Trading in your Golden Years: The Effects of Early Pension Withdrawal on Individual Investments *

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Abstract

We examine the causal effects of a policy allowing early withdrawal of pension funds on individuals' investment behavior. Upon turning 55, eligible individuals may withdraw a portion of their pension savings. Using detailed brokerage data, we find that this liquidity access triggers increased trading, of 9% to 18%, especially in riskier, leveraged assets, without improving investment performance. Trading costs rise and portfolio volatility increases, particularly among males and lower-income investors, ultimately diminishing retirement wealth.

Keywords: Household Finance, Pension Investment, Retail Trading, Individual Portfolio Risk

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1 Introduction

In the United States, the long-standing debate among politicians and policy makers on the extent of privatization within the social security system has regained attention as the program faces growing financial uncertainty (CNBC, 2025).[1] Proponents argue that privatization enables individuals to benefit from investment opportunities and potentially earn higher returns. However, critics caution that allowing millions of inexperienced individuals to invest their savings in volatile stock and bond markets, compounded by high investing costs, poses significant risks (Kinsley, 2014). Similar concerns arise in the context of retirement savings and pension systems around the world due to the changing demographics (Stewart, Jain, and Sandbrook, 2019). Pension savings are intended to provide sufficient income for individuals' financial well-being after retirement, but many defined contribution plans allow early withdrawals, offering flexibility to households facing financial shocks or seeking personal investment opportunities. Although these early withdrawals offer short-term benefits, they also raise the risk of promoting over-consumption and suboptimal investment choices, which could undermine long-term retirement security. Whether early access to pension funds enhances or jeopardizes retirement security remains an open question.

Given the aging population in many economies and the substantial role of retirement savings in household wealth (Census, 2021), understanding liquidity provisions within pension systems holds significant welfare implications.[2] While recent research has

[1] President Donald Trump's efforts to cut federal government spending have ignited discussion about the future of Social Security and the idea of privatization has been regained attention. Proposals for the privatization of social security system in the U.S. dates back to the late 1990s. President George W. Bush outlined the reform of "partial privatization" of social security, allowing individuals to divert their savings in social system into private account for investments, which gave rise to increasing scrutiny. President Barack Obama opposed privatization and promised to protect social security from republican plans to privatize.(The White House Office of the Press Secretary, 2010)

[2] According to The Wealth of Households 2021 Report, retirement accounts constituted 34.1% of aggregate household wealth, ranking as the largest component of household portfolios. More details can be found via this link.

focused on the impact of early access on consumption and debt, little is known about how individuals invest the cash-outs.[3] This is an important gap, as investment decisions, particularly those involving risk, have significant consequences on individual retirement wealth.

In this paper, we provide novel evidence on how granting early access to retirement savings causes individuals to adjust their investment behavior, using a unique institutional setting in Singapore. At age 55, Singapore residents become eligible to withdraw a tax-free lump sum from their Central Provident Fund (CPF), a mandatory defined-contribution pension plan, well before the official retirement age of 63.[4] This age-based rule provides a sharp and predictable increase in funding liquidity without altering lifetime income or other fundamentals.

The CPF system covers over 4 million Singapore residents, with total balances exceeding SGD 500 billion (about US$ 370 billion) as of March 2022. The liquidity unlocked at age 55 is significant: CPF members who turned 55 withdrew a combined SGD 4.6 billion (US$3.4 billion) in 2020 alone, with seven out of ten opting for early lump sum withdrawals.[5] This liquidity event presents investors with both opportunities and risks. On the one hand, the additional liquidity might help individuals to rebalance their portfolio to achieve better diversification, thereby lowering overall risk. On the

[3]Bassett, Fleming, and Rodrigues (1998) evaluate workers' choice to invest the 401(k) plan assets and suggest that many of them, particularly from the lower-income group, do not use 401(k) plans to save for retirement. Argento, Bryant, and Sabelhaus (2015) show that individuals withdraw early from retirement accounts to smooth consumption in response to idiosyncratic shocks, especially those in the lower-income group. Burman, Coe, and Gale (1999). Hurd and Panis (2006) find that most of the cash-out is directed to investments and savings, while Utkus and Young (2011) find that 40% of the survey respondents utilized their 401(k) loans for investment purposes, and 35% borrowed for consumption. Agarwal, Pan, and Qian (2020) report evidence that early access to pension savings in Singapore stimulates increases in bank balances and credit card debt payments.

[4]The age to withdraw pension savings in Singapore was set at 55, coinciding with the retirement age in 1960s and 1970s. Although the retirement age has gradually increased over the decades, the withdrawal age has remained fixed. More information on the policies can be found in CPF homepage and Ministry of Manpower's employment practices on retirement.

[5]There are 2.1 million CPF members who have at least one contribution paid for them in the current or preceding three months. CPF membership statistics, including aggregated CPF balances, can be found via this link. Source: CPF Trend May 2022 and Key CPF Statistics 2020.

other hand, limited cognitive abilities and behavioral biases could drive individuals to overtrade, incur higher transaction costs, take on idiosyncratic risks, and ultimately reduce their retirement wealth. Indeed, Singapore's nationally representative Retirement and Health Study (RHS) indicates a substantial share of CPF members intend to invest these early withdrawals, underscoring the relevance of understanding how pension access influences investment behavior.[6]

Unlike cash windfall (e.g. Bermejo et al., 2022; Bulman, Goodman, and Isen, 2022; Cookson, Gilje, and Heimer, 2022) or access to credit (e.g. Célerier and Matray, 2019), CPF withdrawals are neither unexpected nor linked to broader economic shocks and other life events. The staggered nature of treatment across individuals, determined by an individual's birthdate, allows us to implement a difference-in-differences strategy with individual and time fixed effects.[7] This design facilitates a clean identification of how liquidity access, rather than broader life-cycle factors, shapes financial decisions. We further validate our identification using a battery of falsification tests, including examining alternative age thresholds (50, 54, 60) where no liquidity events occur and analyzing foreign investors who are not subject to the CPF system.

We link this liquidity boost to detailed account-level administrative data from a major brokerage firm to assess how investors respond at both the intensive and extensive margins of trading behavior. The demographic characteristics of the brokerage firm's clients align well with CPF account holders in terms of key dimensions and hence makes a representative sample.[8] Our data covers a large share of retail trading in Singapore, over a decade of trading histories and include both equity (common stocks

[6]Source: What do CPF members do with the cash withdrawals from their CPF after age 55? The RHS also shows that among those who withdrew, the median and average amounts withdrawn were SGD 9,000 and SGD 33,000 respectively.

[7]Appendix Figure A.2 shows that individuals' birthdates are uniformly distributed across months, furhter supporting the randomness of treatment timing..

[8]We show in Figure A.1 that the demographic distribution of all individuals having accounts with the brokerage firm aligns with the distribution of CPF account holders, particularly for the individuals falling into the 55 years age group. (The CPF member statistics is available via this link).

and exchange-traded funds (ETFs)) as well as Contract for Differences (CFDs). CFDs are a form of highly leveraged OTC derivative used for speculative trading and are tied to underlying assets such as common stocks, stock indices, commodities and currencies. CFD trading is highly leveraged, typically requiring individuals to maintain a margin of about 5% to 20% of contract notional value. As such, trading in CFD products can be regarded as engaging in high-risk securities trading.[9] We exploit the staggered timing of CPF eligibility to track trading activities, trading costs, portfolio risk and investment return outcomes in equities and CFDs.

We begin by examining how individuals' trading behavior changes once they become eligible to withdraw pension savings at age 55. Our identification strategy leverages within-individual variation and compares trading behavior before and after age 55, while controlling for time and individual fixed effects. First, we observe a significant increase in deposits into brokerage accounts following the age-55 treshold, consistent with a rise in funding liquidity. It should be noted that individuals may alter their investment activities without necessarily withdrawing funds directly from their CPF accounts. The mere availability of liquidity and the option value of access to CPF funds enhances financial flexibility, which may serve as implicit collateral or reduce perceived precautionary savings needs.

Second, we find a significant increase in individual trading activity post-55, both in terms of the number of trades and the dollar value of trades. For example, the average dollar value of equity trades rises by 9% (SGD 1,596), while trading in leveraged CFDs increases by 18% (SGD 4,268). These increases represent economically meaningful fractions of the median CPF withdrawal of SGD 9,000. Interestingly, among investors trading both equities and CFDs, the uptick in activity is more pronounced in CFDs, suggesting that access to liquidity disproportionately fuels risk-taking at the

[9]CFD products are currently traded in many other countries, including Australia, the United Kingdom, throughout the Euro Zone, Japan, Canada, South Africa, Switzerland, Canada, New Zealand.

intensive margin. On the extensive margin, we observe a 38% increase in the number of new accounts opening, suggesting that the access to liquidity also encourages broader participation in investment..

Third, we examine how portfolio risk evolves around the liquidity event.[10] If individuals use CPF access to rebalance into safer and more diversified portfolios as they approach retirement, we would expect volatility to decline. Instead, we find a significant 25% to 29% increase in return volatility of both equity and CFD portfolios post-55. WE also confirm that the observed increased trading activity is not purely reallocative within their existing portfolios. These results hold after accounting for market-wide volatility and point to a behavioral shift toward riskier investment positions, rather than improved diversification.

Fourth, we assess the financial consequences of increased trading. We expect increased trading activity to result in higher trading costs, including higher brokerage commissions and, in the case of CFDs, higher financing charges as well. Consistent with this expectation, trading costs increase significantly, by 10% for equities and 39% for CFDs, following age-55 access. These figures understate the full cost, as they exclude bid-ask spreads and price impact. More importantly, we find no improvement in net investment performance. On average, individuals incur significant gross losses in equity and, especially in CFD investments, on their post-55 trades. Specifically, individual buy trades significantly underperform their sell trades, with the net buy minus sell portfolio losing approximately 0.9% to 1.5% in equity trading and 4% to 10% in CFD, depending on their investment holding period.[11] This underperformance is especially costly when

[10]Previous research offers mixed findings on the relationship between liquidity and risk appetite. Some studies suggest a negative relationship between risk aversion and liquid income (Andersen and Nielsen, 2011; Calvet, Campbell, and Sodini, 2009; Calvet and Sodini, 2014; Cohn et al., 1975; Meeuwis, 2020; Paravisini, Rappoport, and Ravina, 2017; Wachter and Yogo, 2010), while others indicate a constant (Chiappori and Paiella, 2011) or positive link (Cohen and Einav, 2007).

[11]Our findings are unlikely to be driven by market-wide fluctuations for several reasons. First, the average monthly market portfolio returns is positive: average return of the Singapore Straits Times Index, STI (MSCI World Index) during our sample period is approximately 0.1% (1%). Second, with

compared to the government-guaranteed CPF interest rate of 2.5% to 6% for the money left in the CPF account. The cumulative evidence suggests that early access to pension liquidity not only fails to improve investment outcomes, it often worsens them.

Additionally, these behavioral responses are largely absent in placebo groups—non-residents who are ineligible for CPF access, and individuals turning ages 50, 54, or 60—reinforcing the causal interpretation of our results.

Finally, we explore heterogeneity in these effects across investor characteristics, focusing on gender and income. We find that male investors increase their equity trading more than female investors, and exhibit a larger rise in portfolio volatility without an improvement in the portfolio performance, consistent with literature suggesting greater overconfidence among males (e.g., Barber and Odean (2001)). Interestingly, the increase in CFD trading is similar across genders, suggesting that the risk-seeking behavior in these leveraged products transcends typical gender differences in trading.

We also find stark differences across income groups. Low-income investors show larger behavioral responses to CPF access: they increase equity trading by 10% and CFD trading by an astonishing 93%, and their equity portfolio volatility rises significantly by 10%. High-income individuals, in contrast, show no meaningful change in trading activity. These findings support the notion that liquidity constraints are more binding for low-income individuals, and that CPF access disproportionately enables risk-taking among this group — especially among those already engaged in active trading.

In summary, early access to retirement savings increases trading in private accounts but does not improve investment performance. Individuals, particularly males and those from lower income group, take on greater portfolio risk, while existing participants in riskier asset classes further intensify their exposure. These behaviors ultimately erode

the staggered difference-in-differences (DID) setting and the inclusion of year-month time fixed effects, we rule out the possible influence of other time-varying common shocks. Third, we adjust the individual portfolio performance using a two-factor model, incorporating the excess returns on the MSCI World Index and STI, which produces similar results.

retirement wealth. Our findings highlight important trade-offs in pension system design, especially regarding liquidity access and the structure of post-withdrawal investment options.

Our study contributes to several strands of literature. First, we offer new evidence on the role of liquidity access within retirement savings systems, focusing on how individuals deploy withdrawals in financial markets. Beshears et al. (2015) document heterogeneity in the liquidity of defined-contribution plans across countries, including Singapore's CPF. Beshears et al. (2014) argue that a socially optimal liquidity in retirement savings should include a mix of fully liquid and illiquid accounts. Agarwal, Pan, and Qian (2020) provide evidence of the impact of early pension withdrawals on household consumption and saving decisions. However, much less in known about the impact of liquidity on investment behavior. This omission is important given that investment is a key use of withdrawn pension savings (Hurd and Panis, 2006; Poterba and Venti, 1998; Utkus and Young, 2011). We contribute new evidence using high-frequency, individual-level trading data to show how early access to retirement wealth alters trading intensity, portfolio risk, and investment performance. Our findings broaden the debate on optimal pension design by highlighting the investment-side consequences of liquidity in pre-retirement years.

Second, we contribute to research on retail investor behavior by documenting how liquidity from pension withdrawals amplify well-known behavioral tendencies such as overtrading and risk-seeking.[12] While retail investors are known to suffer from overconfidence and limited cognitive bandwidth (e.g. Barber and Odean (2001),

[12]Previous literature has showed that investors suffer from behavioral biases that may worsen their investment performance. These biases may stem from limited cognitive ability to process information (Merton et al., 1987; Peng and Xiong, 2006), overconfidence (Barber and Odean, 2001) and other forms of irrationality, e.g., sensation seeking (Grinblatt and Keloharju, 2009), familiarity bias (Grinblatt and Keloharju, 2001) and disposition effect (Barber et al., 2007; Odean, 1998). Individuals exhibit a tendency for excessive trading that turns out to be detrimental to investment performance. (Barber and Odean, 2000, 2001; Barber et al., 2022; Odean, 1999).

empirical evidence on how these behaviors manifest in response to discretionary liquidity injections, particularly in risky asset classes, is scarce.[13] We show that access to pension wealth increases retail activity in leveraged products without corresponding performance gains. These result provide new causal evidence on how funding liquidity can exacerbate behavioral biases, especially in complex financial instruments.

Lastly, we add to the growing literature on aging and financial decision-making. Prior research shows that cognitive decline and the lower levels of financial literacy among older individuals are associated with weaker investment performance (Fong et al., 2021; Lusardi and Mitchell, 2011a, 2011b, 2011c).[14] Studies have also identified a negative relationship between age and the quality of financial decision-making (Agarwal et al., 2009; Gamble et al., 2015; Korniotis and Kumar, 2011).[15] On the other hand, older individuals often possess more wealth and resources to manage, and the knowledge gained from past experience may enhance their financial decision-making abilities (Eberhardt, Bruine de Bruin, and Strough, 2019; Li et al., 2015).[16] Our findings suggest that the

[13]Few studies related to retail investors' trading in leveraged products. Schmitz and Weber (2012) investigates the trading behavior of retail investors in warrants and find evidence for the disposition effect.Schroff, Meyer, and Burghof (2013) study individual trading behavior in leveraged bank-issued products during the earnings announcement period and conclude that individual investors tend to be more optimistic (overconfident) regardless of the results of earnings surprise. Bian et al. (2021) focus on margin trading during the 2015 market turmoil in China and analyze margin investors' characteristics. Recent studies document an explosion in retail trading in derivatives, which accentuates trading losses(Bryzgalova, Pavlova, and Sikorskaya, 2023).

[14]Lusardi and Mitchell (2011a), Lusardi and Mitchell (2011c) and Lusardi and Mitchell (2011b) highlight that older individuals tend to be less financial literate, lacking fundamental financial concepts regarding saving, retirement planning, mortgages, and other financial decisions. Additionally, Fong et al. (2021) examines financial literacy among individuals aged 50-70 in Singapore, revealing a notable gap in understanding risk diversification and adherence to age-appropriate investment paths.

[15]Agarwal et al. (2009) examine household credit behavior over the life cycle and conclude that older adults make more financial mistakes than middle-aged individuals, evidenced by higher borrowing rates and more credit card fees. Korniotis and Kumar (2011) demonstrate that older investors exhibit poorer stock selection and risk diversification skill. In a similar vein, Gamble et al. (2015) investigate how age-related cognitive changes impact financial decision-making, revealing that decreased cognitive ability is associated with decreased financial literacy.

[16]Eberhardt, Bruine de Bruin, and Strough (2019) show that the higher levels of experience-based knowledge and lower levels of negative emotions among older individuals positively impact their credit card repayment decisions, money management, and overall financial outcomes. Likewise, Li et al. (2015) illustrates that experience-based knowledge and domain-specific expertise can contribute to improved financial decisions, reflected in higher credit scores and better management in debt payment and health

provision of liquidity at age 55 induces suboptimal trading behavior, including increased risk taking and performance deterioration among individuals near retirement. By linking pension system design to behavioral outcomes in financial markets, our paper highlights an important yet underexplored channel through which aging and policy interact to shape retirement security.

The remainder of this paper is organized as follows: Section 2 introduces the institutional details and background information. Section 3 describes the data sample and the empirical strategy employed in our analysis. In Section 4, we present the results of our study and discuss the findings. Lastly, Section 5 analyzes the heterogeneity effects. Section 6 concludes the paper by summarizing the key findings and implications.

2 Background

2.1 Retirement Savings in Singapore

The Central Provident Fund (CPF) is the cornerstone of Singapore's social security system, a mandatory defined-contribution pension plan that covers all Singaporeans and Permanent Residents. It serves as the primary vehicle for retirement savings and also supports housing, medical expenses, and insurance. Monthly contributions are made by both employees and employers. For individuals below age 55, employees contribute 20% of gross income, while employers contribute an additional 17%.[17]

CPF savings are allocated into three separate accounts. The Ordinary Account (OA), which receives 40% - 60% of contributions, can be used for housing, investments and retirement. The Special Account (SA) (16% - 30%) is reserved for retirement and investment in selected long-term products, while the Medisave Account (MA) is

insurance.

[17]The CPF contribution rates decline modestly with age. More details can be found at link.

designated for healthcare expenses. CPF savings earn government-guaranteed interest of 2.5% to 6% per annum, depending on the account type and represents a risk-free return on pension savings.[18] Funds within CPF are subject to investment restrictions under the CPF Investment Scheme (CPFIS), including limits on a list of approved stocks and asset classes and does not permit investments in foreign securities or leveraged products like CFDs.[19]

Access to CPF savings is restricted prior to age 55. However, upon turning 55, individuals become eligible for a partial, unconditional withdrawal of their CPF savings. Specifically, a Retirement Account (RA) is created at age 55 and automatically funded with a minimum retirement sum (e.g., SGD 181,000 in 2020). CPF members may withdraw any amount in excess of the required balance, and those who do not meet the minimum can still withdraw up to SGD 5,000. Withdrawals are made in cash and deposited directly into individuals' bank accounts, with no restrictions on how the funds are used.

The scale and liquidity of these withdrawals are economically meaningful. For example, CPF members who turned 55 in 2020 withdrew a total of SGD 4.6 billion. According to Singapore's Retirement and Health Study (RHS), many individuals report plans to invest their withdrawn funds, raising questions about the financial consequences of decentralized investment behavior near retirement.

While previous work has studied the effects of pension liquidity on consumption, there is limited evidence on how access to retirement wealth affects individual investment decisions. Given behavioral frictions such as present bias, overconfidence, and limited financial literacy, it is unclear whether such liquidity access improves or harms long-term financial outcomes. In this paper, we exploit the institutional feature of CPF

[18]The Ordinary Account (OA) offers a minimum annual interest rate of 2.5%, while other accounts could yield a rate of up to 6% per annum if certain qualifying conditions are met. These interest rates have been stable during our sample period from 2013 to 2022.

[19]Details of the CPF savings and investments schemes are available via this link.

withdrawals at age 55 as a natural experiment to study how liquidity access affects portfolio allocation, trading behavior, and investment performance among individual investors.

3 Data and Methodology

3.1 Data

We obtain account-level trading data from a financial service provider that serves a large retail investor base in Singapore. As shown in Figure A.1, the demographic profile of individual account holders in this dataset closely mirrors that of CPF member pool, lending external validity to our analysis. Our dataset covers a nine-year period from January 2013 to January 2022 and includes detailed individual account-level daily trading transactions data, portfolio valuations, and demographic attributes such as birth date, gender, age, nationality, annual income, and occupation. We aggregate the daily trades to construct investor-level monthly trading activity and performance metrics. The trading data is matched with Bloomberg data for daily price and foreign exchange rate information.

To assess how access to retirement savings influences trading behavior, we exploit the CPF policy that permits early withdrawals at age 55. Specifically, for each individual who turns 55 in month t (the event month), we extract trading data from months $t-15$ to $t+12$, covering 28 months around the liquidity event. This data is segmented into three sub-periods: the benchmark (or control) period (months $t-15$ to $t-4$), the pre-event period (months $t-3$ to $t-1$), and the post-event period (months t to $t+12$). This framework allows us to evaluate changes in investment behavior across a consistent event window. The data contains individual trades in two classes of securities: equities and contract for differences (CFDs).

3.2 Investment Types: Equities and Contracts for Differences (CFDs)

The individuals in our sample predominantly trade in two asset classes: Equities and Contracts for Differences (CFDs), which differ markedly in terms of risk and complexity. Equities include common shares and non-leveraged equity exchange traded funds (ETFs) listed across major global stock exchanges, including Singapore (SGX), the U.S. (New York Stock Exchange (NYSE), NASDAQ, American Stock Exchange (AMEX),), London Stock Exchange (LSE), and several Asia-Pacific markets (Malaysia's Kuala Lumpur Stock Exchange (KLSE), Indonesia Stock Exchange (IDX), Philippines Stock Exchange (PSE), Stock Exchange of Thailand (SET), Hong Kong Stock Exchange (HKSE), Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SZSE), Tokyo Stock Exchange (TSE), and Australia Stock Exchange (ASX)). Trades may be cash settled within one to three working days, and short-selling is not permitted by the brokerage. Trades may be settled in Singapore dollars or foreign currencies, depending on investor preferences.

The Contracts for Differences (CFDs) are are over-the-counter (OTC) derivatives that allow investors to speculate on price movements of underlying assets—including equities, indices, commodities, and currencies—without owning the asset. CFDs are traded on margin, typically requiring a 5–10% initial margin, depending on asset risk. Returns are marked to market daily, and margin calls must be settled within two business days. If unmet, positions may be forcibly liquidated.

Unlike listed, standardized derivative contracts (e.g. futures and options), CFDs are not exchange traded or regulated in many jurisdictions. They offer leveraged exposure and allow both long and short positions without requiring security borrowing. While long positions confer rights to dividends and stock splits, they do not confer voting rights; short sellers must cover dividends. The cost of CFD trading includes both

commissions and daily financing charges on the notional position value, not just the investor's margin. As CFD contracts do not have a set expiry date, individuals incur charges until the position is closed.

CFDs are considered high-risk instruments and are banned or tightly regulated in many countries. For instance, the U.S. SEC and CFTC prohibit CFD trading due to the lack of centralized clearing. Hong Kong's SFC also restricts their use. In Singapore, the Monetary Authority of Singapore (MAS) allows CFD trading but mandates a financial suitability assessment. Investors who do not meet the eligibility criteria must complete mandatory e-learning and pass a competency quiz. In Europe, the ESMA and UK's FCA impose leverage caps and require firms to disclose loss rates: the FCA reports that 82% of CFD clients incur losses.

By comparing trading behavior in non-leveraged equities versus leveraged CFDs, we can distinguish shifts in risk-taking behavior from general increases in market participation. This distinction is critical to identifying whether access to CPF liquidity induces portfolio rebalancing, speculative activity, or both.

3.3 Empirical Strategy

To investigate how the early access to pension savings affects investor behavior, we exploit the policy feature of Singapore's CPF system that allows individuals to withdraw retirement savings upon turning 55. This creates a quasi-experimental setting around a liquidity event tied to a deterministic age threshold. Following Agarwal, Pan, and Qian (2020), we employ an event study design centered on the 55th birthday. For each individual i who turns 55 in month t , we construct a 28-month event window from $t-15$ to $t+12$. This is partitioned into three segments: a benchmark period (months $t-15$ to $t-4$), a pre-event period (months $t-3$ to $t-1$) and the post-event period (months t to $t+12$).

The baseline specification is:

$$Y_{i,t} = \alpha + \beta_1 \times D_{i,(-3m,-1m)} + \beta_2 \times D_{i,(0m,12m)} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is the dependent variable that represents various aspects of individual i's trading behavior during month t, such as trading volume, number of trades and portfolio risk. γ_i serves as individual fixed effects to control for time-invariant differences in individual investors' behavior. δ_t represents time fixed effects at the year-month level, intended to absorb macroeconomic and seasonal shocks. Robust standard errors are clustered at the individual level. The indicator variable $D_{i,(-3m-1m)}$ is a pre-period dummy variable that equals 1 for months $t-3$ to $t-1$, i.e. the three months prior to individual is 55^{th} birthday; and $D_{i,(0m,12m)}$ takes the value of 1 for months t to $t+12$, representing the twelve months immediately following the birthday, respectively and zero otherwise. The parameter α measures the average response of trading behavior during the benchmark period, months $t-12$ to $t-4$, while β_1 and β_2 capture the average change in the outcome variable in the pre-event and post-event periods relative to the benchmark.

To investigate monthly dynamics of the outcome variable, we estimate an event-time regression using month specific indicators:

$$Y_{i,t} = \alpha + \sum_{s=-3}^{12} \beta_s \times D_{i,(sm)} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{2}$$

Here, $D_{i,(sm)}$ equals 1 if month t is s months away from the 55^{th} birthday (s equals 0 denoting the birth month), and zero otherwise, where $s \in [-3, 12]$. A negative (positive)

value of s refers to months before (after) individual $i's$ birth year-month, and all other variables are similar to Equation 1.

A key identification assumption for a valid Difference-in-Difference (DID) estimation is the absence of a parallel pre-trends. To verify this, we test whether the coefficients $\beta_{-3}, ..., \beta_{-1}$ are statistically indistinguishable from zero. A lack of significant pre-trends strengthens the interpretation of post-55 changes as causal effects of access to CPF funds. Importantly, the 55^{th} birthday early withdrawal date is a policy-determined threshold based on legacy retirement age rules set before the 1970s. It is orthogonal to contemporaneous economic shocks or individual choices during our 2013–2022 sample period. Moreover, Appendix Figure A.2 confirms that birth months are uniformly distributed, mitigating concerns about seasonality or selection.

This empirical strategy allows us to isolate the causal impact of liquidity access on individual investment decisions, including changes in trading intensity, risk exposure, and performance outcomes.

4 Early Pension Savings Withdrawal and Individual Investments

4.1 Summary Statistics

Our sample of trading data from a major brokerage firm in Singapore encompasses 25,866 individuals who trade equities and 1,293 individuals who trade Contract for Differences (CFDs). Among these, 666 investors trade both equity and CFDs. We focus on two primary metrics of individual trading behavior: trading frequency (#Trades) and dollar trading volume ($Volume). #Trades is calculated as the number of trades executed by an individual in a given month. For equities, $Volume is the total dollar

value of shares traded per month, while for CFDs, it is the notional value of contracts multiplied by the margin required, aggregated monthly. All transactions in foreign currencies are converted to SGD using contemporaneous exchange rates. To minimize the influence of outliers, we winsorize all dollar trading volume at the 99^{th} percentile.

Table 1 presents that, on average, individuals execute 1.3 equity trades and 10 CFD trades per month. The mean monthly dollar trading volume for equities is SGD 17,750 and SGD 15,679 in CFD margin requirements, highlighting the greater trading intensity and risk associated with CFDs trading. Table 1 shows that 79% (1,020 out of 1,293) of CFD traders are male, and male investors trade more frequently than their females counterparts. A super-majority of all accounts (96%) belong to Singapore residents subject to CPF regulations, and more than half of the individuals have linked their brokerage accounts to their CPF savings, facilitating the use of their retirement funds for trading.

We also examine differences in trading behavior by grouping individuals into terciles based on their trading intensity, measured by the percentage of months with active trading. The most active tercile of equity traders execute an average of 3.7 trades per month, while the most active tercile of CFD traders average 24.5 trades. Sorting by self-reported annual income at account opening reveals that trading intensity remains high across both low- and high-income groups.

[Insert Table 1 here]

4.2 Changes in Trading Activities

Given that individuals become eligible for early CPF withdrawals upon turning 55, we do not expect any substantial change in demographics or trading behavior in the immediate pre-event period. Accordingly, the coefficient β_1 in Equation 1 should not differ from zero. We explore whether the liquidity increase from CPF withdrawals results

in additional fund flows into their brokerage accounts, providing a link to increased trading (Hurd and Panis, 2006; Jappelli and Pistaferri, 2010). Agarwal, Pan, and Qian (2020) show that individuals exercise the option to withdraw funds from CPF upon turning 55 and subsequently deposit these into their bank accounts. While we cannot observe how CPF withdrawals are allocated across other asset classes such as real estate/bonds or used for debt repayment, we examine cash flows into brokerage accounts to assess the investment-related impact of this liquidity shock (Argento, Bryant, and Sabelhaus, 2015; Armour, Hurd, and Rohwedder, 2016; Beshears et al., 2012).

As a first step, we trace changes in the funds within individual trading accounts once they reach age 55. Specifically, we analyze individual deposits and withdrawals into their brokerage accounts aggregated at monthly level. Although not all trades are settled via the cash account, tracking inflows and outflows provides insights into the link between age 55 and access to funding liquidity.

Using Equation 2, with the dependent variable $Y_{i,t}$ set as monthly cash deposits, or cash withdrawals, we capture the dynamic responses in cash flows into individual brokerage accounts following CPF early withdrawal eligibility. Figure 1 shows a significant increase in cash deposits to brokerage accounts immediately following the 55^{th} birthday: deposits rise by SGD 374 in month t (the birthday month) and by another SGD 626 in month $t+1$. Cash withdrawals from brokerage accounts occur later, around months $t+4$ and $t+5$, suggesting staggered usage of the additional liquidity (details of the regression coefficients are reported in Appendix Table A.1). These patterns confirm that the observed changes in trading behavior are indeed accompanied by an increase in investable funds.

[Insert Figure 1 here]

4.2.1 Average Response

Table 2 presents average treatment effects based on Equation 1. Panel A of Table 2 reports changes in dollat trading volume ($Volume). Equity $Volume increases by SGD 1,596 in the post-55 period, equivalent to a 9% rise relative to the benchmark period ($t-15$ to $t-4$) and this increase is primarily driven by buy trades. CFD $Volume increases even more sharply by SGD 4,267, representing a 33%, increase. The increase is also asymmetric, with CFD buy trades growing by 45% compared to a 34% increase in sell trades. The absence of significant effects in the pre-event period ($t-3$ to $t-1$) supports the validity of the parallel trends assumption.

[Insert Table 2 here]

Panel B of Table 2, examines the changes in the number of trades (#Trades). We find that individuals increase their monthly equity trades by 5% in the post-55 period. Although the CFD trade frequency also increases in the post-period, this change is not statistically significant. Given the right-skewed and count-like nature of #Trades data, a Poisson regression with fixed effects confirms the robustness of our results (see Table A.2).

Overall, the average response results in Table 2 suggest that individuals significantly increase their trading activity upon accessing CPF savings. Importantly, this increase is not merely the result of reallocation within the existing CPF Investment Scheme (CPFIS). While CPFIS permits certain investments before age 55, the observed surge in trading extends beyond its scope. Specifically, as shown in Appendix Table A.6, we find a notable rise in trading of foreign securities, which are not permitted under CPFIS. This, coupled with the marked increase in CFD activity, suggest that the liquidity boost influences trading behavior rather than simple portfolio reshuffling.

To mitigate concerns that our findings are driven by pandemic-related shifts in retail investor behavior, we replicate the baseline analysis using data only up to January 2020, prior to Singapore's first confirmed COVID-19 case. The results (Appendix Table A.3,) remain robust, with effect magnitudes similar to the full-sample estimates. This confirms that our findings are not confounded by broader market disruptions or structural changes in investor behavior during the pandemic period.

while our baseline sample focuses on individuals who traded at least once before and after age 55, indicating relatively active engagement with their brokerage accounts, we further explore whether CPF access influences participation on the extensive margin, specifically, through new account openings. To do this, we expand the sample to include all individuals, regardless of trading history, and track monthly account openings around age 55. On average, approximately 770 new accounts are opened each month prior to the CPF eligibility age. Following Equation 2, we regress the total number of new account openings on dummy variables representing months surrounding age 55 without fixed effects. As shown in Figure 3, we observe a statistically significant jump of 230–290 additional new accounts opened in the month of or immediately after turning 55, corresponding to a 38% increase. This pattern suggests that CPF liquidity access encourages not only increased trading by existing investors but also encourage market entry by faciliating new participants.

4.2.2 Dynamic Response

We now examine the monthly evolution of trading behavior following access to liquidity in pension savings using Equation 2. In Figure 2a, we observe a persistent rise in equity $Volume over the 12-month post-event, peaking at increases of between SGD 1,624 to SGD 3,301 per month, representing a 10% to 20% increase above the benchmark period. Buy trades contribute more to this rise than sell trades. By contrast, $Volume for

CFD trades spikes sharply, by over SGD 5,000 or 42% to 47%, in the first two months post-event but quickly dissipates. (Detailed estimates are provided in Appendix Table A.4). Consistent with average effects in Table 2, the magnitude of $Volume increase is notably greater for CFDs compared to equities.[20]

[Insert Figure 2 here]

Figure 2b presents the evolution of trading fequency (#Trades) when individuals reach the age of 55. The buy plus sell #Trades for equities increase by 0.07 to 0.13 per month (a 6% to 12% increase), with the strongest gains in the buy-side activity. CFD trades also surge initially, by 33% in the first one to two months post-55, but the effect is short-lived (see Appendix Table A.5 for detailed dynamic estimates of #Trades). These patterns reinforce the earlier findings: early pension withdrawals trigger a sustained increase in equity trading and a short-lived but intense burst in CFD speculation.

4.2.3 Equities v.s. CFDs

The above findings indicate that individuals' trading responses to early pension withdrawals differ across the two asset classes. However, the differences in trading behavior may simply reflect heterogeniety in the types of investors who chose to equities versus CFDs. To address this and better isolate within-investor shifts in behavior, we focus on the subset of individuals who trade both equities and CFDs.

Among the 1,293 individuals who trade CFDs, 666 also engage in equity trade. Panel A of Table 3 shows that this subgroup is predominantly composed of male Singapore residents, all of whom are eligible for CPF withdrawals. When comparing their trading activities with the full sample presented in Table 1, these individuals

[20]To mitigate the concern regarding anticipation effect that individuals may strategically plan investment in advance, we further extend both the pre-period and post-period for the dynamic response analysis. The results presented in in Figure A.3, remain consistent with our earlier findings.

exhibit higher engagement in equities, with an average monthly $Volume of SGD 119,677, compared to the overall average of SGD 17,750 for the full sample. In contrast, their average $Volume in CFDs aligns closely with the full CFD-trading sample.

To assess how these individuals shift their trading intensity across the two asset classes in response to CPF withdrawal eligibility, we adopt the same event study approach around age 55. We introduce a CFD indicator variable D_{CFD} to differentiate CFD trading from equity trading: D_{CFD} is set to 1 for CFD trades and 0 for equity trades and extend the model specification in Equation 1 as follows:

$$Y_{i,t} = \alpha + \sum_{s=-3}^{12} \beta_s \times D_{i,(sm)} + \sum_{s=-3}^{12} \theta_s \times D_{i,(sm)} * D_{CFD} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{3}$$

where $Y_{i,t}$ is the number of trades executed by individual i in month t. We are interested in the coefficient θ_s, representing the interaction between D_{CFD} and the month dummy variable $D_{i,(sm)}$ and captures the relative change in CFD trading (vs equity trading) in month s around the 55^{th} birthday.

Panel B of Table 3 displays the regression estimates. Consistent with earlier patterns, individuals who trade both assets trade CFDs at a much higher baseline frequency than equities. More importantly, we find that early access to CPF savings leads to a disproportionate increase in CFD trading. The interaction coefficients θ_s indicate a statistically and economically significant rise in CFD trading during the first two months following CPF withdrawal eligibility. Specifically, investors execute an additional 3.4 CFD trades per month relative to equities in this immediate post-access window.

Overall, these results confirm that the liquidity from early pension access prompts investors, who exposed to equities and CFDs, to a pronounced increase in trading of

riskier, leveraged assets. By holding individual and time effects constant and comparing behavior across asset classes for the same set of investors, we provide compelling within-subject evidence of heightened risk-taking at the intensive margin.

[Insert Table 3 here]

4.3 Changes in Portfolio Volatility

In light of the increase in trading frequency and dollar volume, we next investigate the impact of the increased liquidity in pension savings on risk taking. This question contributes to a broader literature exploring how changes in liquidity or income affect household investment risk. Prior evidence on the effect of changes in financial liquidity or income on risk-taking behavior is mixed. Some research indicate increased liquidity shocks lead households to allocate more to risky assets (e.g., Andersen and Nielsen, 2011; Meeuwis, 2020; Paravisini, Rappoport, and Ravina, 2017), while other studies find little effect on risk-exposure (Brunnermeier and Nagel, 2008).[21] Other evidence shows a positive relationship between risk aversion and liquidity (Ameriks and Zeldes, 2011). Related to our setting, Ameriks and Zeldes (2011) observe that older investors tend to lower their stock market participation as retirees annuitize wealth. Therefore, the relationship between liquidity and risk-taking appears to be context dependent. In our setting, early access to retirement savings offers a quasi-experimental shock to investment liquidity. We test whether this liquidity shift prompts individuals to change the riskiness of their portfolios.

[21] Andersen and Nielsen (2011) show that windfall wealth from inheritance has a positive effect on stock market participation. Paravisini, Rappoport, and Ravina (2017) estimate the risk-aversion parameter from lending market, finding that investors become more risk-averse after experiencing a negative housing wealth shock. Focusing on retirement investors, Meeuwis (2020) observe a reduction in risk aversion and an increased equity allocation in response to positive and persistent labor income shocks. While Brunnermeier and Nagel (2008) find no discernible effect of liquidity fluctuations on the risky asset share in portfolios.

To measure changes in risk exposure, we compute the monthly volatility of individuals' portfolio, defined as the standard deviation of daily returns on each individual's holdings within a given month.[22] We then standardize this measure by computing a Variance Ratio—the ratio of portfolio volatility in a given month to the investor's average volatility during a 12-month benchmark period (months –15 to –4 before turning 55).

The *Variance Ratio* for individual i in month t is given by:

$$Variance\ Ratio_{i,t} = \frac{\sigma_{i,t}}{\sigma_{i,T=[-15,-4]}}, t \in [-3, 12] \tag{4}$$

where $\sigma_{i,t}$ is individual i's monthly portfolio volatility at time t, and $\sigma_{i,T=[-15,-4]}$ is their average volatility over the benchmark period. We examine this measure for two periods: t_1 from months -3 to -1 denoting the pre-trend period and t_2 from months 0 to 12 representing the post-period. A *Variance Ratio* of 1 suggests no change in volatility relative to the benchmark period, while values above (below) 1 imply an increase (decrease) in portfolio volatility. Since equities and CFDs have inherent unconditional volatilities, we compute the *Variance Ratio* for each asset class separately. Given that individual trading intensity may directly contribute their portfolio volatility, we also control for monthly trading volume to disentangle pure risk-taking from higher trading activity.

Table 4 reports the regression results following the specification in Equation 1 with *Variance Ratio* as the dependent variable. The coefficient for the post-period M[0, 12] is significantly positive, indicating that portfolio volatility increases once individuals gain access to their retirement savings. the estimates reveal that the equity portfolio

[22]Due to availability of holding data, the sample period for volatility analysis is from January 2015 to January 2022.

volatility increases by 25% in the post-55 period while the increase is 29% for the CFD portfolio. [23] These effects remain significant even after controlling for changes in dollar trading volume, suggesting that the increase in volatility reflects a shift toward riskier investments rather than just increased trading activity. We also rule out alternative explanations such as portfolio rebalancing or increased diversification. While individuals do trade a broader set of securities and a larger number of securities post-withdrawal (Appendix Table A.6 and Table A.7), the resulting increase in volatility implies that diversification is not the dominant motive.

In sum, access to pension savings leads to a statistically robust and economically meaningful rise in portfolio volatility, driven by both higher trading activity and increased allocation to riskier, more idiosyncratic positions. This finding complements our earlier results and reinforces the interpretation that early access to retirement savings induces risk-taking behavior, especially so for investors exposed to leveraged instruments like CFDs.

[Insert Table 4 here]

4.4 Effect on Investment Performance

Our preceding analyses show that access to pension savings increases retail investors' trading frequency, trading volume, and risk exposure—particularly through leveraged CFDs and more volatile portfolios. But do these behaviors improve investment performance?

[23] To assess whether the rise in volatility stems from broader market conditions or idiosyncratic trading choices, we decompose portfolio risk. Specifically, we regress daily portfolio returns on two market factors, the excess return on the MSCI World Index and the Singapore Straits Times Index (STI), and compute the standard deviation of the residuals as a proxy for idiosyncratic volatility. Specifically, we regress daily returns on the portfolio held by individual i on day t $R_{i,t}$ within each month on two factors, excess returns on MSCI index and STI index, denoted as $MSCI_t$ and STI_t , i.e. depicted by the regression $R_{i,t} = R_f + \beta_{i,1} MSCI_t + \beta_{i,2} STI_t + \epsilon_{i,t}$. We then use standard deviation of the regression residuals ($\epsilon_{i,t}$) to replace the volatility estimates in Equation 1. We find that idiosyncratic volatility rises significantly: by 10% for equity portfolios and 21% for CFDs post-55.

Prior studies consistently find that active trading by retail investors typically leads to underperformance, largely attributed to excessive trading driven by overconfidence and behavioral biases. (e.g., Barber and Odean, 2000, 2001; Barber et al., 2007, 2022; Grinblatt and Keloharju, 2001, 2009; Odean, 1998, 1999; Peng and Xiong, 2006). Transaction costs are a major driver of such underperformance.(Barber and Odean, 2000; French, 2008) In particular, when involved in leveraged trading, unskilled investors tend to induce higher volatility and amplifies losses from behavioral biases and speculative behavior (Subrahmanyam et al., 2021).

In contrast, some studies suggest that wealthier or more sophisticated investors may use liquidity shocks to pursue more informed trading strategies, potentially generating positive returns Peress (2004) , Bui et al. (2022). In our setting, individuals may view early CPF access as an opportunity to capitalize on private investment opportunities, but the empirical question remains: does this shift toward more aggressive trading improve portfolio performance?

To evaluate investment outcomes, we analyze ex-post returns on trades initiated in the month an individual turns 55. While Table A.8 shows that the average individuals' holding period is 52 days for equities and 22 days for CFDs, we evaluate performance over a 12-month window to capture both short and medium term effects.

For each individual i who turns 55 in month t, we track the returns in the following 12 months for the portfolio of securities bought or sold in month t . We denote the monthly returns on the portfolio of securities bought (sold) as $R^B_{i,k}$ ($R^S_{i,k}$) and difference between the buy portfolio and sell portfolio returns as $R^{BmS}_{i,k}$, where $k = 1..., 12$ months. Specifically, we calculate $R^B_{i,k}$ ($R^S_{i,k}$) by taking the weighted average returns on the securities bought (sold) in month t and held for the next k months:

$$R_{i,k} = \sum_j \omega_{i,j,t} \times r_{j,t+k}, k \in [1, 12] \tag{5}$$

$\omega_{i,j,t}$ is the dollar trading volume weight of security j bought (or sold) in month t by investor i. The net-buy portfolio return $R_{i,k}^{BmS}$ is the difference between the buy portfolio returns $R_{i,k}^{B}$ and sell portfolio returns $R_{i,k}^{S}$. We evaluate individual portfolio performance over the period January 2013 to January 2022, and focus on the net-buy portfolio return $R_{i,k}^{BmS}$. The results are displayed in Table 5.

[Insert Table 5]

Table 5 shows that investors experience significant and persistent losses on both equity and CFD trades initiated after turning 55. On average, individuals lose between 0.9% and 1.5% in the months following their investments. The losses in their CFD portfolio are larger, but more short-lived, with losses of between 4% and 10% concentrated in the first four months post-trade. These results underscore the poor market timing and selection abilities of individual investors in our sample, particularly when trading leveraged instruments.

One channel exacerbating underperformance is transaction costs. These include commission fees for equity trades, and both commission and financing charges for CFDs, which involve interest on margin positions. Commission rates for equities (shares and ETFs) range between 0.05% to 0.18%, depending on the market where the security in traded and trade size. For CFDs, the commission rate vary across underlying assets types and financing charges differ for long and short positions.[24] Using trade-level commission data, we compute monthly commission expenses for each account. Monthly account-level financing charges for CFDs are obtained directly from the dataset.

[Insert Table 6]

[24]For instance, the commission rates for CFDs tracking equities are between 0.128% and 0.4%. CFDs tracking world indices charge flat fees of about USD 0.4 to USD 2 per contract. CFDs tracking commodities charge flat fees of about USD 0.1 to USD 5 per contract, and all FX currency pair CFDs do not charge any commission. The finance charges for CFDs differ in long and short positions, ranging from 2.75% to 7%. Interestingly, despite the typical borrowing cost associated with shorting, the finance charges for long positions are typically higher than that for short positions.

Table 6 presents the regression results based on Equation 1 with trading cost as the dependent variable. Consistent with expectations, monthly trading costs rise significantly after individuals gain access to CPF. For equities, trading costs increase by SGD 4.82 per month, representing a 10% rise relative to the pre-access period. For CFDs, the increase is more substantial at SGD 93.49 per month which is equivalent to a 39% rise. These estimates likely understate the true cost, as they do not account for implicit expenses such as bid-ask spreads and market impact.

To combine return and cost outcomes, we compute the cumulative after-cost returns over the 12-month period following CPF access. Figure 4a illustrates that for equity trades, stocks that the individuals sold outperforms the stocks bought, resulting in persistently negative buy minus sell portfolio returns, averaging -1.5% per month. Moreover, these losses are robust across different holding periods. The post-55 CFD trades are worse. As shown in Figure 4b, the buy-minus-sell portfolio yields a 4% loss within the first month, with losses extending over the subsequent four months. These patterns indicate that not only are investors trading more frequently after CPF access, but they are also making suboptimal investment choices that result in wealth destruction.

[Insert Figure 4]

We supplement these trade-based analyses with holding-based portfolio returns using daily account-level portfolio data. This enables us to assess performance from the perspective of the overall portfolio, rather than just recent trades. We calculate monthly returns for each individual's portfolio and adjust them for risk using a two-factor model that includes the MSCI World Index and the Singapore Straits Times Index (STI).[25]

[25]For individual i's equity portfolio, we use the 28 month period around age 55 to estimate portfolio exposure to two common factors, return on world market index, $MSCI$ and the Singapore stock market index, STI :$(R_{i,t} = R_f + \beta_{i,1} MSCI_t + \beta_{i,2} STI_t + \epsilon_{i,t})$. Using the estimated $\hat{\beta_{i,1}}$ and $\hat{\beta_{i,2}}$, we obtain individual i's risk-adjusted equity portfolio monthly return as $\hat{\alpha_{i,t}} = R_{i,t} - R_f - \hat{\beta_{i,1}} MSCI_t - \hat{\beta_{i,2}} STI_t$, for $t \in [-15, 12]$.

For each individual i, we regress their risk-adjusted portfolio excess return $\alpha_{i,t}$ on pre- and post-period dummy variables following Equation 1.

[Insert Table 7]

Table 7 presents the estimates for holding-based returns for equities and CFDs, considering gross returns, returns net of transaction costs, and risk-adjusted return (α). The results confirm the earlier findings that individuals incur significant negative gross returns on their equity holdings at 0.28% per month, with net returns of -0.29% and an alpha of -0.22%. The losses on CFD holdings are larger at 7.2% (8.2% after trading costs) per month. Importantly, there is no substantial change in their holding-based returns during the post-55 period. After adjusting for risk, we find no improvement in performance in the three months leading up to, or the twelve months following, their 55th birthday.

Taken together, we conclude that liquidity in the retirement account leads to poorer investment outcomes. Individuals trade more often, increase the portfolio volatility, incur higher trading costs, and experience significant losses in both equities and CFDs. The consequences are particularly severe for leveraged trading, where amplified losses are common. These effects are conservative estimates, as we do not benchmark performance against passive portfolios of equivalent risk or account for the opportunity cost of leaving funds in CPF, which guarantees a minimum return of 2.5% annually. Our findings suggest that while liquidity access provides flexibility, it also opens the door to financially detrimental behaviors among retail investors, underscoring the need for careful policy consideration around the design of retirement withdrawal schemes.

4.5 Falsification Tests

Our main findings suggest that access to retirement savings at age 55 triggers a substantial behavioral response among individuals: trading activity increases, portfolio volatility rises, and investment performance deteriorates. While our empirical design leverages a clearly defined and policy-driven liquidity event, a natural concern is whether the observed changes are in fact driven by other unobserved factors that coincide with age 55, such as shifts in income, expectations about retirement, or age-related cognitive changes. To address this concern, we conduct a set of falsification tests to validate the identification strategy and strengthen the causal interpretation of our results.

We begin by analyzing a sub-sample of non-residents. These individuals are not eligible to participate in the CPF scheme and thus do not experience a liquidity event at age 55. If the changes we observe in our main sample are indeed driven by CPF access rather than age itself or general life-cycle effects, we should see no such changes among non-residents. As reported in columns (1) and (4) of Table 8, we find no significant shifts in trading behavior for non-residents around age 55, whether measured by the number of trades or dollar trading volume. This provides direct evidence that the observed effects in our main sample are not due to age-related factors alone.

Next, we perform placebo tests by applying the same empirical specification to Singaporean residents at other ages where no CPF liquidity access occurs. Specifically, we consider age 50, 54, and 60 as placebo cut-off ages. At these ages, individuals do not gain additional access to their CPF funds, even though there are some discrete changes in contribution rates.[26] As shown in columns (2) to (4), and (5) to (8) of Table 8 , there are no statistically or economically significant changes in either equity or CFD trading around these placebo ages. The absence of trading responses at age 54 is

[26]Contribution to the retirement savings by the employers and individuals are reduced discretely at ages 50, 55, and 60. While these changes affect the disposable income and changes in the retirement savings, they do not create a similar liquidity boost of the savings.

particularly informative—it suggests that individuals are not merely ramping up trading in anticipation of CPF access. Similarly, the lack of any effect at age 60 reinforces the conclusion that the observed behaviors at age 55 are not part of a broader age-related trend in trading.

Collectively, these falsification tests provide strong support for our identification strategy. They confirm that the behavioral changes we observe are not artifacts of aging, time trends, or other life-cycle transitions. Rather, they are uniquely and causally linked to the sudden increase in financial liquidity from CPF access at age 55. This strengthens our interpretation that the early withdrawal feature of the Singapore pension system materially alters household investment behavior, often in ways that erode, rather than enhance, financial well-being.

[Insert Table 8]

5 Heterogeneity Test

We now examine whether the effects of early pension withdrawal vary across investor characteristics, focusing on heterogeneity by gender and income. These dimensions are particularly relevant in light of prior research suggesting that men tend to be more overconfident and risk-seeking (Barber and Odean, 2000, 2001; Odean, 1999), while financial constraints can amplify responses to liquidity shocks (Agarwal, Pan, and Qian, 2020; Lu et al., 2017).

5.1 Gender Differences

To assess whether men and women respond differently to the CPF liquidity event, we split the sample by gender and analyze changes in trading behavior surrounding age 55 based on subsmaple following Equation 1. As shown in columns (1) - (2) of Table

9, equity trading increases significantly only among male investors. Specifically, men increase their monthly equity trading volume by 15% (SGD 2,948) following CPF access, while women exhibit no significant change. This finding is consistent with prior evidence that men tend to trade more actively and react more strongly to financial shocks.

Interestingly, for leveraged CFDs, reported in columns (3) - (4) in Table 9, we observe no gender difference in the response of dollar trading volume. Both male and female investors increase their CFD trading after turning 55, with male investors increasing volume by SGD 4,736 and females by SGD 5,564. This suggests that CFD traders, regardless of gender, are more speculative and uniformly responsive to liquidity injections. The similarity in behavior may reflect the inherently high-risk, leveraged nature of CFDs, which attracts investors with a stronger appetite for speculation.

[Insert Table 9]

Figure 5 shows the dynamic trading response by gender. Equity trading volume among male investors increases sharply and persistently after CPF access, while female investors maintain a flat and stable pattern. For CFDs, both genders exhibit a short-term surge in trading volume that fades within two months.

[Insert Figure 5]

To further explore whether the rise in portfolio risk following access to CPF savings varies by gender, we analyze the changes in variance ratio in columns (5) - (8) of Table 9. Among equity investors, male investors exhibit a statistically significant 13% increase in portfolio volatility following CPF withdrawals, while female investors female investors do not exhibit a statistically significant change, though the magnitude of the post-period coefficient suggests a substantial (56%) increase in variance ratio. For CFD portfolio, male investor increase their portfolio volatility by 38% while female investors show no

significant change.[27] These findings suggest that men respond to CPF liquidity with larger increases in portfolio risk.

Turning to trading performance, columns (9) - (12) of Table 9 presents the estimate for the average response of portfolio net returns. Across both asset classes and genders, we find no statistically significant change in returns following CPF access, which suggests that neither male nor female investors improve their investment performance post-55. Overall, these results confirm that male investors mainly drives the excessive trading activity and bear the bulk of the rise in risk following liquidity boost from pension savings, consistent with prior findings that men are more overconfident and prone to excessive trading.

5.2 Income Effects

We next explore whether the effects of liquidity access vary by income, particularly for financially constrained individuals. Lu et al. (2017) document that liquidity-constrained households are more likely to take out the 401k loans and Agarwal, Pan, and Qian (2020) report that liquidity-constrained households respond more strongly to positive income shocks in terms of consumption. We expect the effect of retirement savings on investments behavior will be more pronounced among lower-income individuals, who are likely to be financially constrained. Additionally, individuals actively trading CFD may also face liquidity constrains due to the leveraged nature of these investments.

To explore variations in the effects across income groups, we classify individuals into three income brackets based on self-reported annual income at account opening: below SGD 60,000 (low income), SGD 60,000–100,000 (medium income), and above

[27]The economic magnitude is derived relative to the average of outcome variable in the benchmark period as the constant term.

SGD 100,000 (high income). We then examine changes in trading volume and frequency among the subsample of these income groups

As presented columns (1) - (4) of Table 10, low-income individuals respond most strongly to CPF access. Their equity trading volume increases by SGD 1,239 (10%), and CFD trading volume nearly doubles, increasing by SGD 7,180 (93%) relative to the benchmark period. On the other hand, high-income individuals exhibit no significant change in trading behavior. Figure 6 reinforces these findings, showing a pronounced and persistent increase in trading among low-income individuals and muted responses among the high-income group. Detailed changes across all horizons are in Table A.10 in the Appendix. These results are consistent with a liquidity-constraint channel: investors with fewer financial resources respond more aggressively when granted access to pension savings.

We further refine the analysis by exploring trading activeness within the low-income group. Splitting this group into three subgroups: Low activeness, Mid activeness, and High activeness (based on pre-event monthly trade counts), we find that the trading response is concentrated among the most active traders. Table A.11, and Figures A.4 and A.5. show that highly active low-income investors significantly increase both trading frequency and volume, while passive traders show little change. This suggests that liquidity access enables already-engaged investors to scale up their speculative activities.

Further, columns (5) - (8) of Table 10 present estimates of the average response of portfolio volatility across income groups following Equation 1. The overall effect of CPF early withdrawal is positive and significant for equity portfolio volatility. Among low-income investors, equity portfolio volatility rises significantly by 10%, while the increase among high-income investors are large but statistically insignificant. In contrast, the CPF portfolio volatility does not increase across different income groups. Similarly, columns (9) - (12) of Table 10 show no statistically significant change in net returns

across either asset class or income group following CPF access. This reinforces the conclusion that the increased trading and risk-taking behaviors do not translate into improved investment performance.

Taken together, these heterogeneity results paint a clear picture. The negative consequences of early pension withdrawals, excessive trading, higher risk exposure, and increased costs, are disproportionately borne by males and low-income investors. These groups are more likely to respond to liquidity access by engaging in risky and costly trading behaviors, yet, as shown earlier, they do not achieve superior investment performance. Rather than enhancing financial outcomes, early access appears to exacerbate financial fragility, especially among the most vulnerable investors.

These findings have important policy implications. Given that CPF serves as the primary retirement vehicle for many Singaporeans, designing mechanisms that limit harmful responses to liquidity access, such as default investment options or targeted financial advice, may help safeguard long-term financial security.

[Insert Table 10]

[Insert Figure 6]

6 Conclusion

We provide novel evidence that early access to retirement savings significantly alters individual investment behavior. We exploit a unique provision in Singapore's CPF pension system that allows residents to access their retirement funds at age 55, before the retirement age. Using a proprietary and comprehensive individual-level trading data from a leading financial institution in Singapore, we document the causal effects of this withdrawal policy on trading behavior, risk-taking and trading performance. We find that individuals increase their trading volume by 9% for equity trading and 18% for

CFDs (margin trading) after early pension withdrawals. Further, we observe a 38% increase in new brokerage account opening following CPF early withdrawal, suggesting this liquidity event also encourages broader participation in investment markets.

This increased trading activity is accompanied by heightened risk-taking, evidenced by a significant (24% to 28%) increase in the investment portfolio volatility after pension savings become accessible for private investments. Moreover, increased trading in equities and CFDs leads to the higher trading costs (10% to 39%) and accentuates investment losses. Our findings indicate that the increase in trading activity post-early withdrawal is not mainly driven by portfolio rebalancing or diversification strategies. Overall, the evidence suggests that enhanced liquidity in pension savings for private investments may erode individuals' retirement wealth.

These effects above show distinct variations across demographics, which are more pronounced among male traders, consistent with the idea that overconfidence is more prevalent among male investors. Interestingly, both genders exhibit similar increase in CFD trading , indicating that speculative trading in derivatives is less influenced by gender. These effects are also particularly pronounced among lower income individuals, who are likely to face greater liquidity constraints.

To evaluate the net effects of early pension withdrawal, we conduct a back-of-the-envelope analysis. Early pension withdrawal grants individuals the flexibility to smooth their consumption, and save on borrowing costs, which ranges from 0.8% to 2.8% between 2013 and early 2022. Additionally, individuals may enjoy the returns through investments in equities or other securities. According to the estimates of excess return discussed in Section 4.4, the average monthly return is -0.3% to -8.2% in the equities and CFDs, ignoring the 2.5% guaranteed rate offered by the CPF. Based on the portfolio holdings of individuals in our sample, the net loss of early pension withdrawals is approximately 5.8% annually, or equivalent to SGD 13.8 million in aggregate for all

individuals.[28] Home-ownership in Singapore is high at 90% and serves as a safety net, mitigating investment losses.[29] Hence, the consequences of deteriorating retirement savings from early pension withdrawal is expected to be more severe in economies where safety nets are less prevalent.

[28]Based on the portfolio holdings of individuals in our sample shown in Table A.12, among our sample of 26,465 individuals, 25,206 (95%) trade only equities, 331 (1.2%) trade only CFDs, and 928 (3.6%) trade both equities and CFDs. For those trading both, their portfolios are on average composed of 79% equities and 21% CFDs. To calculate the net return, we derive the following formula: $(2\%-2.5\%)+[95\%*(-0.3\%*12)+1.2\%*(-8.2\%*12)+3.6\%*((-0.3\%*12)*79\%+(-8.2\%*12)*21\%)] = -5.8\%$. The 5.8% net loss is equivalent to SGD 13.8 million in aggregate across all individuals, given that the median amount of cash withdrawal is approximately SGD 9,000 according to CPF statistics.

[29]Source: Department of Statistics, Singapore

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Table 1: Summary Statistics: Equity and CFD Trades

Panel A: Variable distribution

Equity

	N	mean	std	min	50%	75%	max
#Trade	608,200	1.3	6.3	0.0	0.0	1.0	956.0
$Volume	608,200	17,750	85,993	0	0	164	3,256,828

CFD

	N	mean	std	min	50%	75%	max
#Trade	30,900	10.0	53.0	0.0	0.0	3.0	3254.0
$Volume	30,900	15,679	60,341	0	0	5,083	1,297,414

Panel B: Variable distribution by demographic and characteristics

	Equity			CFD		
	#Investor	#Trade	$Volume	#Investor	#Trade	$Volume
All Accounts	25,866	1.3	17,750	1,293	10.0	15,679
by Gender						
Female	9,514	1.0	12,907	273	9.0	14,827
Male	16,352	1.5	20,580	1,020	10.3	15,907
by Nationality						
Foreigner	956	1.0	13,737	37	23.4	16,402
Singaporean/PR	24,910	1.3	17,903	1,256	9.6	15,659
by CPF Usage						
No	10,893	1.2	17,240	462	8.6	14,417
Yes	14,973	1.4	18,120	831	10.8	16,353
by Trading Activeness						
Active	8,627	3.7	49,926	454	24.5	38,534
Mid	8,840	0.5	6,794	409	6.4	9,600
Non-Active	8,399	0.1	1,304	430	0.8	1,471
by Annual Income						
Below $30 K	8,104	1.2	15,065	327	10.5	15,354
30K∼60 K	6,655	1.1	13,930	318	6.8	11,505
60K∼100 K	5,066	1.4	19,134	303	10.8	16,807
Above $100 K	5,876	1.6	25,005	344	11.8	18,895

Notes: The CFD and equity trades in our sample are either executed 15 months before or 12 months after individuals' 55^{th} birthday, and are truncated at 99% level based on dollar trading volume. The sample period is from January 2013 to January 2022. Initial margin requirement varies for the underlying securities of CFD contracts, the risk of any gain or loss in trading CFD can be amplified by margin. The calculation for equity dollar trading volume is as follows: $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ For CFD dollar trading volume: $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All values displayed in above table are in SGD. Individuals without gender, nationality, CPF usage, annual income information are not reported in above table.

Table 2: Effect of CPF Early Withdrawal on Trading

Panel A: $Volume						
		Equity			CFD	
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	16,889***	11,328***	10,558***	12,854***	6,708***	6,522***
	(288)	(201)	(202)	(994)	(561)	(492)
M[-3,-1]	-241	-23	-350	1,378	750	988
	(421)	(295)	(304)	(1,517)	(806)	(761)
M[0,12]	1,596***	1,448***	588	4,268**	2,987***	2,193**
	(566)	(398)	(394)	(1,919)	(1,091)	(955)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,679	467,901	496,214	30,054	28,206	29,459
Number of accounts	24,796	19,825	20,847	1,249	1,167	1,224
Mean of DV	17,585	11,976	10,788	14,935	8,139	7,622
R^2	0.41	0.39	0.39	0.34	0.32	0.34
Panel B: #Trades						
		Equity			CFD	
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	1.08***	0.77***	0.59***	6.95***	3.74***	3.58***
	(0.01)	(0.01)	(0.01)	(0.50)	(0.27)	(0.26)
M[-3,-1]	-0.02	-0.01	-0.01	0.33	0.20	0.05
	(0.02)	(0.01)	(0.01)	(0.68)	(0.38)	(0.36)
M[0,12]	0.05**	0.06***	0.01	1.26	0.78	0.54
	(0.03)	(0.02)	(0.02)	(0.98)	(0.53)	(0.51)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,679	467,901	496,214	30,054	28,206	29,459
Number of accounts	24,796	19,825	20,847	1,249	1,167	1,224
Mean of DV	1.10	0.79	0.60	7.56	4.12	3.83
R^2	0.45	0.43	0.44	0.36	0.36	0.34

Notes: This table presents the average response of dollar trading volume and trading frequency before and after individuals turning age 55 by estimating Equation 1. The dependent variables are dollar trading volume in Panel A and number of trades in Panel B. We regress the outcome variables on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of outcome variables during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. Equity dollar trading volume is calculated as $Contract\ Value = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All values displayed in above table are in SGD. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Effect of CPF Early Withdrawal on Trading: Individuals Trading both Equities and CFD

Panel A: Summary Statistics

	Equity			CFD	
	#Investor	#Trade	$Volume	#Trade	$Volume
All Accounts	666	5.0	119,677	13.1	17,714
by Gender					
Female	148	4.1	57,898	10.2	17,243
Male	518	5.2	138,261	14.0	17,874
by Nationality					
Foreigner	14	2.5	674,022	42.7	27,789
Singapore/PR	652	5.0	108,767	12.5	17,516
by CPF Usage					
No	207	5.7	245,957	10.8	15,746
Yes	459	4.6	64,891	14.1	18,568
by Annual Income					
Below $30 K	172	4.4	65,394	12.3	17,940
30K∼60 K	172	3.7	57,531	8.6	13,940
60K∼100 K	146	6.2	193,185	15.5	17,490
Above $100 K	176	5.7	175,438	16.4	21,454

Notes: The CFD and equity trades in above table are based on subsample of individuals who trade both assets 15 months before their 55^{th}birthday, and are truncated at 99% level based on dollar trading volume. The sample period is from January 2013 to January 2022. Initial margin requirement varies for the underlying securities of CFD contracts, the risk of any gain or loss in trading CFD can be amplified by margin. Equity dollar trading volume is calculated as $Contract\ Value = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$. CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All values displayed in above table are in SGD. Individuals without Gender, Nationality, CPF Usage, Annual Income information are not reported in above table.

Panel B: Changes in Trading Frequency for Individuals Trading Both Equities and CFD

	#Trades		
	Buy&Sell	Buy	Sell
	(1)	(2)	(3)
D*M-3	0.42	0.50	0.43
	(1.15)	(0.86)	(0.92)
D*M-2	0.65	0.59	0.50
	(1.13)	(0.80)	(0.85)
D*M-1	0.79	1.09	0.62
	(1.08)	(0.86)	(0.71)
D*M0	1.77	1.32	1.59
	(1.68)	(1.18)	(1.16)
D*M1	3.35*	2.65*	2.46*
	(1.96)	(1.41)	(1.32)
D*M2	3.52	2.58	2.87*
	(2.43)	(1.76)	(1.72)
D*M3	0.14	0.38	-0.16
	(1.35)	(1.00)	(0.94)
D*M4	1.30	0.69	1.27
	(1.49)	(1.05)	(1.06)
D*M5	2.47	1.44	1.82
	(3.36)	(2.21)	(2.22)
D*M6	1.96	1.48	0.91
	(2.89)	(1.88)	(1.92)
D*M7	1.52	0.70	1.29
	(1.99)	(1.26)	(1.40)
D*M8	-0.51	-0.11	-0.48
	(1.50)	(1.01)	(1.02)
D*M9	0.79	0.46	0.74
	(1.80)	(1.26)	(1.38)
D*M10	-0.03	0.39	-0.14
	(1.34)	(1.11)	(0.97)
D*M11	-0.91	-0.54	-0.50
	(1.03)	(0.74)	(0.76)
D*M12	1.86	1.49	0.82
	(1.92)	(1.29)	(1.28)
Other Coefs		omitted for reporting	
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Observations	41,280	31,650	32,008
Number of accounts	652	645	651
Mean of DV	6.40	4.25	4.06
R^2	0.27	0.24	0.24

Notes: This table compares the dynamic response in the trading frequency for a sub-sample who trade both equities and CFD. Following Equation 3, We regress individuals' #Trades on a dummy variable D identifying the product type whether it is an equity or CFD trade, dummy variables that identify months before or after individuals' 55^{th} birthday and their interaction terms. We focus on the coefficients of interactions, thus other coefficients are omitted from reporting for brevity. We split sample into the universe of buy and sell trades, buy-only trades, and sell-only trades. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effect of CPF Early Withdrawal on Portfolio Volatility

	Variance Ratio			
	Equity	CFD	Equity	CFD
	(1)	(2)	(3)	(4)
constant	1.03***	0.92***	1.00***	0.49**
	(0.06)	(0.11)	(0.04)	(0.24)
M[-3,-1]	0.05	0.48	0.05	0.46
	(0.04)	(0.41)	(0.04)	(0.40)
M[0,12]	0.25*	0.29*	0.25*	0.26*
	(0.13)	(0.15)	(0.13)	(0.15)
log($Volume)			0.01	0.10***
			(0.00)	(0.03)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	197,077	16,976	197,077	16,976
Number of accounts	17,071	1,060	17,071	1,060
Mean of DV	1.15	1.11	1.15	1.11
R^2	0.31	0.28	0.31	0.28

Notes: To investigate the shift in risk-taking behavior, we evaluate the risk-taking by measuring individuals' portfolio volatility, as defined as variance ratio following Equation 4. This table presents the average response of the variance ratio before and after individuals turn 55 by estimating Equation 1. In columns (1) - (2), we regress the portfolio variance ratio on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of portfolio variance ratio during benchmark period when it is 4 to 15 months prior to turning 55. In columns (3) - (4), we control for the monthly trading activity, measured by the logarithm of one plus dollar trading volume. The sample period is from January 2015 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Portfolio Performance: Cumulative Gross Return

Horizon/Month	Equity Buy-Sell	CFD Buy-Sell
1	-0.87%***	-3.9%**
	(-7.0)	(-2.05)
2	-1.08%***	-5.57%**
	(-7.01)	(-2.11)
3	-0.93%***	-7.41%**
	(-5.15)	(-2.32)
4	-1.16%***	-10.25%***
	(-5.32)	(-2.78)
5	-1.23%***	-1.21%
	(-5.08)	(-0.28)
6	-1.35%***	0.07%
	(-4.98)	(0.01)
7	-1.49%***	-0.51%
	(-5.12)	(-0.1)
8	-1.47%***	4.05%
	(-4.72)	(0.61)
9	-1.34%***	2.17%
	(-3.98)	(0.27)
10	-1.36%***	5.84%
	(-3.76)	(0.79)
11	-1.35%***	0.79%
	(-3.53)	(0.11)
12	-1.16%***	2.48%
	(-2.79)	(0.3)
Obs	5931	387

Notes: We track the returns for the portfolio of securities bought or sold buy individual i in month t in the following 12 months. We denote the monthly returns on the portfolio of securities bought (sold) as $R^B_{i,k}$ ($R^S_{i,k}$) and difference between the buy and sell portfolio returns as $R^{BmS}_{i,k}$, where $k = 1..., 12$. we calculate $R^B_{i,k}$ ($R^S_{i,k}$) by taking the dollar trading volume weighted average returns on the securities bought (sold) in month t and held for the next k months. The monthly portfolio return measures are sampled from January 2013 to January 2022. We focus on the return on the net buy portfolio (buy trades minus sell trades) and perform a t-test and compare k^{th} month portfolio returns with zeros to evaluate the trading decisions and timing skills. The t-statistics are displayed in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Effect of CPF Early Withdrawal on Trading Cost

	Trading Cost	
	Equity Buy&Sell	CFD Buy&Sell
constant	49.88***	242.05***
	(0.72)	(15.89)
M[-3,-1]	-0.51	48.26**
	(1.03)	(22.88)
M[0,12]	4.82***	93.49***
	(1.41)	(31.16)
Individual FE	Yes	Yes
Year-Month FE	Yes	Yes
Observations	585,679	30,054
Number of accounts	24,796	1,249
Mean of DV	52.01	289.60
R^2	0.41	0.48

Notes: This table presents the average response of the monthly trading cost before and after individuals turn age 55 by estimating Equation 2. The sample period is from January 2013 to January 2022. We regress the monthly trading cost on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of monthly trading cost during benchmark period when it is 4 to 15 months prior to turning 55. All values displayed in above table are in SGD. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effect of CPF Early Withdrawal on Trading Performance

	Equity			CFD	
	Gross	Net	Alpha	Gross	Net
	(1)	(2)	(3)	(4)	(5)
constant	-0.28***	-0.29***	-0.22***	-7.20***	-8.16***
	(0.02)	(0.02)	(0.03)	(2.41)	(2.36)
M[-3,-1]	0.03	0.04	-0.27***	3.75	3.89
	(0.03)	(0.03)	(0.05)	(4.15)	(4.12)
M[0,12]	0.00	0.00	-0.39***	2.77	2.96
	(0.03)	(0.03)	(0.06)	(4.38)	(4.30)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	500,901	500,901	500,901	23,989	23,989
Number of accounts	22,480	22,480	22,480	1,094	1,094
Mean of DV	-0.27	-0.29	-0.42	-5.50	-6.35
R^2	0.12	0.12	0.07	0.07	0.07

Notes: This table presents the average response in the trading performance (monthly portfolio return) for equity trading and CFD trading respectively before and after individuals turn age 55 by estimating Equation 1. The dependent variables are monthly portfolio gross and net-of-cost returns for equity trading in columns 1-2, for CFD trading in columns 4-5. The dependent variable in column 3 is the risk-adjusted equity portfolio return based on a two-factor model (excess returns on the MSCI World Index and the Singapore Straits Times Index (STI)). We regress on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of monthly portfolio return during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2015 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Falsification Test

	Equity $Volume				CFD $Volume			
	Foreigner	Age 50	Age 54	Age 60	Foreigner	Age 50	Age 54	Age 60
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
constant	14,321***	16,770***	17,043***	17,588***	3,976	16,435***	13,853***	15,512***
	(1,944)	(266)	(273)	(318)	(6,672)	(831)	(1,360)	(814)
M[-3,-1]	-3,815	73	-30	25	3,954	-1,825	4,817**	-1,286
	(2,956)	(402)	(425)	(481)	(9,817)	(1,308)	(2,017)	(1,173)
M[0,12]	-1,831	244	5	-217	8,821	-1,081	4,721*	-2,098
	(3,671)	(525)	(535)	(623)	(13,158)	(1,589)	(2,656)	(1,590)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,401	678,078	593,942	468,760	839	33,848	22,630	29,857
Number of accounts	950	28,823	25,127	19,743	37	1,410	946	1,250
Mean of DV	13,080	16,887	17,042	17,492	8,178	15,740	16,529	14,406
R^2	0.12	0.41	0.41	0.41	0.31	0.38	0.33	0.32

Notes: This table aims for a set of falsification tests where present the dynamic response in the dollar trading volume for foreigners (column 1 & 5), treatment at age 50 (column 2 & 6), treatment at age 54 (column 3 & 7) and treatment at age 60 (column 4 & 8) by estimating Equation 1. We regress the monthly dollar trading volume (buy and sell trades) on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of monthly dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All values displayed in above table are in SGD. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Heterogeneity Test: Effect of CPF Early Withdrawal by Gender

	$Volume				Variance Ratio				Portfolio Net Return			
	Equity		CFD		Equity		CFD		Equity		CFD	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
constant	19,940.35***	11,284.23***	12,812.16***	7,545.38***	1.06***	0.96***	0.91***	0.93***	-0.33***	-0.22***	-9.63***	-1.91
	(420.93)	(305.36)	(1,191.38)	(1,407.47)	(0.03)	(0.19)	(0.13)	(0.12)	(0.02)	(0.03)	(2.89)	(2.47)
M[-3,-1]	368.10	-155.50	496.28	4,523.65*	0.03	0.08*	0.59	0.08	0.04	0.03	5.50	-2.78
	(627.50)	(449.34)	(1,674.31)	(2,383.88)	(0.06)	(0.04)	(0.53)	(0.16)	(0.04)	(0.04)	(5.16)	(3.35)
M[0,12]	2,947.02***	583.52	4,735.68**	5,564.10**	0.14***	0.51	0.35*	0.11	0.02	-0.03	4.58	-4.11
	(836.47)	(586.57)	(2,316.00)	(2,632.56)	(0.05)	(0.41)	(0.19)	(0.21)	(0.05)	(0.05)	(5.29)	(4.51)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	368,351	217,328	23,648	6,406	134,184	62,893	13,304	3,672	317,289	183,612	19,065	4,924
Number of accounts	15,612	9,184	985	264	11,178	5,893	836	224	14,264	8,216	864	230
Mean of DV	21,305.60	11,534.73	15,003.69	10,582.18	1.12	1.21	1.15	0.99	-0.32	-0.23	-6.91	-4.21
R^2	0.41	0.41	0.32	0.30	0.18	0.34	0.28	0.23	0.12	0.11	0.07	0.09

Notes: This table presents the average response of dollar trading volume (buy and sell trades), variance ratio, and portfolio net return before and after individuals turn age 55 across gender. We regress the corresponding outcome variables on pre-55$^{\text{th}}$ birthday peiord dummy $M[-3,-1]$, post-period dummy variable $M[0,12]$ based on subsample of male and female investors. The constant term represents the average estimation of monthly dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All specifications include individual fixed effects, year-month fixed effects and gender year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

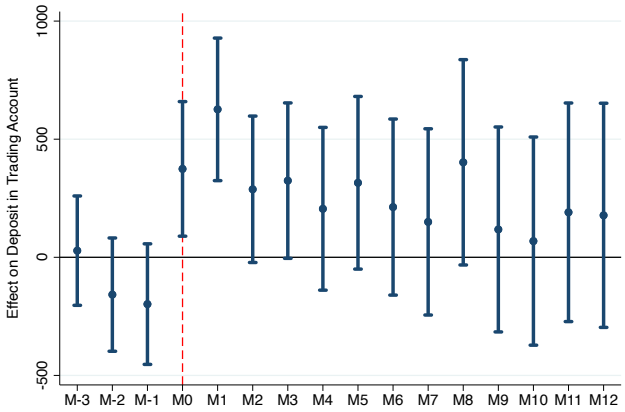
Table 10: Heterogeneity Test: Effect of CPF Early Withdrawal by Income

	$Volume				Variance Ratio				Portfolio Net Return			
	Equity		CFD		Equity		CFD		Equity		CFD	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
constant	12,878.28***	29,124.08***	7,724.06***	14,176.08***	1.04***	0.96***	0.93***	0.84***	-0.27***	-0.32***	-8.84***	-5.34
	(285.07)	(1,079.46)	(1,195.39)	(2,314.01)	(0.02)	(0.20)	(0.11)	(0.19)	(0.02)	(0.04)	(2.05)	(4.05)
M[-3,-1]	-526.50	644.92	1,517.33	705.57	-0.01	0.19	-0.03	0.22	0.06*	-0.08	3.46	2.37
	(412.30)	(1,542.38)	(1,310.71)	(3,554.07)	(0.03)	(0.12)	(0.13)	(0.22)	(0.03)	(0.07)	(3.51)	(5.26)
M[0,12]	1,239.11**	1,219.56	7,180.27***	3,096.76	0.10**	0.63	0.29	0.38	0.08*	-0.13	5.18	-2.16
	(547.67)	(2,214.98)	(2,384.81)	(4,534.69)	(0.05)	(0.43)	(0.19)	(0.36)	(0.04)	(0.08)	(3.55)	(8.05)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	337,693	129,675	15,009	7,890	99,675	54,639	8,123	4,664	278,136	118,441	11,497	6,752
Number of accounts	14,246	5,538	623	332	9,096	4,302	515	290	12,443	5,342	536	305
Mean of DV	13,394.82	29,727.82	11,205.93	15,611.95	1.09	1.27	1.08	1.04	-0.23	-0.38	-5.93	-6.06
R^2	0.39	0.38	0.27	0.30	0.10	0.33	0.23	0.30	0.11	0.14	0.06	0.08

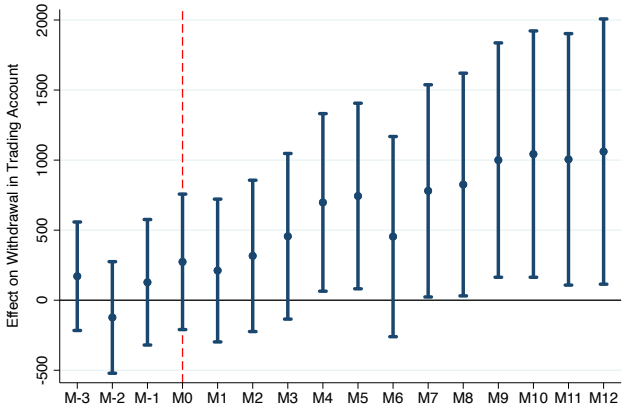
Notes: This table presents the average response of dollar trading volume (buy and sell trades), variance ratio and portfolio net return before and after individuals turn age 55 by income groups. We regress the monthly dollar trading volume on pre-55$^{\text{th}}$ birthday peiord dummy $M[-3,-1]$, post-period dummy variable $M[0,12]$ based on subsample of low income group (below SGD 60,000) and high income group (above SGD 100,000). The constant term represents the average estimation of monthly dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We also examine whether mid-income group and high-income group response homogeneously by testing the statistical significance of difference between the coefficients of the two income groups (Mid, High) in the post-period $M[0,12]$. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All specifications include individual fixed effects, year-month fixed effects and gender $\times$ year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Dynamic Responses of CPF Early Withdrawal on Cash Transfer in Trading Account

(a) Deposit



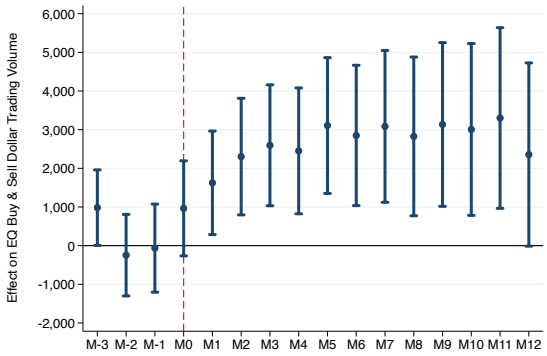
(b) Withdrawal



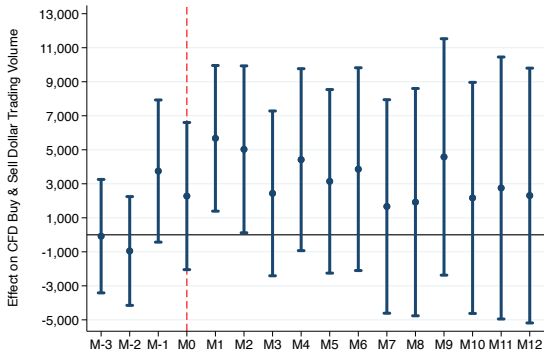
Notes: This figure shows the dynamic response of the cash transfer in individuals' trading account before and after individuals turn age 55 following Equation 2. The confidence intervals of coefficients are plotted at 95% level.

Figure 2: Dynamic Responses of Trading, Equity & CFD

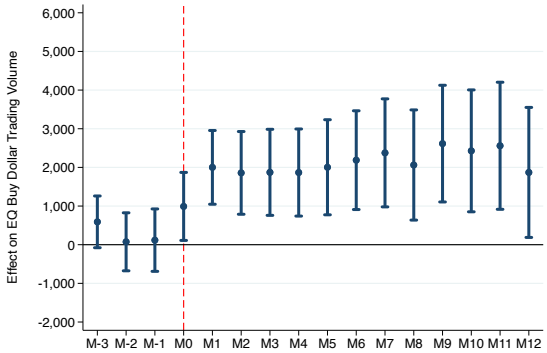
(a) Dynamic Responses of Dollar Trading Volume



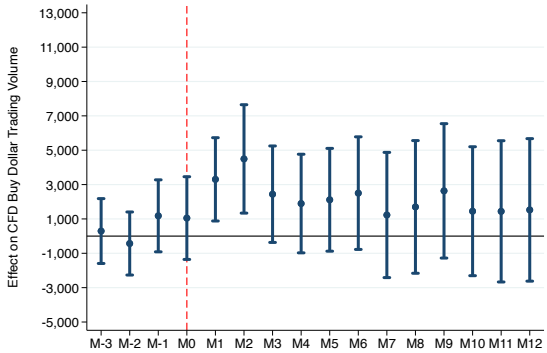
(a.1) Equity Buy&Sell



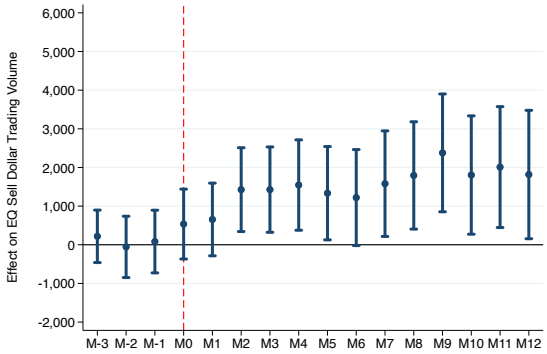
(a.2) CFD Buy&Sell



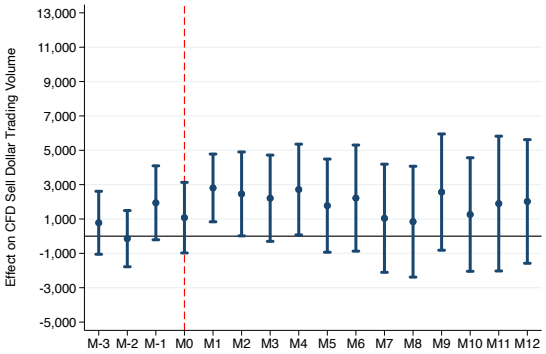
(a.3) Equity Buy



(a.4) CFD Buy



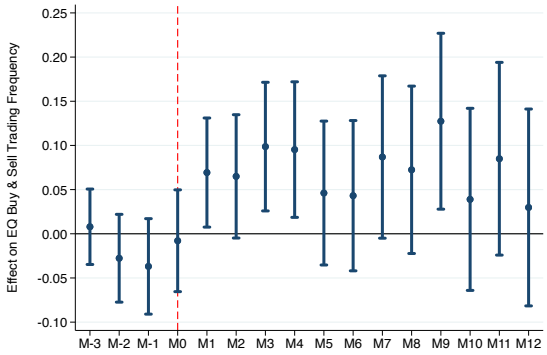
(a.5) Equity Sell



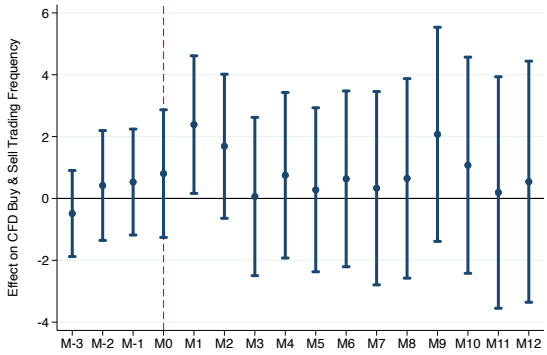
(a.6) CFD Sell

Notes: This figure shows the dynamic response of the dollar trading volume for equities and CFD before and after individuals turn age 55 following Equation 2. We plot the estimation of β_s and their 95% confidence interval.

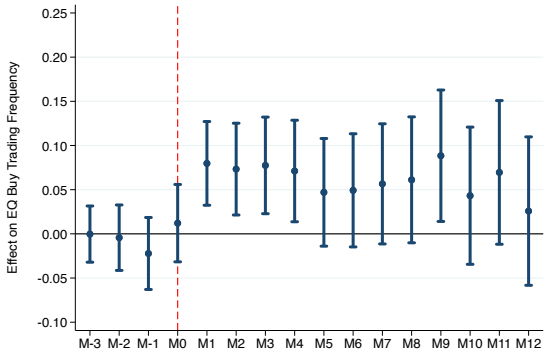
(b) Dynamic Responses of Trading Frequency



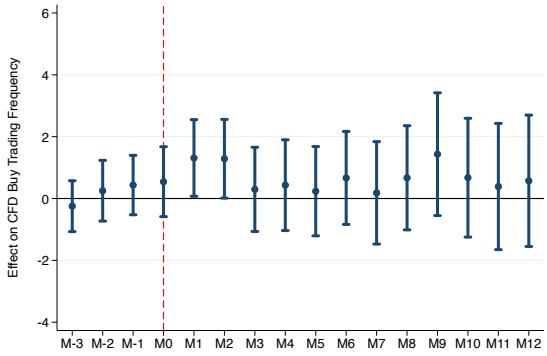
(b.1) Equity Buy&Sell



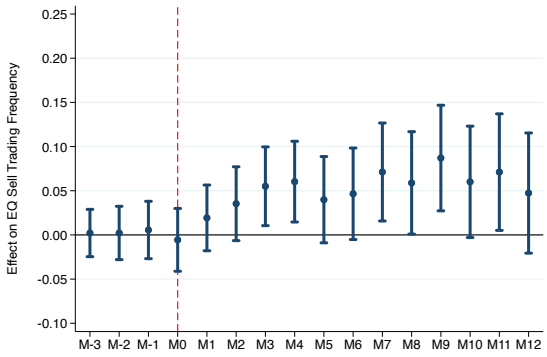
(b.2) CFD Buy&Sell



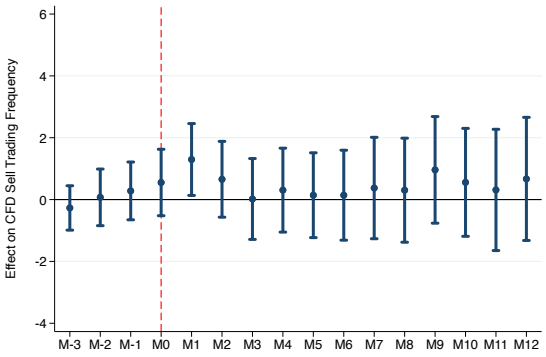
(b.3) Equity Buy



(b.4) CFD Buy



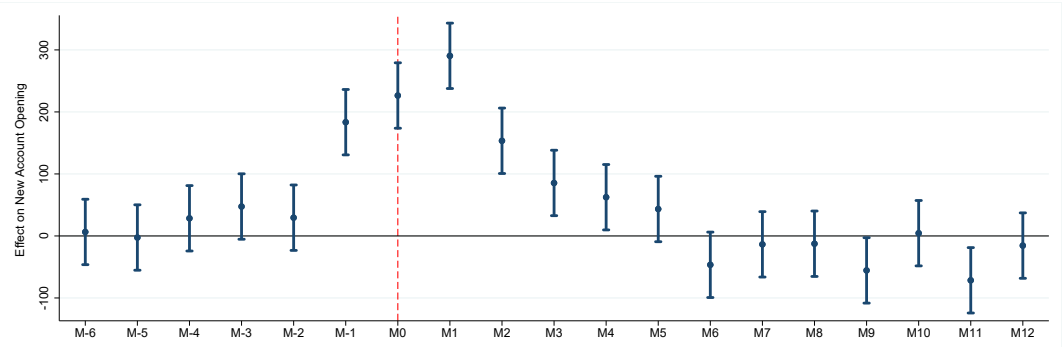
(b.5) EQ Sell



(b.6) CFD Sell

Notes: This figure shows the dynamic response of the number of trades for equities and CFD before and after individuals turn age 55 following Equation 2. We plot the estimation of β_s and their 95% confidence interval.

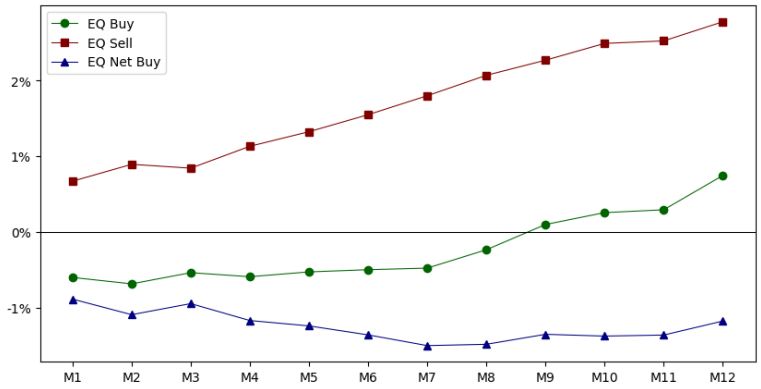
Figure 3: Dynamic Response of New Account Opening



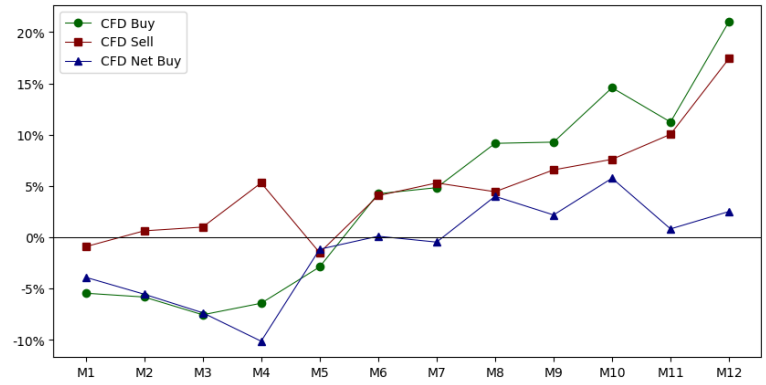
Notes: This figure shows the dynamic response of new account opening before and after age 55. The dependent variable is the total number of accounts opening in each month relative to age 55. We regress outcome variable on a set of dummy variables representing each month surrounding the age 55. We plot the estimates and their 95% confidence interval. To better observe the anticipation effect on account opening, we extend the pre-period to be 6 months prior to individual's 55^{th} birthday while the benchmark period will be 7 to 15 months prior to age 55.

Figure 4: 12-month Portfolio Cumulative Returns

(a) Equity Portfolio 12-month Cumulative Returns



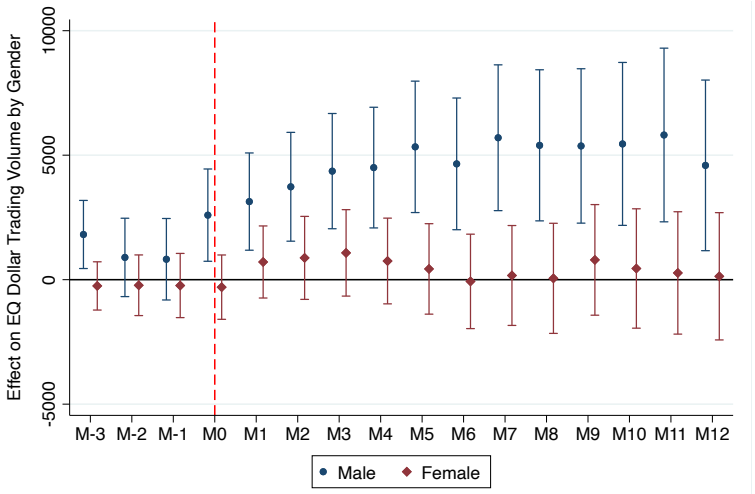
(b) CFD Portfolio 12-month Cumulative Returns



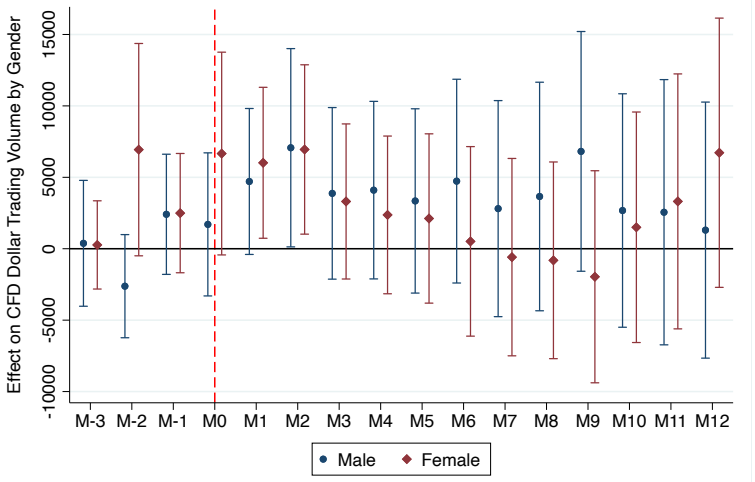
Notes: Above figures show average 12-month cumulative net return for equities (CFD) buy portfolio, equities (CFD) sell portfolio, and equities (CFD) net buy portfolio after adjusting cost. We track the returns for the portfolio of securities bought or sold buy individual i in month t in the following 12 months. We denote the monthly returns on the portfolio of securities bought (sold) as $R^B_{i,k}$ ($R^S_{i,k}$) and difference between the buy and sell portfolio returns as $R^{BmS}_{i,k}$, where $k = 1..., 12$. We calculate buy (sell) portfolio return $R^B_{i,k}$ ($R^S_{i,k}$) by taking the dollar trading volume weighted average returns on the securities bought (sold) in month t and held for the next k months. Then we derive net portfolio return by subtracting trading cost incurred during and after month t.

Figure 5: Dynamic Responses of Dollar Trading Volume by Gender, Equity & CFD

(a) EQ



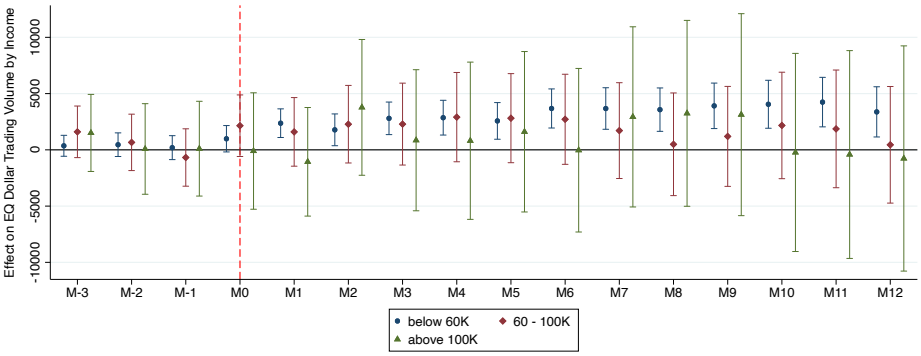
(b) CFD



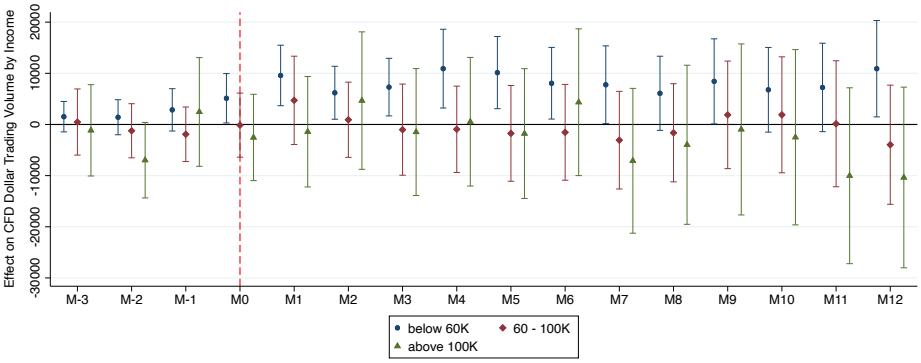
Notes: This figure shows the dynamic response of dollar trading volume for equities and CFD before and after individuals turn age 55 based on sub-samples splitted by gender following Equation 2. The confidence interval of coefficients are plotted at 95% level.

Figure 6: Dynamic Responses of Dollar Trading Volume by Income, Equity & CFD

(a) Equity



(b) CFD



Notes: This figure shows the dynamic response of dollar trading volume for equity and CFD before and after individuals turn age 55 based on sub-samples splitted by gender following Equation 2. The confidence interval of coefficients are plotted at 95% level.

Internet Appendix

Trading in your Golden Years: The Effects of Early Pension Withdrawal on Individual Investments

June 2025

A Internet Appendix

Table A.1: Dynamic Responses of CPF Early Withdrawal on Cash Transfer

	Deposit	Withdrawal	Net Withdrawal
	(1)	(2)	(3)
constant	1,814***	4,269***	-2,455***
	(76)	(146)	(158)
M-3	28	171	-143
	(118)	(198)	(229)
M-2	-158	-123	-35
	(122)	(203)	(230)
M-1	-198	128	-326
	(130)	(228)	(256)
M0	374**	274	100
	(145)	(247)	(276)
M1	626***	212	414
	(154)	(260)	(294)
M2	288*	317	-29
	(158)	(276)	(304)
M3	325*	456	-132
	(168)	(302)	(336)
M4	205	698**	-493
	(176)	(323)	(354)
M5	315*	744**	-428
	(186)	(338)	(372)
M6	213	454	-241
	(190)	(364)	(398)
M7	150	780**	-631
	(201)	(386)	(421)
M8	402*	826**	-424
	(222)	(405)	(439)
M9	118	1,000**	-882*
	(221)	(427)	(469)
M10	69	1,043**	-974**
	(225)	(449)	(484)
M11	191	1,005**	-815
	(236)	(458)	(499)
M12	178	1,061**	-883*
	(242)	(483)	(518)
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Observations	461,166	461,166	461,166
Number of accounts	18,561	18,561	18,561
Mean of DV	1,919	4,562	-2,643
R^2	0.18	0.29	0.23

Notes: This table presents the dynamic response in cash transfer in individuals' trading accounts before and after individuals turn age 55 by estimating Equation 2. We regress the monthly cash transfer on a dummy variable that equals 1 if it is t ($t \in [-3, 12]$) months before or after individuals' 55^{th} birthday. The constant term represents the average estimation of monthly cash transfer during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Effect of CPF Early Withdrawal on Trading Frequency (Poisson Regression)

	#Trades					
	Equity			CFD		
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	1.30***	0.79***	0.67***	3.14***	2.48***	2.46***
	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)	(0.07)
M[-3,-1]	-0.01	0.00	-0.01	0.04	0.06	0.01
	(0.02)	(0.02)	(0.02)	(0.08)	(0.09)	(0.09)
M[0,12]	0.05**	0.08***	0.02	0.16	0.20*	0.12
	(0.02)	(0.03)	(0.03)	(0.12)	(0.11)	(0.12)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,478	467,773	496,043	30,036	28,188	29,441
Number of accounts	24,781	19,815	20,834	1,248	1,166	1,223
Mean of DV	1.10	0.79	0.60	7.57	4.12	3.84
Log-likelihood	-7.28e+05	-4.78e+05	-4.09e+05	-1.96e+05	-1.12e+05	-1.11e+05

Notes: This table presents the average response of trading frequency before and after individuals turning age 55 by estimating poisson regression with individual fixed effect and year-month fixed effect. The dependent variables are the number of trades. We regress the outcome variables on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of outcome variables during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. Equity dollar trading volume is calculated as $Contract\ Value = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Effect of CPF Early Withdrawal on Trading (based on sample before Covid-19)

Panel A: $Volume						
		Equity			CFD	
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	13,671***	9,503***	8,335***	11,993***	6,413***	6,074***
	(324)	(246)	(210)	(1,070)	(673)	(525)
M[-3,-1]	301	327	-89	-269	-52	171
	(437)	(326)	(281)	(1,293)	(853)	(682)
M[0,12]	2,144***	1,923***	906**	2,692	2,135*	1,597*
	(575)	(440)	(374)	(1,934)	(1,211)	(944)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,229	259,523	301,515	18,883	17,383	18,490
Mean of DV	14,785	10,508	8,782	13,298	7,465	6,883
R^2	0.40	0.37	0.37	0.34	0.32	0.34
Panel B: #Trades						
		Equity			CFD	
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.92***	0.66***	0.51***	5.98***	3.38***	3.05***
	(0.02)	(0.01)	(0.01)	(0.46)	(0.27)	(0.26)
M[-3,-1]	0.01	0.02	0.00	0.08	0.00	0.04
	(0.02)	(0.02)	(0.01)	(0.60)	(0.36)	(0.33)
M[0,12]	0.08***	0.09***	0.03**	0.70	0.21	0.42
	(0.03)	(0.02)	(0.02)	(0.84)	(0.48)	(0.47)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,229	259,523	301,515	18,883	17,383	18,490
Mean of DV	0.96	0.71	0.52	6.33	3.49	3.26
R^2	0.46	0.42	0.43	0.38	0.36	0.35

Notes: This table presents the average response of dollar trading volume and trading frequency before and after individuals turning age 55 based on subsample trades before COVID-19 (January 2020)[30] by estimating Equation 1. The dependent variables are dollar trading volume in Panel A and number of trades in Panel B. We regress the outcome variables on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of outcome variables during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Dynamic Responses of CPF Early Withdrawal on Trading Volume

	Equity			CFD		
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	16,394***	11,029***	10,098***	13,361***	7,131***	6,660***
	(405)	(279)	(282)	(1,341)	(745)	(656)
M-3	983**	591*	218	-80	295	779
	(498)	(341)	(346)	(1,700)	(962)	(934)
M-2	-246	75	-55	-951	-430	-143
	(538)	(383)	(405)	(1,630)	(935)	(834)
M-1	-64	118	83	3,748*	1,181	1,942*
	(582)	(412)	(414)	(2,130)	(1,068)	(1,097)
M0	964	991**	536	2,278	1,050	1,078
	(627)	(449)	(461)	(2,205)	(1,227)	(1,047)
M1	1,624**	2,001***	655	5,674***	3,304***	2,809***
	(683)	(487)	(480)	(2,183)	(1,235)	(1,005)
M2	2,304***	1,858***	1,426***	5,027**	4,494***	2,461**
	(769)	(546)	(553)	(2,501)	(1,608)	(1,245)
M3	2,596***	1,872***	1,427**	2,436	2,440*	2,210*
	(798)	(568)	(563)	(2,470)	(1,431)	(1,280)
M4	2,452***	1,867***	1,545***	4,419	1,896	2,715**
	(831)	(575)	(597)	(2,727)	(1,463)	(1,346)
M5	3,107***	2,003***	1,334**	3,144	2,115	1,777
	(896)	(628)	(616)	(2,751)	(1,525)	(1,382)
M6	2,851***	2,187***	1,221*	3,860	2,502	2,217
	(926)	(652)	(634)	(3,039)	(1,671)	(1,574)
M7	3,086***	2,376***	1,580**	1,666	1,229	1,043
	(1,002)	(713)	(697)	(3,199)	(1,857)	(1,605)
M8	2,826***	2,062***	1,794**	1,921	1,699	843
	(1,047)	(727)	(708)	(3,406)	(1,968)	(1,644)
M9	3,134***	2,615***	2,378***	4,579	2,634	2,567
	(1,081)	(770)	(777)	(3,543)	(1,994)	(1,725)
M10	3,006***	2,428***	1,804**	2,169	1,449	1,260
	(1,134)	(805)	(781)	(3,463)	(1,912)	(1,685)
M11	3,302***	2,559***	2,010**	2,752	1,441	1,898
	(1,192)	(839)	(798)	(3,926)	(2,095)	(2,000)
M12	2,357*	1,870**	1,817**	2,309	1,526	2,020
	(1,209)	(858)	(847)	(3,818)	(2,114)	(1,834)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,679	467,901	496,214	30,054	28,206	29,459
Number of accounts	24,796	19,825	20,847	1,249	1,167	1,224
Mean of DV	17,585	11,976	10,788	14,935	8,139	7,622
R^2	0.41	0.39	0.39	0.34	0.32	0.34

Notes: This table presents the dynamic response in dollar trading volume before and after individuals turn age 55 by estimating Equation 2. We regress the monthly dollar trading volume on a dummy variable that equals 1 if it is t ($t \in [-3, 12]$) months before or after individuals' 55^{th} birthday. The constant term represents the average estimation of monthly dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Dynamic Responses of CPF Early Withdrawal on Trading Frequency

	Equity			CFD		
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	1.08***	0.77***	0.57***	7.14***	3.80***	3.61***
	(0.02)	(0.01)	(0.01)	(0.67)	(0.36)	(0.34)
M-3	0.01	-0.00	0.00	-0.49	-0.25	-0.27
	(0.02)	(0.02)	(0.01)	(0.71)	(0.42)	(0.37)
M-2	-0.03	-0.00	0.00	0.42	0.25	0.07
	(0.03)	(0.02)	(0.02)	(0.91)	(0.50)	(0.47)
M-1	-0.04	-0.02	0.01	0.53	0.44	0.28
	(0.03)	(0.02)	(0.02)	(0.87)	(0.49)	(0.48)
M0	-0.01	0.01	-0.01	0.80	0.54	0.55
	(0.03)	(0.02)	(0.02)	(1.05)	(0.58)	(0.55)
M1	0.07**	0.08***	0.02	2.39**	1.31**	1.30**
	(0.03)	(0.02)	(0.02)	(1.13)	(0.63)	(0.59)
M2	0.06*	0.07***	0.04*	1.69	1.29**	0.66
	(0.04)	(0.03)	(0.02)	(1.19)	(0.65)	(0.63)
M3	0.10***	0.08***	0.06**	0.06	0.30	0.02
	(0.04)	(0.03)	(0.02)	(1.30)	(0.69)	(0.67)
M4	0.10**	0.07**	0.06***	0.75	0.43	0.31
	(0.04)	(0.03)	(0.02)	(1.36)	(0.75)	(0.69)
M5	0.05	0.05	0.04	0.28	0.24	0.14
	(0.04)	(0.03)	(0.02)	(1.35)	(0.74)	(0.70)
M6	0.04	0.05	0.05*	0.63	0.66	0.14
	(0.04)	(0.03)	(0.03)	(1.45)	(0.77)	(0.74)
M7	0.09*	0.06	0.07**	0.33	0.18	0.37
	(0.05)	(0.03)	(0.03)	(1.59)	(0.84)	(0.84)
M8	0.07	0.06*	0.06**	0.65	0.67	0.30
	(0.05)	(0.04)	(0.03)	(1.64)	(0.86)	(0.86)
M9	0.13**	0.09**	0.09***	2.07	1.43	0.96
	(0.05)	(0.04)	(0.03)	(1.76)	(1.01)	(0.88)
M10	0.04	0.04	0.06*	1.07	0.67	0.56
	(0.05)	(0.04)	(0.03)	(1.78)	(0.98)	(0.89)
M11	0.08	0.07*	0.07**	0.19	0.39	0.31
	(0.06)	(0.04)	(0.03)	(1.91)	(1.04)	(1.00)
M12	0.03	0.03	0.05	0.54	0.57	0.67
	(0.06)	(0.04)	(0.03)	(1.99)	(1.08)	(1.01)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,679	467,901	496,214	30,054	28,206	29,459
Number of accounts	24,796	19,825	20,847	1,249	1,167	1,224
Mean of DV	1.10	0.79	0.60	7.56	4.12	3.83
R^2	0.45	0.43	0.44	0.37	0.36	0.34

Notes: This table presents the dynamic response in the number of trades before and after individuals turn age 55 by estimating Equation 2. We regress the monthly number of trades on a dummy variable that equals 1 if it is t ($t \in [-3, 12]$) months before or after individuals' 55^{th} birthday. The constant term represents the average estimation of monthly number of trades during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6: Effect of CPF Early Withdrawal on Trading: Foreign Equity v.s Local Equity

	$Volume		#Trades	
	Foreign Equity	Local Equity	Foreign Equity	Local Equity
	(1)	(2)	(3)	(4)
constant	3,570***	11,136***	0.35***	0.93***
	(135)	(181)	(0.01)	(0.01)
M[-3,-1]	61	68	-0.01	-0.00
	(215)	(268)	(0.02)	(0.02)
M[0,12]	481*	1,173***	0.03	0.06**
	(263)	(357)	(0.03)	(0.03)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	585,679	585,679	585,679	585,679
Number of accounts	24,796	24,796	24,796	24,796
Mean of DV	3,795	11,674	0.36	0.96
R^2	0.39	0.37	0.64	0.56

Notes: This table presents the average response of dollar trading volume of foreign equities and local equities before and after individuals turning age 55 by estimating Equation 1. We regress the outcome variables on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of outcome variables during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. Equity dollar trading volume is calculated as $ContractValue = Execution\ Price * Execution\ Quantity * Multiplier * FXrate$ and CFD dollar trading volume is calculated as $Margin\ Required\ Cash = Execution\ Price * Execution\ Quantity * Multiplier * FXrate * Margin$. Multiplier is applied to indices and commodities for CFD contracts, where each price worth $Multiplier$ times the notional price in dataset. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Effect of CPF Early Withdrawal on Trading: Number of Securities Traded

	#Securities					
	Equity			CFD		
	Buy&Sell	Buy	Sell	Buy&Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.54***	0.46***	0.78***	0.86***	0.85***	1.14***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.05)
M[-3,-1]	0.01	-0.00	0.00	0.05	0.06	0.08
	(0.01)	(0.01)	(0.01)	(0.06)	(0.05)	(0.07)
M[0,12]	0.06***	0.03**	0.07***	0.18**	0.18**	0.24**
	(0.01)	(0.01)	(0.02)	(0.08)	(0.07)	(0.09)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585,679	585,679	585,679	30,054	30,054	30,054
Number of accounts	24,796	24,796	24,796	1,249	1,249	1,249
Mean of DV	0.57	0.47	0.82	0.95	0.94	1.25
R^2	0.54	0.54	0.56	0.51	0.52	0.57

Notes: This table presents the average changes in the unique number of securities traded by individuals before and after they turning age 55 based on subsample trades by estimating Equation 1. We regress the outcome variables on a dummy variable that equals 1 if it is 3 months prior to individuals' 55^{th} birthday and a dummy variable that equals 1 if it is 0 to 12 months after. The constant term represents the average estimation of outcome variables during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. We split sample trades into the universe of buy and sell trades, buy-only trades, sell-only trades. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Average Holding Period (Days): Equity and CFD

	mean	std	min	25%	50%	75%	max
Equity	52	57	0	13	33	70	378
CFD Long	21	28	0	5	12	27	291
CFD Short	23	37	0	4	11	29	357

Table A.9: Dynamic Responses of CPF Early Withdrawal on Trading Volume by Gender

	Equity		CFD	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
constant	19,089***	11,371***	13,277***	8,951***
	(580)	(444)	(1,638)	(1,389)
M-3	1,815***	-251	379	266
	(698)	(494)	(2,245)	(1,569)
M-2	894	-224	-2,622	6,937*
	(803)	(622)	(1,840)	(3,775)
M-1	821	-235	2,410	2,493
	(835)	(658)	(2,144)	(2,120)
M0	2,592***	-300	1,704	6,663*
	(946)	(659)	(2,553)	(3,605)
M1	3,137***	711	4,708*	6,016**
	(996)	(738)	(2,603)	(2,683)
M2	3,731***	875	7,069**	6,949**
	(1,115)	(850)	(3,537)	(3,011)
M3	4,360***	1,076	3,876	3,309
	(1,181)	(885)	(3,061)	(2,757)
M4	4,502***	750	4,101	2,367
	(1,236)	(878)	(3,167)	(2,804)
M5	5,335***	432	3,346	2,118
	(1,346)	(927)	(3,288)	(3,010)
M6	4,651***	-70	4,733	515
	(1,349)	(968)	(3,635)	(3,370)
M7	5,701***	169	2,808	-589
	(1,494)	(1,024)	(3,854)	(3,509)
M8	5,396***	54	3,657	-812
	(1,548)	(1,128)	(4,077)	(3,497)
M9	5,371***	794	6,815	-1,963
	(1,582)	(1,133)	(4,277)	(3,770)
M10	5,453***	450	2,676	1,501
	(1,669)	(1,223)	(4,165)	(4,098)
M11	5,811***	271	2,556	3,314
	(1,780)	(1,254)	(4,731)	(4,533)
M12	4,590***	136	1,303	6,720
	(1,748)	(1,304)	(4,568)	(4,787)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	368,351	217,328	23,648	6,406
Mean of DV	15,612	9,184	985	264
R^2	21,306	11,535	15,004	10,582
r2	0.41	0.41	0.32	0.30

Notes: This table presents the dynamic response in the dollar trading volume (buy and see trades) for equity trading and CFD trading respectively before and after individuals turn age 55 by estimating Equation 2. We regress monthly dollar trading volume on a dummy variable that equals 1 if it is t ($t \in [-3, 12]$) months before or after individuals' 55^{th} birthday. The constant term represents the average estimation of monthly dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Dynamic Responses of CPF Early Withdrawal on Dollar Trading Volume by Income Groups

	Equity			CFD		
	below 60K	60K - 100K	above 100K	below 60K	60K - 100K	above 100K
	(1)	(2)	(3)	(4)	(5)	(6)
constant	11,943***	17,350***	29,202***	7,283***	12,136***	16,849***
	(396)	(856)	(1,556)	(1,633)	(2,137)	(3,323)
M-3	360	1,601	1,503	1,525	475	-1,149
	(475)	(1,169)	(1,747)	(1,516)	(3,286)	(4,538)
M-2	458	664	78	1,412	-1,230	-6,978*
	(536)	(1,279)	(2,054)	(1,744)	(2,688)	(3,753)
M-1	195	-680	105	2,858	-1,916	2,449
	(543)	(1,301)	(2,149)	(2,108)	(2,709)	(5,400)
M0	986*	2,145	-104	5,119**	-129	-2,543
	(598)	(1,396)	(2,639)	(2,459)	(3,182)	(4,289)
M1	2,370***	1,597	-1,063	9,581***	4,720	-1,419
	(649)	(1,556)	(2,462)	(3,011)	(4,385)	(5,488)
M2	1,780**	2,281	3,775	6,202**	922	4,670
	(721)	(1,758)	(3,078)	(2,635)	(3,736)	(6,830)
M3	2,800***	2,289	852	7,305**	-1,015	-1,480
	(738)	(1,856)	(3,198)	(2,867)	(4,526)	(6,306)
M4	2,859***	2,908	809	10,915***	-939	535
	(788)	(2,024)	(3,565)	(3,920)	(4,286)	(6,390)
M5	2,572***	2,815	1,607	10,139***	-1,739	-1,777
	(831)	(2,020)	(3,637)	(3,591)	(4,756)	(6,450)
M6	3,677***	2,716	-33	8,060**	-1,531	4,350
	(886)	(2,042)	(3,708)	(3,566)	(4,758)	(7,291)
M7	3,674***	1,710	2,930	7,766**	-3,069	-7,099
	(942)	(2,171)	(4,085)	(3,870)	(4,850)	(7,196)
M8	3,573***	494	3,245	6,097*	-1,626	-3,968
	(983)	(2,327)	(4,214)	(3,690)	(4,875)	(7,904)
M9	3,912***	1,195	3,127	8,426**	1,880	-967
	(1,031)	(2,266)	(4,579)	(4,235)	(5,341)	(8,499)
M10	4,051***	2,169	-231	6,784	1,888	-2,498
	(1,087)	(2,413)	(4,491)	(4,215)	(5,758)	(8,708)
M11	4,243***	1,865	-416	7,240	139	-10,023
	(1,122)	(2,668)	(4,711)	(4,401)	(6,258)	(8,739)
M12	3,374***	448	-769	10,904**	-3,959	-10,361
	(1,138)	(2,643)	(5,105)	(4,797)	(5,916)	(8,975)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	337,693	114,619	129,675	15,009	7,099	7,890
Number of Accounts	14,246	4,857	5,538	623	292	332
Mean of DV	13,395	18,249	29,728	11,206	11,893	15,612
R^2	0.39	0.44	0.38	0.27	0.33	0.30

Notes: This table presents the dynamic response in the dollar trading volume (both buy and sell trades) for equity trading and CFD trading respectively before and after individuals turn age 55 by estimating Equation 2. We regress monthly dollar trading volume on a dummy variable that equals 1 if it is t ($t \in [-3, 12]$) months before or after individuals' 55^{th} birthday. The constant term represents the average estimation of dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The sample period is from January 2013 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: Average Responses of CPF Early Withdrawal on Dollar Trading Volume for Low-income Group

	$Volume		#Trades	
	Equity	CFD	Equity	CFD
	(1)	(2)	(3)	(4)
constant	14,359***	10,497***	1.08***	5.77***
	(318)	(1,423)	(0.02)	(0.94)
M[-3,-1]	-324	1,274	-0.04*	-0.12
	(296)	(1,314)	(0.02)	(0.82)
M[-3,-1] × Frequent	-300	-1,725	-0.03**	-0.43
	(266)	(1,158)	(0.01)	(0.47)
M[-3,-1] × Most Active	-2,606**	4,247	-0.02	2.54
	(1,176)	(4,336)	(0.08)	(1.97)
M[0,12]	-231	3,520	-0.03	0.35
	(586)	(2,474)	(0.04)	(1.63)
M[0,12] × Frequent	-76	-202	-0.03**	-0.08
	(239)	(1,495)	(0.01)	(0.53)
M[0,12] × Most Active	3,600***	7,848*	0.38***	8.18***
	(1,368)	(4,287)	(0.09)	(2.20)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	337,626	15,009	337,626	15,009
Number of Accounts	14,241	623	14,241	623
Mean of DV	14,620	13,459	1.11	7.17
R^2	0.41	0.35	0.53	0.35

Notes: This table presents the average response of the dollar trading volume and trading frequency (both buy and sell trades) for equity trading and CFD trading respectively before and after individuals turn age 55 for a low-income subsample (with annual income below $60K). We further split the low-income group into three categories based on their pre-event trading activeness, measured by the monthly average number of trades. We subsequently have two dummy variables: *High Activeness* and *Mid Activeness*, which equal 1 if individuals are classified as high trading activeness and medium trading activeness respectively. We then interact the 3-month pre-period dummy variable and 12-month post-period dummy variable with trading activeness dummy variables *Mid Activeness* and *High Activeness*. The constant term represents the average estimation of dollar trading volume during benchmark period when it is 4 to 15 months prior to turning 55. The estimation of 3-month pre-period dummy variable and 12-month post-period dummy variable represent the response in trading activities for reference group who have low trading activeness in our sample. The sample period is from January 2013 to January 2022. All specifications include individual fixed effects and year-month fixed effects. We cluster standard errors at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

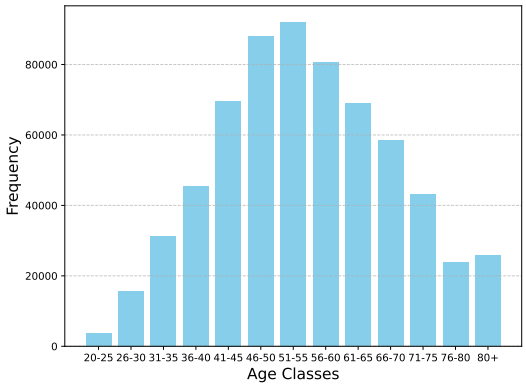
Table A.12: Summary Statistics: Individual Portfolio Value (in SGD)

Panel A: Equity traders								
	N	mean	std	min	25%	50%	75%	max
Portfolio	26,134	42,301	378,859	0	0	0	0	44,958,190
Panel B: CFD traders								
Portfolio	1,259	11,517	36,068	0	0	522	8,976	1,565,796
Initial Margin	1,259	4,556	21,775	0	0	0	1,256	916,054
Margin	1,259	15%	27%	0%	0%	0%	20%	100%
Panel C: Individuals Trading Both Equities and CFDs								
Equity portfolio	928	41,053	242,293	0	0	0	7,581	10,113,720
CFD portfolio	928	11,162	31,448	0	0	386	9,142	1,565,796
CFD Initial Margin	928	4,093	15,723	0	0	0	1,300	518,547
Margin	928	15%	27%	0%	0%	0%	19%	100%

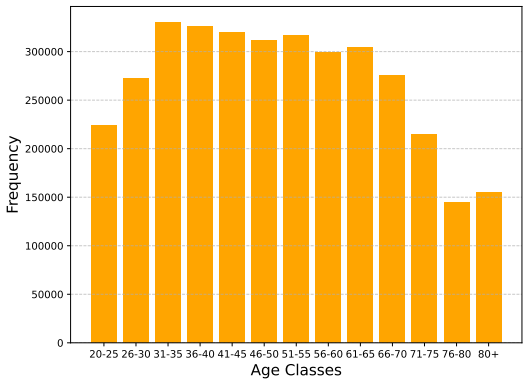
Notes: This table presents the distribution of monthly portfolio values for equity traders, CFD traders, and individuals who trade both. We analyze individual-level daily portfolio holdings from January 2015 to January 2022, aggregating the data to a monthly level by calculating the average daily portfolio value.

Figure A.1: Demographic Distribution: Brokerage Accounts vs. CPF Accounts

(a) Age Distribution

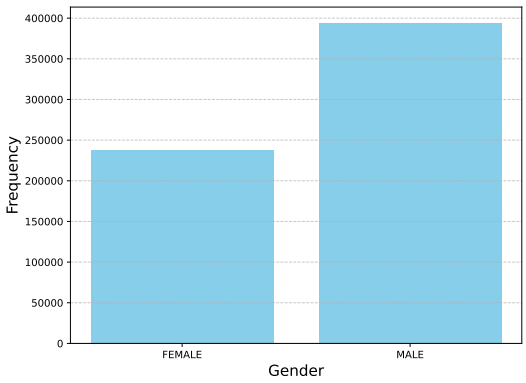


(a.1) Brokerage Accounts

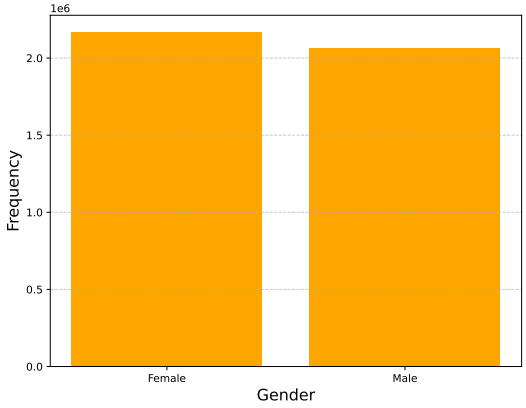


(a.2) CPF Accounts

(b) Gender Distribution

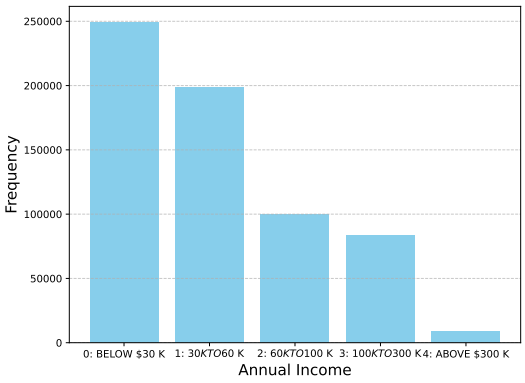


(b.1) Brokerage Accounts



(b.2) CPF Accounts

(c) Income Distribution



(c.1) Brokerage Accounts

Figure A.2: Distribution of Individuals' Birthdays across Months

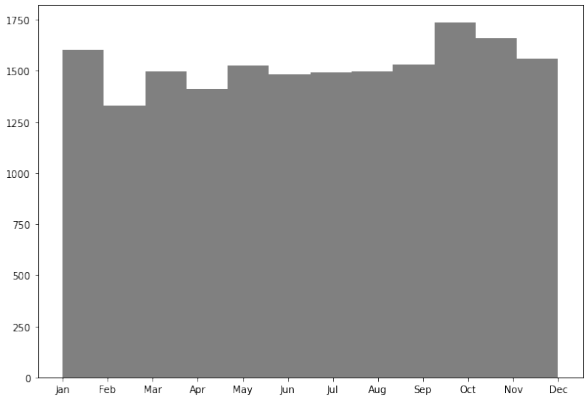
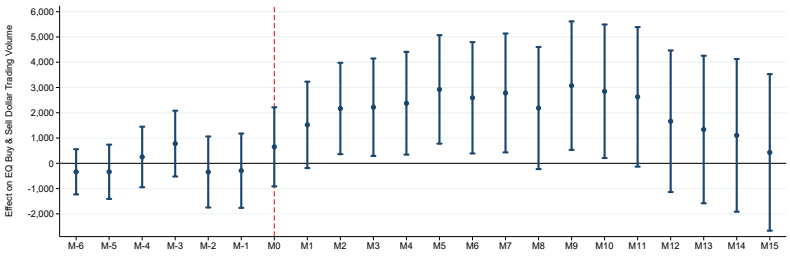
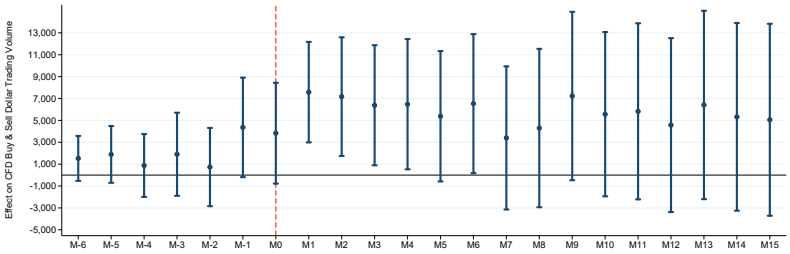


Figure A.3: CPF Early Withdrawal on Trading, Equity & CFD (extended pre-period and post period)

(a) Dynamic Responses of Dollar Trading Volume

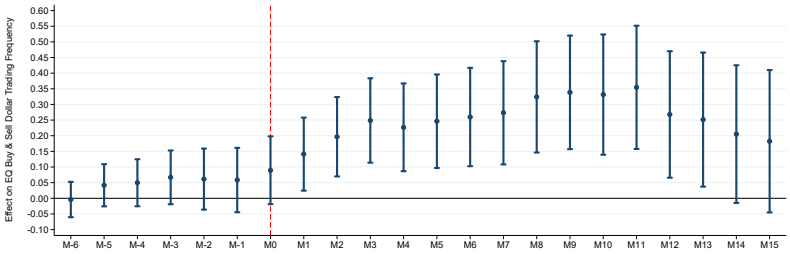


(a.1) Equity Buy&Sell

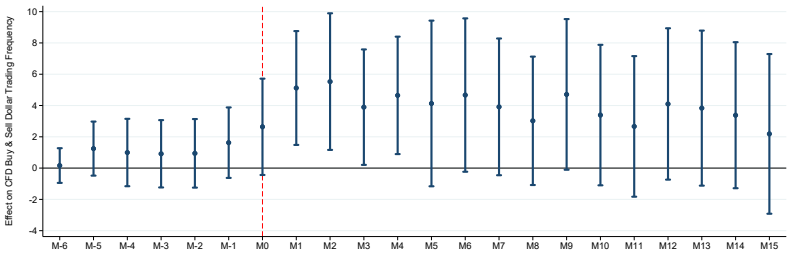


(a.2) CFD Buy&Sell

(a) Dynamic Responses of Trading Frequency



(a.1) Equity Buy&Sell

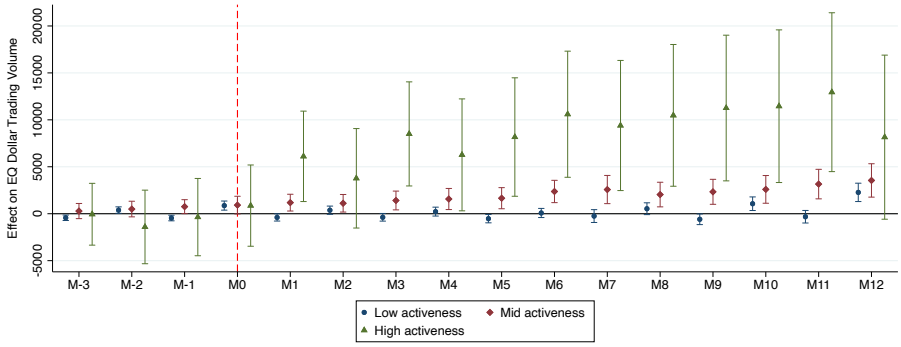


(a.2) CFD Buy&Sell

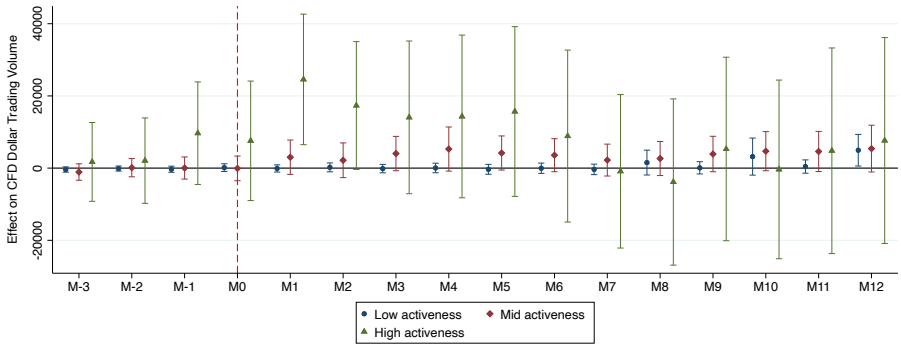
Notes: This figure shows the dynamic response of the dollar trading volume for equities and CFD before and after individuals turn age 55 by extending the pre-period to 6 months prior to each individual's 55^{th} birthday and extending the post-period to 15 months after. We plot the estimation of β_s and their 95% confidence interval.

Figure A.4: CPF Early Withdrawal on on Dollar Trading Volume for low-Income (below 60K) by trading activeness, Equity & CFD

(a) Equity



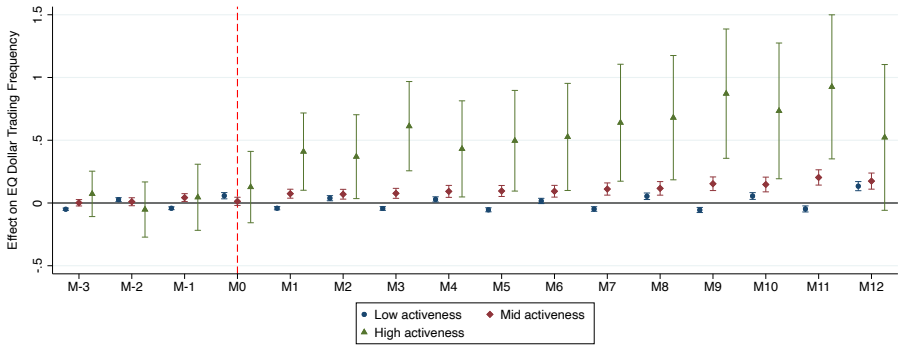
(b) CFD



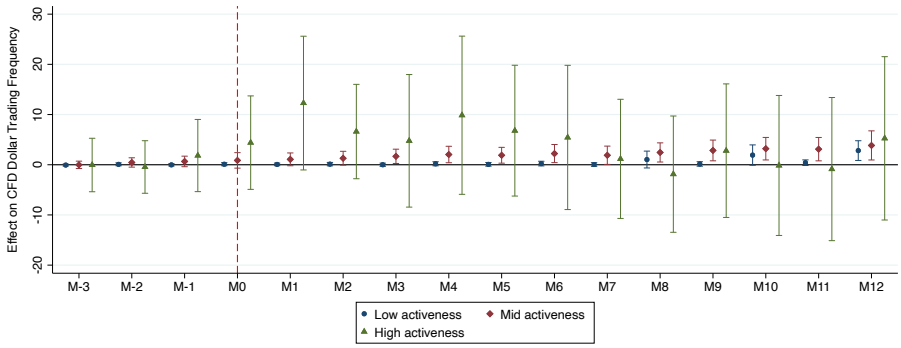
Notes: This figure shows the dynamic response of dollar trading volume for equity and CFD before and after individuals turn age 55 based on sub-samples of low-income group. We further split the low-income group into three categories "High", "Mid" and "Low" based on their pre-event trading activeness, measured by the monthly average number of trades. We estimate the dynamic response for each trading activeness group following Equation 2. The confidence interval of coefficients are plotted at 95% level.

Figure A.5: Dynamic Responses of CPF Early Withdrawal on Trading Frequency for low-Income (below 60K) by trading activeness, Equity & CFD

(a) Equity



(b) CFD



Notes: This figure shows the dynamic response of trading frequency for equity and CFD before and after individuals turn age 55 based on sub-samples of low-income group. We further split the low-income group into three categories "High", "Mid" and "Low" based on their pre-event trading activeness, measured by the monthly average number of trades. We estimate the dynamic response for each trading activeness group following Equation 2. The confidence interval of coefficients are plotted at 95% level.