Duration-Hedging Trades, Return Momentum and Reversal

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Abstract

We study the duration-hedging trades of duration-sensitive strategic investors, i.e., pensions and life insurers. We use longevity shocks to identify their duration-hedging trades. Longevity shocks affect these investors' liability duration and induce them to adjust their asset duration. When longevity shocks are low (high), they buy more short- (long-) duration stocks and sell more long- (short-) duration stocks. Because prior winners (losers) have shorter (longer) duration, they behave like momentum (contrarian) traders when longevity shocks are low (high). We further verify this channel using capital flows and cross-state longevity variations.

JEL classification: G11, G12, G22, H55, J11, J32

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1. Introduction

Duration risk affects asset prices and portfolio choices (see, e.g., Dechow et al., 2004; Da, 2009; Hasler et al., 2019; Weber, 2018; Chen and Yang, 2019; Gormsen and Lazarus, 2019; Chen, 2020; Gonçalves, 2020b). However, little is known about how investors trade against the duration risk and its price impacts. This paper fills this gap. Specifically, we consider two types of long-term duration-sensitive investors, i.e., pensions and life insurers. We use longevity shocks to identify their duration-hedging trades. Unexpected changes of life expectancy affect their liability duration. Pensions and life insurers adjust their asset duration accordingly to match asset duration with liability duration, which helps maintain long-term solvency and meet regulatory mandates.[1] Such duration-hedging incentive affects their investment. For example, pensions and life insurers' preferences for short- (long-) duration stocks could vary with longevity condition. They tend to buy more short- (long-) duration stocks and sell more long- (short-) duration stocks when longevity decreases (increases). As illustrated in Figure 1, changes in stock duration of pensions follow longevity shocks (with a correlation coefficient of 0.28). Moreover, as shown in Chen and Yang (2019), past winner stocks have shorter duration than past loser stocks (see also Figure 2). This implies that pensions and life insurers tend to buy winners and sell losers when the longevity shocks are low, i.e., they tend to be momentum traders. Similarly, they tend to be contrarian traders when the longevity shocks are high. We find supporting evidence from trading activities and fund flows of pensions and life insurers.

Our main contributions can be summarized in three ways. First, to the best of our knowledge, this is the first paper studying the duration-driven trading activities in stock markets. We provide direct trading evidence to Chen and Yang (2019) that duration risk contributes to return momentum or reversal, depending on the longevity condition. Second, this paper joins the large literature on investment styles of institutional investors , e.g., whether institutional investors are momentum or contrarian traders.[2] We show that pensions

[1]For example, the National Association of Insurance Commissioners requires insurers to manage their duration risk (see, NAIC (2017)).

[2]See, e.g., Lakonishok et al. (1992), Grinblatt et al. (1995), Nofsinger and Sias (1999), Wermers (1999),

and life insurers could follow either momentum or contrarian style, depending on the duration characteristic of stocks and longevity status. Third, examining the holdings of pensions and life insurers, we also offer direct evidence to demonstrate how longevity risk affects portfolio choice and stock prices while is lack in earlier studies.[3]

Pensions and life insurers provide long-term financial solutions for life-related shocks, such as pensions, annuities, and life insurances. Their liabilities and assets are usually long term, which makes them sensitive to duration risk. When discount rates move, the values of these investors' assets and liabilities vary, which may expose them to underfunding problems. To minimize long-term shortfalls, pensions and life insurers must adjust their portfolios so that their asset duration matches their liability duration, which creates duration-hedging trades. Their asset duration depends on the assets they invest in, e.g., stocks and bonds,[4] and is affected by market prices. In this paper, we focus on the equity investment of pensions and life insurers.[5] On the other hand, their liability duration is affected largely by the longevity shocks to participants, i.e., the longevity risk, which is an exogenous shock. Therefore, we use longevity shocks to identify their duration-hedging trades in stock markets.

Longevity risk captures unexpected changes of life expectancy. We measure longevity shocks as the innovations of the weighted average period life expectancy in the U.S. population. Life expectancy in the U.S. increased from 73.27 years in 1951 to 81.82 years in 2017, an average increase of 0.13 years per year, which is substantial. For example, this implies that the claim period of annuity holders increases by 13%. Longevity shock is also volatile,

Griffin et al. (2003), Sias (2004), Gompers and Metrick (2001), Grinblatt and Keloharju (2001), Badrinath and Wahal (2002), Yan and Zhang (2007), Cremers and Pareek (2015), Edelen et al. (2016).

[3]For example, DellaVigna and Pollet (2007), Cocco and Gomes (2012), and Koijen et al. (2016) study the impacts of longevity risk on portfolio choice and sector returns but they don't provide holdings/trading evidence.

[4]Pensions and life insurers invest most of their assets in stocks and bonds. On average, pensions invest 50.5% (33.0%) of assets in equities (bonds) over 1981-2017 while life insurers invest 27.4% (47.8%) of assets in equities (bonds) over 2005-2017. Other invested assets include cash and cash equivalents, loans, etc.

[5]Pensions and life insurers are important players in stock markets. In the U.S., retirement plans invested $7.3 trillion in the equity markets in 2017 (Investment Company Institute, 2018) while life insurers invested $2.2 trillion in common stocks in 2017 (American Council of Life Insurers, 2018). Nevertheless, pensions and life insurers also adjust their bond portfolio according to longevity shocks. For example, Appendix A and Figure A1 show that changes in bond duration of life insurers also track longevity shocks. Chen et al. (2021) study their bond investment.

with an annual standard deviation of 0.16 years. Such volatile longevity shocks affect households' intertemporal consumption and investment decisions, which translate into activities of pensions and life insurers and affect their preference for short- or long-duration stocks.

Motivated by this observation, we examine the quarterly trading activities of pensions and life insurers. We first use the Thomson-Reuters Institutional Holdings (TR-13F) Database to identify pensions over 1981-2017. This is a long sample; however, the classification of pensions may be less accurate. Alternatively, we use the life insurers' data from the National Association of Insurance Commissioners over 2005-2017 as a robustness check.

We show that pensions and life insurers are momentum or contrarian traders in three steps. First, we confirm the momentum effects among stocks held by pensions and life insurers. We show that a momentum strategy strengthens during periods of low longevity shocks but it becomes insignificant during periods of high longevity shocks. Second, conditioning on the longevity status, we identify winner and loser stocks from the holdings of pensions and life insurers, based on the stock durations, the changes of stock durations over a quarter, and the trade size, without reference to historical stock returns. For example, during periods of low longevity shocks, a stock is classified as a winner (loser) stock if its duration and change of duration are below (above) the market median and its net buy (sell) size is above the market median. We use Dechow et al. (2004) duration measure. Then we examine momentum returns among these identified stocks. We find stronger momentum (reversal) among these identified stocks than over the entire universe of stocks. For example, the momentum strategy has an alpha from the Fama-French five-factor model (α_{FF5}) of 2.43% per month (t-statistic = 3.37) when the longevity shock is low. When the longevity shock is high, the contrarian strategy generates an α_{FF5} of 1.11% per month (t-statistic = 2.09). Third, we exclude these identified stocks from the entire stock universe and we find that momentum is no longer significant among the remaining stocks. This validates the success of identifying winners and losers from duration-driven trades. It confirms that pensions and life insurers behave like momentum (contrarian) traders during periods of low (high) longevity shocks.

One might be concerned about whether investors consider equity duration risk in practices, since stock duration is a relatively new concept in the literature and Dechow et al. (2004) measure is not available before the publication. We show that in the Gordon model, stock duration equals the price-dividend ratio. Therefore, an often used variable, the price-dividend ratio, (or, similarly, the dividend yield) contains the duration information. We use the price-dividend ratio as a proxy of duration to identify winners and losers, and find similar (though slightly weaker) results as using Dechow et al. (2004) duration. This suggests that investors implicitly take into account of duration risk when using the price-dividend ratios in practices, even though they might not explicitly use Dechow et al. (2004) measure.

We dig deeply and provide more direct evidence to understand the mechanism underlying our findings, in three ways. First, we study the net capital flows of pensions and show that long-duration stocks attract more capital flows than short-duration stocks when the longevity shock is high. This gives us direct evidence of how household fund flows react to longevity shocks. Second, we show that duration-driven portfolio rebalancing predicts future momentum returns, after controlling for performance-driven flows suggested in Lou (2012). Third, using the identified stocks, we show that pension fund returns positively (negatively) load on the momentum factor when longevity is low (high).

Last, we exploit the cross-sectional variations of longevity shocks at the state level to address the omitted variables and endogeneity concerns. Longevity risks vary across states. We identify local pensions which serve within-state customers only. These pensions are affected by local longevity shocks, but they trade in the same national stock markets where stocks face the same nationwide economic conditions. We show that pensions from states with opposite (e.g., negatively correlated) longevity shocks trade in opposite directions. This verifies that local longevity shocks influence local pensions' trades. It rules out the concern that omitted variables such as business cycles may affect both longevity and pensions' trades. It also rules out the reverse causality that pensions may trade in a manner that anticipates momentum (or reversal), because such a reverse causality suggests that pensions from different states should trade in the same direction.

This paper adds to the recent literature on duration risk. Several papers propose different approaches to estimate stock durations and discuss their asset-pricing implications (see, e.g., Dechow et al., 2004; Da, 2009; Weber, 2018; Gormsen and Lazarus, 2019; Chen, 2020; Gonçalves, 2020a). Some papers study the impacts of duration-hedging demand. For example, Greenwood and Vayanos (2010) find that pensions' demand for duration hedging affects the term structure of British gilts. Klinger and Sundaresan (2019) show that demand for duration hedging from underfunded defined benefit pension plans drives negative swap spreads. Chen et al. (2021) study the duration-driven trades of pensions and life insurers in corporate bond markets. This paper studies the impacts of duration-driven trading activities on cross-sectional stock return variations.

This paper relates to the literature on the asset-pricing implications of longevity risk and the life-related products. Pensions, annuities, and life insurances are important parts of household portfolios and significantly affect securities markets (Chalmers and Reuter, 2012; Previtero, 2014; Sialm et al., 2015a,b; Da et al., 2018).[6] At the aggregate level, Bisetti et al. (2017) and Chen and Yang (2019) show that longevity risk is a systemic risk. Specifically, Chen and Yang (2019) model longevity risk as time preferences shocks in a consumption-based model. They show that longevity risk is negatively priced among lots of test portfolios and it helps explain momentum profits.[7] Our paper complements their results in three important ways: (1) We offer trading evidence of duration-sensitive investors (pensions and life insurers) and study how duration-hedging trades contribute to return momentum or reversals. (3) We provide further evidence on how capital flows to short- and long-duration stocks when longevity changes. (3) This paper demonstrates how longevity risk influences stock holdings of institutional investors. These are not examined by Chen and Yang (2019).

Furthermore, this paper also contributes to the literature on investment styles of institutional investors and their price impacts. Prior studies find some mild or somewhat conflicting evidence that institutions follow momentum or contrarian trading.[8] For exam-

[6]Also, see Madrian and Shea (2001), Benartzi and Thaler (2001), Agnew et al. (2003), Huberman and Jiang (2006), Cohen and Schmidt (2009), and Christoffersen and Simutin (2017) for more discussions of pension plan structure and the behavior of pension participants and pension funds.

[7]See, e.g., Bali et al. (2016), Daniel and Moskowitz (2016), and Ehsani and Linnainmaa (2021) for recent discussions on momentum literature.

[8]See Vayanos and Woolley (2013) for theoretical discussions.

ple, Grinblatt et al. (1995), Nofsinger and Sias (1999), Wermers (1999), Griffin et al. (2003), Grinblatt and Keloharju (2001), Sias (2004), Yan and Zhang (2007), and Edelen et al. (2016) show momentum or interperiod momentum trading among institutional investors. However, Lakonishok et al. (1992) and Gompers and Metrick (2001) find little evidence of momentum trading among pension funds and other institutional investors. Badrinath and Wahal (2002) show that institutions behave as momentum traders when entering stocks but as contrarian traders when existing or rebalancing stocks. More related to our work, Cremers and Pareek (2015) find that momentum become stronger among stocks held by short holding-horizon of institutional investors. Our paper adds to the literature in two ways. First, we show that duration is an important stock characteristic affecting investment styles of pensions and life insurers. This follows the spirit of Daniel et al. (1997), emphasizing the importance of stock characteristics. Second, we show that pensions and life insurers can behave as momentum or contrarian traders and their investment styles vary with the longevity condition. This potentially solves the mixed findings in the literature.

The rest of the paper proceeds as follows. Section 2 discusses the data sources and main measures. Section 3 presents the main results, showing that pensions are momentum or contrarian traders. Section 4 provides robustness checks, using the price-dividend ratio as a proxy of stock duration or using life insurers data. Section 5 investigates the economic mechanism by examining the fund flows and trading activities of pensions. Section 6 addresses the omitted variables and endogeneity concerns. Finally, Section 7 concludes.

2. Data and measures

2.1. Data

2.1.1. Pension data

Quarterly pension-holdings data are obtained from the Thomson-Reuters Institutional Holdings (TR-13F) Database. This dataset contains ownership information about the securities holdings and transactions by all institutional managers with investment discretion over $100 million or more, but it does not include international equity holdings, bond holdings, or other various derivatives. To extract pension-holdings information from the TR-13F, we apply the institutional investor classification (IIclass) proposed by Brian Bushee.[9] The IIclass classifies institutional investors according to their legal types. We select two manager types which are related to pensions, i.e., public pension funds (PPS) and corporate pension funds (CPS). The sample period for pension holdings is 1981-2017.[10]

2.1.2. Stock prices and financial data

Stock prices and other financial data are obtained from the CRSP and Compustat. Penny stocks traded below $1 are excluded from the sample, to avoid potential microstructure noise. For each equity holding, the historical identifier (CUSIP) is mapped to its permanent security identifier (PERMNO in CRSP). Trades can occur at any time during a quarter, but because we are limited to quarterly data, we assume that pension funds trade only at the end of each quarter. Thus we use vintage dates from the corresponding quarter-end to adjust for stock splits and other distribution events.

2.1.3. Mortality Data

The annual US data of population and exposure are obtained from the Human Mortality Database (HMD).[11] We use HMD to estimate longevity risk. The sample period is from 1951 to 2017.

[9] The Thomson-Reuters dataset classifies institutions into five types, namely (1) banks, (2) insurance companies, (3) investment companies, (4) independent investment advisors, and (5) all others. This classification does not distinguish pension funds from other institutions. Also, this classification is not reliable after 1998. Therefore, we use the IIclass instead of the Thomson-Reuters classifications. The IIclass is available at `https://accounting-faculty.wharton.upenn.edu/bushee/`.

[10] TR-13F data start from 1980Q1. However, the IIclass starts from 1981, and the mortality data that are discussed in Subsection 2.1.3 are available until the year 2017. As a result, the merged data are over 1981Q1-2017Q4.

[11] Available at `https://usa.mortality.org`. In the HMD database, exposure, i.e., the population exposure-to-risk of death during certain age-time interval, is based on annual population estimates with some corrections (see Andreeva (2019) for more details).

2.2. Measures

2.2.1. Stock durations

We compute the Macaulay duration for stocks, following Dechow et al. (2004), Weber (2018), and Chen and Yang (2019). Dechow et al. (2004) assume that one can forecast the stream of cash flows up to horizon J, and that the remaining cash flows beyond J will be a perpetuity. The duration is computed as follows:

$$Dur = \frac{\sum_{j=1}^{J} j \cdot CF_j/(1+R)^j}{P_0} + \left(J + \frac{1+R}{R}\right) \cdot \frac{\sum_{j=J+1}^{\infty} CF_j/(1+R)^j}{P_0}, \tag{1}$$

where P_0 is the market equity at time 0, CF_j is the net cash flow to equity holders at time j, and R is the discount rate. Cash flows are computed from earnings and changes of book equity, i.e., $CF_j = \text{Earnings}_j + \text{Book equity}_{j-1} - \text{Book equity}_j$. Earnings are computed from the book equity and the return on equity (ROE). Dechow et al. (2004) assume that book equity grows at the rate of sales growth (SGR). They further assume that SGR and ROE follow two separate first-order autoregressive processes (AR(1)). These processes are assumed to converge to a long-run mean of 6% for SGR and 12% for ROE. The estimated AR(1) coefficients are 0.21 and 0.56 for SGR and ROE, respectively. Dechow et al. (2004) also assume a constant discount rate for all stocks, i.e., 12% per year.[12] The duration estimates are then matched with the stock price data, assuming a one-quarter reporting lag.

2.2.2. Longevity risk

Life expectancy at birth provides a straightforward description of the aging of a population. However, it ignores the life expectancy of older people. In this paper, we use the weighted average of the period life expectancy of different ages as a more comprehensive measure of the longevity risk of a population. In particular, we consider the average life expectancy, E_t, as the average of period life expectancy in year t, weighted by the corresponding

[12] Gonçalves (2020b) improves upon Dechow et al. (2004) by computing the discount rates for each stock from the present value identities. In addition, Gonçalves (2020b) uses a vector autoregressive model of 12 state variables to forecast future cash flows, instead of an AR(1) process.

exposure. More specifically, E_t is computed as follows:

$$E_t = \frac{\sum_{x=0}^{99}(x + e_{x,t})E_{x,t}}{\sum_{x=0}^{99} E_{x,t}}, \tag{2}$$

where $e_{x,t}$ is the period remaining life expectancy for a person aged x in year t, and $E_{x,t}$ is the corresponding exposure. We restrict the age range to 0-99 years, as the data for age 100 and beyond are not reliable.

We measure longevity risk as changes of the weighted average period life expectancy, i.e., the first-order difference of E_t, as follows:

$$\Delta E_t = E_t - E_{t-1}. \tag{3}$$

ΔE_t provides a comprehensive, model-free measure of longevity risk, which captures the longevity shocks across all ages over time.[13] We consider different longevity risk conditions over the sample. In particular, *High Longevity Shock* refers to the periods when ΔE_t is greater than the sample median. That is, the longevity shock is greater than the sample median. Similarly, *Low Longevity Shock* refers to the periods when ΔE_t is less than the sample median. We use the sample median as the reference point to control for the average longevity shocks, as longevity has a time trend. The sample median is estimated from a 30-year rolling window. We also use the full-sample median as a robustness check of the main results and report the results in Appendix B.

[13]Alternatively, longevity risk can be measured using the Lee-Carter model (Lee and Carter, 1992), which is a linear extrapolation model for mortality forecast. Our results remain unchanged if we use the mortality index estimates from the Lee-Carter model. We choose the weighted period life expectancy as our longevity measure, due to its ease of interpretation.

3. Main results

3.1. *Descriptive statistics*

Table 1 presents summary statistics of stocks and the longevity risk. Panel A summarizes longevity risk, ΔE_t. ΔE_t has a mean of 0.13 years and a standard deviation of 0.16 years. Moreover, ΔE_t has a positive mean, indicating that life expectancy has increased over the past decades. Unit root tests indicate that E_t follows a random walk process and that ΔE_t is stationary.[14] Moreover, ΔE_t is negatively correlated with the momentum factor, with a correlation of -0.32. This suggests that momentum profits are high (low) when mortality (longevity) risk is high.

Panels B and C display the characteristics of the winner and loser stocks, including monthly returns and durations. Winners and losers are from the top and bottom 10% performers over the past 11 months, with a one-month lag, respectively. To investigate the time-varying momentum profits, we further split the sample into periods of low and high longevity shocks, based on the longevity risk level. We see that winners have shorter durations than losers (the duration difference is about 2.4 years). Comparing these two periods, we find that momentum profits are low when the longevity shock is high. For example, the average monthly return of the winners during the period of low longevity shocks is 1.33% higher than that of the losers. However, when the longevity shock is high, losers have slightly higher average returns than winners. This is because losers have longer durations and are preferred by investors faced with higher longevity shocks. In other words, losers (winners) provide hedging against longevity (mortality) risks.

[14] In particular, the Augmented Dickey-Fuller (ADF) test for E_t has a p-value of 0.6325, and this result is confirmed by another stationary test (the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test), which has a p-value less than 0.01. The ADF test for ΔE_t has a p-value less than 0.01, and the p-value for the KPSS test is greater than 0.1.

3.2. *Momentum returns and pensions trading activities*

As winners have shorter durations than losers, when the longevity shock is low, pensions adjust their portfolio durations by buying winners (and/or selling losers), i.e., they are momentum traders. In contrast, when the longevity shock is high, pensions adjust their portfolio durations by buying losers (and/or selling winners), i.e., they are contrarian traders. In this subsection, we first replicate the momentum returns. Then, we show that pensions are momentum (contrarian) traders when the longevity shock is low (high).

3.2.1. *Replicating momentum returns*

We start by replicating momentum returns over the stocks held by pensions. At the beginning of month t, we sort stocks based on their cumulative returns over month $t-12$ to month $t-2$. Following the literature (e.g., Jegadeesh and Titman, 1993, 2001; Daniel and Moskowitz, 2016), we skip one month between portfolio formation and the holding period. All stocks are sorted into ten decile portfolios, with portfolio 1 being the losers and portfolio 10 the winners. We compute the value-weighted portfolio returns and rebalance the portfolios every month. Table 2 reports the average portfolio returns and alphas from various asset-pricing models for 10 momentum portfolios, namely, the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model.

We observe strong momentum over the entire sample in Panel A, as documented in the literature. The winner portfolio has an average return of 1.51% per month (t-statistic = 4.24), while the loser portfolio has an average monthly return of 0.51% per month (t-statistic = 1.14). The momentum strategy (W-L) has a monthly average return of 1.00% (t-statistic = 2.43) and an annual Sharpe ratio of 0.41. The Fama-French five-factor alpha (α_{FF5}) for the winners is 0.77% per month (t-statistic = 3.35), and the α_{FF5} for the losers is -0.39 (t-statistic = -1.12) per month, while W-L has an α_{FF5} of 1.16% per month (t-statistic = 2.17). The momentum strategy has significant alphas in the CAPM and the Fama-French three-factor model, but it is insignificant in the Carhart four-factor model and the Fama-French six-factor model, i.e., $\alpha_{Carhart} = 0.13\%$ (t-statistic = 0.70) and $\alpha_{FF6} = 0.16\%$ (t-statistic = 0.74), because these two models include a momentum factor.

If momentum returns are associated with duration hedging, we would expect momentum returns to vary with the longevity conditions. For example, winners (losers) should become more (less) attractive when the longevity shock is low, as winners (losers) have shorter (longer) durations. Therefore, momentum should strengthen during periods of low longevity shocks. Similarly, momentum should weaken during periods of high longevity shocks. We test this implication in Panels B and C. Turning to the *Low Longevity Shock* period in Panel B, we see that the differences between the winners' and losers' returns become larger and more significant. For example, the momentum strategy has an average monthly return of 1.6% per month (t-statistic = 3.46). Similarly, the alphas of the CAPM, and the Fama-French three- and five-factor models become larger, compared to the entire sample case. For example, W-L has an α_{FF5} of 1.77% per month (t-statistic = 2.80). These results suggest that duration-driven trades may contribute to the momentum returns. That is, when longevity shock is low, the momentum returns increase, because investors buy winners and sell losers to decrease their portfolio durations.

In the *High Longevity Shock* period in Panel C, the average returns and alphas decrease in magnitude and become insignificant (or significantly negative). Winners no longer outperform losers. Instead, the average return for losers (1.64% per month, t-statistic = 2.01) is slightly higher than that for winners (1.62% per month, t-statistic = 3.24), resulting in a negative W-L return of -0.02% per month (t-statistic = -0.03). Similarly, the alpha for the Fama-French five-factor model is -0.34% per month (t-statistic = -0.6). These results indicate that when the longevity shock is high, momentum is no longer profitable, because investors want to increase their portfolio durations by buying long-duration stocks (losers) and selling short-duration stocks (winners). This finding is similar to the momentum crashes documented by Daniel and Moskowitz (2016).

3.2.2. Duration-driven trades of pensions

In this subsection, we investigate the duration hedging-driven trading activities of pensions. We are interested in identifying winners and losers from the duration-driven trades of pensions.[15] As losers generally have longer durations than winners, investors tend to buy losers and sell winners when the longevity shock increases, and *vice versa* when the longevity shock decreases. More specifically, we compare the duration of stock i, the change of its duration over the last quarter, and the trades of stock i by pensions with those of market medians, under both high and low longevity shock conditions. We use both the level and the change of stock duration to measure stock i's duration in absolute and relative manners. We compare them with the corresponding market median to control for the aggregate market movements. For example, when the longevity shock is high, if stock i has a longer duration, and a larger increase in duration over the last quarter, and pensions buy greater shares of stock i than that of the market median, then stock i belongs to the loser group. To summarize, we identify potential winners and losers when the longevity shock is high or low, as follows:

- *High Longevity Shock*
  - Buy losers: $Dur_{it} > Dur_t$ and $\Delta Dur_{it} > \Delta Dur_t$ and $Trade_{it} > Trade_t$,
  - Sell winners: $Dur_{it} < Dur_t$ and $\Delta Dur_{it} < \Delta Dur_t$ and $Trade_{it} < Trade_t$,
- *Low Longevity Shock*
  - Sell losers: $Dur_{it} > Dur_t$ and $\Delta Dur_{it} > \Delta Dur_t$ and $Trade_{it} < Trade_t$,
  - Buy winners: $Dur_{it} < Dur_t$ and $\Delta Dur_{it} < \Delta Dur_t$ and $Trade_{it} > Trade_t$,

where i indicates stock i traded by pension funds; and $Dur_t, \Delta Dur_t$, and $Trade_t$ are the market medians of duration, the change of duration, and the trade size in quarter t, respectively. The trade size is defined as the change of shares divided by the number of shares outstanding at the end of the previous quarter. Importantly, we use the longevity condition,

[15] Cremers and Pareek (2015) consider a related measure, i.e., the holding horizon of institutional investors, which is different from asset duration studied in this paper.

duration and pension trades available at time t to identify winners and losers, but we don't use the previous stock return information as in Jegadeesh and Titman (1993).

Due to duration hedging, pensions would behave like momentum traders when the longevity shock is low and contrarian traders when the longevity shock is high. If we can successfully identify winners and losers from the duration-driven trades of pensions, then we would expect to observe even stronger momentum (reversal) among this subset of identified stocks when the longevity shock is low (high), compared with the whole stock universe.

Table 3 presents the momentum returns, using the subset of winners and losers identified from duration-driven trades (the average number of stocks in a month is 602). Panel A displays the momentum returns over the low longevity shock period, using winner and loser stocks identified from pensions' trades. We observe stronger momentum returns during this period. The average return of the momentum strategy (W-L) portfolio is 2.3% per month (t-statistic = 3.88), 0.7% higher than that of the entire pension stock universe over the low longevity shock period (reported in Panel B of Table 2). The alphas from all five models are larger and become more statistically significant. The momentum strategy (W-L) generates a higher annual Sharpe ratio of 0.78, compared to a Sharpe ratio of 0.63 for the entire pension stock universe over the low longevity shock period. Even the alphas from the Carhart and the Fama-French six-factor models are significantly positive during this period ($\alpha_{Carhart}$ = 1.03%, t-statistic = 3.01; α_{FF6} = 1.03%, t-statistic = 2.79), while for the entire pension stock universe, they are not statistically significant. These results confirm our prediction that when the longevity shock is low, pensions buy short-duration stocks (i.e., winners) and sell long-duration stocks (i.e., losers), to decrease their portfolio durations. Therefore, pensions appear to be momentum traders during the low longevity shock period.[16]

Examining the high longevity shock period in Panel B, we see strong reversal as winners underperform losers. The loser portfolio has an average return of 1.96% per month (t-statistic = 2.65), which is 0.71% higher than the average returns of the winner portfolio (1.26% per month). The contrarian strategy (i.e., loser minus winner, L-W) has an average return of

[16] In an analysis of the holding data from German stock markets, Baltzer et al. (2019) also find that mutual funds are momentum traders.

0.71% per month, although this is not statistically significant (t-statistic = 1.11). The annual Sharpe ratio of this contrarian strategy is 0.304. In contrast, the Sharpe ratio of a similar strategy using the entire pension stock universe (Panel C of Table 2) is only -0.011. The Fama-French five-factor alpha (α_{FF5}) of the L-W strategy is 1.11% per month (t-statistic = 2.09). The alphas for the L-W strategy from the Carhart four-factor model and the Fama-French six-factor model are positive and significant, with $\alpha_{Carhart} = 1.02\%$ (t-statistic = 2.77) and $\alpha_{FF6} = 1.21\%$ (t-statistic = 3.35). This result indicates that when the longevity shock is high, pensions buy long-duration stocks (i.e., losers) and sell short-duration stocks (i.e., winners) to increase their portfolio durations. Therefore, pensions appear to be contrarian traders during the high longevity shock period.

Panel C combines the momentum and contrarian strategies over the entire sample. That is, investors take a long (short) position in winners (losers) when the longevity shock is low, but take a long (short) position in losers (winners) when the longevity shock is high. We denote this a "trend-chasing" strategy. This trend-chasing strategy avoids momentum crashes and improves the overall momentum returns. Its annual Sharpe ratio is 0.623, which is higher than the annual Sharpe ratio (0.408) of the simple momentum strategy in Panel A of Table 2. In particular, this strategy has significantly positive average returns and alphas from all five models. Even the alphas from the Carhart four-factor model and the Fama-French six-factor model are positive and significant, with $\alpha_{Carhart} = 1.38\%$ (t-statistic = 2.36) and $\alpha_{FF6} = 1.42\%$ (t-statistic = 2.36), indicating that the trend-chasing strategy improves upon the simple momentum strategy.

To further illustrate this improvement, Figure 3 plots the cumulative returns of the simple momentum strategy and the trend-chasing strategy over 1981-2017. The simple momentum strategy adopts the W-L portfolio, which is long on winners and short on losers. For the trend-chasing strategy, the winners and losers are identified through the stock durations, the change of durations, and the trade sizes of pension funds, and we use the momentum strategy when the longevity shock is low while using the contrarian strategy when the longevity shock is high. Because it avoids momentum crashes, the trend-chasing strategy is superior to the simple momentum strategy. In particular, after the large momentum crash in 2009, the trend-chasing cumulative returns are more than 10 times those of the simple momentum strategy, based on a logarithmic scale.

Our previous analysis shows that we can identify winner and loser stocks based on duration-driven trades, instead of historical stock returns. Next, we remove these winners and losers (which are identified by duration-driven trades) from the whole stock universe and reexamine the momentum strategy over the remaining stocks. We expect momentum to substantially weaken over the remaining stocks if we successfully identify winners and losers. Table 4 reports the results.

Consistent with our prediction, Panel A of Table 4 shows that after we remove the identified stocks, momentum indeed becomes insignificant. For example, the average return of the W-L portfolio is 0.77% per month (t-statistic = 1.37), less than half of the 1.6% reported in Panel A of Table 2. Also, $\alpha_{FF5} = 0.92\%$ per month (t-statistic = 1.26), and becomes insignificant. That is, the momentum strategy becomes unprofitable after we remove the identified stocks.

In the high longevity shock period in Panel B of Table 4 , we see that the average returns and alphas are mostly indistinguishable from zero. For example, comparing these results with the results we obtain before removing the identified stocks (Panel C, Table 2), we see that $\alpha_{FF6} = -0.05\%$ per month (t-statistic = -0.15), which is insignificant. This suggests that both momentum and reversal disappear after we remove the identified stocks. Again, this validates that we can successfully identify winner and loser stocks based on duration-driven trades.

4. Robustness checks: Alternative measure and data

4.1. Alternative measure: Price-dividend ratio

Previous results show that pensions adjust their stock portfolio duration when faced with longevity shocks. But one may be concerned whether pensions consider equity duration risks in practices. For example, although the concept of duration is popular in fixed-income securities, it gains attention in equities only recently. Moreover, our duration measure, Dechow et al. (2004) measure, is not available before the publication. This is a misconception. In fact, a widely used measure, the price-dividend ratio (or, equivalently, the dividend yield) contains the duration information. This can be seen from the Gordon model.

Assuming that dividends grow at a constant rate of g forever and there is a constant discount rate of R, the Gordon model suggests that the stock price at time 0, P_0, is

$$P_0 = \frac{Div_1}{R-g}, \tag{4}$$

where Div_1 is the dividend at time 1. This suggests that the modified stock duration, D, is

$$D = -\frac{\partial lnP_0}{\partial R} = \frac{1}{R-g} = \frac{P_0}{Div_1}. \tag{5}$$

Thus, we see that the modified duration equals the price-dividend ratio, which is the reciprocal of the dividend yield.

Next, we use the price-dividend ratio as a proxy for the stock duration to identify winners and losers, and repeat the analysis in Section 3.2.2. The price-dividend ratio is calculated as stock price divided by dividends distributed in the past twelve months. Only stocks with non-missing price-dividend ratios are included.Table 5 presents the momentum and contrarian returns, using the subset of winners and losers identified by the price-dividend ratios. Panel A shows strong momentum returns during low longevity periods. The average return of the momentum strategy (W-L) portfolio is 1.01% per month (t-statistic = 2.65), with α_{FF5} = 1.17% (t-statistic = 2.71). Panel B shows that losers portfolio outperforms winners portfolio by 1.20% per month, but it is insignificant. The alphas for the L-W strategy from the Carhart four-factor model and the Fama-French six-factor model are positive and significant, with $\alpha_{Carhart}$ = 1.49% (t-statistic = 2.89) and α_{FF6} = 1.18% (t-statistic = 2.39). Overall, these results are similar to those reported in Table 3, although the magnitudes are smaller. This suggests that the price-dividend ratio captures some duration information, although it may be less accurate than Dechow et al. (2004) duration measure. Therefore, our results are not limited by the availability of Dechow et al. (2004) measure and investors clearly pay attention to the duration risk.

4.2. Alternative data: Evidence from life insurers

4.2.1. Life insurer data

Previously, we use pensions data from the TR-13F data. However, the classification of pensions may be less accurate. In this subsection, we examine the main results with an alternative dataset, i.e., life insurer data. The stock holding and trading data of life insurers are from "Schedule D", provided by the National Association of Insurance Commissioners (NAIC), the regulatory authority of the US insurance industry. One shortcoming is that we are unable to differentiate annuities and life insurances in "Schedule D" data. In fact, because annuities and life insurances naturally offset each other in terms of duration risk, life insurers' duration-hedging demand could be weakened. Therefore, this possible natural hedging scenario increases the hurdle of our robustness checks. The data in Schedule D are retrieved from SNL Financial. The sample period is from 2005Q1 to 2017Q4.

Using the end-of-year stock holdings and date-stamped trades, we calculate direct stock positions at the end of each quarter for each life insurer. That is, stock holding at the end of a given quarter of year t equals the reported shares of the stock holding at the end of year $t-1$, plus the shares of stocks purchased from the beginning of year t to the end of the given quarter, minus stocks sold during the same period. In addition, as life insurers often hold some mutual funds, they indirectly hold some stocks via these mutual funds. Therefore, we merge the mutual fund holdings data from the Thomson-Reuters Mutual Fund Holdings Database with the NAIC data to compute the aggregate stock holdings of life insurers. Specifically, we merge these two datasets based on the mutual fund names.

4.2.2. Duration-driven trades of life insurers

As we do for pensions, we identify winner and loser stocks from the trading activities of life insurers. The average number of stocks in a month is 663. Table 6 summarizes the duration-driven trades of life insurers. Panel A computes momentum returns over the low longevity shock period while Panel B computes contrarian returns over the high longevity shock period. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. When the longevity shock is low, the identified winners significantly outperform the losers. For example, the average return of the W-L portfolio is 1.78% per month (t-statistic = 2.68) and its α_{FF5} is 1.45% per month (t-statistic = 2.42). In contrast, during high longevity shock periods, identified losers significantly outperform winners. For example, the L-W portfolio has an α_{FF5} of 2.24% per month (t-statistic = 2.15).

Panel C (D) computes momentum returns over the low (high) longevity shock period, after excluding winners and losers identified from life insurers' trades. Similar to the findings from our analysis of pension data, momentum returns are insignificant after we remove these stocks. In the low longevity shock period (Panel C), it can be seen that average returns and alphas from all models are small in magnitude and statistically insignificant. For example, the average return of the W-L portfolio is 0.72 per month (t-statistic = 1.07), and its α_{FF5} is 0.57% per month (t-statistic = 1.07). In the high longevity shock period (Panel D), we see that alphas and average returns are also insignificant.

To summarize, using life insurers' data, we find results similar to those we find with pensions data. As pensions data have a longer period of time, we use these data for the main analyses.

5. Inspecting the mechanism

Above we show that pensions and life insurers are motivated by duration-hedging demand, and therefore trade winners and losers as momentum (contrarian) traders when the longevity shock is low (high), because winners have shorter durations than losers. In this section, we further explore the underlying mechanism.

Pensions might trade because of capital flows or portfolio rebalancing purposes. First, in Section 5.1, we examine how pensions' trades motivated by capital flows can incorporate the duration-hedging purposes. It is well documented that capital flows affect fund performances and asset prices (Gruber, 1996; Zheng, 1999; Sapp and Tiwari, 2004; Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012; Asness et al., 2013). Similarly, we expect that duration-driven capital flows should generate trades and affect stock prices. We analyze the impacts of net capital flows to pensions and show that more funds flow to long-duration stocks when the longevity shock is high. This is direct evidence of how household fund flows react to longevity shocks. Second, pensions may rebalance their portfolios to address the duration concerns. In Section 5.2, we show that duration-driven portfolio rebalancing predicts future momentum returns. Last, if pensions behave like momentum (contrarian) traders when longevity shocks are low (high), then we expect pension fund returns have positive (negative) exposures to the momentum factor when longevity shocks are low (high). We test this prediction in Section 5.3.

5.1. Capital flows and pensions' trades

We investigate how capital flows to pensions affect their trades of short- (long-) duration stocks for duration-hedging purposes. We expect that when the longevity shock is high, more capital will flow to long-duration stocks than to short-duration stocks, and *vice versa* when the longevity shock is low. We examine this hypothesis in this subsection.

First we define pension fund flows. Fund flows for mutual funds are commonly defined as the net growth in fund assets beyond reinvested dividends, which are typically computed from fund returns and total net assets (see, e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lou, 2012).[17] However, as the TR-13F data comprise holding information

[17]Specifically, the net flows to fund i at time t are calculated as $\frac{TNA_{i,t}-TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net assets of fund i at the end of quarter t, and $R_{i,t}$ is the fund return over the period.

of pensions but not information on capital gains, income distributions, or fund returns, we cannot compute fund flows in this way. Instead, we compute net capital flows to a pension fund based on some simplified assumptions.

Let $\theta_{i,j,t}$ be the number of shares of stock j held by fund i at the end of quarter t; $P_{j,t}$ be the price of stock j at the end of quarter t; and J_i be the total number of stocks in this fund. Changes in pension holdings from quarter $t-1$ to t are due to portfolio rebalancing and/or net capital flows in/out of the fund. Assume that fund i is rebalanced immediately after $t-1$. Let $\theta^*_{i,j,t-1}$ be the number of shares of stock j held by fund i after portfolio rebalancing. As portfolio rebalancing incurs zero costs, we have

$$\sum_{j=1}^{J_i} \theta_{i,j,t-1} P_{j,t-1} = \sum_{j=1}^{J_i} \theta^*_{i,j,t-1} P_{j,t-1}. \tag{6}$$

We also assume that immediately after portfolio rebalancing, there is a net capital flow of a total dollar amount of $X_{i,t}$ to fund i, which affects the portfolio holdings proportionally.[18] That is, pension funds proportionally adjust (expand or liquidate) their existing holdings of stocks, based on a transaction price $P_{j,t-1}$ for stock j, and the number of shares of stock j held by fund i becomes $\theta_{i,j,t}$.[19] As portfolio rebalancing incurs zero net costs, the dollar amount of capital flow during quarter t is

$$X_{i,t} = \sum_{j=1}^{J_i} \theta_{i,j,t} P_{j,t-1} - \sum_{j=1}^{J_i} \theta_{i,j,t-1} P_{j,t-1}. \tag{7}$$

The net flows to fund i in quarter t ($flow_{i,t}$) are thus defined as the total dollar amount of

[18] $X_{i,t}$ can be positive (net inflows) or negative (net outflows).

[19] This is largely reasonable; however, as Lou (2012) notes, fund managers may deviate from existing holdings in some situations, due to liquidity and other constraints.

net capital flows scaled by the total net asset before the capital flows.[20] That is,

$$flow_{i,t} = \frac{X_{i,t}}{TNA_{i,t-1}} = \frac{\sum_{j=1}^{J_i}(\theta_{i,j,t} - \theta_{i,j,t-1})P_{j,t-1}}{\sum_{j=1}^{J_i}\theta_{i,j,t-1}P_{j,t-1}}. \tag{8}$$

Next, we compute the holdings of pension fund i after portfolio rebalancing. As fund i proportionally adjusts its holdings after the capital flows, its holding of stock j after portfolio rebalancing but before capital flows is

$$\theta^*_{i,j,t-1} = \frac{\theta_{i,j,t}}{1 + flow_{i,t}} = \theta_{i,j,t}\frac{\sum_{j=1}^{J_i}\theta_{i,j,t-1}P_{j,t-1}}{\sum_{j=1}^{J_i}\theta_{i,j,t}P_{j,t-1}}. \tag{9}$$

Finally, we run regressions to investigate the trading behavior of pensions in response to capital flows under different longevity conditions. The dependent variable is the percentage change of shares, $PCS_{i,j,t}$, which measures the trades of stock j by fund i in quarter t due to net capital flows. $PCS_{i,j,t}$ is calculated as changes in the number of shares of stock j held by pension fund i after net capital flows (i.e., $\theta_{i,j,t} - \theta^*_{i,j,t-1}$), scaled by its holding at the beginning of quarter t, and adjusted for stock splits (Lou, 2012). The key variable of interest is pension fund flows, $flow_{i,t}$, as defined in Eq. (8). We use a dummy variable to indicate high longevity shock periods, $\mathbb{I}^{\text{High}}_{\text{Longevity},t}$, which equals 1 if the longevity shock is higher than the median of a 30-year rolling window, and 0 otherwise. We use a dummy variable to indicate long-duration stocks, $\mathbb{I}^{\text{Long}}_{\text{Dur},j,t}$, which equals 1 if stock j is classified as a long-duration stock (i.e., if its duration and changes in duration are greater than the sample median), and 0 otherwise. To summarize, the model is as follows:

$$\begin{aligned} PCS_{i,j,t} = & [\alpha_0 + \mathbb{I}^{\text{Long}}_{\text{Dur},j,t}(\alpha_D + \alpha_L \mathbb{I}^{\text{High}}_{\text{Longevity},t})] + [\beta_0 + \beta_L \mathbb{I}^{\text{High}}_{\text{Longevity},t} \\ & + \beta_D \mathbb{I}^{\text{Long}}_{\text{Dur},j,t} + \beta_{L,D}\mathbb{I}^{\text{High}}_{\text{Longevity},t}\mathbb{I}^{\text{Long}}_{\text{Dur},j,t}] flow_{i,t} + \gamma Controls + \varepsilon_{i,j,t}. \end{aligned} \tag{10}$$

Following Lou (2012), we perform panel ordinary least square regressions with quarter fixed

[20] To validate our capital flow measure, we apply our approach to the mutual fund holdings data and compare our approach with the standard approach (e.g., Lou (2012)). We find these two capital flow measures have a correlation coefficient of 0.7. See more details in Appendix C.

effects, and the robust standard errors are clustered at the pension fund level. All of the continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

Table 7 presents the results. It can be seen that $\beta_{L,D} = 0.0851$ and is significant in Model (1). This result confirms our hypothesis that during high longevity shock periods, the increase of shares in long-duration stocks is more sensitive to capital inflows than that of short-duration stocks. For example, we see that one standard deviation increase in net capital flows leads to 0.44 standard deviations increase in the purchase of stocks in general while 0.72 standard deviations increase in the purchase of long-duration stocks when longevity is high. In Model (2) of Table 7, we further control for fund ownership, $Ownership_{i,j,t}$, which is defined as the percentage of outstanding shares of stock j that are held by fund i at the end of quarter t. We see similar results as those for Model (1).

In untabulated results, we replace $PCS_{i,j,t}$ with the changes in the number of shares of stock j held by pension fund i (i.e., $\theta_{i,j,t} - \theta_{i,j,t-1}$) in Eq. (10) and run similar regressions. We find the coefficient of the triple interaction term ($\mathbb{I}^{\text{High}}_{\text{Longevity},t}\mathbb{I}^{\text{Long}}_{\text{Dur},j,t}flow_{i,t}$) is still positive and significant. This indicates that pensions are more likely to purchase stocks of longer duration when there is a positive longevity shock, providing direct evidence that pensions adjust the duration of their stock investment according to longevity shocks. This result also provides trading evidence for the positive correlation between their stock portfolio duration and longevity risk, as shown in Figure 1.

5.2. *Portfolio rebalancing and return momentum*

In this subsection, we study how duration-hedging affects portfolio rebalancing and its price impacts. To do so, we need to calculate the flows in or out of short- and long-duration stocks within pension fund i due to portfolio rebalancing.[21] First, we compute the flows to stock j due to portfolio rebalancing, as $P_{j,t-1}(\theta^*_{i,j,t-1} - \theta_{i,j,t-1})$. Second, we split the holdings of pension fund i in quarter t into two groups: short-duration stocks and long-duration

[21] As we assume that net capital flows affect pension holdings proportionally, net capital flows to short- and long-duration stocks have similar effects as fund flows due to portfolio rebalancing.

stocks. Then we calculate the flows to short-duration and long-duration stock holdings due to portfolio rebalancing as follows:

$$flow_{i,t}^{short,rebalance} = \frac{\sum_j^{\text{short-duration stocks}} P_{j,t-1}(\theta^*_{i,j,t-1} - \theta_{i,j,t-1})}{TNA_{i,t-1}}, \quad (11)$$

$$flow_{i,t}^{long,rebalance} = \frac{\sum_j^{\text{long-duration stocks}} P_{j,t-1}(\theta^*_{i,j,t-1} - \theta_{i,j,t-1})}{TNA_{i,t-1}}, \quad (12)$$

where $flow_{i,t}^{short,rebalance}$ measures the portfolio-rebalancing flows to short-duration stocks in fund i during quarter t, and $flow_{i,t}^{long,rebalance}$ measures the portfolio-rebalancing flows to long-duration stocks of fund i during quarter t.

Figure 4 plots the aggregate annual portfolio-rebalancing flows to short- (long-) duration stocks and longevity risk. To compute aggregate portfolio-rebalancing flows, we aggregate all of the pension funds and treat them as a single giant fund. To compute annualized flows, we aggregate the dollar portfolio-rebalancing flows to short-duration (long-duration) stocks over four quarters within a year for this giant fund, and then scale these flows by the total net assets of the giant fund at the beginning of the year. As expected, portfolio-rebalancing flows to long-duration stocks closely follow longevity shocks (a correlation coefficient of 0.26), while portfolio-rebalancing flows to short-duration stocks move in the opposite direction of longevity shocks (a correlation coefficient of -0.16).

Next, we study the price impacts of portfolio-rebalancing flows to short- (long-) duration stocks. Lou (2012) proposes a flow-based explanation for stock price momentum. Specifically, past winning funds invest capital inflows in past winners, while past losing funds liquidate past losers, which generates momentum. He shows that the trade induced by the performance-chasing fund inflow is an important driver of stock momentum effects. As we show that duration-hedging demand drives fund flows to stocks with long or short durations, similar to Lou (2012), it is natural to ask whether duration-driven fund flows contribute to momentum.

5.2.1. Variable construction

We first construct the expected trade induced by performance-driven inflow for stock j at quarter t, $\mathsf{E}_t[FIT_j]$, following Lou (2012):

$$\mathsf{E}_t[FIT_j] = \frac{\sum_i \theta_{i,j,t} \times \mathsf{E}_t\left[flow_i\right] \times PSF_t}{\sum_i \theta_{i,j,t}}, \tag{13}$$

where $\theta_{i,j,t}$ is the number of shares of stock j held by fund i in quarter t, $\mathsf{E}_t\left[flow_i\right]$ is the expected capital flow to fund i in quarter t conditional on the lagged fund performance,[22] and PSF_t is the partial scaling factor, namely, the sensitivity of trades to fund flows.[23]

In a similar fashion, we construct the trades induced by duration-driven portfolio rebalancing for stock j at quarter t, $DurTrade_{j,t}$, as follows:

$$DurTrade_{j,t} = \frac{\sum_i \theta_{i,j,t} \times \left(flow_{i,t}^{long,rebalance} \times PSF_{j,t}^{long} + flow_{i,t}^{short,rebalance} \times PSF_{j,t}^{short}\right)}{\sum_i \theta_{i,j,t}}, \tag{14}$$

where $flow_{i,t}^{long,rebalance}$ ($flow_{i,t}^{short,rebalance}$) is the fund flows to long- (short-) duration stocks due to portfolio rebalancing, and $PSF_{j,t}^{long}$ and $PSF_{j,t}^{short}$ are the partial scaling factors estimated for $flow_{i,t}^{long,rebalance}$ and $flow_{i,t}^{short,rebalance}$, respectively.[24]

[22] Following Lou (2012), the lagged fund performance is measured as the fund's return in the previous year, and is then market return-adjusted by subtracting the CRSP universe weighted-average return over the same period. Our results remain similar if we use the market-adjusted fund return over the previous two or four quarters.

[23] Similar to Lou (2012), we regress the trading of stocks, namely the percentage change of shares ($PCS_{i,j,t}$) on fund flows ($flow_{i,t}$) in each quarter, and we retain the coefficient of $flow_{i,t}$ as PSF.

[24] We use the following regression model to estimate the corresponding coefficients:

$$\begin{aligned} PCS_{i,j,t} = &\alpha_0 + \beta_1 flow_{i,t}^{long,reblance} + \beta_2 flow_{i,t}^{short,reblance} + \beta_3 \cdot \mathbb{I}_{\text{Dur},j,t}^{\text{Long}} \cdot flow_{i,t}^{long,reblance} \\ &+ \beta_4 \cdot \mathbb{I}_{\text{Dur},j,t}^{\text{Short}} \cdot flow_{i,t}^{short,reblance} + \beta_5 \mathbb{I}_{\text{Dur},j,t}^{\text{Long}} + \beta_6 \mathbb{I}_{\text{Dur},j,t}^{\text{Short}} + \varepsilon_{i,j,t}, \end{aligned}$$

where $PCS_{i,j,t}$ measures the trades of stock j by fund i in quarter t due to portfolio rebalancing, calculated as the change in the number of shares of stock j held by pension fund i due to portfolio rebalancing (i.e., $\theta_{i,j,t-1}^{*} - \theta_{i,j,t-1}$), scaled by the number of shares held by fund i at the beginning of quarter t, and $\mathbb{I}_{\text{Dur},j,t}^{\text{Long}}$ ($\mathbb{I}_{\text{Dur},j,t}^{\text{Short}}$) equals one if stock j's duration and change in duration are greater (less) than the sample median, and zero otherwise. $PSF_{j,t}^{long}$ is calculated as $\beta_1 + \beta_3 \cdot \mathbb{I}_{\text{Dur},j,t}^{\text{Long}}$, and $PSF_{j,t}^{short}$ is calculated as $\beta_2 + \beta_4 \cdot \mathbb{I}_{\text{Dur},j,t}^{\text{Short}}$.

5.2.2. *Regression results*

Similar to Lou (2012), we run the following Fama-MacBeth quarterly regression to examine whether duration-driven trades contribute to momentum returns:

$$ret_{j,t+1:t+3} = \beta_0 + \beta_1\, DurTrade_{j,t} + \beta_2\, \mathsf{E}_t[FIT_j] + \gamma\, Controls + \varepsilon_{j,t+1:t+3}, \qquad (15)$$

where $ret_{j,t+1:t+3}$ is stock j's return over month $t+1$ to $t+3$. Other control variables include the cumulative stock return over month $t-12$ to $t-1$, the one-month stock return in month t, the long-term past returns (defined as the return over month $t-48$ to $t-13$), the book-to-market ratio, the market equity, and the average monthly turnover ratio within the quarter. All of the continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

The regression results are reported in Table 8. Model (1) replicates the main result in Lou (2012), and it can be seen that performance-driven flows contribute to momentum. The coefficient of $\mathsf{E}_t[FIT_j]$ in Model (1) is significantly positive ($\beta_2 = 0.2857$). In Model (2) we use duration-driven trades, $DurTrade$. The coefficient of $DurTrade$ is significantly positive ($\beta_1 = 0.1648$), suggesting that the trades induced by duration-driven portfolio rebalancing contribute to the momentum effects. In Model (3) we further control for $\mathsf{E}_t[FIT_j]$. The coefficients of $DurTrade$ and $\mathsf{E}_t[FIT_j]$ are both significantly positive, suggesting that duration-driven portfolio rebalancing remains an important factor in explaining the momentum effect even after we control for performance-driven fund flows. For example, we see that one standard deviation increase in $DurTrade$ ($\mathsf{E}_t[FIT_j]$) leads to 10% (8%) increase in the quarterly return, relative to its mean. Overall, Table 8 shows the importance of duration-driven trades in shaping momentum returns, which complements the findings of Lou (2012) with pension fund data.

5.3. *Pensions' exposure to the momentum factor*

If pensions adjust their stock holdings according to the longevity risk and become momentum traders during periods of low longevity shocks and contrarian traders during periods of high longevity shocks, we should expect that the pension fund returns on these identified stocks have different exposures to the momentum factor during high and low longevity periods. We run quarterly time-series regressions of pension fund returns on those identified stocks against the momentum factor. We use winners and losers, as identified in Section 3.2.2. We compute fund returns on these identified stocks as the difference between fund returns on losers (winners) and winners (losers) during high (low) longevity periods. Fund returns are adjusted for the net capital flows, as in Section 5.1. We regress fund returns of identified stocks on the quarterly Carhart four factors.

Table 9 reports regression results. Column (1) shows that momentum factor (MOM) is insignificant. That is, fund returns don't have a strong exposure to momentum factor over the whole sample. In Column (2), we differentiate high and low longevity periods by adding a dummy variable, $\mathbb{I}^{\text{High}}_{\text{Longevity}}$, which equals one during periods of high longevity shocks. We include an interaction term of momentum factor and $\mathbb{I}^{\text{High}}_{\text{Longevity}}$ to capture the different exposures of fund returns to the momentum factor during high and low longevity periods. Column (2) shows that pension fund returns have a significantly positive loading (i.e., 0.243) on the momentum factor, whereas the coefficient on the interaction term is significantly negative (i.e., -0.365). These results imply that fund returns on the identified stocks are positively related to the momentum factor when the longevity risk is low, while negatively load on momentum factor when the longevity risk is high, which is consistent with our predictions.

6. Omitted variables and endogeneity concerns

One may wonder whether omitted variables drive our results. How may the impacts of longevity risk be differentiated from those of other economic shocks? For example, business cycles may affect longevity. The reverse causality between longevity risk, pensions' trades, and return momentum may also be possible. For example, pension funds may trade in a way that anticipates and magnifies return momentum, instead of being driven by duration-hedging demand. We address these omitted variables and endogeneity concerns in three steps, as follows.

First, we consider longevity shocks which are orthogonal to business cycles. That is, we apply the Hodrick–Prescott filter to compute the business cycle components of real GDP growth. Then, we regress longevity shocks against the cyclical component of GDP growth and several price-based measures which might capture business cycles, including the term spread, default spread, and aggregate dividend yield. We use the residuals as the orthogonal component of longevity risk and repeat the previous analyses. We find similar results to those described above (see details in Appendix D).

Second, we examine the correlation between longevity shocks and investor sentiment, using sentiment data from Jeffrey Wurgler's website.[25] We find that longevity risk and investment sentiment have a negligible correlation (-0.035). Thus, sentiment is unlikely to drive our results.

Last, as a more stringent test, we tap on the cross-sectional variations of longevity shocks at the state level, and examine their impacts on pensions' trading directions. We use US Mortality Data to estimate the longevity risks in each state. We see a large variation of longevity risk across states. Longevity shocks are positively correlated between some states, but negatively correlated between other states. For example, Ohio and Indiana have the highest correlation of 0.87 while Massachusetts and Alaska have the lowest correlation coefficient of -0.27. We examine the trades of local pensions, i.e., pensions only serve within-state customers. We manually collect the operational information of pension funds to identify local pension funds. Local pensions' trades are affected by local longevity shocks. Meanwhile, these pensions trade stocks in the same national markets where stocks face the same nationwide economic conditions. Given the motivation of duration-driven trades, we expect that pension funds located in states with opposite (e.g., negatively correlated) longevity risks should trade oppositely, as they face opposite longevity shocks. Similarly, pensions in states with similar (e.g., positively correlated) longevity shocks should trade in the same direction.

[25] Available at `http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx`.

We test this prediction in this subsection. This test helps address the omitted variables and endogenous concerns in three ways. First, it takes advantage of the cross-sectional variations of state-level longevity risks to establish a casual link between longevity shocks and pensions' trades. Second, it distances the longevity risk from nationwide economic conditions such as business cycles, as we use local longevity shocks at the state level, while most stocks are affected by nationwide business cycles. Third, it addresses the reverse causality between longevity risk, pensions' trades, and return momentum. If pension funds trade in a manner that anticipates and magnifies return momentum, then pensions from states with negatively correlated local longevity shocks would trade in the same direction, rather than in the opposite directions.

We first test this prediction at the fund level. We compare the trading directions of two funds, by running the following fund-pair regression:

$$\begin{aligned} CounterTrade_{i,j,k,t} =& \alpha_0 + \alpha_t + \beta_1 LongevityCorr_{j,k} + \beta_2 flow_{i,j,t} + \beta_3 flow_{i,k,t} \\ &+ \beta_4 Ownership_{i,j,t} + \beta_5 Ownership_{i,k,t} + \varepsilon_{i,j,k,t}, \end{aligned} \tag{16}$$

where i, j, k, and t represent stock i, fund j, fund k, and quarter t , respectively, and α_0 and α_t represent a constant and quarter t fixed effect, respectively. $CounterTrade_{i,j,k,t}$ is a dummy variable which equals one if fund j and fund k trade stock i in opposite directions. Specifically, it equals one if fund j increases (decreases) its holding of stock i in quarter t and fund k decreases (increases) its holding of stock i in quarter t, and zero otherwise. $LongevityCorr_{j,k}$ captures the correlation of longevity shocks between the states where funds j and k operate. We further control for the net capital flows to funds j and k and their ownership in stock i (as defined in Section 5.1).

Panel A of Table 10 reports the fund-pair regression results. We consider two different measures of $LongevityCorr_{j,k}$. In Column (1), $LongevityCorr_{j,k}$ is measured as the correlation coefficient of longevity risks between the two states where funds j and k operate. This reveals the effect of the longevity correlation on trade directions, based on all of the funds from all of the states. We expect to see $\beta_1 < 0$ in Column (1). That is, funds from states where longevity risks are positively correlated tend to trade in the same directions. In Column (2), $LongevityCorr_{j,k}$ is a dummy that equals one if the longevity risks in two states are negatively correlated, and 0 otherwise. This focuses on funds from negatively correlated states. We expect that $\beta_1 > 0$ in Column (2), as funds from states where longevity risks are negatively correlated tend to trade in opposite directions. The results from Panel A confirm these predictions.

It is possible that these fund-pair regression results may be dominated by a few states with many funds. To address this issue, we run similar regressions at the state level. That is, we aggregate the trades of all local pensions within the same state and treat this as a single giant fund. Let j and k represent state j and state k, respectively. $CounterTrade_{i,j,k,t}$ is a dummy variable which equals one if state j and state k trade stock i in opposite directions. $LongevityCorr_{j,k}$ captures the correlation of longevity shocks between states j and k. Panel B of Table 10 reports the state-pair regression results. Again, we see that at the state level, pensions from two states with negatively correlated longevity shocks trade in opposite directions.

The results in Table 10 thus confirm that local longevity shocks affect local pensions' trades. Moreover, these results rule out the concerns of omitted variables such as economic conditions and reverse causality that pensions may trade in a way anticipating momentum.

7. Conclusion

Duration risk has profound impacts on equity returns and portfolio choice. As households are exposed to longevity shocks, these generate duration-hedging demand among duration-sensitive strategic investors, such as pensions and life insurers. Using longevity risk as an exogenous shock, we find that when faced with an unexpected decrease (increase) in longevity, pensions and life insurers buy more short- (long-) duration stocks and sell more long- (short-) duration stocks, therefore, they are momentum (contrarian) traders. We also provide direct evidence of fund flows to support this conclusion. Specifically, we show that when the longevity shock is high, funds flow more into long-duration stocks than short-duration stocks, and *vice versa* when the longevity shock is low. We address omitted variables and endogeneity concerns by exploiting the cross-sectional variations of longevity risks at the state level. Our results highlight the crucial role of the duration-driven trades of long-term investors in asset pricing and asst allocation.

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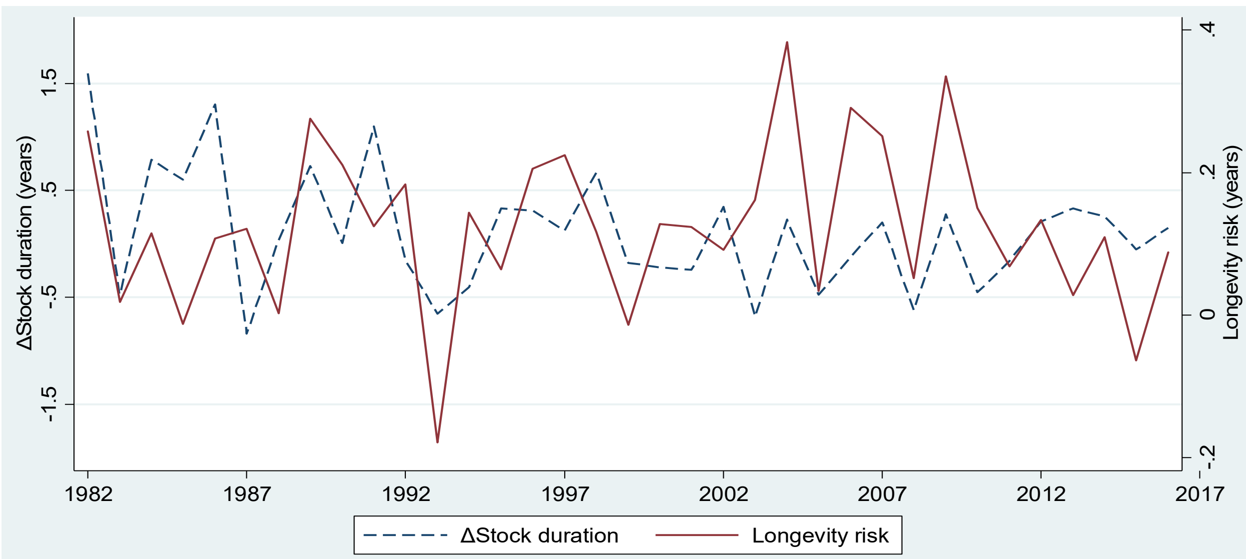

Fig. 1. Changes in stock duration of pensions and longevity risk

This plot shows the changes in duration of pensions' stock holdings (the blue dashed line), together with longevity risk (the red solid line). Longevity risk is measured as the first-order difference of the weighted average period life expectancy.

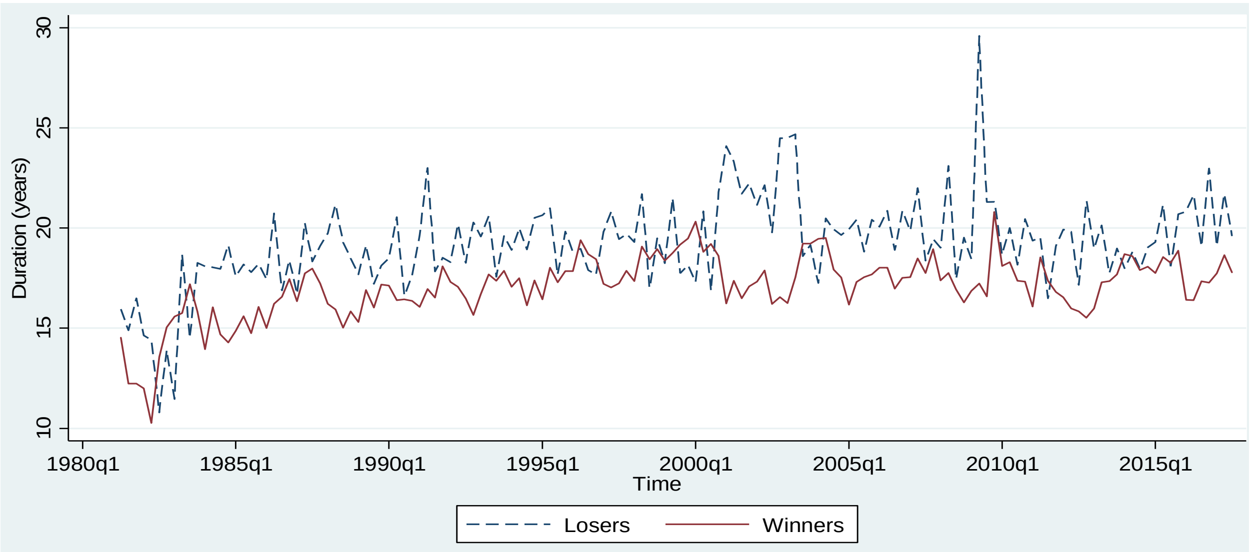

Fig. 2. Durations of winners and losers

This plot shows the durations of winners (red solid line) and losers (blue dashed line) over 1981-2017, which are estimated quarterly .

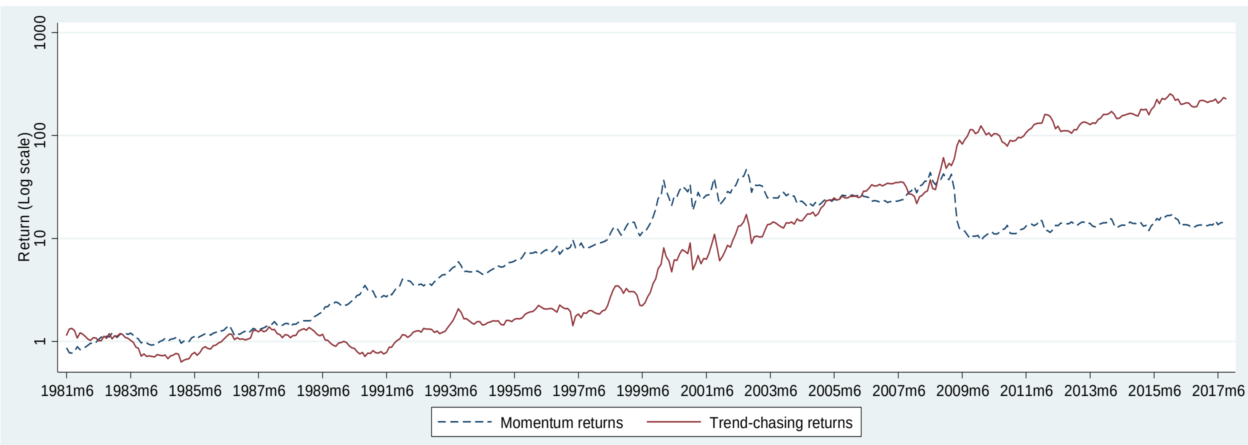

Fig. 3. Cumulative returns of the momentum strategy and the trend-chasing strategy

This plot shows the cumulative returns (on a logarithmic scale) of the momentum strategy (blue dashed line) and the trend-chasing strategy (red solid line) over 1981-2017.

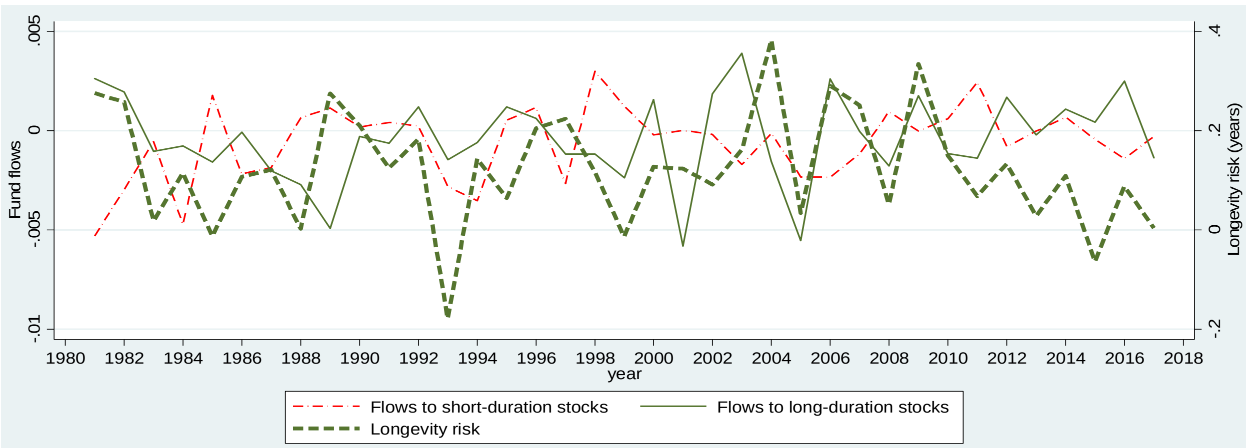

Fig. 4. Fund flows and longevity risk

This plot shows the aggregate annual fund flows to short- and long-duration stocks due to portfolio rebalancing, together with longevity risk. The red dash-dotted line shows the aggregate fund flows to short-duration stocks; the green solid line shows the aggregate fund flows to long-duration stocks; the green dashed line shows the longevity risk. Longevity risk is measured as the first-order difference of the weighted average period life expectancy.

Table 1. **Stock characteristics and longevity risk: Descriptive statistics**

This table summarizes the key statistics of longevity risk and stock characteristics. The following statistics are reported: mean, standard deviation (Std. Dev.), 1^{st}, 25^{th}, 50^{th}, 75^{th} , and 99^{th} percentiles (P1, P25, P50, P75, and P99). Panel A summarizes the longevity risk, ΔE_t, from 1951 to 2017. Panels B and C present the monthly returns and durations of winner and loser stocks over high and low longevity shock periods, respectively. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. Winners and losers are from the top and bottom 10% performers over the past 11 months, with a one-month lag. Panel D shows the statistics of the duration factor, including the monthly mean, monthly standard deviation, annual Sharpe ratio and the correlation with the momentum factor (MOM). The sample period is June 1981 to September 2017.

			Panel A Longevity risk				
	Mean	Std. Dev.	P1	P25	P50	P75	P99
ΔE_t	0.13	0.16	-0.22	0.02	0.13	0.22	0.51
			Panel B Winner stocks				
	Mean	Std. Dev.	P1	P25	P50	P75	P99
High longevity shock periods							
Monthly return (%)	2.01	16.25	-35.06	-7.14	1.00	10.00	49.71
Duration (years)	17.33	6.92	4.27	14.86	16.72	18.26	46.64
Low longevity shock periods							
Monthly return (%)	1.73	17.62	-40.74	-7.45	0.77	9.65	55.90
Duration (years)	17.32	6.30	6.06	15.16	16.84	18.23	44.13
			Panel C Loser stocks				
	Mean	Std. Dev.	P1	P25	P50	P75	P99
High longevity shock periods							
Monthly return (%)	2.22	20.86	-39.81	-8.85	0.00	10.32	71.07
Duration (years)	19.78	11.50	3.23	14.52	17.05	21.04	71.29
Low longevity shock periods							
Monthly return (%)	0.40	21.87	-47.78	-11.29	-1.18	9.68	71.19
Duration (years)	19.75	10.66	4.10	14.85	17.30	21.12	68.88
			Panel D Duration factor				
	Mean	Std. Dev.	Annual		Corr with MoM		
			Sharp ratio	Whole sample	High longevity	Low longevity	
Duration factor	0.61%	1.87%	1.14	0.43	0.46	0.43	

Table 2. **Replicating momentum returns**

This table replicates the momentum returns over the entire sample (in Panel A), the low longevity shock period (in Panel B), and the high longevity shock period (in Panel C). It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is greater (less) than the median of a 30-year rolling window. The t-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

					Panel A Entire sample						
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	0.51	0.88	1.06	0.97	0.95	0.98	0.97	1.10	1.09	1.51	1.00
	(1.14)	(2.79)	(4.00)	(3.95)	(4.55)	(4.79)	(4.97)	(4.96)	(4.26)	(4.24)	(2.43)
α_{CAPM}	-0.86	-0.23	0.03	0.01	0.02	0.08	0.09	0.17	0.13	0.37	1.24
	(-3.22)	(-1.26)	(0.18)	(0.07)	(0.22)	(1.03)	(1.09)	(1.90)	(0.87)	(1.76)	(3.39)
α_{FF3}	-0.90	-0.32	-0.06	-0.11	-0.06	-0.00	0.04	0.16	0.20	0.62	1.53
	(-3.49)	(-1.70)	(-0.37)	(-0.92)	(-0.66)	(-0.04)	(0.43)	(2.04)	(1.39)	(3.03)	(3.95)
α_{FF5}	-0.39	-0.14	0.08	-0.14	-0.09	-0.15	-0.13	0.03	0.19	0.77	1.16
	(-1.12)	(-0.57)	(0.37)	(-0.95)	(-0.86)	(-1.93)	(-1.60)	(0.36)	(1.08)	(3.35)	(2.17)
$\alpha_{Carhart}$	0.00	0.31	0.48	0.14	0.11	-0.02	-0.07	-0.03	-0.16	0.14	0.13
	(0.02)	(2.04)	(3.77)	(1.29)	(1.44)	(-0.22)	(-0.77)	(-0.36)	(-1.81)	(0.80)	(0.70)
α_{FF6}	0.23	0.31	0.47	0.05	0.04	-0.15	-0.19	-0.10	-0.08	0.40	0.16
	(1.48)	(2.04)	(3.62)	(0.43)	(0.53)	(-1.91)	(-2.45)	(-1.13)	(-0.93)	(2.53)	(0.74)
					Panel B Low longevity shock period						
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.16	0.64	0.89	0.75	0.67	0.86	0.77	0.93	0.96	1.44	1.60
	(-0.31)	(1.66)	(2.73)	(2.51)	(2.68)	(3.24)	(3.01)	(3.21)	(2.79)	(2.99)	(3.46)
α_{CAPM}	-1.20	-0.21	0.09	0.01	-0.05	0.16	0.07	0.20	0.20	0.56	1.76
	(-3.98)	(-0.86)	(0.44)	(0.06)	(-0.41)	(1.48)	(0.65)	(1.66)	(1.01)	(1.90)	(3.90)
α_{FF3}	-1.20	-0.29	0.01	-0.10	-0.15	0.05	0.01	0.18	0.28	0.82	2.02
	(-3.89)	(-1.12)	(0.05)	(-0.60)	(-1.23)	(0.47)	(0.08)	(1.63)	(1.43)	(3.00)	(4.29)
α_{FF5}	-0.74	-0.13	0.11	-0.14	-0.18	-0.10	-0.16	0.06	0.29	1.03	1.77
	(-1.81)	(-0.42)	(0.41)	(-0.72)	(-1.39)	(-1.06)	(-1.48)	(0.48)	(1.30)	(3.70)	(2.80)
$\alpha_{Carhart}$	-0.12	0.52	0.72	0.17	0.08	0.03	-0.09	-0.08	-0.18	0.22	0.33
	(-0.53)	(2.99)	(4.25)	(1.20)	(0.80)	(0.32)	(-0.79)	(-0.72)	(-1.65)	(0.97)	(1.28)
α_{FF6}	0.10	0.51	0.68	0.09	0.01	-0.10	-0.22	-0.14	-0.08	0.51	0.42
	(0.45)	(2.96)	(4.15)	(0.56)	(0.11)	(-1.03)	(-2.24)	(-1.21)	(-0.78)	(2.80)	(1.45)
					Panel C High longevity shock period						
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	1.64	1.28	1.34	1.34	1.42	1.18	1.32	1.39	1.31	1.62	-0.02
	(2.01)	(2.54)	(3.23)	(3.55)	(4.40)	(4.01)	(4.71)	(4.54)	(3.79)	(3.24)	(-0.03)
α_{CAPM}	-0.32	-0.31	-0.09	-0.04	0.11	-0.10	0.09	0.10	0.02	0.06	0.38
	(-0.76)	(-1.26)	(-0.42)	(-0.27)	(0.87)	(-0.93)	(0.75)	(0.77)	(0.07)	(0.20)	(0.72)
α_{FF3}	-0.34	-0.35	-0.15	-0.13	0.08	-0.11	0.08	0.12	0.07	0.26	0.60
	(-0.94)	(-1.62)	(-0.83)	(-0.90)	(0.69)	(-1.13)	(0.73)	(1.06)	(0.35)	(1.07)	(1.18)
α_{FF5}	0.59	0.02	0.19	-0.07	0.14	-0.16	-0.07	-0.03	-0.06	0.25	-0.34
	(1.50)	(0.07)	(0.93)	(-0.44)	(1.15)	(-1.29)	(-0.59)	(-0.24)	(-0.25)	(0.91)	(-0.60)
$\alpha_{Carhart}$	0.24	0.01	0.15	0.05	0.17	-0.12	-0.03	0.02	-0.16	-0.05	-0.29
	(1.28)	(0.03)	(1.17)	(0.38)	(1.65)	(-1.16)	(-0.25)	(0.16)	(-1.11)	(-0.25)	(-1.25)
α_{FF6}	0.66	0.07	0.23	-0.05	0.16	-0.16	-0.08	-0.05	-0.09	0.20	-0.46
	(3.00)	(0.26)	(1.53)	(-0.32)	(1.53)	(-1.29)	(-0.73)	(-0.37)	(-0.62)	(1.04)	(-1.92)

Table 3. **Momentum and contrarian among duration-driven traded stocks**

This table shows the momentum returns over the low longevity shock period (in Panel A), the contrarian returns over the high longevity shock period (in Panel B), and the combined returns over the entire sample (in Panel C), using stocks that are duration-driven traded by pensions. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. The t-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Duration-driven momentum strategy (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.56	0.33	0.84	0.91	0.57	0.95	0.58	1.05	0.86	1.74	2.30
	(-0.84)	(0.72)	(2.37)	(3.38)	(2.04)	(4.02)	(2.10)	(3.82)	(2.51)	(3.58)	(3.88)
α_{CAPM}	-1.65	-0.57	0.03	0.19	-0.17	0.26	-0.15	0.34	0.15	0.89	2.54
	(-3.68)	(-1.99)	(0.13)	(0.98)	(-0.97)	(1.71)	(-1.04)	(1.86)	(0.67)	(2.88)	(4.32)
α_{FF3}	-1.72	-0.66	-0.07	0.02	-0.31	0.16	-0.26	0.29	0.18	1.07	2.79
	(-3.70)	(-2.34)	(-0.23)	(0.14)	(-1.78)	(1.02)	(-1.73)	(1.66)	(0.82)	(3.37)	(4.63)
α_{FF5}	-1.21	-0.49	0.03	-0.07	-0.42	-0.08	-0.44	0.08	0.06	1.22	2.43
	(-2.35)	(-1.57)	(0.08)	(-0.40)	(-2.39)	(-0.58)	(-2.84)	(0.43)	(0.23)	(3.76)	(3.37)
$\alpha_{Carhart}$	-0.51	0.14	0.62	0.35	-0.13	0.20	-0.36	0.01	-0.23	0.52	1.03
	(-1.38)	(0.54)	(2.31)	(2.10)	(-0.77)	(1.32)	(-2.35)	(0.03)	(-1.40)	(2.07)	(3.01)
α_{FF6}	-0.27	0.14	0.58	0.21	-0.26	-0.02	-0.50	-0.13	-0.27	0.76	1.03
	(-0.76)	(0.55)	(2.04)	(1.17)	(-1.60)	(-0.12)	(-3.20)	(-0.83)	(-1.56)	(3.36)	(2.79)
Panel B Duration-driven contrarian strategy (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	L-W
Avg. returns	1.96	1.26	1.04	1.38	1.17	1.26	1.19	1.43	1.23	1.26	0.71
	(2.65)	(2.28)	(2.23)	(2.93)	(3.13)	(4.06)	(4.12)	(4.24)	(3.54)	(2.41)	(1.11)
α_{CAPM}	0.08	-0.43	-0.39	0.06	-0.24	-0.02	-0.06	0.20	-0.13	-0.30	0.37
	(0.17)	(-1.60)	(-1.16)	(0.24)	(-1.59)	(-0.10)	(-0.46)	(1.04)	(-0.56)	(-0.97)	(0.68)
α_{FF3}	0.06	-0.48	-0.53	0.03	-0.29	-0.04	-0.08	0.21	-0.14	-0.15	0.21
	(0.16)	(-1.97)	(-1.68)	(0.11)	(-1.99)	(-0.21)	(-0.59)	(1.16)	(-0.62)	(-0.48)	(0.38)
α_{FF5}	0.92	0.01	-0.22	0.02	-0.23	-0.13	-0.24	0.02	-0.19	-0.19	1.11
	(2.48)	(0.02)	(-0.60)	(0.06)	(-1.35)	(-0.71)	(-1.70)	(0.11)	(-0.71)	(-0.63)	(2.09)
$\alpha_{Carhart}$	0.52	-0.15	-0.27	0.23	-0.23	-0.02	-0.18	0.07	-0.32	-0.50	1.02
	(1.52)	(-0.66)	(-0.73)	(1.13)	(-1.52)	(-0.13)	(-1.35)	(0.43)	(-1.68)	(-2.25)	(2.77)
α_{FF6}	0.97	0.05	-0.19	0.05	-0.22	-0.13	-0.25	0.00	-0.21	-0.24	1.21
	(2.88)	(0.19)	(-0.49)	(0.20)	(-1.32)	(-0.70)	(-1.92)	(0.03)	(-1.05)	(-1.12)	(3.35)
Panel C Duration-driven trend-chasing strategy (Entire sample)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L/L-W
Avg. returns	0.12	0.67	1.06	1.02	0.82	1.03	0.88	1.04	1.01	1.82	1.70
	(0.24)	(2.05)	(3.97)	(5.06)	(3.76)	(4.93)	(3.48)	(4.23)	(3.31)	(4.40)	(3.64)
α_{CAPM}	-1.22	-0.44	0.07	0.10	-0.11	0.12	-0.06	0.10	0.01	0.65	1.87
	(-3.53)	(-2.16)	(0.38)	(0.76)	(-0.88)	(0.96)	(-0.46)	(0.63)	(0.07)	(2.43)	(3.88)
α_{FF3}	-1.19	-0.49	0.01	-0.01	-0.21	0.01	-0.16	-0.00	-0.02	0.73	1.93
	(-3.26)	(-2.40)	(0.08)	(-0.12)	(-1.63)	(0.10)	(-1.14)	(-0.01)	(-0.11)	(2.73)	(3.76)
α_{FF5}	-0.83	-0.37	0.06	-0.14	-0.33	-0.18	-0.31	-0.10	-0.05	0.99	1.82
	(-2.07)	(-1.51)	(0.20)	(-1.11)	(-2.37)	(-1.65)	(-2.10)	(-0.59)	(-0.24)	(3.46)	(3.01)
$\alpha_{Carhart}$	-0.70	-0.15	0.32	0.11	-0.11	0.06	-0.10	-0.02	-0.07	0.67	1.38
	(-1.70)	(-0.63)	(1.30)	(0.82)	(-0.87)	(0.57)	(-0.62)	(-0.15)	(-0.35)	(2.36)	(2.36)
α_{FF6}	-0.50	-0.13	0.28	-0.04	-0.24	-0.12	-0.26	-0.10	-0.08	0.93	1.42
	(-1.26)	(-0.51)	(1.00)	(-0.28)	(-1.94)	(-1.18)	(-1.53)	(-0.63)	(-0.39)	(3.11)	(2.36)

Table 4. **Momentum disappears after excluding duration-driven traded stocks**

This table shows momentum returns over the low longevity shock period (in Panel A) and the high longevity shock period (in Panel B), after excluding the winners and losers identified from pensions' trades. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. Alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. The *t*-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Low longevity shock period											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	0.50	0.67	0.97	0.82	0.68	0.80	0.89	0.98	0.98	1.27	0.77
	(0.96)	(1.60)	(2.86)	(2.48)	(2.31)	(2.54)	(3.40)	(3.20)	(2.48)	(2.75)	(1.37)
α_{CAPM}	-0.54	-0.18	0.19	0.05	-0.05	0.11	0.20	0.23	0.20	0.39	0.92
	(-1.52)	(-0.57)	(0.68)	(0.24)	(-0.28)	(0.52)	(1.06)	(1.28)	(0.80)	(1.19)	(1.68)
α_{FF3}	-0.55	-0.32	0.06	-0.06	-0.20	-0.02	0.08	0.17	0.25	0.62	1.17
	(-1.47)	(-0.94)	(0.23)	(-0.31)	(-1.10)	(-0.08)	(0.45)	(1.03)	(1.05)	(2.10)	(1.99)
α_{FF5}	-0.17	-0.20	0.05	-0.06	-0.25	-0.13	-0.18	0.03	0.29	0.76	0.92
	(-0.34)	(-0.50)	(0.17)	(-0.27)	(-1.34)	(-0.64)	(-1.22)	(0.19)	(1.16)	(2.38)	(1.26)
$\alpha_{Carhart}$	0.64	0.53	0.72	0.27	0.02	-0.00	-0.02	-0.09	-0.17	-0.07	-0.71
	(2.44)	(1.89)	(2.86)	(1.52)	(0.10)	(-0.02)	(-0.11)	(-0.54)	(-1.01)	(-0.25)	(-1.71)
α_{FF6}	0.76	0.47	0.59	0.20	-0.07	-0.11	-0.23	-0.17	-0.05	0.18	-0.59
	(2.73)	(1.70)	(2.60)	(1.08)	(-0.39)	(-0.53)	(-1.60)	(-0.95)	(-0.34)	(0.68)	(-1.37)
Panel B High longevity shock period											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	1.49	0.46	1.22	1.24	1.33	1.13	1.17	1.46	1.25	1.61	0.12
	(1.78)	(0.84)	(2.58)	(2.99)	(3.79)	(3.17)	(4.26)	(4.31)	(3.48)	(3.11)	(0.15)
α_{CAPM}	-0.53	-1.09	-0.25	-0.13	-0.01	-0.15	-0.01	0.19	0.01	0.12	0.66
	(-1.22)	(-2.79)	(-0.82)	(-0.62)	(-0.05)	(-0.81)	(-0.07)	(0.96)	(0.03)	(0.37)	(1.23)
α_{FF3}	-0.61	-1.14	-0.34	-0.15	-0.02	-0.18	-0.01	0.24	0.11	0.32	0.93
	(-1.60)	(-3.15)	(-1.29)	(-0.69)	(-0.14)	(-0.94)	(-0.08)	(1.30)	(0.42)	(1.23)	(1.92)
α_{FF5}	0.33	-0.82	-0.03	0.05	-0.09	-0.23	-0.07	0.14	-0.08	0.40	0.07
	(0.79)	(-2.11)	(-0.09)	(0.19)	(-0.53)	(-1.19)	(-0.38)	(0.74)	(-0.25)	(1.32)	(0.12)
$\alpha_{Carhart}$	0.08	-0.80	-0.07	0.06	0.05	-0.17	-0.07	0.15	-0.11	0.06	-0.02
	(0.31)	(-2.30)	(-0.29)	(0.31)	(0.28)	(-0.87)	(-0.41)	(0.80)	(-0.54)	(0.25)	(-0.05)
α_{FF6}	0.42	-0.78	0.01	0.07	-0.08	-0.23	-0.08	0.13	-0.11	0.36	-0.05
	(1.46)	(-1.96)	(0.03)	(0.36)	(-0.50)	(-1.17)	(-0.43)	(0.71)	(-0.44)	(1.34)	(-0.15)

Table 5. **Momentum and contrarian among duration-driven traded stocks: Identified by price-dividend ratios**

This table shows the momentum returns over the low longevity shock period (in Panel A) and the contrarian returns over the high longevity shock period (in Panel B), using stocks that are duration-driven traded by pensions. Stock duration is proxied by its price-dividend ratio. The price-dividend ratio is calculated as stock price divided by dividends distributed in the past twelve months. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. The *t*-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Duration-driven momentum strategy (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	0.66	1.04	1.31	1.35	1.06	1.09	0.98	1.31	1.23	1.66	1.01
	(1.71)	(3.23)	(4.69)	(4.77)	(4.90)	(4.25)	(4.01)	(5.24)	(5.20)	(5.88)	(2.65)
α_{CAPM}	-0.39	0.19	0.49	0.50	0.21	0.15	0.14	0.42	0.37	0.72	1.11
	(-1.34)	(0.66)	(1.91)	(1.99)	(1.19)	(0.79)	(1.02)	(2.56)	(2.32)	(3.48)	(2.81)
α_{FF3}	-0.71	-0.15	0.19	0.27	-0.01	-0.04	-0.01	0.29	0.21	0.61	1.33
	(-2.62)	(-0.67)	(1.02)	(1.34)	(-0.04)	(-0.23)	(-0.04)	(1.78)	(1.26)	(3.24)	(3.52)
α_{FF5}	-0.77	-0.40	-0.03	0.05	-0.21	-0.26	-0.19	0.13	-0.06	0.40	1.17
	(-2.59)	(-1.69)	(-0.18)	(0.27)	(-1.24)	(-1.64)	(-1.30)	(0.80)	(-0.37)	(1.90)	(2.71)
$\alpha_{Carhart}$	-0.12	0.28	0.47	0.52	0.10	-0.08	-0.10	0.16	-0.09	0.23	0.34
	(-0.36)	(1.37)	(2.57)	(2.30)	(0.49)	(-0.41)	(-0.61)	(0.94)	(-0.58)	(1.34)	(0.96)
α_{FF6}	-0.23	0.01	0.23	0.30	-0.09	-0.27	-0.26	0.05	-0.29	0.08	0.31
	(-0.76)	(0.02)	(1.35)	(1.51)	(-0.47)	(-1.63)	(-1.66)	(0.29)	(-2.25)	(0.46)	(0.92)
Panel B Duration-driven contrarian strategy (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	L-W
Avg. returns	1.65	0.95	0.97	0.99	0.87	0.97	0.81	1.09	1.22	0.45	1.20
	(2.24)	(1.83)	(2.14)	(2.18)	(1.91)	(2.88)	(2.39)	(2.60)	(2.73)	(0.81)	(1.38)
α_{CAPM}	0.65	0.01	0.10	0.12	0.03	0.19	0.05	0.31	0.42	-0.45	1.09
	(1.12)	(0.07)	(0.50)	(0.61)	(0.17)	(1.05)	(0.28)	(1.45)	(1.88)	(-1.42)	(1.34)
α_{FF3}	0.58	0.01	-0.03	0.08	-0.01	0.16	0.03	0.28	0.40	-0.43	1.01
	(0.96)	(0.06)	(-0.13)	(0.41)	(-0.06)	(0.85)	(0.19)	(1.28)	(1.92)	(-1.37)	(1.20)
α_{FF5}	0.97	0.20	0.19	0.10	0.06	0.03	-0.16	-0.05	0.12	-0.68	1.65
	(1.91)	(0.87)	(0.72)	(0.51)	(0.36)	(0.13)	(-0.90)	(-0.21)	(0.61)	(-2.11)	(2.26)
$\alpha_{Carhart}$	0.90	0.13	0.11	0.14	0.02	0.14	-0.04	0.19	0.25	-0.59	1.49
	(2.20)	(0.74)	(0.56)	(0.82)	(0.09)	(0.70)	(-0.22)	(1.03)	(1.54)	(-2.62)	(2.89)
α_{FF6}	0.64	0.08	0.05	0.03	0.03	0.03	-0.10	0.02	0.26	-0.53	1.18
	(1.63)	(0.44)	(0.18)	(0.19)	(0.18)	(0.15)	(-0.57)	(0.10)	(1.43)	(-2.15)	(2.39)

Table 6. **Robustness: Evidence from life insurers**

This table summarizes the robustness check using life insurer data. Panel A shows the momentum returns over the low longevity shock period while Panel B shows the contrarian returns over the high longevity shock period, using stocks that are duration-driven traded by life insurers. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is greater (less) than the median of a 30-year rolling window. Panel C (D) shows the momentum returns over a low (high) longevity shock period, after excluding the winners and losers identified from life insurers' trades. The t-statistics are reported in parentheses. The sample period is June 2005 to September 2017.

Panel A Duration-driven momentum strategy (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.76	-0.10	0.61	0.45	0.21	0.55	0.66	0.58	0.41	1.02	1.78
	(-0.78)	(-0.13)	(1.02)	(0.91)	(0.37)	(1.33)	(1.45)	(1.28)	(0.76)	(1.38)	(2.68)
α_{CAPM}	-1.37	-0.54	0.21	0.05	-0.18	0.23	0.33	0.21	0.03	0.58	1.95
	(-2.85)	(-1.54)	(0.59)	(0.17)	(-0.75)	(1.33)	(1.46)	(0.73)	(0.12)	(1.45)	(3.09)
α_{FF3}	-1.35	-0.53	0.21	0.07	-0.17	0.24	0.33	0.21	0.04	0.58	1.93
	(-2.75)	(-1.43)	(0.58)	(0.23)	(-0.70)	(1.34)	(1.49)	(0.77)	(0.13)	(1.35)	(2.90)
α_{FF5}	-0.86	-0.41	0.14	-0.02	-0.04	0.25	0.41	0.15	0.17	0.59	1.45
	(-1.87)	(-1.22)	(0.45)	(-0.08)	(-0.20)	(1.66)	(1.74)	(0.58)	(0.59)	(1.67)	(2.42)
$\alpha_{Carhart}$	-0.70	0.03	0.59	0.30	-0.02	0.27	0.26	-0.01	-0.17	0.18	0.87
	(-1.52)	(0.10)	(1.94)	(1.00)	(-0.10)	(1.66)	(1.24)	(-0.03)	(-0.66)	(0.46)	(1.75)
α_{FF6}	-0.22	0.13	0.52	0.21	0.11	0.28	0.34	-0.06	-0.03	0.20	0.42
	(-0.57)	(0.51)	(1.83)	(0.61)	(0.47)	(1.94)	(1.45)	(-0.24)	(-0.11)	(0.55)	(0.88)
Panel B Duration-driven contrarian strategy (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	L-W
Avg. returns	3.00	1.31	1.56	1.51	1.46	1.04	0.94	1.30	1.05	0.94	2.06
	(1.89)	(1.59)	(1.84)	(1.82)	(2.51)	(1.85)	(2.16)	(2.83)	(1.41)	(1.62)	(1.42)
α_{CAPM}	0.42	-0.37	-0.16	-0.15	0.04	-0.31	-0.28	-0.01	-0.31	-0.59	1.00
	(0.53)	(-0.92)	(-0.34)	(-0.35)	(0.24)	(-0.91)	(-1.75)	(-0.03)	(-0.69)	(-1.51)	(1.07)
α_{FF3}	0.55	-0.37	0.02	0.06	0.08	-0.26	-0.38	0.03	-0.31	-0.80	1.35
	(0.68)	(-0.95)	(0.04)	(0.20)	(0.51)	(-0.86)	(-1.84)	(0.11)	(-0.66)	(-2.51)	(1.33)
α_{FF5}	1.22	-0.31	0.20	0.29	0.24	-0.41	-0.39	0.05	-0.50	-1.02	2.24
	(1.56)	(-0.79)	(0.46)	(0.72)	(1.37)	(-1.41)	(-1.95)	(0.20)	(-1.10)	(-2.67)	(2.15)
$\alpha_{Carhart}$	0.22	-0.51	-0.14	-0.08	0.02	-0.25	-0.36	0.08	-0.19	-0.68	0.90
	(0.50)	(-1.30)	(-0.41)	(-0.25)	(0.10)	(-0.84)	(-1.62)	(0.34)	(-0.53)	(-2.40)	(1.60)
α_{FF6}	0.50	-0.67	-0.16	-0.05	0.11	-0.41	-0.33	0.19	-0.24	-0.74	1.25
	(1.07)	(-1.58)	(-0.47)	(-0.15)	(0.58)	(-1.35)	(-1.43)	(0.78)	(-0.66)	(-2.22)	(1.95)

Table 6 *Continued:* **Robustness: Evidence from life insurers**

Panel C Momentum returns after excluding duration-driven stocks (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.49	-0.14	0.29	0.15	0.56	0.44	0.14	0.56	0.15	0.24	0.72
	(-0.53)	(-0.20)	(0.44)	(0.32)	(1.26)	(1.14)	(0.31)	(1.18)	(0.34)	(0.44)	(1.07)
α_{CAPM}	-1.09	-0.67	-0.18	-0.25	0.17	0.10	-0.22	0.22	-0.21	-0.17	0.92
	(-2.71)	(-2.25)	(-0.77)	(-1.63)	(0.80)	(0.82)	(-1.13)	(1.10)	(-1.24)	(-0.48)	(1.64)
α_{FF3}	-1.05	-0.65	-0.18	-0.25	0.17	0.10	-0.22	0.22	-0.21	-0.16	0.89
	(-2.51)	(-2.03)	(-0.76)	(-1.40)	(0.74)	(0.78)	(-1.12)	(1.09)	(-1.24)	(-0.46)	(1.45)
α_{FF5}	-0.60	-0.66	-0.29	-0.35	0.07	0.13	-0.09	0.19	-0.23	-0.04	0.57
	(-1.59)	(-2.07)	(-1.08)	(-1.76)	(0.31)	(0.97)	(-0.55)	(1.00)	(-1.14)	(-0.10)	(1.07)
$\alpha_{Carhart}$	-0.26	-0.14	0.17	-0.00	0.28	0.11	-0.28	0.08	-0.43	-0.56	-0.30
	(-0.62)	(-0.49)	(0.71)	(-0.03)	(1.14)	(0.77)	(-1.50)	(0.44)	(-2.75)	(-1.86)	(-0.55)
α_{FF6}	0.17	-0.16	0.05	-0.11	0.17	0.13	-0.16	0.06	-0.45	-0.43	-0.60
	(0.49)	(-0.58)	(0.19)	(-0.53)	(0.75)	(0.97)	(-0.90)	(0.30)	(-2.40)	(-1.33)	(-1.32)

Panel D Momentum returns after excluding duration-driven stocks (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	2.36	0.70	1.26	1.80	1.04	1.40	1.37	1.70	1.05	1.75	-0.61
	(1.26)	(0.71)	(1.18)	(2.37)	(1.64)	(2.70)	(3.93)	(3.08)	(2.24)	(2.65)	(-0.30)
α_{CAPM}	-0.11	-1.23	-0.55	0.36	-0.30	0.13	0.26	0.38	-0.35	0.39	0.50
	(-0.10)	(-1.62)	(-0.96)	(1.03)	(-1.04)	(0.69)	(1.04)	(1.36)	(-0.85)	(0.77)	(0.41)
α_{FF3}	0.18	-1.01	-0.43	0.33	-0.30	0.16	0.23	0.33	-0.52	0.20	0.02
	(0.13)	(-1.55)	(-0.71)	(0.98)	(-1.02)	(0.79)	(0.92)	(1.09)	(-1.56)	(0.44)	(0.01)
α_{FF5}	1.10	-0.69	-0.22	0.38	-0.31	0.22	0.04	0.16	-0.70	0.19	-0.91
	(0.80)	(-0.83)	(-0.36)	(0.94)	(-0.95)	(0.98)	(0.15)	(0.71)	(-1.66)	(0.37)	(-0.53)
$\alpha_{Carhart}$	-0.25	-1.14	-0.59	0.22	-0.34	0.16	0.30	0.37	-0.44	0.36	0.62
	(-0.35)	(-1.54)	(-1.32)	(0.98)	(-1.24)	(0.77)	(1.33)	(1.31)	(-1.40)	(0.87)	(0.85)
α_{FF6}	0.15	-0.96	-0.59	0.11	-0.41	0.22	0.17	0.24	-0.55	0.62	0.47
	(0.18)	(-1.08)	(-1.30)	(0.43)	(-1.32)	(0.93)	(0.73)	(1.09)	(-1.55)	(1.52)	(0.52)

Table 7. **Capital flows, stock durations, and longevity shocks**

This table presents the regression analysis of capital flows and longevity shocks, using panel ordinary least square regressions with quarter fixed effects. Following Lou (2012), the dependent variable ($PCS_{i,j,t}$) measures the trades of stock j by fund i in quarter t due to net capital flows, calculated as the change in the number of shares of stock j held by pension fund i after net capital flows, scaled by its holding at the beginning of quarter t. $flow_{i,t}$ is defined as the net capital flow to pension fund i in quarter t divided by the fund's total net assets at the end of the previous quarter. $\mathbb{I}^{\text{High}}_{\text{Longevity},t}$ is an indicator of high longevity shock in quarter t, which equals 1 if the longevity shock is greater than the median of a 30-year rolling window, and 0 otherwise. $\mathbb{I}^{\text{Long}}_{\text{Dur},j,t}$ is an indicator of long-duration stocks in quarter t, which equals 1 for stocks with durations and changes of durations greater than the sample medians, and 0 otherwise. $Ownership_{i,j,t}$ is the percentage of outstanding shares of stock j that are held by fund i at the end of quarter t. All of the continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. The t-statistics, presented in parentheses, are computed from standard errors clustered at the fund-quarter level. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is June 1981 to September 2017.

	(1)	(2)
$flow_{i,t} \times \mathbb{I}^{\text{High}}_{\text{Longevity},t} \times \mathbb{I}^{\text{Long}}_{\text{Dur},j,t}$	0.0851***	0.0850***
	(5.00)	(5.00)
$flow_{i,t} \times \mathbb{I}^{\text{Long}}_{\text{Dur},j,t}$	-0.0576***	-0.0576***
	(-2.97)	(-2.97)
$flow_{i,t} \times \mathbb{I}^{\text{High}}_{\text{Longevity},t}$	0.3397***	0.3397***
	(2.88)	(2.88)
$\mathbb{I}^{\text{High}}_{\text{Longevity},t} \times \mathbb{I}^{\text{Long}}_{\text{Dur},j,t}$	0.0014**	0.0014**
	(2.17)	(2.16)
$\mathbb{I}^{\text{High}}_{\text{Dur},j,t}$	-0.0005	-0.0004
	(-0.70)	(-0.70)
$flow_{i,t}$	0.1342***	0.1342***
	(2.64)	(2.64)
$Ownership_{i,j,t}$		-0.0001
		(-0.93)
Constant	-0.0075***	-0.0072***
	(-4.00)	(-3.70)
Observations	1,394,609	1,394,609
R-squared	0.3379	0.3380
Quarter FE	Yes	Yes

Table 8. **Duration-driven portfolio rebalancing and return momentum**

This table reports quarterly Fama-MacBeth forecasting regressions of future stock returns. The dependent variable is the cumulative stock returns over the following three months. The key independent variables are: (1) $DurTrade$, the aggregate duration-driven portfolio-rebalancing trades, and (2) $E_t[FIT]$, the aggregate expected performance-driven flow-induced trades, following Lou (2012). The control variables are the cumulative stock return in the previous 11 months ($ret_{t-12:t-1}$), the one-month stock return (ret_t), the long-run past returns ($ret_{t-48:t-13}$), defined as the cumulative returns from month $t-48$ to $t-13$, the book-to-market ratio (bm), the natural logarithm of firm size ($\log(MktCap)$), and the average monthly turnover ratio within the quarter ($turnover$). All of the continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. The t-statistics, shown in parentheses, are computed from standard errors using Newey-West corrections of four lags. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is June 1981 to September 2017.

	(1)	(2)	(3)
	$ret_{t+1:t+3}$	$ret_{t+1:t+3}$	$ret_{t+1:t+3}$
$DurTrade$		0.1648***	0.1678***
		(2.61)	(2.63)
$E_t[FIT]$	0.2857***		0.2735***
	(2.78)		(2.75)
ret_t	-0.0434***	-0.0441***	-0.0438***
	(-3.80)	(-3.94)	(-3.90)
$ret_{t-12:t-1}$	0.0055	0.0051	0.0050
	(0.74)	(0.69)	(0.68)
$ret_{t-48:t-13}$	-0.0023*	-0.0024*	-0.0024*
	(-1.91)	(-1.93)	(-1.96)
$\log(MktCap)$	-0.0010	-0.0011	-0.0011
	(-0.75)	(-0.81)	(-0.81)
bm	0.0036	0.0038	0.0037
	(1.03)	(1.11)	(1.06)
$turnover$	-0.0249	-0.0251	-0.0247
	(-1.05)	(-1.05)	(-1.04)
$Constant$	0.0474**	0.0454**	0.0484**
	(2.42)	(2.32)	(2.46)
Observations	192,988	192,988	192,988
R^2	0.0670	0.0677	0.0694

Table 9. **Pension fund returns and momentum factor**

This table reports the quarterly time-series regressions of pensions returns on identified winners and losers against the momentum factor. The dependent variable, pension returns are computed as the difference between fund returns on losers (winners) and winners (losers) during high (low) longevity period. Column (1) uses the Carhart four-factor model. To differentiate exposures to the momentum factor during high (low) longevity periods, Column (2) adds an indicator variable for periods of high longevity shocks ($\mathbb{I}^{\text{High}}_{\text{Longevity}}$) and its interaction term with the momentum factor (MOM). The t-statistics are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is June 1981 to September 2017.

	(1)	(2)
α (%)	0.47	0.29
	(1.30)	(0.62)
MKTRF	0.0569	0.0321
	(1.11)	(0.68)
SMB	0.0460	0.0497
	(0.59)	(0.67)
HML	-0.281***	-0.267***
	(-2.73)	(-2.74)
MOM	0.0855	0.243**
	(1.20)	(2.50)
$\mathbb{I}^{\text{High}}_{\text{Longevity}}$		0.00242
		(0.33)
$\mathbb{I}^{\text{High}}_{\text{Longevity}} \times MOM$		-0.365***
		(-2.95)

Table 10. **Endogeneity tests: Longevity correlation and trading directions**

This table examines whether local pensions from two states with negatively correlated longevity shocks trade in opposite directions. Local pensions are those that only serve within-state customers. The dependent variable is a dummy variable which equals one if fund j and fund k trade stock i in opposite directions, and 0 otherwise. $LongevityCorr_{j,k}$ captures the correlation of longevity shocks between the states where funds j and k operate. In Column (1), $LongevityCorr_{j,k}$ is measured as the correlation coefficient of longevity shocks between two states where funds j and k operate. In Column (2), $LongevityCorr_{j,k}$ is a dummy that equals one if the longevity risks in two states are negatively correlated, and 0 otherwise. $flow_j$ is defined as the net capital flow to pension fund j in quarter t divided by the fund's total net assets at the end of the previous quarter. $Ownership_j$ is the percentage of outstanding shares of stock i that are held by fund j at the end of quarter t. Panel A shows the fund-level regressions. Panel B shows the state-level regressions. That is, the trades of all local pensions within the same state are aggregated and treated as a single giant fund. All of the continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. The t-statistics, presented in parentheses, are computed from standard errors clustered at the state level. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is June 1981 to September 2017.

	Panel A Fund-level		Panel B State-level	
	(1)	(2)	(3)	(4)
$LongevityCorr_{j,k}$	-0.0908***	0.0387**	-0.1215***	0.0418***
	(-3.76)	(2.27)	(-3.05)	(2.92)
$flow_j$	0.0013	0.0021	0.0009	0.0025
	(0.27)	(0.42)	(0.18)	(0.45)
$flow_k$	0.0042	0.0051	-0.0016	0.0002
	(0.66)	(0.77)	(-0.51)	(0.04)
$ownership_j$	-0.0036**	-0.0034*	-0.0035**	-0.0033
	(-2.70)	(-2.01)	(-2.58)	(-1.66)
$ownership_k$	-0.0010*	-0.0012	-0.0015**	-0.0017
	(-2.00)	(-1.17)	(-2.33)	(-1.54)
Constant	0.6768***	0.6214***	0.6985***	0.6278***
	(38.24)	(64.80)	(27.72)	(52.92)
Observations	11,250,516	11,250,516	6,227,415	6,227,415
R^2	0.0054	0.0046	0.0070	0.0059
Quarter fixed effect	Yes	Yes	Yes	Yes

Online Appendices

A. Longevity risk and bond duration of life insurers

In addition to equity investment, pensions and life insurers also hold bonds. Clearly, they might adjust their bond holdings when facing longevity shocks. For example, they might invest more in long-term bonds when longevity increases. As the bond holdings data of pensions (e.g., eMAXX data) are less complete with a short sample period, we consider the bond holdings of life insurers, which are available from NAIC data. Figure A1 plots the changes in bond duration of life insurers. We see that changes in bond duration of life insurers trace longevity risk, with a correlation coefficient of 0.27. That is, these investors adjust both stock and bond holdings according to the longevity shocks.

B. Using the full-sample longevity estimate

In the main results, we classified longevity shock conditions by using 30-year rolling-window estimates of longevity risk. In this subsection, we define longevity shock conditions based on the full-sample longevity estimates. That is, *High Longevity Shock* (*Low Longevity Shock*) is defined as the periods when longevity shocks are greater (less) than the full-sample median. We repeat and report the main results in Tables B1 and B2. Both tables report the average returns and alphas from various models for 10 momentum portfolios.

Table B1 presents trend-chasing returns among duration-driven traded stocks that are identified from pension trades, using the full-sample longevity estimates to define longevity shock conditions. Panel A presents momentum returns over low longevity shock periods. The average return of the W-L portfolio is 2.39% per month (t-statistic = 4.07), and alphas from all five models are significantly positive. In Panel B, the contrarian returns over high longevity shock periods are reported. The loser-minus-winner (L-W) portfolio has an average return of 0.72% per month (t-statistic = 1.15). The Fama-French five-factor alpha for the L-W portfolio is 1.12% per month (t-statistic = 2.13). Alphas for the L-W portfolios from the Carhart four-factor model and the Fama-French six-factor model are also significantly positive, with $\alpha_{Carhart} = 1.06\%$ (t-statistic = 3.14) and $\alpha_{FF6} = 1.20\%$ (t-statistic = 3.40). Panel C reports the trend-chasing returns over the entire sample, using the momentum strategy over low longevity shock periods and the contrarian strategy over high longevity shock periods. Overall, the results in Table B1 are similar to those in Table 3.

Table B2 presents momentum returns after excluding the winners and losers identified from pensions' trades, using the full-sample longevity estimates to define longevity shock conditions. As in Table 4, we can see that after we remove these stocks, momentum becomes insignificant. For example, α_{FF5} is insignificant in both low and high longevity shock periods.

C. *Validating the capital flow measure*

We validate our capital flow measure with the mutual fund holdings data. Fund flows for mutual funds are usually defined as the net growth in fund assets beyond reinvested dividends, which can computed from fund returns and total net assets (see, e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lou, 2012). First, we apply this standard approach to compute the fund flows. Second, we apply our approach to compute the capital flows for mutual funds. Figure C1 plots the fund flows computed from these two measures. Despite of the approximation errors, our measure closely tracks the standard measure, with a correlation coefficient of 0.7.

D. *Differentiating longevity risk and business cycles*

To differentiate longevity risk from business cycles, we consider longevity shocks which are orthogonal to business cycles. First, we apply the Hodrick–Prescott filter to compute the business cycle components of real GDP growth. Then, we regress longevity shocks against the cyclical component of GDP growth and several price-based measures which might capture business cycles, including the term spread, default spread, and aggregate dividend yield. We use the residuals as the orthogonal component of longevity risk and repeat the analyses in Section 3.2.2. Table D1 reports the results. Similar to Table 3, Table D1 shows strong momentum (contrarian) when longevity is low (high).

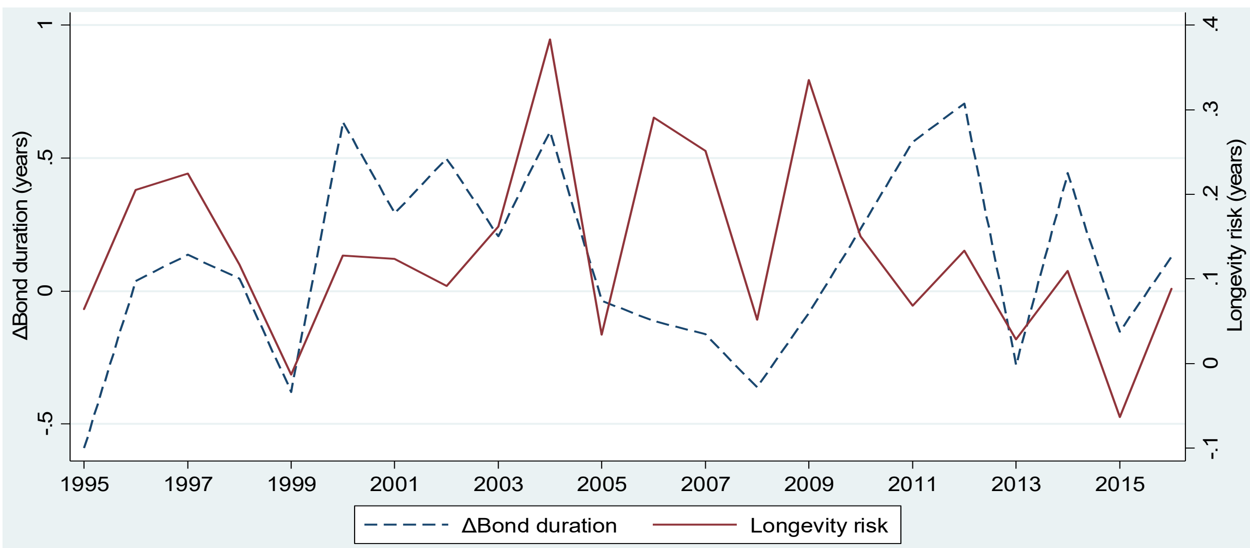

Fig. A1. Changes in bond duration of life insurers and longevity risk

This plot shows the changes in bond duration of life insurers (the blue dashed line), together with longevity risk (the red solid line).

Table B1. **Robustness: Trend-chasing returns among duration-driven traded stocks, using full-sample longevity estimates**

This table shows the momentum returns over the low longevity shock period (in Panel A), the contrarian returns over the high longevity shock period (in Panel B), and the combined returns over the entire sample (in Panel C), using stocks that are duration-driven traded by pensions. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is greater (less) than the median of the full sample. The *t*-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Duration-driven momentum strategy (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.56	0.43	0.90	0.95	0.64	0.94	0.61	1.14	0.91	1.82	2.39
	(-0.84)	(0.94)	(2.53)	(3.47)	(2.30)	(4.05)	(2.18)	(4.22)	(2.66)	(3.75)	(4.07)
α_{CAPM}	-1.77	-0.54	0.03	0.18	-0.15	0.21	-0.17	0.38	0.16	0.91	2.68
	(-3.99)	(-1.91)	(0.12)	(0.87)	(-0.86)	(1.35)	(-1.12)	(2.13)	(0.68)	(2.91)	(4.64)
α_{FF3}	-1.86	-0.64	-0.08	-0.02	-0.31	0.09	-0.29	0.33	0.19	1.11	2.97
	(-4.02)	(-2.28)	(-0.28)	(-0.12)	(-1.75)	(0.59)	(-1.87)	(1.90)	(0.84)	(3.40)	(4.96)
α_{FF5}	-1.36	-0.48	0.02	-0.10	-0.41	-0.13	-0.47	0.12	0.06	1.25	2.61
	(-2.68)	(-1.53)	(0.06)	(-0.56)	(-2.33)	(-0.94)	(-2.90)	(0.68)	(0.25)	(3.82)	(3.67)
$\alpha_{Carhart}$	-0.60	0.17	0.63	0.32	-0.12	0.14	-0.39	0.04	-0.24	0.55	1.15
	(-1.63)	(0.65)	(2.34)	(1.92)	(-0.69)	(0.88)	(-2.47)	(0.24)	(-1.43)	(2.08)	(3.33)
α_{FF6}	-0.39	0.16	0.59	0.19	-0.24	-0.06	-0.53	-0.09	-0.27	0.78	1.17
	(-1.09)	(0.63)	(2.10)	(1.06)	(-1.48)	(-0.45)	(-3.24)	(-0.58)	(-1.59)	(3.35)	(3.15)
Panel B Duration-driven contrarian strategy (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	L-W
Avg. returns	1.91	1.16	0.96	1.30	0.98	1.21	1.00	1.36	1.14	1.20	0.72
	(2.69)	(2.14)	(2.11)	(2.79)	(2.58)	(4.00)	(3.49)	(3.94)	(3.18)	(2.29)	(1.15)
α_{CAPM}	0.24	-0.37	-0.34	0.09	-0.34	0.02	-0.17	0.19	-0.14	-0.26	0.50
	(0.60)	(-1.45)	(-1.04)	(0.36)	(-2.12)	(0.13)	(-1.47)	(1.02)	(-0.60)	(-0.82)	(0.97)
α_{FF3}	0.24	-0.41	-0.45	0.05	-0.38	0.00	-0.19	0.20	-0.15	-0.13	0.37
	(0.73)	(-1.81)	(-1.47)	(0.22)	(-2.51)	(0.01)	(-1.61)	(1.10)	(-0.65)	(-0.42)	(0.73)
α_{FF5}	1.02	0.07	-0.20	0.01	-0.35	-0.10	-0.34	0.07	-0.14	-0.11	1.12
	(2.88)	(0.24)	(-0.54)	(0.05)	(-1.95)	(-0.54)	(-2.43)	(0.37)	(-0.53)	(-0.33)	(2.13)
$\alpha_{Carhart}$	0.63	-0.11	-0.23	0.23	-0.33	0.01	-0.28	0.09	-0.31	-0.43	1.06
	(2.01)	(-0.51)	(-0.64)	(1.19)	(-2.13)	(0.07)	(-2.29)	(0.51)	(-1.65)	(-1.95)	(3.14)
α_{FF6}	1.06	0.10	-0.18	0.04	-0.35	-0.10	-0.35	0.06	-0.16	-0.14	1.20
	(3.31)	(0.39)	(-0.45)	(0.15)	(-1.96)	(-0.53)	(-2.69)	(0.33)	(-0.79)	(-0.63)	(3.40)
Panel C Duration-driven trend-chasing strategy (Entire sample)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L/L-W
Avg. returns	0.10	0.70	1.08	0.97	0.85	0.96	0.87	1.07	1.00	1.86	1.76
	(0.19)	(2.14)	(3.98)	(4.81)	(3.90)	(4.54)	(3.42)	(4.36)	(3.33)	(4.53)	(3.82)
α_{CAPM}	-1.26	-0.42	0.07	0.05	-0.09	0.04	-0.07	0.13	0.01	0.70	1.96
	(-3.65)	(-2.05)	(0.42)	(0.37)	(-0.69)	(0.30)	(-0.49)	(0.83)	(0.07)	(2.68)	(4.17)
α_{FF3}	-1.24	-0.47	0.02	-0.07	-0.19	-0.07	-0.17	0.03	-0.02	0.79	2.02
	(-3.37)	(-2.29)	(0.10)	(-0.61)	(-1.44)	(-0.57)	(-1.18)	(0.21)	(-0.11)	(3.02)	(4.05)
α_{FF5}	-0.85	-0.33	0.08	-0.19	-0.30	-0.26	-0.32	-0.08	-0.06	1.02	1.88
	(-2.12)	(-1.36)	(0.28)	(-1.45)	(-2.14)	(-2.38)	(-2.15)	(-0.48)	(-0.30)	(3.61)	(3.13)
$\alpha_{Carhart}$	-0.72	-0.13	0.34	0.06	-0.08	-0.02	-0.11	0.00	-0.08	0.71	1.43
	(-1.75)	(-0.52)	(1.38)	(0.43)	(-0.66)	(-0.18)	(-0.67)	(0.02)	(-0.40)	(2.50)	(2.49)
α_{FF6}	-0.50	-0.09	0.31	-0.08	-0.21	-0.21	-0.27	-0.09	-0.10	0.94	1.45
	(-1.29)	(-0.36)	(1.13)	(-0.58)	(-1.69)	(-1.96)	(-1.59)	(-0.56)	(-0.48)	(3.21)	(2.45)

Table B2. **Robustness: Momentum disappears after excluding duration-driven traded stocks, using full-sample longevity estimates**

This table shows the momentum returns over the low longevity shock period (in Panel A) and the high longevity shock period (in Panel B), after excluding duration-driven traded stocks by pensions. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is greater (less) than the median of the full sample. The *t*-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Low longevity shock period											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	0.53	0.73	1.02	0.86	0.79	0.83	1.00	1.02	1.03	1.30	0.77
	(1.00)	(1.72)	(3.01)	(2.60)	(2.71)	(2.64)	(3.81)	(3.36)	(2.64)	(2.84)	(1.37)
α_{CAPM}	-0.62	-0.20	0.17	0.03	0.01	0.09	0.26	0.23	0.20	0.36	0.98
	(-1.72)	(-0.61)	(0.61)	(0.17)	(0.05)	(0.45)	(1.41)	(1.21)	(0.80)	(1.10)	(1.77)
α_{FF3}	-0.65	-0.35	0.02	-0.08	-0.15	-0.04	0.14	0.17	0.26	0.63	1.28
	(-1.68)	(-1.03)	(0.07)	(-0.43)	(-0.83)	(-0.22)	(0.77)	(0.96)	(1.10)	(2.09)	(2.13)
α_{FF5}	-0.25	-0.23	0.03	-0.08	-0.19	-0.16	-0.12	0.02	0.29	0.75	1.00
	(-0.51)	(-0.56)	(0.10)	(-0.37)	(-1.01)	(-0.78)	(-0.75)	(0.10)	(1.16)	(2.33)	(1.35)
$\alpha_{Carhart}$	0.59	0.52	0.70	0.25	0.08	-0.03	0.04	-0.12	-0.17	-0.09	-0.67
	(2.17)	(1.78)	(2.82)	(1.39)	(0.47)	(-0.14)	(0.21)	(-0.67)	(-0.98)	(-0.32)	(-1.59)
α_{FF6}	0.71	0.46	0.59	0.19	0.01	-0.13	-0.17	-0.20	-0.06	0.14	-0.57
	(2.49)	(1.61)	(2.65)	(0.98)	(0.05)	(-0.64)	(-1.11)	(-1.06)	(-0.38)	(0.55)	(-1.31)
Panel B High longevity shock period											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	1.50	0.29	1.12	1.18	1.20	1.14	1.12	1.31	1.17	1.47	-0.03
	(1.85)	(0.53)	(2.37)	(2.84)	(3.36)	(3.23)	(4.06)	(3.78)	(3.24)	(2.95)	(-0.03)
α_{CAPM}	-0.31	-1.14	-0.23	-0.08	-0.02	-0.04	0.00	0.12	0.00	0.09	0.40
	(-0.73)	(-3.09)	(-0.80)	(-0.38)	(-0.14)	(-0.24)	(0.02)	(0.61)	(0.01)	(0.29)	(0.75)
α_{FF3}	-0.37	-1.18	-0.31	-0.09	-0.04	-0.06	0.01	0.17	0.09	0.26	0.64
	(-1.04)	(-3.45)	(-1.22)	(-0.42)	(-0.23)	(-0.35)	(0.05)	(0.88)	(0.34)	(1.12)	(1.33)
α_{FF5}	0.60	-0.86	-0.01	0.09	-0.16	-0.15	-0.02	0.09	-0.06	0.37	-0.23
	(1.41)	(-2.34)	(-0.03)	(0.37)	(-0.89)	(-0.76)	(-0.11)	(0.44)	(-0.18)	(1.31)	(-0.39)
$\alpha_{Carhart}$	0.23	-0.87	-0.08	0.09	0.02	-0.06	-0.05	0.08	-0.10	0.03	-0.19
	(0.97)	(-2.63)	(-0.34)	(0.49)	(0.10)	(-0.31)	(-0.28)	(0.44)	(-0.48)	(0.15)	(-0.66)
α_{FF6}	0.65	-0.83	0.01	0.11	-0.15	-0.15	-0.02	0.08	-0.08	0.34	-0.31
	(2.62)	(-2.15)	(0.06)	(0.54)	(-0.90)	(-0.74)	(-0.14)	(0.43)	(-0.31)	(1.39)	(-0.96)

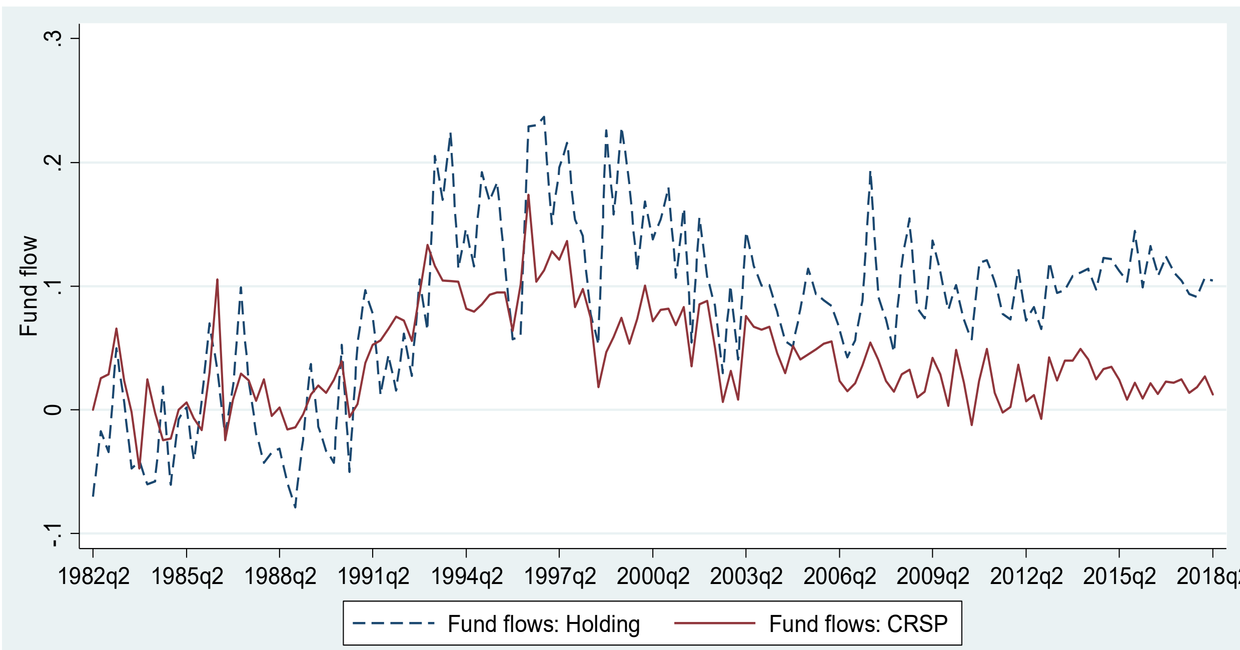

Fig. C1. Mutual fund flows

This plot compares two measures of fund flows, using the mutual fund holdings data. The blue dashed line shows the fund flows using our approach, as described in Section 5.1. The red solid line shows the fund flows using the standard approach as in Lou (2012).

Table D1. **Momentum and contrarian among duration-driven traded stocks: Using orthogonalized longevity shocks**

This table shows the momentum returns over the low longevity shock period (in Panel A), the contrarian returns over the high longevity shock period (in Panel B), using stocks that are duration-driven tradeded by pensions. We use longevity shocks which are orthogonal to business cycles. It reports the average returns (Avg. returns) and alphas (in % per month) for 10 momentum portfolios. The momentum portfolios are based on the previous 11-month returns with a one-month lag. The differences between the winners and losers (W-L or L-W) are reported in the last column. The alphas are computed from the CAPM, the Fama-French three-factor model, the Fama-French five-factor model, the Carhart four-factor model, and the Fama-French six-factor model. A high (low) longevity shock period is defined as one in which the longevity shock is higher (lower) than the median of a 30-year rolling window. The *t*-statistics are reported in parentheses. The sample period is June 1981 to September 2017.

Panel A Duration-driven momentum strategy (Low longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	W-L
Avg. returns	-0.46	0.38	0.82	1.03	0.64	0.97	0.71	1.19	0.93	1.92	2.38
	(-0.68)	(0.84)	(2.36)	(3.88)	(2.21)	(4.02)	(2.54)	(4.31)	(2.65)	(4.04)	(3.96)
α_{CAPM}	-1.63	-0.59	-0.05	0.24	-0.19	0.19	-0.13	0.37	0.09	0.93	2.56
	(-3.46)	(-2.12)	(-0.20)	(1.14)	(-1.04)	(1.23)	(-0.80)	(1.84)	(0.43)	(3.07)	(4.27)
α_{FF3}	-1.75	-0.71	-0.19	0.09	-0.31	0.09	-0.20	0.34	0.15	1.14	2.89
	(-3.72)	(-2.60)	(-0.84)	(0.52)	(-1.79)	(0.66)	(-1.29)	(1.84)	(0.73)	(3.66)	(4.86)
α_{FF5}	-1.48	-0.68	-0.24	-0.06	-0.44	-0.14	-0.35	0.17	0.08	1.33	2.81
	(-3.29)	(-2.61)	(-1.07)	(-0.34)	(-2.53)	(-1.13)	(-2.26)	(1.00)	(0.33)	(4.28)	(4.45)
$\alpha_{Carhart}$	-0.55	0.04	0.37	0.50	-0.11	0.16	-0.28	0.05	-0.28	0.53	1.08
	(-1.50)	(0.18)	(1.97)	(2.86)	(-0.64)	(1.10)	(-1.71)	(0.29)	(-1.83)	(2.06)	(3.17)
α_{FF6}	-0.34	0.04	0.30	0.34	-0.23	-0.06	-0.42	-0.11	-0.34	0.73	1.07
	(-0.98)	(0.16)	(1.69)	(1.94)	(-1.40)	(-0.47)	(-2.51)	(-0.69)	(-2.30)	(3.09)	(2.91)
Panel B Duration-driven contrarian strategy (High longevity shock period)											
Portfolio	Losers	2	3	4	5	6	7	8	9	Winners	L-W
Avg. returns	1.92	1.39	1.15	1.14	1.01	1.20	1.10	1.32	1.10	0.93	0.98
	(2.35)	(2.44)	(2.30)	(2.22)	(2.46)	(3.91)	(3.85)	(3.89)	(3.14)	(1.77)	(1.38)
α_{CAPM}	0.04	-0.20	-0.24	-0.06	-0.22	0.11	0.11	0.33	0.02	-0.29	0.33
	(0.09)	(-0.60)	(-0.66)	(-0.22)	(-1.07)	(0.59)	(0.63)	(1.71)	(0.08)	(-0.91)	(0.52)
α_{FF3}	0.19	-0.18	-0.35	-0.12	-0.28	0.06	0.00	0.28	-0.05	-0.28	0.47
	(0.39)	(-0.47)	(-0.86)	(-0.46)	(-1.48)	(0.31)	(0.02)	(1.59)	(-0.23)	(-0.86)	(0.68)
α_{FF5}	1.45	0.46	0.24	0.05	-0.20	-0.08	-0.30	0.03	-0.23	-0.64	2.09
	(2.74)	(1.05)	(0.49)	(0.17)	(-0.90)	(-0.41)	(-1.94)	(0.15)	(-0.87)	(-1.66)	(2.59)
$\alpha_{Carhart}$	0.80	0.22	-0.01	0.08	-0.20	0.06	-0.13	0.15	-0.23	-0.65	1.46
	(1.77)	(0.60)	(-0.03)	(0.34)	(-0.99)	(0.32)	(-0.82)	(0.85)	(-1.25)	(-3.08)	(3.05)
α_{FF6}	1.32	0.36	0.16	-0.01	-0.22	-0.08	-0.27	0.06	-0.18	-0.53	1.85
	(3.42)	(1.05)	(0.36)	(-0.04)	(-1.08)	(-0.45)	(-1.78)	(0.34)	(-0.88)	(-2.41)	(4.18)