difference between a life insurer's share and industry-level natural hedging share (see Appendix ID). Life insurance share is defined as direct premium written (DPW) for life insurance divided by the sum of DPW for life insurance and annuities.

RFYInsurer A dummy variable equal to 1 if an insurer has stronger incentives to reach for yield (RFY), defined as having an RFY above the sample median. RFY is calculated as the value-weighted average deviation of corporate bond yields from rating-and-maturity-matched benchmarks.

DerivativeUser A dummy equals 1 if an insurer uses interest rate derivatives.

ExaminationIntensity The number of financial and market conduct examinations conducted by each state insurance department, scaled by the number of domiciled life insurers.

Panel E: Firm Characteristics

InsurerDepFirm Firms categorized as insurer-dependent if the average share of their bonds held by life insurers exceeds the cross-sectional median; otherwise classified as noninsurer-dependent. Source: Mergent FISD, 1990–2019.

ROA Firm profitability, calculated as operating income before depreciation divided by average total assets (current and previous year). Source: Compustat, 1975–2019.

ln(Assets) Natural logarithm of total assets (firm size). Source: Compustat, 1975–2019.

Leverage Ratio of total debt to total assets. Source: Compustat, 1975–2019.

TobinsQ Market-to-book ratio, where market value is estimated as book assets plus the market value of common stock, minus the book value of common stock and deferred taxes. Source: Compustat, 1975–2019.

Age Number of years since IPO, or since the first CRSP date if IPO date is unavailable. Source: Compustat and CRSP, 1975–2019.

Cash Cash and cash equivalents / total assets. Source: Compustat, 1975–2019.

EquityIssues (Sale of equity - purchases of equity)/ lagged assets. Source: Compustat, 1975–2019.

NetIncomeGrowth Log growth rate of net income. Source: Compustat, 1975–2019.

Tangibility Ratio of net property, plant, and equipment (PP&E) to lagged total assets. Source: Compustat, 1975–2019.

Internet Appendix for

“Longevity Shocks and Debt Market Transmission”

Intended for online publication only

IA U.S. Life Expectancy and Longevity Shocks, 1950–2018

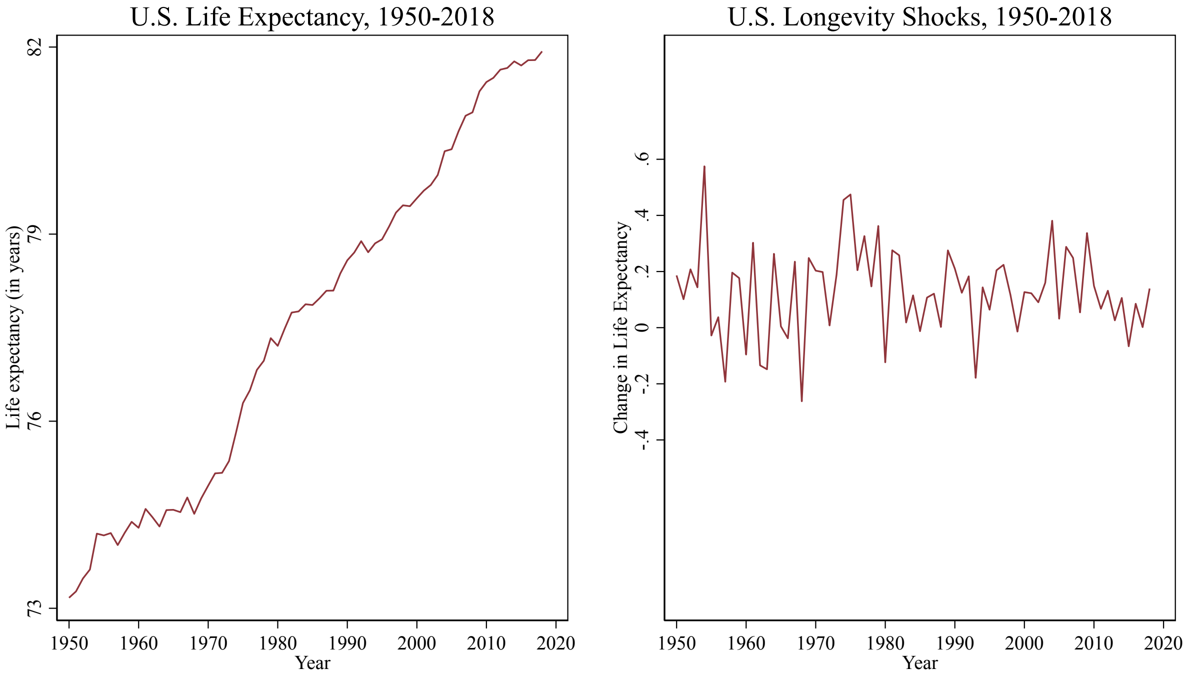


Figure A.1: U.S. Life Expectancy and Longevity Shocks, 1950-2018

The figure shows the weighted average period life expectancy in the US from 1950-2018. Life expectancy estimates are based on data from the Human Mortality Database.

IB NAIC Designation and Risk-based Capital Requirements for Bonds

This table shows the 2018 NAIC bond designation (based on S&P ratings) and the corresponding risk-based capital (RBC) requirement for life insurers. See https://www.naic.org/ for details.

	S&P ratings	Risk-based Capital
NAIC Designation 1	AAA/AA+/AA/AA-/A+/A/A-	0.39%
NAIC Designation 2	BBB+/BBB/BBB-	1.26%
NAIC Designation 3	BB+/BB/BB-	4.46%
NAIC Designation 4	B+/B/B-	9.70%
NAIC Designation 5	CCC+/CCC/CCC-	22.31%
NAIC Designation 6	CC/C/D	30.00%

IC Robustness

First, we consider the impacts of bond liquidity. If bond market liquidity comoves with factors that drive longevity shocks, bond duration adjustments may reflect movements in aggregate bond market liquidity rather than longevity shocks. We use Trade Reporting and Compliance Engine (TRACE) data to calculate the Amihud illiquidity ($Amihud$) of individual bonds and then compute the average across all bonds as the market illiquidity measure. The sample period is shorter because we are constrained by TRACE data, which are available from 2002 to 2019. The results in Column (1) of Appendix Table IC show that the illiquidity variable has a negative coefficient, indicating that life insurers reduce the duration of their bond portfolio when the market illiquidity increases. However, our main results remain robust when we include market illiquidity in the baseline specification. The coefficient of longevity shocks remains significant and positive.

Second, we control for changes in corporate bonds holdings of other institutional investors, such as mutual funds and pension funds. Column (2) of Appendix Table IC shows that changes in pension funds' holdings are positively related to changes in the duration of life insurers' corporate bond holdings. By contrast, changes in mutual funds' corporate bond holdings are negatively related to insurance firms' bond duration changes. Importantly, we find that even after controlling for corporate bond holdings of other institutional investors, longevity shocks positively affect insurance firms' bond maturities.

Table IC:
Effect of longevity shocks on insurers' bond portfolio duration

The table reports regressions of changes in insurers' corporate-bond portfolio duration ($\Delta InsDuration_{i,t}$) to lagged longevity shocks ($LongevityShocks_{t-1}$). Column (1) controls for market-wide corporate bond illiquidity ($Amihud$). $Amihud$ illiquidity is computed from TRACE data. The sample period is from 2002 to 2019. Column (2) controls for ownerships by mutual funds ($MutualFundShare$) and pensions ($PensionShare$). The sample period is from 1995 to 2019. See Appendix A for variable descriptions. Standard errors, clustered by insurers, are reported in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$.

	(1)	(2)
LongevityShocks	0.684***	0.703***
	(0.119)	(0.094)
Amihud	-0.537***	
	(0.099)	
Δ MutualFundShare		-11.332***
		(1.259)
Δ PensionShare		5.843***
		(1.773)
Δ Treasury1Y	-0.014	-0.056***
	(0.017)	(0.014)
TermSpread	0.062***	0.120***
	(0.012)	(0.010)
CreditSpread	0.281***	-0.068**
	(0.036)	(0.029)
CPIGrowth	0.031*	-0.067***
	(0.019)	(0.012)
GDPGrowth	0.188***	0.081***
	(0.018)	(0.010)
Ln(InsAssets)	-0.097***	-0.013
	(0.030)	(0.019)
InsLeverage	0.224	0.108
	(0.179)	(0.123)
RBCRatio	-0.002	-0.001
	(0.001)	(0.001)
InsROA	0.094	-0.001
	(0.407)	(0.301)
NPWGrowth	0.032**	0.018*
	(0.013)	(0.010)
Observations	11,261	15,242
R-squared	0.09	0.08
Insurer FE	Yes	Yes

ID Natural Hedge Ratio of Life Insurance Companies

We derive the natural hedge ratio for life insurance using a Lee-Carter mortality model (Lee and Carter, 1992). This model expresses the log of mortality rate ($m_{x,t}$ for age x in year t) as:

$$\log\left(m_{x,t}\right) = \alpha_x + \beta_x \kappa_t, \tag{D.1}$$

where α_x is a static age function, $\beta_x \kappa_t$ captures the age-period effect, with κ_t representing the overall mortality trend (mortality index) and β_x modulating its age-related impact. Standard identification constraints are $\sum_t \kappa_t = 0$ and $\sum_x \beta_x = 1$.

The probability of an individual aged x dying in year t is approximated as $q_{x,t} \approx 1 - \exp(-m_{x,t})$. This approximation assumes a stationary population and a constant mortality rate within each year. The *ex post* survival probability to time $t+T$ for an individual aged x at time t is $S_{x,t}(T) = S_{x,t}(T) = \prod_{s=1}^{T} \left(1 - q_{x+s-1,t+s}\right)$, where $q_{x,t}$ is unknown prior to time t and $S_{x,t}(T)$ is unknown before time $t+T$. The expected survival probability is $p_{x,u}\Big(T, \kappa_t\Big) = \mathbb{E}\Big(S_{x,u}(T)|\mathcal{F}_t\Big) = \mathbb{E}\Big(S_{x,u}(T)|\kappa_t\Big)$, where $\mathcal{F}_t$ is the filtration up to time t. This is the spot survival probability when $u = t$ and the forward survival probability when $u > t$.

For an annuity portfolio of individuals aged $x_1, x_2, \ldots, x_k$ at time 0, paying \$1 annually until death, the future liability per surviving annuitant at time t is:

$$FL_t^A = \frac{1}{k} \sum_{x=x_1}^{x_k} \sum_{s=1}^{\infty} (1+r)^{-s} p_{x,t}(s, \kappa_t), \tag{D.2}$$

where r is the annual interest rate and superscript A denotes an annuity business line.

The *ex post* probability of an individual aged x at time t surviving to time $t+T-1$ and dying in year $t+T$ is $D_{x,t}(T) = \prod_{s=1}^{T-1} \Big(1 - q_{x+s-1,t+s}\Big) \cdot q_{x+T-1,t+T}$, and the expected death probability is $q_{x,u}\Big(T, \kappa_t\Big) = \mathbb{E}\Big(D_{x,u}(T)|\mathcal{F}_t\Big) = \mathbb{E}\Big(D_{x,u}(T)|\kappa_t\Big)$. For a life insurance portfolio of the same cohort, paying \$ upon death, the future liability per death at time t is:

$$FL_t^L = \frac{1}{k} \sum_{x=x_1}^{x_k} \sum_{s=1}^{\infty} (1+r)^{-s} q_{x,t}(s, \kappa_t), \tag{D.3}$$

where superscript L denotes a life insurance business line.

The natural hedge simulation assumes: (1) Annuity and life insurance for cohorts aged 35-80 (matching the US population). (2) Annuities pay \$1 annually until death or year 20. (3) 20-year term life insurance pays \$1 upon death. (4) Constant interest rate $r = 1\%$. (5) US mortality index estimated from HMD data (1933-2018, ages 0-99). (5) Time 0 is the end of 2018. (7) 10,000 simulations from the Lee-Carter model.

For a portfolio with X annuity shares and θX life insurance shares, the total liability at time 0 is $FL_0 = (FL_0^A + \theta FL_0^L)X$. The natural hedge minimizes the variance of its portfolio's future liability, $\mathrm{Var}(FL_0)$, with respect to θ. Let P^A and P^L be the total premiums collected from annuities and life insurance, respectively, and then the proportion of premiums collected from the life insurance business is calculated as

$$\frac{P^L}{P^A + P^L} = \frac{\theta \mathbb{E}(FL_0^L)}{\mathbb{E}(FL_0^A) + \theta \mathbb{E}(FL_0^L)}. \tag{D.4}$$

The simulation yields an optimal life insurance premium proportion ($\frac{P^L}{P^A+P^L}$) of 81.9%, consistent across various cohort sets and contract horizons. This is significantly higher than the industry average of 31.6% observed between 1995 to 2019.

IE Difference-in-differences analysis with must-access PDMPs

We perform the difference-in-differences analysis, using the staggered rollouts of the must-access prescription drug monitoring programs (PDMPs) in some states. However, one challenge is that the adoption of must-access PDMPs was not random. For example, Ouimet, Siminitze, and Ye (2024) show that it was driven by the age-adjusted opioid overdose death rates of the states. States that adopted must-access PDMPs earlier typically exhibited worse pre-policy opioid abuse and faster-rising opioid-related mortality. That is, some observables generate different trends for treated and control groups, leading to bias in the standard DiD estimation.

To address this treatment selection issue, we follow Moser and Voena (2012) and augment the standard DiD method in two ways. First, it adds the interactions of treatment and year ($Treat \times t$), which allows treated and control groups to have different baseline slopes. Without this term, a pre-existing upward drift in treated states could be misattributed to the treatment. Using these interaction terms, we can compare the deviation from each group's own baseline trend and measure the treatment effects caused by must-access PDMPs. Second, it includes the interaction of time trend ($f(t)$) and the pre-policy selection variables which can predict the treatment in a state. We follow Li, Lu, and Wang (2016) and use the third-order polynomial function of t as $f(t)$. We choose MMEBase (per-capita Morphine Milligram Equivalent opioids dispensed through retail pharmacies one year before the must-access PDMP) as the selection variable, which is the key determinant of the adoption of state-level PDMP policy (Johnson et al., 2024).[21] This interaction term allows the outcome path to vary systematically with observable pre-policy opioid risk, not just by the treatment status. As a result, the identifying assumption becomes conditional parallel trends: after removing the time-varying influence of pre-policy selection variables and the treated-specific slope, treated and control states would have evolved in parallel. In our data, we verify that there is no statistically significant differences in pre-policy trends between treated and control states, supporting the conditional parallel-trend assumption.

Table IE reports the DID estimates: the coefficient on *PDMPState* × *Post* is significantly positive ($p < 0.05$), indicating that local insurers in treated states adjust duration upward after the adoption of must-access PDMPs.

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[21] MME stands for Morphine Milligram Equivalents. It's a potency-standardized dose metric: different opioids are converted to the amount of morphine that would provide an equivalent effect. We include following strong types of opioid: fentanyl, hydromorphone, levorphanol, oxycodone, and oxymorphone (Cornaggia et al., 2022). The data on opioid prescription and distribution are from https://www.slcg.com.

Table IE: Difference-in-differences analysis with must-access PDMPs

This table presents the difference-in-differences results around the implementation of must-access Prescription Drug Monitoring Programs (PDMPs) in some states, using the DiD methodology of Moser and Voena (2012) and Li, Lu, and Wang (2016). A state is "treated" (a dummy *PDMPState* = 1) after implementing a PDMP with a must-access provision. The control group comprises states without PDMPs or without a must-access provision. *Post* indicates the first year after adopting PDMPs with a must-access provision or later years. MMEBase is the per-capita morphine-milligram-equivalent opioids dispensed through retail pharmacies one year before the must-access PDMP. t is the calendar year. See Appendix A for variable definitions. Standard errors, clustered by state, are in parentheses. The sample period is from 1999 to 2019. $^{*}p<0.10$, $^{**}p<0.05$, and $^{***}p<0.01$.

PDMPState × Post	0.214^{**}
	(0.094)
PDMPState $\times t$	-0.010
	(0.009)
MMEBase $\times t$	-0.000
	(0.000)
MMEBase $\times t^2$	-0.000
	(0.000)
MMEBase $\times t^3$	0.000^{*}
	(0.000)
t	0.031^{**}
	(0.015)
t^2	-0.004^{**}
	(0.002)
t^3	-0.000^{**}
	(0.000)
ΔTreasury1Y	-0.123^{***}
	(0.027)
TermSpread	0.004
	(0.020)
CreditSpread	0.077
	(0.052)
CPIGrowth	-0.063^{*}
	(0.032)
GDPGrowth	0.161^{***}
	(0.036)
StateGDPGrowth	1.851
	(1.861)
StatePopGrowth	-12.185^{**}
	(5.506)

Table IE: Continued

Ln(InsAssets)	-0.007
	(0.037)
InsLeverage	-0.307
	(0.214)
RBCRatio	-0.002***
	(0.001)
InsROA	-0.594
	(0.724)
NPWGrowth	0.025
	(0.016)
Constant	0.092
	(0.238)
Observations	5378
R-squared	0.074