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Abstract

The momentum effect is postulated to be a consequence of the disposition effect, which in turn, is a result of the interplay between the typically dominant diminishing sensitivity feature of prospect theory and the loss aversion feature. However, studies have shown that older individuals can exhibit a reverse disposition effect due to their heightened loss aversion compared to younger individuals. This paper hypothesises that as the population ages, the disposition effect of the average investor starts to diminish, thereby inducing a corresponding weakening of the momentum effect. We find empirical evidence showing that the long-horizon momentum profits are negatively related to changes in the proportion of the older population.

JEL Classification: G000, G350, C320

Keywords: Momentum, demographics, prospect theory, loss aversion, diminishing sensitivity, aging population, disposition effect

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1. Introduction

The momentum effect was first highlighted by Jegadeesh and Titman (1993), whose research demonstrated that trading strategies involving the purchase of past winners and the sale of past losers yield significant positive abnormal returns which are unrelated to their systematic risks or to delayed stock price responses to common factors. This effect was subsequently incorporated into a formal framework by Carhart (1997), who proposed that the patterns observed in U.S. average stock returns are most effectively captured by employing the three Fama-French factors, complemented by a fourth, momentum factor.

Subsequent to these foundational works, various theoretical explanations have been proposed to explain the momentum effect. However, risk-based theories have generally been deemed inadequate, often due to a lack of empirical support (Liu et al., 2005; Fama and French, 1996). Behavioural-based theories, on the other hand, are more widely acknowledged as probable explanations for the momentum effect. In particular, Grinblatt and Han (2005) employed the prospect theory to suggest that the disposition effect, which arises from investors' tendencies to prematurely sell their winning investments while holding onto their losing ones, leads to price underreaction to information. This, in turn, creates a discrepancy between a stock's fundamental value and its equilibrium price, resulting in a slower speed of price adjustment to fundamentals and thereby engendering short-term momentum.

Li and Yang (2013) however underscored that the hypothesis advanced by Grinblatt and Han (2005) predominantly focuses on the diminishing sensitivity characteristic of prospect theory, to elucidate the positive relation between investors' risk aversion and stock returns, which subsequently leads to the disposition effect and price momentum. They argue that the original prospect theory, as posited by Kahneman and Tversky (1979) and Tversky and Kahneman (1992), in fact encompasses three key elements: (i) investors evaluate outcomes based on their perceptions of gains and losses relative to a reference point, as opposed to final wealth levels; (ii) investors exhibit greater sensitivity to losses than to gains of equivalent magnitude, a phenomenon known as loss aversion; (iii) investors demonstrate risk aversion for gains and risk-seeking behaviour for losses, a feature referred to as diminishing sensitivity. While diminishing sensitivity generally leads to a positive correlation between investors' risk aversion and stock returns, the loss aversion feature can result in a negative correlation as investors are more inclined to divest stocks with prior losses than those with prior gains. Consequently, the ultimate variation of risk aversion to stock returns is determined by the interplay between the two prospect theory preferences of diminishing sensitivity and loss aversion. Li and Yang (2013) calibrated these interactions to the empirical values derived from various studies (Wu and Gonzalez, 1996; Tanaka et al., 2010; Tversky and Kahneman, 1992), and discovered that the feature of diminishing sensitivity tends to be the primary driver in predicting the disposition effect and hence price momentum.

While previous research has collectively demonstrated that individual investors, on average, exhibit the disposition effect (Grinblatt and Keloharju, 2001; Odean, 1998), a comprehensive analysis by Dhar and Zhu (2006) of the trading records of 79,995 individual investors from a large discount brokerage firm surprisingly revealed that nearly a fifth of them either do not exhibit a disposition effect or display a reverse disposition effect. Notably, they calculated a significantly negative correlation between the age of the investor and the disposition effect, indicating that the disposition effect tends to weaken and can even reverse as investors age. This suggests that the influence of the loss aversion feature of prospect theory intensifies relative to that of diminishing sensitivity as individuals grow older. This finding is substantiated by a survey of 660 randomly selected customers of a large German car manufacturer conducted by Gachter, Johnson and Hermann (2007), which found that older individuals are generally more loss averse than their younger counterparts. Indeed, Eric Johnson from Columbia University (Benartzi, 2010) noted that retirees often exhibit "hyper loss aversion", potentially being up to five times more loss averse than the average individual.

Depping and Freund (2011, 2013) offered an explanation for the heightened loss aversion observed in older individuals. They posited that as individuals age, they experience a typical decline in resources across various domains, including cognitive (e.g., memory), social (e.g., loss of loved ones), sensorimotor (e.g., hearing), and physical (e.g., health). Consequently, their motivation shifts from a predominant focus on gains during young adulthood to an increasingly stronger orientation towards loss prevention in older adulthood. This shift also heightens their awareness of potential losses. Neurological factors may also contribute to the heightened loss aversion among older individuals. For instance, Grubb et al. (2016) found that the risk preference in young adults is influenced by the volume of grey matter in a specific region of their right posterior parietal cortex (rPPC), with a reduced volume indicating a lower risk tolerance. Given that the reduction of grey matter in parietal regions is characteristic of normal aging, the decrease in rPPC grey matter volume in older adults consequently modulates their risk preferences, leading to increased loss aversion. On a different note, a study by Guttman et al. (2021) revealed that the thickness of the posterior cingulate cortex (PCC) mediates the relationship between age and loss aversion, suggesting that cortical thinning of the PCC is likely one of several factors contributing to changes in decision-making throughout the lifespan. Given that PCC thickness declines linearly with age (Lemaitre et al., 2012; Storsve et al., 2014), they suggested that PCC thinning may emerge as a significant factor in loss aversion when a certain threshold of atrophy begins in middle age.

In this paper, we propose a hypothesis that the momentum effect, which is attributed to investors' disposition effect driven by the predominance of the diminishing sensitivity feature of prospect theory over the loss aversion feature, is influenced by the aging population. Specifically, as the proportion of older investors (who typically exhibit higher loss aversion) increases, the disposition effect might weaken or even reverse, leading to a reduction in the momentum effect. Our empirical findings support this hypothesis, indicating a negative relation between the long-horizon returns of the momentum factor and changes in the proportion of the older population. These results hold firm even when controlled for factors such as shorting, market cap partitions, sentiment, trading volume, trading costs and speed of information diffusion, investor sophistication, governance, varying time periods, time trend, and alternative time horizon definitions.

There are several motivations for our work. Firstly, it is situated within the broader context of demographic shifts, specifically the aging population, that will significantly impact the US and numerous other developed economies in the forthcoming decades. According to projections from the US Census Bureau, the proportion of older individuals is anticipated to rise from the current 17.3% to 24.4% by 2060. However, this demographic shift is not solely characterized by an increase in the proportion of elderly within the population but is also marked by a notable augmentation in their financial influence, particularly in terms of stock market ownership. Data from the Federal Reserve[2] indicates that U.S. citizens aged over 70 currently own 29.5% of corporate equities and mutual funds, a substantial increase from the 21.7% ownership stake recorded in 1990. Concurrently, individuals within the 55-to-69 age bracket have also expanded their share of stock market ownership, now controlling 45%, up from 37.2% in the same period. Given the profound influence of demographic forces and the impending dramatic changes, research exploring demographic transitions is poised to garner increasing attention and importance. Secondly, our study contributes to the existing body of knowledge on the drivers of the long-horizon returns of the momentum effect. Carhart's four-factor model, which is widely adopted by both practitioners and academics for asset pricing, and the growing popularity of smart beta strategies that create exposures to different risk premiums, including value and momentum, underscore the need for a deeper understanding of the momentum factor. To the best of our knowledge, our study is the first to establish a connection between demographic changes and the momentum effect, thereby filling a critical gap in the existing literature. This novel exploration should advance academic discourse and also provide valuable insights for investment strategies in an era of significant demographic changes.

The remainder of this paper is organized as follows: Section 2 expands on the overlapping generations model as proposed by Li and Yang (2013), illustrating that the momentum effect is a function of the change in the proportion of older investors, and formulates a testable hypothesis. Section 3 outlines the data sample utilized and the methodology employed. Section 4 presents the empirical findings and the results of robustness checks. Finally, Section 5 provides a conclusion to the paper.

[2] https://www.federalreserve.gov/econres/scfindex.htm

2. Demographic changes, loss aversion and the momentum effect

2.1 An overlapping generations model

Following Li and Yang (2013), we assume an overlapping generations model (OLG) with three distinct generations of investors (age-1, age-2 and age-3), each with unitary mass. The economy comprises two traded asset: a riskless asset (bond) which is traded at constant gross risk-free rate R_f>1, and a risky asset (stock) which represents a claim to a stream of dividends. The dividend growth rate θ_{t+1} is independently and identically distributed (i.i.d.) over time and can equally likely take a high value θ_H or a low value θ_L with $0 < \theta_L < \theta_H$.

The investors are assumed to hold heterogeneous beliefs about θ_{t+1} and possess the capacity to alter their one-period-ahead dividend forecast throughout their lifetime. Consequently, an investor who was initially optimistic may become pessimistic, potentially prompting them to sell the stock they had initially purchased. This introduces the potential for prospect theory to influence their selling behaviour and the stock's price P_t which is determined by investors' trading behaviour.

The gross return on the stock between time t and t+1 is

$$R_{t+1} = \frac{P_{t+1}+D_{t+1}}{P_t} \tag{1}$$

where D_t is the dividend collected at time t.

When investor i enters the market at time t=1, he is endowed with $W_{1,i}$ units of consumption goods. He can trade at ages 1 and 2, leaving his final wealth as $W_{3,i}$ and his capital gain as $X_{3,i}$. His utility at time t, U_t^i, is expressed as

$$U_t^i = E_t^i[v(X_{3,i})] \tag{2}$$

where $E_t^i[\,.\,]$ is the investor's expectation operator at time t,

$X_{3,i} = W_{3,i} - R_f^2 W_{1,i}$ is his capital gain(/loss), and

$v(X) = \begin{cases} X^\alpha & if\ x \geq 0 \\ -\lambda(-X)^\alpha & if\ x < 0 \end{cases}$ is the standard value function of prospect theory used to evaluate the capital gains(/losses).

It can be seen that the parameter α governs the concavity(/convexity) of the value function and lies between 0 and 1, while the parameter λ controls the loss aversion.

In each period that trading occurs, the stocks are initially held by z_t mass of age 2-1 and $(1-z_t)$ mass of age-3 investors. These are age-2 and age-3 investors who have already purchased stocks in previous periods. Each investor (age-1, age-2-0, age-2-1 and age-3) then makes his investment decision h_i to maximise his expected utility U_t^i based on his belief $q_{i,t}$ and the state of economy S_t which is observable to all investors and is represented by

$$S_t = (\theta_t,\ f_{t-1},\ z_t) \tag{3}$$

where f_t denotes the price-dividend ratio at time t.

The optimal investor decision is therefore

For age-2-1 investors: $$h_{21}\{S_t, q_{i,t}\} = 1_{\{E_t^i[v(G_{1\to1}^{t+1})] \geq v(G_{1\to0}^{t})\}} \tag{4}$$

For age 2-0 investors: $$h_{20}\{S_t, q_{i,t}\} = 1_{\{E_t^i[v(G_{0\to1}^{t+1})] \geq 0\}} \tag{5}$$

For age 1 investors: $$h_1\{S_t, q_{i,t}\} = 1_{\widetilde{U_1}(S_t, q_{i,t}) \geq \widetilde{U_0}(S_t, q_{i,t})} \tag{6}$$

where $G_{i\to j}^t$ is his gain(/loss) at time t if he decides to move his stock position from state i to state j, and i and j can take either value 1 or 0, with 1 representing buying(/ownership) of the stock and 0 representing selling(/non-ownership) of the stock.

In essence, all age-3 investors are assumed to divest their stock holdings, given their impending exit from the economy at the end of the period. Meanwhile, age-1 and age-2-0 investors evaluate their decision to purchase stock by comparing their utilities derived from buying stock versus not buying. Consequently, optimistic investors among the age-1 and age-2-0 cohorts will retain their stock holdings. The decision of age-2-1 investors to continue holding the stock is contingent upon their expectations of the future dividend growth rate, with those harbouring pessimistic expectations likely to sell their stock.

The equilibrium stock price is therefore determined by the aggregate trading behaviour H_i of the different types of investors in the financial market

$$H_1(S_t) + H_{20}(S_t) + H_{21}(S_t) = 1 \tag{7}$$

In solving for equilibrium prices within the general equilibrium model, Li and Yang (2013) demonstrate that the disposition effect fundamentally pertains to the divergent behaviours of the age-2-1 investor group in response to good versus bad dividend news. Their state-dependent behaviours exert influence on the stock price by shifting the demand function, thereby generating either momentum or reversal.

We can re-write the aggregate trading behaviour based on the law of large numbers as

$$E[h_1\{S_t,q_{i,t}\} \mid S_t] + (1-z_t)E[h_{20}\{S_t,q_{i,t}\} \mid S_t] + z_tE[h_{21}\{S_t,q_{i,t}\} \mid S_t] = 1 \quad (8)$$

Substituting equations (4) to (6) into (8), we get

$$E[1_{\widehat{U_1}(S_t, q_{i,t}) \geq \widehat{U_0}(S_t, q_{i,t})} \mid S_t] + (1-z_t)E[1_{\{E_t^i[v(G_{0\to1}^{t+1})] \geq 0\}} \mid S_t] + z_tE[1_{\{E_t^i[v(G_{1\to1}^{t+1})] \geq v(G_{1\to0}^{t})\}} \mid S_t] = 1 \quad (9)$$

Since the momentum effect *WML* is measured as the difference between the average returns on the portfolio containing stocks with better performance R_t^{winner} and that containing stocks with worse performance R_t^{loser}

$$WML = R_t^{winner} - R_t^{loser} \quad (10)$$

Therefore by combining equation (1), (2), (9) and (10), we can see that WML can be expressed as a function of

$$WML = f\left(\frac{z_{t+1}}{z_t}, \alpha_{21}, -\lambda_{21}\right) \quad (11)$$

The momentum effect is therefore driven by (i) the change in proportion of age-2-1 investors, (ii) the concavity (or convexity) of their value function of prospect theory, and (iii) their degree of loss aversion.

2.2 Hypothesis development

From equation (11), we hypothesise that in a world where older people exhibit higher loss aversion λ than younger people, an increase in the proportion of the older population $\frac{z_{t+1}}{z_t}$ will lead the loss aversion feature of prospect theory for the average investor λ_{21} to start dominating the diminishing sensitivity feature α_{21}. This, in turn, results in a reduction of the disposition effect and a weakening of the momentum effect. Consequently, the returns of the momentum factor, *WML,* are anticipated to be negatively related to changes in the proportion of the older population, $d^{Old}/_{Popn}$.

We express our hypothesis as the regression equation

$$WML_t = \alpha_0 + \alpha_1\, d^{Old}/_{Popnt} + \alpha_2\, ControlVar_t + \varepsilon_t \tag{12}$$

where α_0, α_1 and α_2 are the regression coefficients,
$ControlVar_t$ represents the relevant control variables, and
ε_t is the random disturbance term.

A few salient points regarding our regression equation merit attention. Firstly, in line with Lee (2013), our empirical tests on the momentum factor are focused on long-horizons rather than shorter time-frames. This approach is adopted to mitigate the impact of short-term market noise that often obscures true long-term relationships. Furthermore, as Arnott and Chaves (2012) emphasize, "long horizons provide a better test for low frequency population changes." Secondly, it is crucial to note a distinction in our study from other momentum research. While in many studies the term 'time horizon' refers to the holding period of the formed portfolio, in our context, the term 'long-horizon returns' (used interchangeably with long-run returns) simply denotes the cumulative returns of the momentum factor over the specified time horizon. This distinction underscores the unique perspective adopted in our research and further emphasizes our focus on the long-term effects of demographic changes on the momentum factor.

3. Data sample and methodology

We discuss in this section the data sources and definitions of the variables used.

Following Fama and French (2012) and Carhart (1997), we define the momentum factor as the difference in returns between the winner portfolio and the loser portfolio. The portfolios are formed at the end of month t based on the lagged momentum returns of the stocks (measured as the stock's cumulative return from t-11 to t-1 month). The stock universe from which the portfolios are constructed encompasses all firms listed on the NYSE, AMEX and NASDAQ. The long-horizon returns of the momentum factor are then computed as the cumulative return over a ten-year period. This time frame is consistent with that employed in studies such as Lee (2013) and Campbell and Shiller (1998). All data used for our calculations are downloaded from the website of Kenneth French[3].

[3] The returns reported by Kenneth French are all multiplied by 100, and the data is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Our demographic structure variable, $^{Old}/_{Popn}$, is measured as the proportion of population aged 65 years old and above, and is consistent with the definition used by Graham and Kumar (2006) and Poterba (2001). The chosen threshold age of 65 years also corresponds to Richard Johnson's definition of the "hyper loss averse" retirees. The demographic variation variable is therefore expressed as the annual change in the old-to-population ratio, $d^{Old}/_{Popn}$. The US and international population data used for the calculation of the demographic variables are downloaded from the US Census Bureau and OECD websites.

We include a number of control variables in our study.

The first control variable employed in our analysis is the US nominal GDP growth rate over the last ten years.The inclusion of this variable is motivated the research of Maio and Philip (2018), which suggests that economic activity plays a pivotal role in explaining the momentum anomaly. Specifically, they found that past winners typically yield higher average returns than past losers due to their larger macroeconomic risks. This conclusion finds resonance in the work of Liu et al. (2005), who observed that recent winners have temporarily higher loadings than recent losers on the industrial production growth rate, which accounts for more than half of the observed momentum profits. These studies collectively suggest a positive relationship between the momentum factor and economic activity. However, it is also imperative to consider the demographic factors that might influence economic activity. A considerable body of academic literature (Bloom et al., 2010; Maestas et al., 2013) posits that an aging population tends to impede economic growth due to a range of factors, including reduced labour force participation, increased healthcare costs, diminished resources for growth-generating investments, lower savings rate, and shifts in consumption patterns. To ensure that our demographic variable is not merely a proxy for economic activity, we have incorporated the US nominal GDP growth rate over the last ten years GDP_growth_t as a control variable. This data is obtained from the US Bureau of Economic Analysis

Our second control variable used is the state of the market, which is informed by the lagged market return. As demonstrated by Cooper, Gutierrez and Hameed (2004) the state of the market contains valuable information about the profitability of momentum strategies. Their findings are consistent with with two key theories by Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (2000), which attribute momentum profits to different behavioural biases. Daniel, Hirshleifer and Subrahmanyam (1998) suggest that overconfidence among investors about their private information precipitates an overreaction. This overreaction is compounded if investors exhibit a self-attribution bias, where successes are attributed to their own skill and failures to external factors. This behaviour amplifies overconfidence when investors encounter confirming news, thereby fuelling the initial overreaction and generating return momentum. This theory implies that momentum profits would be higher in the aftermath of market gains due to elevated overconfidence. Conversely, Hong and Stein (2000) posit a theory based on initial underreaction followed by overreaction. Their model comprises two types of investors: "newswatchers", who rely on private information, and "momentum traders", who depend on past price changes. The slow diffusion of private information leads to an initial underreaction. However, momentum traders, attracted by the ensuing positive serial correlation in returns, subsequently induce an overreaction. The model of Hong and Stein (2000) thereby predicts that momentum profits will be greater following market gains if an increase in wealth leads to a decrease in risk aversion. Both theories collectively suggest that investor behaviour, specifically overconfidence or risk aversion, can significantly influence momentum profits and their variation across different market states. The behavioural biases result in overreaction or underreaction to information, leading to the observed short-term momentum in stock returns. Huang (2006) investigated the proposition of Cooper, Gutierrez and Hameed (2004) in an international context and found supportive evidence. Consequently, we include the market state Mkt_state_t, expressed as a dummy variable that takes the value of one when the market returns have been positive over the last ten years, and zero otherwise, as a control variable.

Our final set of control variables are the Fama-French factors. Although there are no a priori reasons to expect momentum to be driven by these factors, they are included for completeness as the Fama-French factors have been widely recognized in the field of finance for their ability to explain variations in stock returns. The Fama-French factors are constructed using the 6 value-weighted portfolios formed on market capitalisation and book-to-market. The small cap effect FF_SMB_t is calculated as the average return on the three small portfolios minus the average return on the three big portfolios i.e. SMB = 1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth), while the value effect FF_HML_t is calculated as the average return on the two value portfolios minus the average return on the two growth portfolios i.e. HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth). $FF\_Mkt\_Prem_t$ is the excess return on the market and is calculated as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate.

Consistent with the methodology of Fama (1998), Poterba (2001) and Lee (2013), we employ Ordinary Least Squares (OLS) regression on overlapping data to estimate the relation in equation (12). To adjust for the moving average process in the errors induced by the use of overlapping data, we calculate the standard errors using the Newey and West (1987) heteroscedasticity and autocorrelation consistent variance matrix based on the Bartlett kernel. This approach facilitates asymptotically valid hypothesis tests. The time period considered in this study spans from 1936 to 2022, representing the period for which long-term data for the momentum factor is available.

It is noteworthy to mention that the extant academic literature presents several potential control variables that could be incorporated into our empirical model. However, the limited data availability for many of these variables necessitates a judicious approach to their inclusion. In order to maintain the comprehensive length of the time period under study, we have elected to restrict the inclusion of these additional control variables to subsequent robustness checks. This decision is predicated on the need to balance the desire for model robustness with the imperative of maintaining a sufficiently extensive temporal scope for our analysis.

4. Empirical Findings

4.1 Aging population and the long-horizon returns of the momentum factor

Table 1 provides the descriptive statistics and a correlation matrix for the long-horizon momentum factor, along with his relationships with the other explanatory and control variables. Notably, the momentum factor displays a slight negative skewness of -0.503 in its distribution, while its kurtosis of 3.030 suggests that the tails of the distribution are akin to those of a normal distribution. A striking observation from the table is the high negative correlation between the long-horizon momentum factor and the annual change in the old-to-population ratio. This negative contemporaneous relationship is also discernible in Figure 1, which presents time series plots of the long-horizon returns of the momentum factor and the annual change in the old-to-population ratio, with the axis for the latter being reversed. These findings underscore the potential negative influence of demographic shifts on the momentum factor, providing support for our proposed hypothesis.

Our OLS regression result is reported in column 1 of Table 2. As hypothesized, the demographic variation variable exhibits a negative relationship with the long-horizon returns of the momentum factor, a relationship that is significant at the 1% level. Indeed, our results indicate that a 1% annual decline in the old-to-population ratio corresponds to a rise of +630.959% in the ten-year cumulative returns of the momentum factor. This finding lends robust empirical support to our hypothesis: an increase in the proportion of the older population, and the consequent increase in loss aversion, leads to a reduction in the disposition effect and a decrease in the ten-year cumulative momentum profits. This outcome underlines the significant influence of demographic shifts on financial markets, particularly on the momentum factor. Interestingly, none of the regression coefficients of our control variables are significantly related to the momentum factor.

4.2 Robustness checks

4.2.1 Shorting

Prior research (Moskowitz and Grinblatt, 1999; Hong et al., 2000) has demonstrated that momentum profits are primarily derived from the short side of the trade, i.e., the shorting of losers. For instance, Fuertes, Miffre, and Tan (2009) analysed various winner and loser portfolios and discovered that the annualised alphas of the loser portfolios ranged from -12.14% to -7.78%, all significant at the 1% level. Conversely, the winner portfolios yielded alphas of only +1.15% to +7.13%, with significance observed in merely four of the nine portfolios examined. Subsequent studies (Israel and Moskowitz, 2013; Asness et al., 2014; Jegadeesh and Titman, 2001), however, have indicated that the positive return of momentum strategies are derived from both the buy and sell positions of the trade. In light of these findings, we sought to ascertain the robustness of our hypothesis in relation to the role that shorting may play in the returns of the momentum factor.

To this end, we adopted the method of Israel and Moskowitz (2013) by breaking down the portfolios into finer sorts and calculating the momentum factor as the return differences between (i) deciles 1 and 10 (D1_D10), (ii) the average of deciles 1 and 2 and the average of deciles 9 and 10 (D2_D9), (iii) the average of deciles 1 to 3 and the average of deciles 8 to 10 (D3_D8), and (iv) the average of deciles 1 to 4 and the average of deciles 7 to 10 (D4_D7). We then gauge the importance of the of the long and short sides of these strategies, and any asymmetries in their returns, by examining these return differences to determine whether the extreme portfolios behave very differently.

The results of our regressions, as shown in columns 2-5 of Table 2, demonstrate that even as one moves from deciles 10-1 to deciles 7-4, our demographic variation variable remains negatively related to long-horizon momentum profits at a 1% significance level, with the magnitude of the regression coefficients declining monotonically. This consistency in findings across different portfolio combinations reinforces the robustness of our hypothesis and emphasises the significant influence of demographic shifts on long-term momentum profits.

4.2.2 Sentiment

Antoniou et al. (2013) propose that sentiment influences the dissemination of information through a mechanism known as "cognitive dissonance," where individuals exhibit a stronger underreaction to information that contradicts their prevailing sentiment. This suggests that optimistic (pessimistic) sentiment can slow the diffusion of unfavorable (favorable) news among loser (winner) stocks, consequently, momentum profits are positive when investor sentiment is optimistic.

To ensure that our hypothesis holds when accounting for sentiment considerations, we follow the method of Kim and Suh (2018) and employ the University of Michigan consumer sentiment index as a representation of investor sentiment. We then gauge sentiment by taking the mean of the quarterly index readings over the past ten years. However, given that the quarterly survey only commenced in 1960, our robustness check using this measure is limited to data from 1969 to 2022.

As shown in column 6 of Table 2, the regression coefficient for the annual change in the proportion of the older population remains statistically significantly negative, even after controlling for investor sentiment. Moreover, the regression coefficient for the sentiment measure is positive and statistically significant, which aligns with the predictions of academic literature. These results show that our hypothesis is robust to the inclusion of investor sentiment considerations.

4.2.3 Trading volume

Technical analysts have long emphasized the significant role of volume data, postulating its predictive capacity for future price movements. This is encapsulated in the adage, "it takes volume to move prices," suggesting that substantial trading volume is a prerequisite for meaningful price movements. In situations where trading volume is lacking, stock prices may exhibit an underreaction to information. As a consequence, if a country's financial market underreacts to information during periods of low trading activity, the deployment of a momentum strategy in that particular market is likely to yield profitable results.

This notion was empirically examined by Chan, Hameed, and Tong (2000), who investigated the impact of trading volume information on the profitability of momentum strategies in international equity markets. Their findings revealed that momentum portfolios implemented in markets with higher trading volume in the preceding period yielded higher profits. This indicates that the strength of return continuation is amplified following an increase in trading volume.

To ascertain the robustness of our findings in relation to trading volume considerations, we incorporate the variable $Trading\_volume_t$, which represents stocks traded as a proportion of GDP, as a control variable. As evident from Column 7 of Table 2, our analysis aligns with the findings of Chan, Hameed, and Tong (2000), revealing a positive relationship between trading volume and momentum profits. Furthermore, our demographic variable maintains its negative correlation with long-term momentum profits at a 1% significance level, reinforcing the robustness of our initial findings.

4.2.4 Financial development and technological innovation

The existing body of literature posits that underreaction and momentum are most likely to manifest in situations characterised by relative scarcity of information, high trading costs, particularly in relation to short selling, and thin trading. For instance, Hong and Stein (1999) contend that momentum arises due to the slow dissemination of private information in the market. A sluggish rate of information dissemination results in a correspondingly slow rate of information diffusion, thereby leading to elevated momentum profits. Conversely, rapid information dissemination and assimilation lead to swift diffusion and diminished momentum profits. This perspective is corroborated by Hong et al. (2000), who found the momentum effect to be most pronounced for firms where diffusion would be slowest, such as those with limited analyst coverage and small firms.

Trading costs, inclusive of short selling, are likely to influence underreaction, as these costs hinder the arbitrage process that could align prices with their fundamental value (Pontiff, 1996; Shleifer and Vishny, 1997). Similarly, thin trading can augment the risks associated with arbitrage, as arbitrageurs cannot guarantee the ease of finding a counterparty when it becomes necessary to close out a trade. Moreover, thin trading can also lead to a spurious association between consecutive returns (Chordia and Shivakumar, 2006).

To account for the potential impact of trading costs and the speed of information diffusion on momentum profits, we incorporate two proxies in our analysis: the Financial Development Index Fin_devt_t from the International Monetary Fund (IMF) and the Global Innovation Index $Glb\_innovate_t$ from the World Intellectual Property Organization (WIPO) for the United States. These indices serve as effective measures for the aforementioned factors, allowing us to control for their effects in our study.

Columns 8-9 reveal that, in both instances, an aging population exerts a negative impact on long-term momentum profits at 1% significance levels. While there is no strong association between momentum profits and technology innovation which proxies for the speed of information dissemination here, a positive correlation is observed with financial development. This contradicts theories that attribute the profitability of momentum strategies to trading inefficiencies, and aligns with the findings of Korajczyk and Sadka (2004). Their study suggests that transaction costs do not fully account for the return persistence exhibited by past winner stocks, a conclusion that our study corroborates.

4.2.5 Investor sophistication

The magnitude of the disposition effect observed in investors is often linked to investor characteristics associated with increased sophistication, such as income, profession, and trading experience. Dhar and Zhu (2006) and Chen et al. (2007), through their examination of the trading records from a leading brokerage house in the US and China respectively, found that wealthier investors and those in professional occupations exhibit a significantly smaller disposition effect.

To ensure that our findings are not simply acting as a proxy for investor sophistication, we employ net worth as a measure for investor sophistication. This measure was also used by Dhar and Zhu (2006), who endorsed it due to two primary reasons. Firstly, individuals with high income are more likely to have access to financial advice from financial and tax planners, as they can afford such value-added services. Moreover, wealthier investors have more at stake in their investments, making it more worthwhile for them to utilise such services. Secondly, annual income is likely to be correlated with occupations, implying that high-income investors are also more likely to be engaged in professional occupations. The Survey of Consumer Finances (SCF), a triennial cross-sectional survey conducted by the Board of Governors of the Federal Reserve System, provides comprehensive data on the financial status and demographic characteristics of U.S. families. This includes information on families' balance sheets, pensions, and income. Consequently, we sourced the data pertaining to the net worth of the older population from the SCF for the purposes of our study.

As observed in column 10 of Table 2, consistent with our hypothesis, greater investor sophistication among the older population, as indicated by their higher net wealth, exhibits a negative relationship with momentum profits at a 1% significance level. This likely suggests the operation of a lower disposition effect. However, even after controlling for this factor, our demographic variable persists as a significant negative driver of the momentum factor. This lends credence to our theory that other variables, such as the intensifying influence of the loss aversion feature of prospect theory relative to that of diminishing sensitivity, also contribute to the lower disposition effect and subsequent reduction in momentum profits.

4.2.6 Governance

Sherif and Chen (2019) explored the existence of momentum and demonstrated that the quality of governance, encapsulated by accountability, government effectiveness, and corruption control, exerts a significant influence on the stability of financial markets and the institutional frameworks that regulate and manage stock markets. This, in turn, notably impacts international momentum profits. Specifically, their findings indicated a negative correlation between governance quality and momentum returns in the majority of countries.

In a concurrent vein, Imran, Wong, and Ismail (2022) conducted a study encompassing a global sample of 40 countries spanning from 1996 to 2018. Their findings corroborated the negative and significant relationship between the World Governance Indicators index and momentum returns, as initially identified by Sherif and Chen (2019). They attributed the negative coefficient value of the governance indicator to the overreaction hypothesis, suggesting that markets with higher governance quality exhibit lower behavioural bias. In their detailed analysis, four governance indicators, namely control over corruption, government effectiveness, stability, and avoidance of violence, were found to have a statistically significant negative relationship with momentum returns. However, two of the governance indicators did not exhibit a significant relationship.

This study incorporatess various indicators of market governance as control variables in our robustness test. Specifically, we utiltse the six aggregate Worldwide Governance Indicators (WGI) from the World Bank, which include Voice and Accountability $WGI{:}Voice_t$, Political Stability and Absence of Violence/Terrorism $WGI{:}Stability_t$, Government Effectiveness $WGI{:}Govt_t$, Regulatory Quality $WGI{:}Reg_t$, Rule of Law $WGI{:}Law_t$, and Control of Corruption $WGI{:}Ctrl_t$. The data for these indicators, spanning the period from 1996 to 2022, were obtained from the World Bank.

The results of our regression, presented in Column 11 of Table 2, reveal that, after accounting for governance considerations, the older population continues to be a negative and significant driver of long-term momentum profits. Among the six governance indicators, four exhibit statistically significant relationships with the momentum factor. Intriguingly, three of these indicators display positive relationships with momentum returns. Only one of them $WGI{:}Voice\_\&\_accountability_t$, aligns with findings from other studies, showing a negative relationship with momentum returns.

4.2.7 Time trend

To ascertain that our demographic variation variable is not merely a proxy for a time-varying influence, we have also included a time trend as a control variable in our analysis. As shown in column 12 of Table 2, the inclusion of a time trend does not alter our earlier finding that demographics play a significant role in determining the profitability of the momentum factor. Moreover, the lack of significance of the time trend variable suggests that momentum profits are not subject to time-varying effects.

4.2.8 Small caps

Studies by Hong, Lim and Stein (2000), Fama and French (2012) and Rouwenhorst (1998) have found that the momentum effect is significantly more pronounced among small cap stocks compared to large cap stocks, with momentum profits declining as firm size increases. In order to verify that our hypothesis is not limited to specific market cap partitions, we examined the relationship between the demographic variation variable and the long-horizon momentum profits of both small cap and large cap stocks.

The regression results presented in columns 13-14 of Table 2 indicate that the annual change in the proportion of the older population is a statistically significant determinant of long-horizon momentum profits for both small cap and large cap stocks. This suggests that our hypothesis holds across different market cap segmentations, thereby demonstrating its robustness. However, it is worth noting that the significance level of the regression coefficient appears to be higher amongst small cap stocks, while the magnitude of the coefficient is also greater compared to that of large cap stocks. These observations highlight the nuanced influence of demographic shifts on momentum profits across different market cap partitions.

4.2.9 Alternative time horizon definition

This study is centred on the long-run horizon, which we define as a ten-year period. This time frame aligns with those used in other studies (Campbell and Shiller, 1998; Lee, 2013) and is also in line with the intuition of Arnott and Casscells (2003). To ascertain the robustness of our hypothesis to alternative definitions of the time horizon, we also calculated the long-horizon returns as the cumulative five-year returns of the momentum factor.

As shown in column 15 of Table 2, the demographic variation variable continues to exhibit a negative relationship with long-run momentum profits at a 1% significance level, even under this alternative time horizon., and shows that our hypothesis is valid across different time horizons.

4.2.10 Varying time periods

While there are no a priori reasons to believe that the nature of our hypothesized relationship alters over time, we nevertheless split our sample into equal halves and perform separate OLS regressions for the two time periods, 1936-1979 and 1980-2022, to test the robustness of our results. These results are presented in columns 16-17 of Table 2.

The regressions reveal that the annual change in the proportion of the older population is a significant driver of momentum profits in both time periods, indicating that this relationship has remained consistent over time.

4.2.11 Inclusion of all explanatory variables

A meticulous inclusion of all explanatory variables pertinent to our regression model is delineated in Column 18 of Table 1. While the temporal scope of the analysis has been significantly condensed, this methodological approach ensures the inclusion of a broad spectrum of determinants that might influence our hypothesis. Despite this temporal limitation, our demographic variable maintains a negative association with long-horizon momentum profits, a relationship that persists with statistical significance at the 5% level. This finding underscores the enduring impact of demographic factors on the dynamics of long-horizon momentum profits, even when the analysis is constrained by a shortened time frame.

4.2.12 Extension to international markets

Although the following analysis extends beyond the scope of conventional robustness checks and leans more towards potential future research, we have expanded our empirical study to encompass additional international markets. However due to data availability constraints, our exploration of international markets is limited to the United Kingdom, Japan and the developed regions of North America[4], Europe[5], and Asia Pacific

[4] North America includes United States and Canada.
[5] Europe includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdom.

ex Japan[6]. The data is sourced from the websites of Kenneth French and the US Census Bureau, and from Gregory and Christidis (2013).

The charts for each country and developed market region are plotted for the fullest time period for which both long-run returns and demographic variation data are available, as depicted in Figure 3. A graphical examination reveals that while the relationship for Japan appears to be contrary to our hypothesis, the relationships for North America, Europe, Asia Pacific excluding Japan, and the United Kingdom all appear to be at least moderately consistent with our hypothesis.

These observations suggest that the influence of demographic shifts on momentum profits may vary across different geographical contexts, underscoring the complex interplay between demographic changes and financial markets. Nevertheless, the general consistency of our hypothesis across multiple markets reinforces its robustness and global relevance.

5. Conclusion

The momentum effect is an empirically observed phenomenon where stocks that have performed well relative to peers (winners) typically continue to outperform, while stocks that have performed poorly (losers) tend to persist in underperforming. Prospect theory has been employed to explain this phenomenon, positing that individuals' tendency to sell their winners too early while holding onto their losers for too long results in a disposition effect that causes price to underreact to information. This delayed price adjustment to fundamentals subsequently leads to the momentum effect.

While it is generally acknowledged that for the average investor, the disposition effect arises when the diminishing sensitivity feature of prospect theory dominates the loss aversion feature, older individuals can sometimes exhibit a reverse disposition effect. As older individuals face a decline in resources across all domains due to aging, their motivation reorients, leading to higher loss aversion compared to younger individuals. This heightened loss aversion can outweigh their diminishing sensitivity to gains, resulting in a reduction of their disposition effect (or even a reverse disposition effect) and a weakening of the momentum effect.

We hypothesize that as the population ages, the long-horizon returns of the momentum factor should be negatively related to the change in the proportion of the older population. Our empirical findings lend robust support to our hypothesis, demonstrating that our results hold when controlling for shorting, market cap

[6] Asia Pacific ex Japan includes Australia, Hong Kong, New Zealand and Singapore.

partitions, sentiment, trading volume, trading costs and speed of information diffusion, investor sophistication, governance, varying time periods, time trend, and alternative time horizon definitions. These results underscore the significant influence of demographic shifts on momentum profits and the complex interplay between demographic changes and financial markets.

The findings from our study have implications across a broad spectrum of the financial ecosystem, elucidating the critical interplay between demographic trends and financial market dynamics. For retirement planners and pension funds, the insights suggest a pivotal need to incorporate demographic considerations into investment strategies and management practices, potentially enhancing the alignment with evolving population structures to optimize market returns. Investors and financial analysts are provided with a nuanced understanding of how shifts in demographics, particularly the aging of populations, may influence momentum profits, thereby offering a foundation for making more informed decisions that could lead to the development of investment strategies that are resilient to long-term demographic trends. This study also signals to financial market regulators the importance of reassessing oversight mechanisms to mitigate the risks associated with undue volatility and systemic vulnerabilities, highlighted by the significant impact of aging populations on momentum profits and market dynamics. Financial institutions engaged in developing new investment products or adjusting existing ones can incorporate considerations of the changing market conditions influenced by demographic trends, ensuring that these products remain relevant and effective for an aging demographic. Additionally, the findings serve as a base for further academic research into the intersection of demography and financial markets and promoting a deeper understanding of demographic factors within financial economics.

References:

1. Antoniou, C., Doukas, J., and Subrahmanyam, A., 2013. Cognitive Dissonance, Sentiment, and Momentum. Journal of Financial and Quantitative Analysis 48(1), 245-275.
2. Arnott, R. and Casscells, A., 2003. Demographics and Capital Market Returns. Financial Analysts Journal 59(2), 20-29.
3. Arnott, R.D. and Chaves, D.B., 2012. Demographic Changes, Financial Markets, and the Economy. Financial Analyst Journal 68(1), 23-46
4. Asness, C., Frazzini, A., Israel, R., and Moskowitz, T., 2014. Fact, Fiction and Momentum Investing. Journal of Portfolio Management 40th Anniversary edition.
5. Benartzi, S., 2010. Hyper Loss Aversion: Retirees Show Extremely High Sensitivity to Loss, But Shy Away from Guarantees that Require Giving Up Control. Based on interview with Eric Johnson in Behavioral Finance and the Post-Retirement Crisis, prepared and submitted on behalf of Allianz in response to Department of the Treasury/Department of Labor Request for Information regarding lifetime income options in retirement plans
6. Bloom, D., Canning, D., and Fink, G., 2010. Implications of Population Ageing for Economic Growth. Oxford Review of Economic Policy 26(4), 583-612.
7. Carhart, M. 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52, 57–82.
8. Campbell, J. and Shiller, R., 1998. Valuation Ratios and the Long-Run Stock Market Outlook: An Update. National Bureau of Economic Research Working Paper 8221
9. Chan, K., Hameed, A. and Tong, W., 2000. Profitability of Momentum Strategies in the International Equity Markets. Journal of Financial and Quantitative Analysis 35(2), 153-72.
10. Chen, G., Kim, K., Nofsinger, J. and Rui, O., 2007. Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors. Journal of Behavioral Decision Making 20, 425-51.
11. Chordia, T., Shivakumar, L. and Subrahmanyam, A., 2006. The Cross-Section of Daily Variation in Liquidity. In Advances In Quantitative Analysis Of Finance And Accounting: Essays in Microstructure in Honor of David K Whitcomb (pp. 75-110).
12. Cooper, M., Gutierrez, R. and Hameed, A., 2004. Market States and Momentum. Journal of Finance 59(3), 1345-65.
13. Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor Psychology and Security Market Under-and Overreactions. Journal of Finance 53(6), 1839-85.
14. Depping, M. and Freund, A., 2011. Normal Aging and Decision Making: The Role of Motivation. Human Development 54(6), 349-67.
15. Depping, M. and Freund, A., 2013. When Choice Matters: Task-Dependent Memory Effects in Older Adulthood. Psychology and Aging 28(4), 923-36.

16. Dhar, R., and Zhu, N., 2006. Up Close and Personal: Investor Sophistication and the Disposition Effect. Management Science 52(5), 726-40.
17. Fama, E., and French, K., 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance 51(1), 55-84.
18. Fama, E., 1998. Market Efficiency, Long-term Returns and Behavioral Finance. Journal of Financial Economics 49, 283-306.
19. Fama, E. and French, K., 2012. Size, Value and Momentum in International Stock Returns. Journal of Financial Economics 105, 457-72.
20. Fuertes, A., Miffre, J. and Tan, W., 2009. Momentum Profits, Nonnormality risks and the Business Cycle. Applied Financial Economics 19(12), 935-53.
21. Gächter, S., Johnson, E. and Herrmann, A., 2007. Individual-Level Loss Aversion in Riskless and Risky Choices. Centre for Decision Research and Experimental Economics CeDEx Discussion Paper No. 2007–02
22. Graham, J. and Kumar, A., 2006. Do Dividend Clienteles Exist? Evidence on Dividend Preferences of Retail Investors. The Journal of Finance, 61(3), pp.1305-1336.
23. Gregory, A. and Christidis, A., 2013. 'Constructing and Testing Alternative Versions of the Fama-French and Carhart Models in the UK. Journal of Business Finance and Accounting 40(1), 172-214.
24. Grinblatt, M. and Han, B., 2005. Prospect Theory, Mental Accounting, and Momentum. Journal of Financial Economics 78 (2), 311-39.
25. Grinblatt, M. and Keloharju, M., 2001. What Makes Investors Trade?. Journal of Finance 56(2), 598-616.
26. Grubb, M., Tymula, A., Gilaie-Dotan, S., Glimcher, P., and Levy, I., 2016. Neuroanatomy Accounts for Age-Related Changes in Risk Preferences. Nature Communications 7(1).
27. Guttman, Z., Ghahremani D., Pochon J., Dean A., and London, E., 2021. Age Influences Loss Aversion Through Effects on Posterior Cingulate Cortical Thickness. Front Neuroscience
28. Hong, H., Lim, T. and Stein, J., 2000. Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. Journal of Finance 55(1), 265-95.
29. Hong, H. and Stein, J. , 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. Journal of Finance 54(6), 2143-84.
30. Huang, D., 2006. Market States and International Momentum Strategies. Quarterly Review of Economics and Finance 46(3), 437-46.
31. Imran, Z., Wong, W. and Ismail, R., 2022. Governance Quality and Momentum Returns: International Evidence. Journal of Economic and Administrative Sciences, Forthcoming.
32. Israel, R. and Moskowitz, T., 2013. The Role of Shorting, Firm Size, and Time on Market Anomalies. Journal of Financial Economics 108(2), 275-301.
33. Jegadeesh, N. and Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance 48, 65-91.

34. Jegadeesh, N. and Titman, S., 2001. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. Journal of Finance 56(2), 699-720.
35. Kahneman, D. and Tversky, A.,1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263-92.
36. Kim, B. and Suh, S., 2018. Sentiment-Based Momentum Strategy. International Review of Financial Analysis 58, 52-68.
37. Korajczyk, R. and Sadka, R., 2004. Are Momentum Profits Robust to Trading Costs?. Journal of Finance 59(3), 1039-82.
38. Lee, K. F., 2013. Demographics and the Long-Horizon Returns of Dividend-Yield Strategies. Quarterly Review of Economics and Finance 53(2), 202-18.
39. Lemaitre, H., Goldman, A., Sambataro, F., Verchinski, B., Meyer-Lindenberg, A., Weinberger, D., and Venkata, M. 2012. Normal Age-Related Brain Morphometric Changes: Nonuniformity Across Cortical Thickness, Surface Area and Gray Matter Volume?. Neurobiological Aging 33(3), 611–617.
40. Li, Y., and Yang, L., 2013. Prospect Theory, the Disposition Effect, and Asset Prices. Journal of Financial Economics 107(3), 715-39.
41. Liu, L. X., Warner, J., and Zhang, L., 2005. Momentum Profits and Macroeconomic Risk. National Bureau of Economic Research Working Paper No. 11480
42. Maestas, N., Mullen, K., and Powell, D., 2016. The Effect of Population Aging on Economic Growth, the Labor Force and Productivity. National Bureau of Economic Research Working Paper No. w22452.
43. Maio, P. and Philip, D., 2018. Economic Activity and Momentum Profits: Further Evidence. Journal of Banking & Finance 88, 466-482.
44. Moskowitz, T., and Grinblatt, M., 1999. Do Industries Explain Momentum?. Journal of Finance 54(4), 1249-90.
45. Newey, W. and West, K., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-8.
46. Newey, W. and West, K., 1994. Automatic Lag Selection in Covariance Matrix Estimation. Review of Economic Studies 61(4), 631–54.
47. Odean, T., 1998. Are Investors Reluctant to Realize Their Losses?. Journal of Finance 53(5), 1775-98.
48. Pontiff, J., 1996. Costly Arbitrage: Evidence from Closed-End Funds. Quarterly Journal of Economics 111(4), 1135-51.
49. Poterba, J.M., 2001. Demographic Structure and Asset Returns. Review of Economics and Statistics 83(4), 565-84.
50. Rouwenhorst, K., 1998. International Momentum Strategies. Journal of Finance 53(1), 267-84.
51. Sherif, M. and Chen, J., 2019. The Quality of Governance and Momentum Profits: International Evidence. British Accounting Review 51(5), 100835.
52. Shleifer, A. and Vishny, R., 1997. The Limits of Arbitrage. Journal of Finance, 52(1), 35-55.

53. Storsve, A., Fjell, A., Tamnes, C. Westlye, L., Overbye, K. Aasland, H., and Walhovd, K., 2014. Differential Longitudinal Changes in Cortical Thickness, Surface Area and Volume Across the Adult Life Span: Regions of Accelerating and Decelerating Change. Journal of Neuroscience 34 (25), 8488-8498.
54. Tanaka, T., Camerer, C. and Nguyen, Q., 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. American Economic Review 100, 557-71.
55. Tversky, A. and Kahneman, D., 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty 5, 297–323.
56. Wu, G. and Gonzalez, R., 1996. Curvature of the Probability Weighting Function. Management Science 42, 1676-90.

Table1 : Descriptive statistics

	WML_{10Y}	$d^{Old}/_{Popn}$	*FF_Mkt_Prem*	*FF_SMB*	*FF_HML*	*GDP_growth*	*Mkt_state*
Mean	132.591	0.129	119.522	37.497	55.632	100.101	0.943
Standard deviation	100.995	0.115	105.692	55.511	50.836	52.311	0.234
Skewness	-0.503	1.161	0.567	0.972	0.477	0.763	-3.803
Kurtosis	3.030	4.440	2.601	3.382	4.267	3.189	15.461
Maximum	350.441	0.471	393.448	213.165	239.081	255.328	1.000
Minimum	-78.357	-0.079	-40.171	-40.999	-57.898	-10.634	0.000
	Correlation matrix						
WML_{10Y}	1.000	-0.747***	0.109	-0.130	0.289***	0.157	0.054
$d^{Old}/_{Popn}$	-0.747***	1.000	-0.074	0.100	-0.392***	-0.153	-0.062
FF_Mkt_Prem	0.109	-0.074	1.000	-0.372***	0.001	-0.115	0.339***
FF_SMB	-0.130	0.100	-0.372***	1.000	0.220**	0.448***	-0.167
FF_HML	0.289***	-0.392***	0.001	0.220**	1.000	0.654***	0.120
GDP_growth	0.157	-0.153	-0.115	0.448***	0.654***	1.000	0.244**
Mkt_state	0.054	-0.062	0.339***	-0.167	0.120	0.244**	1.000

*Note: Significance levels: *** = 1%, ** = 5%, * = 10%.*

Table 2: Regressions of long-horizon returns of momentum factor against annual change in old-to-population ratio and other control variables, 1936-2022.
The ordinary least squares regressions take the generalised form:

$$WML_t = \alpha_0 + \alpha_1\, dOld/Popn_t + \alpha_2\, FF\_Mkt\_Prem_t + \alpha_3\, FF\_SMB_t + \alpha_4\, FF\_HML_t + \alpha_5\, GDP\_growth_t + \alpha_6\, Mkt\_state_t + \alpha_7\, ControlVar_t + \varepsilon_t$$

where *WML* is the momentum factor and *dOld/Popn* is the annual change in the proportion of older population. The control variables are the Fama-French factors for market premium, size and value which are denoted as *FF_Mkt_Prem*, *FF_SMB* and *FF_HML* respectively, as well as economic activity *Econ_Growth* and market states *Mkt_State*. T-statistics are shown in parentheses and are based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent variance matrix. Lag lengths (l) used to evaluate the serial correlation for the Newey-West correction follows the recommendation by Newey-West (1994) and is computed as l = 4(T/100)^0.25 where T is the number of observations. Significance levels: *** = 1%, ** = 5%, * = 10%.

	(1)	(2)	(3)	(4)	(5)
		Robustness checks			
		Shorting			
		D1 - D10	*D2 - D9*	*D3 - D8*	*D4 - D7*
$d^{Old}/_{Popn}$	-630.959***	-1456.672***	-628.716***	-462.471***	-333.183***
	(-8.149)	(-6.426)	(-6.293)	(-7.748)	(-8.058)
FF_Mkt_Prem	0.064	-0.561*	-0.133	0.061	0.100
	(0.823)	(-1.974)	(-0.766)	(0.558)	(1.217)
FF_SMB	-0.143	-1.417***	-0.448	-0.112	-0.068
	(-0.799)	(-2.990)	(-1.659)	(-0.682)	(-0.578)
FF_HML	0.020	-0.783	-0.088	0.092	0.009
	(0.085)	(-1.103)	(-0.194)	(0.320)	(0.045)
Econ_Growth	0.132	1.473	0.723	0.302	0.286
	(0.377)	(1.324)	(0.988)	(0.659)	(0.915)
Mkt_State	24.375	90.363	59.297	13.906	2.538
	(0.670)	(0.915)	(0.995)	(0.329)	(0.079)
Sentiment	-	-	-	-	-
	-	-	-	-	-
Liquidity	-	-	-	-	-
	-	-	-	-	-
Fin_devt	-	-	-	-	-
	-	-	-	-	-
Gbl_innovate	-	-	-	-	-
	-	-	-	-	-
Wealth	-	-	-	-	-
	-	-	-	-	-
WGI: Voice	-	-	-	-	-
	-	-	-	-	-
WGI: Ctrl	-	-	-	-	-

	-	-	-	-	-
WGI: Govt	-	-	-	-	-
	-	-	-	-	-
WGI:Stability	-	-	-	-	-
	-	-	-	-	-
WGI: Reg	-	-	-	-	-
	-	-	-	-	-
WGI: Law	-	-	-	-	-
	-	-	-	-	-
Year	-	-	-	-	-
	-	-	-	-	-
Constant	169.229***	425.074***	151.622**	121.865**	84.179**
	(4.468)	(3.651)	(2.609)	(2.616)	(2.319)
No of obs	84	84	84	84	84
R-squared	0.620	0.580	0.469	0.492	0.501
F-statistic	20.905	17.686	11.320	12.446	12.860

Table 1 (continued)

	(6)	(7)	(8)	(9)	(10)
	Robustness checks				
	Sentiment	Liquidity	Financial development	Tech innovation	Wealth level
$d^{Old}/_{Popn}$	-401.659***	-610.144***	-541.870***	-260.939***	-129.709***
	(-4.249)	(-4.007)	(-4.511)	(-4.067)	(-2.926)
FF_Mkt_Prem	0.283***	0.383***	0.132	-0.028	-0.187
	(3.470)	(3.800)	(1.051)	(-0.218)	(-1.139)
FF_SMB	-0.041	-1.055***	-1.959***	-1.870***	-1.067**
	(-0.258)	(-3.070)	(-3.635)	(-2.894)	(-2.229)
FF_HML	-0.388	-0.102	-0.022	-0.174	-0.445
	(-1.287)	(-0.196)	(-0.038)	(-0.414)	(-1.131)
Econ_Growth	1.994***	4.284***	2.787**	5.041**	5.859***
	(5.336)	(4.504)	(2.281)	(2.775)	(5.659)
Mkt_State	-19.877	-36.489	-56.899	-29.729	-41.060*
	(-0.615)	(-0.978)	(-1.375)	(-0.873)	(-1.870)
Sentiment	6.076***	-	-	-	-
	(3.787)	-	-	-	-
Liquidity	-	1.041***	-	-	-
	-	(3.253)	-	-	-
Fin_devt	-	-	539.580***	-	-
	-	-	(4.784)	-	-
Gbl_innovate	-	-	-	0.528	-
	-	-	-	(1.243)	-
Wealth	-	-	-	-	-1.736***
	-	-	-	-	(-3.054)
WGI: Voice	-	-	-	-	-
	-	-	-	-	-
WGI: Ctrl	-	-	-	-	-
	-	-	-	-	-
WGI: Govt	-	-	-	-	-
	-	-	-	-	-
WGI:Stability	-	-	-	-	-
	-	-	-	-	-
WGI: Reg	-	-	-	-	-
	-	-	-	-	-
WGI: Law	-	-	-	-	-

	-	-	-	-	-
Year	-	-	-	-	-
	-	-	-	-	-
Constant	-510.004***	-249.896***	-395.997***	-151.100	338.758*
	(-3.059)	(-3.105)	(-3.190)	(-1.517)	(2.021)
No of obs	54	39	34	27	25
R-squared	0.818	0.824	0.851	0.892	0.945
F-statistic	29.616	20.793	21.170	22.530	41.443

Table 1 (continued)

	(11)	(12)	(13)	(14)	(15)
	Robustness checks				
	Governance	Time trend	Small caps		Alt time horizon
			Big	Small	
$d^{Old}/_{Popn}$	-114.719*	-626.278***	-315.096***	-1069.355***	-201.914***
	(-1.985)	(-7.300)	(-5.254)	(-6.706)	(-4.283)
FF_Mkt_Prem	0.022	0.056	0.230**	-0.186	0.054
	(0.148)	(0.854)	(2.338)	(-1.456)	(1.125)
FF_SMB	0.011	-0.157	0.133	-0.654	-0.141
	(0.017)	(-0.662)	(0.787)	(-1.655)	(-1.403)
FF_HML	-1.008***	0.017	0.199	-0.186	-0.009
	(-4.764)	(0.073)	(0.919)	(-0.543)	(-0.057)
Econ_Growth	7.860***	0.119	-0.065	0.377	0.225
	(3.529)	(0.361)	(-0.220)	(0.746)	(0.966)
Mkt_State	-16.897	25.411	-13.965	82.780	13.552
	(-1.137)	(0.739)	(-0.472)	(1.401)	(0.584)
Sentiment	-	-	-	-	-
	-	-	-	-	-
Liquidity	-	-	-	-	-
	-	-	-	-	-
Fin_devt	-	-	-	-	-
	-	-	-	-	-
Gbl_innovate	-	-	-	-	-
	-	-	-	-	-
Wealth	-	-	-	-	-
	-	-	-	-	-
WGI: Voice	-2082.228***	-	-	-	-
	(-5.800)	-	-	-	-
WGI: Ctrl	1351.425***	-	-	-	-
	(5.013)	-	-	-	-
WGI: Govt	1385.728***	-	-	-	-
	(4.917)	-	-	-	-
WGI:Stability	527.163***	-	-	-	-
	(5.949)	-	-	-	-
WGI: Reg	-625.236	-	-	-	-
	(-1.240)	-	-	-	-
WGI: Law	-650.364	-	-	-	-

	(-1.364)	-	-	-	-
Year	-	-0.087	-	-	-
	-	(-0.173)	-	-	-
Constant	-292.274	342.786	101.868***	267.702***	37.781*
	(-0.488)	(0.342)	(2.956)	(4.371)	(1.776)
No of obs	27	84	84	84	84
R-squared	0.969	0.620	0.409	0.607	0.395
F-statistic	36.247	17.704	8.873	19.800	8.371

Table 1 (continued)

	(16)	(17)	(18)
	Robustness checks		
	Varying time periods		All
	1936-1979	1980-2022	variables
$d^{Old}/_{Popn}$	-596.230***	-480.610***	-308.651**
	(-2.941)	(-4.252)	(3.091)
FF_Mkt_Prem	-0.018	0.298***	-1.243***
	(-0.355)	(3.260)	(-5.936)
FF_SMB	-0.473***	-0.403	-0.180
	(-2.835)	(-1.377)	(-0.478)
FF_HML	0.083	0.039	-1.619***
	(0.850)	(0.100)	(-7.307)
Econ_Growth	-0.323**	1.677***	-3.148
	(-2.345)	(4.071)	(-1.203)
Mkt_State	5.140	-28.046	36.086**
	(0.168)	(-0.765)	(2.539)
Sentiment	-	-	5.000
	-	-	(1.279)
Liquidity	-	-	6.257**
	-	-	(3.382)
Fin_devt	-	-	3182.494***
	-	-	(4.142)
Gbl_innovate	-	-	0.691
	-	-	(1.585)
Wealth	-	-	-19.890***
	-	-	(-4.719)
WGI: Voice	-	-	-2732.298***
	-	-	(-5.848)
WGI: Ctrl	-	-	-589.987
	-	-	(-1.473)
WGI: Govt	-	-	1377.930*
	-	-	(2.030)
WGI:Stability	-	-	-71.938
	-	-	(-0.752)
WGI: Reg	-	-	446.360
	-	-	(0.846)
WGI: Law	-	-	-5220.810**

	-	-	(-3.697)
Year	-	-	-47.096***
	-	-	(-3.825)
Constant	259.925***	49.964	105620.969***
	(7.282)	(0.931)	(3.974)
No of obs	41	43	25
R-squared	0.699	0.799	0.995
F-statistic	13.163	23.808	60.489

Figure 1: Time series plots of long-horizon returns of momentum factor versus annual change in old-to-population ratio, 1936-2022

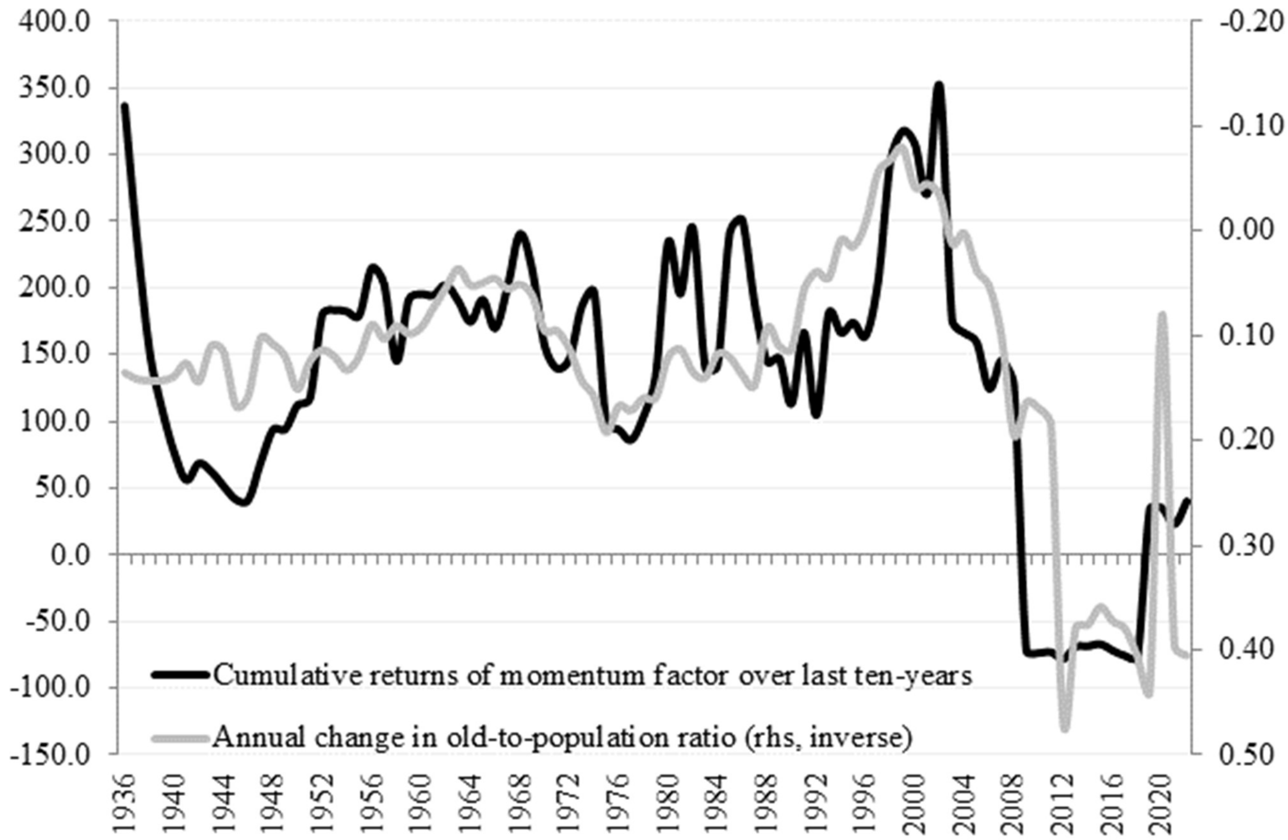
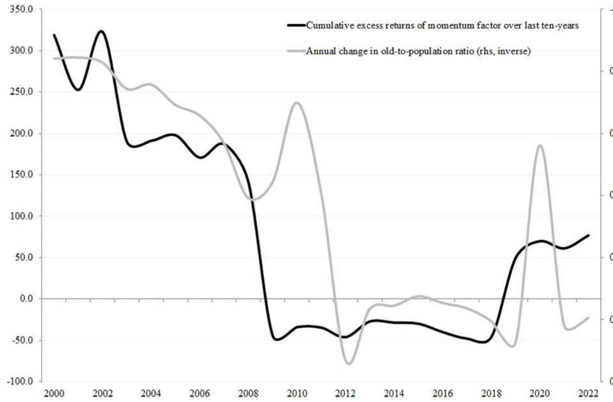
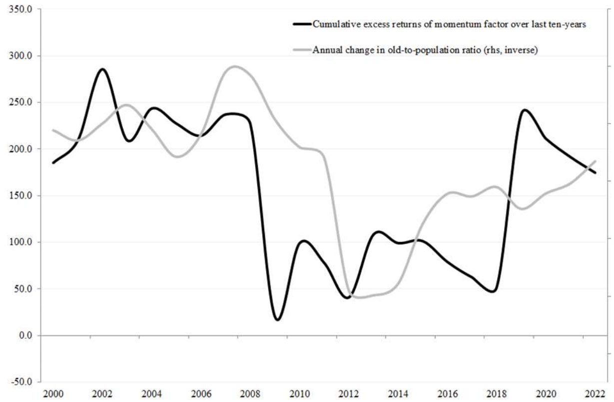


Figure 2: Time series plots of long-horizon returns of momentum factor and annual change in old-to-population ratio for developed international markets

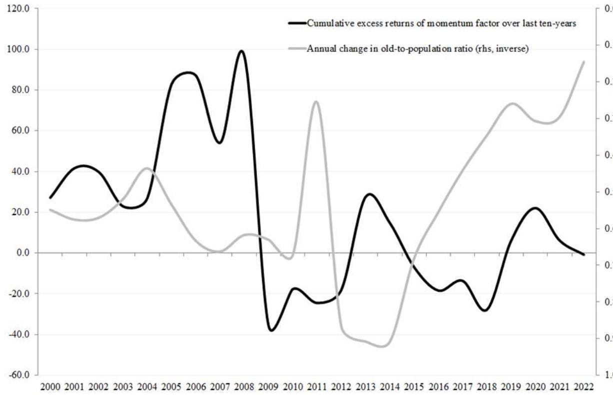
North America, 2000-2022



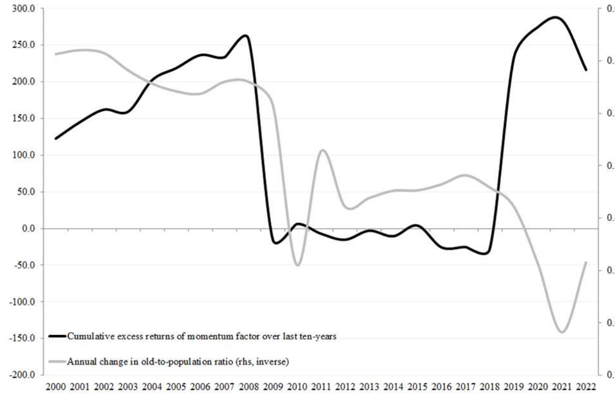
Europe, 2000-2022



Japan, 2000-2022



Asia Pacific ex Japan, 2000-2022



United Kingdom, 1992-2014