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Liquidity shocks and pension fund performance: Evidence from the Early Release Scheme

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Abstract

We study how expectations of fund flows causally affect fund performance by exploiting a quasi-natural experiment in the Australian pension system where an unexpected policy change temporarily allowed fund withdrawals from a pre-specified date in the future. Using fractions of young members, middle-aged members, and government co-contributions for low income earners as instrumental variables, we find an insignificant effect of expected fund outflows on fund performance. A potential explanation is that Australian superannuation funds preemptively engage in liquidity management in response to changes in expectations of future fund flows and that this helps to limit direct and indirect costs in the rebalancing process.

Keywords: Expectations, Fund Flows, Pension Funds, Fund Performance, Liquidity Management, Natural Experiment

JEL Codes: G11, G12, G14, G23, G51

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1 Introduction

A large body of literature studies the flow-performance relationship for mutual funds and pension funds by analyzing how fund flows respond to fund performance.[1] A growing literature studies the flip-side of this relationship: how fund flows affect fund performance. Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004) and Song (2020), among others, study how realized fund flows affect fund performance, primarily through diseconomies of scale. Grinblatt and Titman (1989) and Wermers (2000) demonstrate that realized fund flows result in rebalancing costs and drag down fund performance. However, little is known on how *expectations* regarding future fund flows, rather than actual or realized fund flows, affect fund performance. A likely reason that the effects of expected fund flows on fund performance have not been studied is the empirical challenge of capturing exogenous variation in fund flow expectations that are orthogonal to past, current and future performance, as well as to current realized fund flows. We aim to fill this gap by exploring a quasi-natural experiment in the Australian pension system where the Australian Government announced it would allow temporary withdrawals from Australian superannuation funds starting at a pre-specified date in the future.[2]

This unexpected policy change to the pension system, referred to as the "early release scheme", provides an ideal laboratory to study how changes in fund manager expectations of future fund flows causally affect current fund performance. The Australian pension system restricts withdrawals from superannuation funds such that account-holders are otherwise not able to access the savings until reaching retirement age. The "early release scheme" policy occurred unexpectedly and was announced around one month before actual withdrawals took place. These features ensure that the policy announcement of temporary early withdrawals constitutes a shock to fund flow expectations

[1] See e.g. Ippolito (1992), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Sirri and Tufano (1998), Coval and Stafford (2007), Huang, Wei, and Yan (2007), Chen, Goldstein, and Jiang (2010), Spiegel and Zhang (2013) and Goldstein, Jiang, and Ng (2017), amongst others.

[2] The Australian superannuation system is a compulsory employer funded pension scheme where employers must contribute 9.5% of the employees salary to a dedicated retirement account. A superannuation fund is a registered provider of investment services on behalf of its members.

that is not contemporaneous with actual fund flows. Furthermore, the shock is large. Fund members suffering adverse labor market outcomes are allowed to withdraw up to $10,000 from their accounts. Flows for superannuation funds are usually stable and predictable such that, in normal times, superannuation fund managers are not subject to sudden and large future outflows. The policy announcement is therefore not only exogenous but also economically significant for our sample of pension fund managers. This is in contrast with mutual fund managers, who often experience large outflows and actively form expectations regarding future possible outflows. Crucially, we are able to exploit detailed fund-level information on superannuation fund members including age distributions and shares of low income members, which are not available at fund-level in mutual fund databases. This member information allows us to construct novel instrumental variables to estimate pension fund managers' expectation on future fund outflows.

Using this shock to fund flows, we find a statistically insignificant effect of expected fund outflows on fund performance — funds with higher exposure to early release outflows have similar performance to those that are less exposed. Our findings are robust to treating early release fund outflows as exogenous (i.e. regressing performance onto realized outflows) or alternatively treating these outflows as endogenous and instrumenting for them with ex-ante fund demographic characteristics that are correlated with the amount of early release fund outflows but that do not drive expected performance. Our instrumental variable isolates the variation in realized early release outflows that is driven by ex-ante fund characteristics. Our direct communications with fund managers confirmed that funds used member demographic characteristics to form expectations of outflows after the policy announcement. For these reasons, our instrumental variable approach allows us to interpret our results as capturing the relationship between performance and expected flows.

We do not find evidence to support that expectations of fund flows could significantly affect fund performance. This could reflect that Australian superannuation funds actively engage in liquidity management. In anticipation of future outflows, funds manage their cash-like liquidity by

preemptively rebalancing their portfolios and do so in a way that minimizes transaction costs.

It may be surprising that funds which usually face little unexpected outflow engage in active liquidity management. However, despite the fact that fund flows are usually stable in the Australian pension system, liquidity management for superannuation funds has been a regulatory requirement since the 2008 global financial crisis. The Australian superannuation market is large, with approximately USD 1.9 trillion in assets under management as of year-end 2018, and funds have significant allocations to illiquid assets. Accordingly, the Australian Prudential Regulation Authority (APRA) requires all funds to formulate liquidity management plans that include stress testing and scenario analysis. The liquidity management has helped funds to successfully handle the liquidity stress during the Covid-19 pandemic. Alongside the early release scheme, the Covid-19 pandemic resulted in additional sources of liquidity stress for fund managers due to members shifting their allocations towards cash and losses on currency hedging position due to the falling Australian dollar. As the criteria for early release are determined by Covid-19 induced financial hardship, funds whose membership suffer the most from the pandemic face greater liquidity stress than others. Funds have handled the increasing liquidity stress well as their performance has not been significantly affected by the stress.

Our analysis initially proceeds by examining the early release policy in the context of typical fund flows for superannuation funds. Using regulator data provided by the APRA covering 71 different fund providers, we show that the amount of early release outflows constituted approximately 1.6% of assets under management on average and 26.5% of cash holdings. This is an order of magnitude higher than the typical fund flows observed under normal policy settings. The average fund received over 40,000 applications and made total payments of A$316m in the second quarter of 2020. There exists substantial cross-sectional variation in the exposure of funds to the policy shock. Funds with a greater (lesser) proportion of younger (older) members and those working in industries most affected by Covid-19 are relatively more exposed to early release outflows. Applicants for the early release scheme are required to demonstrate financial hardship such as loss of labor market

earnings to qualify for the scheme. Younger and low income workers disproportionately meet these requirements (Borland and Charlton, 2020; Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing, 2020; Cortes and Forsythe, 2020). The largest early release outflows in our sample exceed A$3.3 billion, or 140% of fund cash holdings and 7.3% of total assets.

We next examine the relationship between fund performance, measured by returns, and fund flows, both prior to and during the Covid-19 pandemic. Using standard panel techniques from the mutual fund literature, we show that long-term past performance (i.e., over past one or three-year horizons) is positively correlated with net flows in normal times using our most general specifications. A positive relationship between past returns and fund flows is consistent with existing findings from the mutual fund literature.[3] We do not detect a similar relationship between past performance and early release outflows — early release outflows are not obviously affected by funds' lagged one-year returns. We also find that early release outflows are higher for funds with lower illiquid asset allocations, fewer older workers and more young or low-income members.

Figure 1 plots the key dates of the early release policy and the performance of the Australian equity market for January - August 2020, as captured by the ASX 200 index.[4] The policy was announced on the 22nd of March 2020, coinciding with the lowest point in the index over the pandemic. Actual payments did not take place until 20 April 2020.

[Insert Figure 1 here]

We estimate the effect of the scheme on fund performance in the quarters during and after policy announcement. We first run both OLS and instrumental variable regressions where the dependent variable is the fund return in the second quarter of 2020, and the key regressor of interest is the ratio of early release outflows to fund assets. While OLS regressions uncover the relationship between fund performance and early release outflows, our instrumental variable regressions help pin down

[3] See, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Frazzini and Lamont (2008), Barber, Huang, and Odean (2016), Berk and Binsbergen (2016) Goldstein, Jiang, and Ng (2017), and Song (2020).

[4] The ASX 200 index is a market capitalization-weighted index of the 200 largest and most liquid equities traded on the Australian Stock Exchange (ASX).

the causal relationship by using cross-sectional variation in outflows driven by fund demographic profiles. Specifically, we use the fraction of members under the age of 35, the fraction of members aged between 35 and 60, and the amount of government co-contributions for low income members in the fund scaled by total assets. As discussed, funds with younger (older) workers are relatively more (less) exposed to the early release outflows as more (less) of their members qualify for early release. Government co-contributions are made to low-income members who are also disproportionately affected by the pandemic. Beyond strong economic justification for our instruments, first stage regressions show that they are strong in the statistical sense while overidentification tests support their exogeneity from our regressions' unobserved components. Instrumental variable regressions are also useful because they help us achieve the main goal of our research, which is to study the impact of *expected* fund flows. The fitted value of the early release ratio from the first stage of the instrumental variable regression can be interpreted as capturing funds' expected fund outflows.

Our regression results demonstrate an economically and statistically insignificant effect of early release on returns. The coefficient on early release suggest that a one percentage point increase in the ratio of early release to assets causes a change in second quarter returns of between -0.1 and 0.43 percent but this effect is statistically insignificant at the 10% level in all specifications. We cannot reject the null of no effect in any regression specification. We find that the main driver of returns over this quarter is the fund's exposure to market risk, as captured by its beta. Given the large positive returns in the ASX 200 index over this period (as per Figure 1), this is not surprising.

As a robustness check, we then consider whether fund returns are affected in the period after announcement but before which outflows actually occur. We follow the similar specification as before except for replacing the second quarter return as the left-hand-side variable with the first quarter return. Though the period between policy announcement and the end of the quarter comprised only approximately 10% of the trading days in the quarter, it is possible that funds very quickly engaged in preemptive liquidity management and incurred large transactions costs in doing so. Market returns during the final days of quarter one were also substantially positive

implying preemptive rebalancing in this period could drive lower returns as funds that become underweight risky assets in anticipation of outflows may underperform those that do not. These regressions using first quarter returns show that the expected early release outflows again do not cause lower fund returns. The coefficient on the ratio of early release to assets is insignificant in both OLS and instrumental variable specifications and with or without additional control variables. The t-statistics again do not exceed even the 10% threshold for any specification. The fund's beta is again important (but with a negative sign, as expected given the large negative market returns over the quarter), as is fund size in our most comprehensive specification. Larger funds or those with more market risk have lower returns during the first quarter of 2020.

Our results suggest that the main effect of a large and unexpected liquidity shock on Australian superannuation funds is to induce preemptive rebalancing, such that funds accumulate sufficient liquidity in anticipation of future outflows. This limits the effect the liquidity shock could have on performance.

These results have important implications for academics and regulators. For academics, we show that even very large pension funds appear to be able to manage liquidity outflows when given sufficient advanced notice. Close to our paper is Lou (2012), who studies how predictable future flows explain future fund performance in the next year, while our paper causally estimates how expectations on future flows affect current fund performance. For regulators, we find that despite the nature of early release outflows are very different from the typical flows experienced by Australian superannuation funds, funds appear to have been able to raise the amount of liquidity needed to meet these cash withdrawals.

2 Data description and summary statistics

We collect superannuation fund and early release data from statistical publications issued by APRA.[5] APRA is an independent statutory authority that supervises superannuation in Aus-

[5] APRA's statistic publications are available at https://www.apra.gov.au/statistics.

tralia. Although the APRA's statistical publications only begin in 2013, the publications provide rich cross-sectional information, such as the membership profile of each superannuation fund in Australia.

2.1 Fund performance and other characteristics

Australian superannuation funds offer a variety of pension products to their members. APRA discloses detailed performance information for default products of superannuation fund (MySuper) products and lifecycle products every quarter.[6] Aggregated fund performance is only released by APRA on an annual basis.

Accordingly, we use quarterly returns for MySuper/Lifecycle products to estimate fund performance at a quarterly frequency. A complexity arises when a superannuation fund has multiple Lifecycle products customized for different age groups. In this case, we compute the weighted average return for Lifecycle products, using the investment amount by product as the weight, as the fund's performance. This concern does not apply to MySuper products, as each superannuation fund has only one MySuper product. We also obtain the investment amounts for for MySuper/Lifecycle products and calculate the quarterly net flow as the quarterly growth in the investment amount of the product minus the corresponding quarter return.

We compare our quarterly fund-level returns to those reported by APRA directly on an annual basis. We regress these annual returns at the fund level onto annual returns calculated by compounding the quarterly returns computed as above. The slope coefficient is 0.884 and is highly statistically significant (t-statistic of 5.3). The R^2 is 0.826. Both the correlation coefficient and R^2 are close to unity suggesting our returns calculated from MySuper/Lifecycle are good proxies for the return of the superannuation fund.

An additional advantage of using return data at a quarterly frequency is that we have enough sample points to estimate the CAPM model to obtain fund alphas and betas. For these CAPM

[6] The term "MySuper" refers to the default product for fund members. For details, see https://treasury.gov.au/programs-and-initiatives-superannuation/mysuper.

regressions we use the ASX200 as the market index and the return of the 3-month bank bill in Australia as the risk-free rate. The estimated fund beta is used to capture the fund's risk exposure to the Australian equity market.

We sum the investment percentage allocation in infrastructure, property, and other assets to calculate the amount of investment in illiquid assets for each MySuper or Lifecycle product each quarter. This variable is intended to capture exposure to liquidity risk via investment in illiquid assets. For the fund with multiple Lifecycle products, we use a similar procedure as before to calculate a fund-level illiquid asset allocation (i.e. we compute the investment-weighted average allocation by product within each fund). We omit the fixed income assets as it contains Australian Treasury bonds, which are relatively liquid insofar as they can be converted to cash relatively easily.

We complement the MySuper/Lifecycle product performance data with the superannuation fund's characteristics and membership profile. We extract the total assets under management and cash holdings for the superannuation funds from APRA annual statistics. In the same publication, each fund also discloses its membership demographics, enabling us to calculate the proportion of young-, mid-, and old-aged members. As discussed in the introduction, we use these additional characteristics on the age profile of the membership and the low-income contribution (normalized with the total assets) as instrumental variables to identify the impact of expected early release on superannuation fund performance.[7]

2.2 Early release data

Every week, APRA collects and publishes fund-level data on the early release scheme. The first outflows occurred on April 20, 2020. In every publication, APRA provides updated statistics for variables such as the total value of early release payments made to members and the number of early release applications paid for the past week. We hand-collect these data up until June 2020, which is the end of the financial year of 2019.

[7] The low-income contribution is a tax offset providing up to $500 to help low-income earners save for retirement. For details, see https://www.ato.gov.au/Individuals/Super/In-detail/Growing-your-super/Low-income-super-tax-offset/.

2.3 Summary statistics

We construct our main sample by merging the early release data as of June 2020 with superannuation fund characteristics as of 2019. To normalize the early release amount for cross-sectional comparison, we compute the ratio of the early release amount to the total assets and total cash holdings of the superannuation fund, respectively. Furthermore, we merge the sample with the MySuper/Lifecycle performance in the first and second quarters in 2020. Our final sample consists of 72 superannuation funds with 73 MySuper/Lifecycle products.[8] We report summary statistics for these data in Table 1.

[Insert Table 1 here]

Panel A of Table 1 reports the summary statistics regarding performance of funds in our sample. The average return in the second quarter of 2020 is 6.2% and -10.4% in the first quarter. On average, our funds have an alpha of 0.0045 and a beta of 0.4317. The dispersion in alpha and beta is notable. The highest beta in our sample is 0.6224, whereas the lowest beta is around one-third of this indicating that our sample of funds have significant dispersion in their exposure to the Australian equity market. That said, even the highest beta among our funds is still lower than most stocks in the Australian equity market, reflecting the diversified nature of the superannuation system. While the interpretation of beta is straightforward, the interpretation of alpha is less so. The superannuation fund's multi-asset investment portfolio makes it difficult to pin down the driver behind the dispersion of alpha. It could reflect the manager skill in investment or the fund exposure to certain risk factors orthogonal to Australian equity, e.g., allocation on illiquid assets.

Panel B presents non-performance related characteristics for our sample funds. The average asset under management (Fund Size) is $21 billion with about $2 billion in cash (Fund Cash), resulting in average cash to asset ratio of about 10.7%. Our sample funds' total assets are close to $1.6 trillion, representing more than half of the size of the entire Australian superannuation system.

[8] There is one superannuation fund in our sample that has both MySuper and Lifecycle products.

There is a large amount of variation in fund exposure to illiquid assets. The average allocation to illiquid assets is 33.5% with a standard deviation of around 20%. Summary statistics for fund membership profiles are also presented in Panel B. The average proportion of young, middle-aged, and old-aged members is 29.82%, 54.58%, and 15.24%, respectively. The respective standard deviations are 11.60%, 8.59%, and 7.16%. The average government low income contribution is about 0.05% of the asset on average, and the standard deviation of this variable is 0.05%. There is significant variation in the age profile and low income contributions within our sample of funds.

We report the summary statistics for early release applications in our sample funds in Panel C. As at the end of June 2020, there are, on average, 40,574 applications for the early release across our funds. The average cumulative amount of early release is $316.21 million (totaling over $24 billion). On average, the early release payment accounts for 26.52% of the fund's cash and 1.63% of the fund's total assets.

3 Fund flows panel analysis

We next examine how fund flows are associated with past fund performance and other fund characteristics. This analysis is closely related with our main empirical results in the following subsection. Here we aim to provide more general understanding of flow-performance relationship in superannuation funds in a broader sample period that uses a quarterly panel of observations by superannuation funds. Our methodology follows a large literature on mutual fund flows that studies flow-performance relationship.

3.1 Estimating fund flows

Our data do not directly report fund flows. We estimate quarterly fund flows for fund i in quarter $t+1$, $f_{i,t+1}$, as in for e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998), and Coval and

Stafford (2007), amongst others

$$f_{i,t+1} = \frac{A_{i,t+1} - A_{i,t} \times (1 + r_{i,t+1})}{A_{i,t}}, \tag{1}$$

where $A_{i,t+1}$ is fund i's total invested assets and $r_{i,t+1}$ is fund i's return in quarter $t+1$. The fund flow, $f_{i,t+1}$, measures the new external flow to superannuation fund i from quarter t to quarter $t+1$, relative to its initial size, excluding any changes coming from return of its initial asset investment.

We require superannuation funds to have at least 15 million dollars of total invested assets. This is mainly to avoid abnormally large percentage fund flows due to small initial fund size, as in Elton, Gruber, and Blake (2001). We winsorize fund flows at 95% and 5% level to ensure our results are not driven by extreme values and outliers. Although quarterly data are available from the APRA since the third quarter of 2013, the number of observations in the first two periods are much smaller than the remaining periods, so our panel analysis uses data starting from the first quarter of 2014.

3.2 Panel regressions

To study how quarterly fund flows are associated with the past performance, we run panel regression of quarterly fund flows on lagged fund returns with time fixed effects and other control variables. Considering that capital allocation decisions of members in retirement funds could be made at longer horizons, we include one year and three year returns that are computed by the APRA by compounding quarterly fund returns. As in Lou (2012), we begin by focusing on the cross-sectional flow-performance relationship within quarter by including time-fixed effects.[9]

For control variables, we include lagged fund flows to capture any persistence of quarterly fund flows; log of quarterly total fund size to check if fund flows differ by lagged fund size, a dummy variable that equals one if the fund has a MySuper product, and dummy variables for four different

[9] These panel regression can be thought of as cross-sectional regressions expanded over broader sample period. The coefficient estimates in the panel regression with time-fixed effects is equivalent to the size-weighted average of the coefficient estimates from cross-sectional regressions at each quarter separately.

fund types: corporate, industry, public sector, and retail.[10] The panel regression for fund i in quarter $t+1$ us given by:

$$f_{i,t+1} = \alpha + r_{i,t} + f_{i,t} + \ln(Size)_{i,t} + D(Balanced)_i + C(Type)_i + \gamma_{t+1} + \varepsilon_{t+1} \tag{2}$$

where $D(Balance)_i$ equals one if fund i has MySuper products, $C(Type)_i$ denotes a categorical variable for fund i with the four possible values of the fund types, and γ_{t+1} are time-fixed effects.

To control any unobserved fund-specific factors that may affect fund flows, we also compare the results in (2) with a stricter version of specification including fund-fixed effects in addition to time-fixed effects:

$$f_{i,t+1} = \alpha + r_{i,t} + f_{i,t} + \ln(Size)_{i,t} + \gamma_{t+1} + \delta_i + \varepsilon_{t+1} \tag{3}$$

where δ_i is fund-fixed effects for fund i. The standard errors are two-way clustered at fund and quarter level in all specifications.

Table 2 reports the results for the specifications in (2) and (3) where returns are either quarterly, annual or three year returns. The lagged quarterly returns have a positive relationship with the quarterly fund flows at the 10% significance level with time-fixed effects in column (1). In column (3) the lagged one year returns are positively associated with quarterly fund flows at the 1% significance level with time-fixed effects: One percentage point increase of the lagged one year returns are associated with 0.22 percentage point increase of quarterly fund flows. In column (5) one percentage point increase of the lagged three year returns are associated with 0.32 percentage point increase of quarterly fund flows at the 1% significance level. With stricter version of controls including fund fixed effects in addition to time fixed effects, only the lagged one year returns are

[10] Industry funds are Registrable Superannuation Entities (RSEs) with a "not for profit" trusteeship and with either an industry or general membership base. Industry base represents where members join the RSE as a result of working in a particular industry sector. Corporate funds are RSEs with a "not for profit" trusteeship and with a corporate membership. Public sector funds are RSEs with a "not for profit" trusteeship and with a government base membership base. Retail funds are RSEs with a "for profit" trusteeship and with a corporate, industry or general membership base. For more detailed definition, see https://www.apra.gov.au/quarterly-superannuation-statistics.

statistically significant at the 10% level in column (4), although the lagged quarterly and three year returns have positive estimates.

These results with time fixed effects (but excluding fund fixed effects) suggest that fund members respond to the lagged fund returns when they choose across different super funds. Once we control for fund fixed effects, fund members tend to respond less to the lagged returns when they decide how much to invest and withdraw over time within the same fund.

[Insert Table 2 here]

In terms of other controls, the dummy variable for retail funds is significantly positive indicating that retail funds on average have experienced higher level of fund flows than the baseline funds — corporate sector funds — in the sample periods, after controlling other variables. Time-varying quarterly fund size negatively predicts quarterly fund flows with time fixed effects. Part of this significance comes from the mechanical relationship that fund flow would be high when its denominator - fund size - is small as in (1). The lagged fund flows tend to predict quarterly flows in addition to the lagged quarterly returns, however the lagged one year and three year returns tend to subsume the explanatory power of the lagged fund flows in predicting quarterly fund flows.

These results together suggest that fund members we include the lagged fund returns, dummy variables for fund types, and fund size as potential variables that may affect quarterly fund flows — namely early release — in the main empirical analysis in the next subsection.

4 Early release and fund performance

Our analysis aims to causally identify the effect of a large unanticipated shock to fund flow expectations on pension fund performance. As discussed in Section 2.3, early release applications resulted in large and unexpected outflows for superannuation funds. Average outflows due to early release are approximately 1.6% of assets under management and 26.5% of cash holdings, compared with average net outflow in normal periods which we calculate to be around 0.2% of assets under

management. Crucially for our purpose, we focus on the variation in fund outflows that is explained by fund demographic profiles that are (i) known ex-ante to fund managers and (ii) used by fund managers to predict future outflows.

The early release policy was designed to provide households with access to an otherwise illiquid form of wealth during a period of severe economic and financial stress. Though the policy can relax household financial constraints in the current period, this comes at a cost of lower expected levels of consumption at some stage over the remainder of the lifecycle. The household either must save more and consume less in future periods of employment to rebuild their retirement savings, or endure a lower level of consumption in retirement, all else being equal.

The sheer size of the outflows can result in an additional cost of the policy beyond the direct effect on a withdrawing households' lifetime consumption patterns. Funds may need to liquidate existing investments in order to have sufficient cash on hand to meet the redemption requirements, and this requires the fund to pay potentially large transaction costs. These costs can be direct in the form of bid-ask spreads in securities markets or indirect in the form of an liquidity premium where less liquid assets trade at discounts to "fair" or "fundamental" value.[11] Funds may also adjust their investment allocations across asset classes to hold greater cash levels than they otherwise would. Deviating from their optimal portfolios can introduce an additional cost to the fund in the form of lower risk-adjusted expected performance in the future.

Each of these three costs (direct transaction costs, liquidity premia and shifts from optimal portfolio allocations) are borne not just by the members who are accessing their superannuation before retirement, but by all members of a given fund. These costs are therefore potential sources of large and important externalities for fund investors. Each investor choosing how much to withdraw will not take into account the effect of their withdrawal on other fund members. In equilibrium, withdrawals will be greater than the socially optimal amount and all members are worse off com-

[11] It is well established in the market microstructure literature that both direct transaction costs and liquidity premia are counter-cyclical, insofar as they are greater during periods of stress like when the policy was announced — see e.g. Brunnermeier and Pedersen (2009); Næs, Skjeltorp, and Ødegaard (2011); Nagel (2012); Adrian and Shin (2010); Chen, Cui, He, and Milbradt (2018).

pared with the social planner allocation. By causally identifying the effect of early release on fund performance, we aim to test for the presence of this externality and to try to quantify it.

The target regression we wish to identify can be written as:

$$r_i = \beta ERA_i + \gamma' \mathbf{x}_i + \varepsilon_i \tag{4}$$

where r_i is the return of the ith fund after the announcement of the early release scheme, ERA_i is the ratio of early release withdrawal to fund size, $\mathbf{x}_i$ is a column vector of observable control variables (discussed below) that includes an intercept term and ε_i is a potentially endogenous error term. The parameter of interest is β, the elasticity of returns to the scaled size of expected withdrawals.

4.1 Identification of the expected early release effect

We are primarily interested in the effect of expectations of fund flow on fund performance rather than realized fund flows. By instrumenting for realized early release, we isolate variation in fund flows that is correlated with fund characteristics that are known ex-ante to fund managers.

As discussed in Section 1, a condition required of applicants for the early release scheme is that they can demonstrate adverse economic conditions, in the form of ongoing unemployment, eligibility for benefits, or loss of work or business income due to Covid-19. Like many of the adverse effects of Covid-19 on labor market outcomes, these criteria apply disproportionately to younger workers compared with older workers.[12] Funds that have a higher proportion of younger members compared with older members were more exposed to early release withdrawals because a greater fraction of their members suffered financial hardship and were eligible for the scheme. Additionally, early release eligibility clearly only applies to members who are yet to reach retirement age and are therefore unable to draw-down on their pension savings.

APRA collects data on fund membership age profiles and we use this information to form two

[12] Borland and Charlton (2020) document the disproportionate impact of Covid-19 on young and low income workers in Australia. See Montenovo, Jiang, Rojas, Schmutte, Simon, Weinberg, and Wing (2020) and Cortes and Forsythe (2020) for comparable evidence in the USA.

instrumental variables based on the proportion of members aged 34 and below (referred to as the "young" cohort) and those between 35 and 60 (referred to as the "middle-aged" cohort) as at the end of the financial year prior to the onset of the Covid-19 pandemic. These instrumental variables are expected to be positively correlated with the amount of early release.[13]

APRA also collects information regarding the amount of superannuation "co-contributions" made on behalf of low income earners by the government. These payments are made to all individuals earning less than $53,564 from business or employment and match the total amount of personal contributions, subject to a cap of $500 (Australian Tax Office, 2020). In addition to fund member age profiles, we also use the amount of low income contributions by fund scaled by total assets as a third instrumental variable for the amount of early release at the fund level. Low income workers in industries like accommodation and food services, warehousing and retail trade are more likely to be casually employed and less likely to work in jobs where working-from-home is a feasible. We again expect this instrumental variable to be positively correlated with the amount early release.

Even if our goal was to identify the effect of actual, realized fund flows, identifying β in Equation (4) would remain challenging due to a number of sources of potential endogeneity. A clear concern is that fund members who are rationally deciding whether or not to access their pension accounts may condition their decision on past, current or expected future fund performance. We may find a negative association between the early release withdrawals at the fund level and fund performance because members eligible to apply to the scheme are more likely to do so when the fund has performed poorly in the past, is performing poorly currently or is expected to perform poorly in the future. These members then may use the scheme to reallocate their savings elsewhere. Though the option to withdraw from one fund and reinvest in another product is continuously available to some members, during our sample period there are also a substantial fraction of employees whose employer contributions are directed to a particular fund as part of an enterprise bargain-

[13] For the middle-aged cohort, we can think of this instrumental variable combined with the young cohort variable as capturing the effect of *not* having workers who are close to retirement age, most of whom are not directly affected by the labour market.

ing agreement.[14] To identify the causal effect of early release on fund performance we need to isolate variation in the amount of early release at the fund level that is uncorrelated with the potential sources of endogeneity. Our instrumental variables approach also offers a solution to this endogeneity problem.

Our instrumental variables have a number of appealing features. First, beyond any statistical tests of instrument strength that are reported below, there is strong economic justification for instrument relevance via the disproportionate impact of the pandemic on young and low income workers. These categories of workers are both more vulnerable to reduced working hours and are employed in vocations that are are less amenable to remote working (such as services and hospitality). Second, superannuation funds are required by law to accurately record and report their membership characteristics to APRA. We can have a high degree that our instrumental variables are accurately and precisely measured. Third, the instrumental variables are pre-determined ahead of the onset of the Covid-19 shock. There are no direct feedback mechanisms that imply fund demographic characteristics could somehow respond to the pandemic in ways that would invalidate our approach. Finally, by virtue of having more instruments than endogenous regressors, we can provide statistical evidence of instrument exogeneity via standard GMM overidentification tests.

Denoting the vector of our three instrumental variables as $\mathbf{z}_i^{iv} = (young_i, mid_i, lowinc_i)'$ and letting $\mathbf{z}_i = \left(\mathbf{z}_i^{iv\prime}, \mathbf{x}_i'\right)'$, we estimate the linear GMM model with heteroskedasticity robust standard errors using the standard two-step efficient GMM estimator given by:

$$\mathbb{E}\left[\mathbf{z}_i \varepsilon_i\right] = 0 \tag{5}$$

where $\varepsilon_i = (r_i - ERA_i - \gamma' \mathbf{x}_i)$ as per Equation (4). As well as an intercept term, the vector $\mathbf{x}_i$ contains categorical variables for fund type (Industry, Public, Retail or Corporate), an indicator variable taking the value one for MySuper balanced products and zero for life-cycle products, log

[14] Legislation was passed by the Australia Federal Parliament on the 25th of August 2020 to allow greater choice of default superannuation contributions for employees covered by enterprise bargaining agreements. See Parliament of Australia (2020) for details.

of fund size as at financial year end 2019, the fund cash-to-asset ratio as at financial year end 2019, the benchmark fund allocation to illiquid assets (as defined in Section 2), the return of the fund over the period 1 Jan 2019 to 31 Dec 2020, other flow into the fund in the second quarter of 2020 (defined as the residual from a regression of total fund flow onto the early release to assets ratio), fund flow during the first quarter of 2020 (which not directly unaffected by early release) and the fund beta estimated over the period covering 2013 to 2019.

Our control variables are important because it is plausible that funds with different demographic characteristics differ in other dimensions that affect performance. For example, funds with more younger members may choose to invest in more high risk or illiquid assets as their expected future redemption cash flows are lower than other funds, all else being equal. These funds may therefore try to earn illiquidity premia or standard risk premia over relatively longer horizons which can affect performance. Funds with more young members may also have less cash on hand for the same reason or have experienced lower employment contributions prior to early release. Our control variables help to ensure that the only effect of fund demographics on performance, conditional on these controls, is via the amount of early release.

4.2 First-stage regressions

Table 3 reports first-stage regression results where the LHS variable is the early release to assets ratio of the fund.[15] These results test for the existence of a strong linear relationship between our instrumental variables and future fund flows. Column (1) presents coefficients from a regression of early release to assets on the fraction of young members in the fund and the fraction of middle-aged members in the fund. Column (2) adds low income contributions to the specification in Column (1). Column (3) adds control variables listed above to the regression in Column (1). Column (4) adds the control variables to the regression in Column (2).

[Insert Table 3 here]

[15] We are estimating Equation (5) via two-step efficient GMM with robust standard errors so these estimates do not map directly to our GMM specification, as they would if were using unadjusted standard errors.

In all four specifications, all of our instrumental variables have positive and economically significant effects on early release. These effects are statistically significant for all but one instrument variable in one specification (low income contributions in Column (4)). An increase in the proportion of young members in the fund of 10% is associated with between a 0.9 and 1.3 percentage point increase in the expected amount of early release withdrawals, compared with a sample average of early release to assets of 1.6%. These effects are significant at the 1% or better level in all specifications. For the proportion of middle-aged members, the comparable estimates are an increase of between 0.36 and 0.53 percentage points, which is significant at the 5% level or better in three of the four specifications, and the 10% level in the remaining specification (Column (1)). The magnitude of the effect of low income contribution on early release is larger than for fund age variables, however, its standard deviation is significantly smaller than that of our other instruments. A one standard deviation increase in this variable is associated with a 0.3 and 0.6 percentage point increase in the early release to assets ratio. In the specification without controls, it is significant at the 5% level but is not statistically significant when other controls are included. Most importantly, the F-statistic of joint instrument significance in the first stage regression exceeds the usual threshold of 10 in all four specifications.

Of the other control variables in the model, we note that funds with more exposure to illiquid assets experience less outflows, while past returns and betas are insignificant. These results suggests that fund members do not obviously use past performance as an input in deciding whether to or how much to withdraw via early release, nor do they clearly take into account fund risk profiles. We also note that net fund inflows from other sources during our sample period where early release outflows take place are negatively correlated with early release. In other words, lower fund contributions from members (e.g. from lower employment contributions) predicts higher early release outflows, as expected.

4.3 Expected fund flows and fund performance

The key implication of Table 3 is that our instrumental variables have a statistically and economically significant effect on the amount of early release. Funds with more younger members, middle-aged members or low income contributions from the government had larger early release withdrawals, even after conditioning on fund characteristics like past returns, asset allocations or risk (in the form of beta). We now use these instruments to causally identify the effect of expected fund flows on fund returns. We do this by estimating the effect of early release on fund returns in the period after the policy's announcement (the second quarter of 2020) using our IV-GMM regressions described in Equation (5). Under our instrumental variable approach, only variation in the early release to assets ratio that is explained by demographic variables (after partialling out other controls) is used to identify its effect on fund returns. We can therefore interpret this coefficient as corresponding to the effect of expected outflows on fund performance.

Table 4 contains coefficients and t-statistics for these regressions. The LHS variable in each regression is the fund return over the second quarter of 2020. Column (1) contains estimates from an OLS regression of returns onto early release with no other control variables. Column (2) instruments for early release using fund age characteristics ($young_i$ and mid_i) only. Column (3) instruments for early release using fund age characteristics and low income contributions ($lowinc_i$). Columns (4)-(6) add controls to the specifications in Columns (1)-(3) respectively.

[Insert Table 4 here]

For all models we detect an statistically insignificant effect of early release on quarter two fund returns. An increase of 10 percentage points in the ratio of early release to assets is associated with a change in fund returns of between -0.04 and 3.2 percentage points, but the associated t-statistics are no larger than 1.50 in any specification.[16] We cannot reject the null hypothesis of no effect at the 10% level in any specification.

[16] We use small sample $N - k$ adjustments when computing all standard errors and parameter covariance matrices for hypothesis testing.

Our first stage regressions in Table 3 demonstrate the strong correlations between early release and observable fund characteristics like asset allocations and past returns. Controlling for the same set of characteristics in the second stage regressions improves the precision of our estimates for the effect of early release and so Columns (4)-(6) are our preferred specifications. The final row of Table 5 contains the p-value from an overidentification test of our exogeneity conditions. The lowest p-value across any of our four IV specifications (Columns (2), (3), (5) and (6)) is 0.36, indicating that we are unable to reject the null of valid instruments in any specification. Given the strength of the instruments, their economic significance and the failure to reject the overidentification test null, our instrumental variables approach allows us to interpret this result causally. Larger expected early release withdrawals did not lead to worse fund performance.

Other than the constant term, the only statistically significant predictor of fund returns in the second quarter of 2020 is fund beta. Funds with higher beta with respect to the ASX 200 index had significantly better returns over this period. The ASX 200 market return in the same quarter was approximately 16%, so it is unsurprising that funds with higher market exposure had better returns.

As a robustness test we also examine whether early release flows affected performance in quarter one of 2020. As discussed in Section 1, the period between policy announcement and this period was brief, with around 85% of trading days in the quarter occurring prior to announcement. Nevertheless, it is possible that funds rebalanced quickly and aggressively in the final days of the first quarter, incurring large direct transaction and indirect costs, such as via reduced risky asset allocations during the market recovery, in doing so.

We repeat the analysis in Table 4 but where the dependent variable is the return in the first quarter of 2020 rather than the second quarter returns. As no right hand side variables are changing, the same first stage regression in Table 3 applies and therefore our preceding analysis of instrument relevance remains valid. While we are using the same instrumental variable approach to estimate the effect of early release on fund returns, the interpretation of these regressions for the first quarter

return are subtly different from those for the second quarter return.

[Insert Table 4 here]

The coefficient on the endogenous regressors is negative but again is statistically insignificant in all six specifications. The size of the coefficient varies from -0.01 to -0.21 across the specifications, but the t-statistics again do not exceed even the 10% threshold in any of the regressions. The largest p-value from overidentification tests of our exogeneity conditions is 0.31, indicating that we are again unable to reject the null of valid instruments in any specification.

We also find some evidence that larger funds and funds with more market exposure had significantly lower returns over the period compared with smaller funds or funds with lower betas. The effect of fund beta is negative, as expected given the -24% total return on the market index over the same quarter. Regarding fund size, it is possible that larger funds pay proportionally greater transaction costs when rebalancing portfolios compared with smaller funds. Without high frequency portfolio holdings data, we cannot provide more definitive evidence supporting this hypothesis.

Our analysis of fund returns over both periods suggest that funds appear to preemptively adjust their portfolios to create sufficient liquidity to meet their outflows and without incurring abnormally large transaction costs. The size of the average early release withdrawal is around ten times as large as the typical quarterly net fund flow. We find that these withdrawals do not impact fund performance, in the cross-section. Funds were able to prepare sufficiently for the amount of withdrawals they were likely to experience and adjust accordingly in a timely fashion. It remains possible that all funds were adversely affected by early release in such a way that results in no variation in performance in the cross-section. For example, if all funds naively formed the same expectations about future outflows regardless of fund characteristics, it may be difficult to capture an effect in the cross-section. Without data capturing higher frequency asset allocations, we cannot investigate this possibility further.

5 Conclusion

The early release withdrawal scheme constitutes a large and significant shock to fund flows in the Australian pension system. Our analysis shows that funds with greater exposure to early release outflows do not suffer significantly worse performance than those that are less exposed. By using variation in early release outflows that are driven by ex-ante fund demographic profiles, we are able to interpret our results through the lens of fund flow expectations. We conclude that fund managers were able to manage the large liquidity shocks without incurring significant transaction costs that dragged on overall fund performance.

It remains an open question as to whether the early release outflows affected the superannuation sector as a whole, or asset prices more broadly. More granular data regarding fund holdings would allow further investigation of these and other interesting questions.

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Figure 1: ASX200 Index Value and Early Release Key Dates

This figure plots the daily ASX 200 market index and the key dates of the early release policy between 1 January 2020 and 31 August 2020. The early release scheme was announced on 22 March 2020. The first early release payment was made on 20 April 2020.

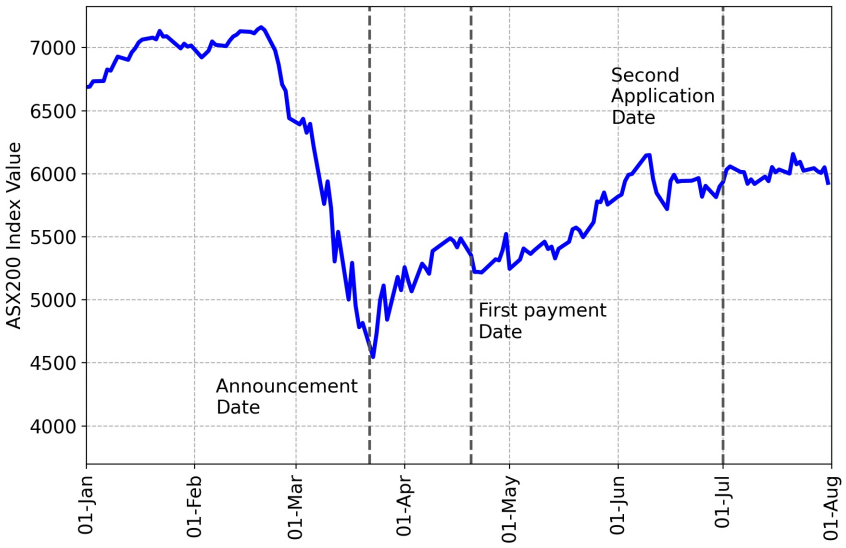

Table 1: Summary Statistics

This table documents summary statistics of superannuation fund performance and flows (Panel A), fund characteristics (Panel B), and early release applications and payments (Panel C) using the Australian Prudential Regulation Authority (APRA) statistical publications from Q3-2013 to Q2-2020. Fund alpha and fund beta are estimated using the CAPM with the ASX200 as the market index and the the Australian 3-month bank bill as the risk-free rate from Q3-2013 to Q4-2019. Other flow is the residual of regressing net fund flows in Q2-2020 on the total early release amount during May-June 2020. Illiquid asset allocation is the sum of investment percentage benchmark allocation in infrastructure, property, and other assets. Fund characteristics in Panel B are from annual fund-level statistics as of June 2019. In Panel C, number of applications and total payments are the sum of weekly early releases during May-June 2020. Cash and assets amounts as of June 2019 are used to normalize the early release total payments. Our final sample consists of 75 superannuation funds.

	Mean	Std	Min	25%	50%	75%	Max
Panel A: Fund Performance & Flow							
Quarterly Return	0.0619	0.0232	-0.0649	0.0527	0.0643	0.0751	0.1026
Lag Quarterly Return	-0.1037	0.0207	-0.1542	-0.1157	-0.1020	-0.0924	-0.0574
One Year Return (1Q2019-1Q2020)	-0.0335	0.0217	-0.0930	-0.0470	-0.0367	-0.0202	0.0279
One Year Return (CY2019)	0.1465	0.0190	0.1164	0.1301	0.1450	0.1562	0.1897
Fund Alpha	0.0045	0.0023	-0.0050	0.0037	0.0046	0.0054	0.0107
Fund Beta	0.4317	0.0753	0.2345	0.3878	0.4239	0.4703	0.6224
Illiquid Asset Allocation	0.3349	0.2054	0.0433	0.2157	0.2800	0.3762	1.0000
Other Flow Q2	-0.0002	0.0205	-0.0281	-0.0163	-0.0015	0.0116	0.0706
Fund Flow Q1	-0.0122	0.0344	-0.0331	-0.0319	-0.0199	-0.0100	0.2021
Panel B: Fund Characteristics							
Fund Size ($b)	20.992	32.814	0.1026	2.3019	7.5226	20.551	172.40
Fund Cash ($b)	1.9874	3.1697	0.0108	0.2264	0.8007	2.1368	14.372
Fund Cash to Assets Ratio	0.1072	0.0419	0.0265	0.0748	0.1061	0.1343	0.2022
Young Members (proportion)	0.2982	0.1160	0.0378	0.2201	0.2795	0.3500	0.6338
Middle-aged Members (proportion)	0.5458	0.0859	0.3142	0.4981	0.5461	0.5952	0.7407
Old-aged Members (proportion)	0.1524	0.0716	0.0337	0.0982	0.1389	0.2013	0.3286
Low Income Contribution	0.0005	0.0005	0.0000	0.0001	0.0003	0.0006	0.0023
Panel C: Early Release Applications							
Number of Applications ('000s)	40.574	84.413	0.0300	3.0832	8.8490	24.623	433.99
Total Payments ($m)	316.21	636.71	0.2763	27.530	79.824	199.72	3,348.6
Total Payments to Cash Ratio	0.2652	0.3294	0.0099	0.0618	0.1116	0.3562	1.4004
Total Payments to Assets Ratio	0.0163	0.0154	0.0005	0.0053	0.0091	0.0222	0.0727

Table 2: Flow-Performance Relationship in 2014-2019

This table presents panel regressions of quarterly fund flows on the lagged fund performance and other fund characteristics from Q1-2014 to Q4-2019. There are four possible values of fund types: $D(industry)$, $D(public)$, $D(retail)$ equals one if fund type is industry, public, retail, respectively, with corporate fund being the basis fund type. Balanced Fund Product equals one if the fund is a balanced fund product (MySuper product). Standard errors are clustered at fund and time level. t-statistics are presented in parenthesis and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Model A	Model B	Model C	Model D	Model E	Model F
Intercept	0.0149*	0.5162***	0.0013	0.5478***	-0.0249***	0.6297***
	(1.70)	(7.83)	(0.16)	(6.67)	(-2.71)	(3.06)
$D_{industry}$	0.0040*	-	0.0015	-	0.0001	-
	(1.65)	-	(0.54)	-	(0.05)	-
D_{public}	0.0097*	-	0.0106*	-	0.0084**	-
	(1.82)	-	(1.68)	-	(2.19)	-
D_{retail}	0.0180***	-	0.0161***	-	0.0085**	-
	(4.22)	-	(4.06)	-	(2.54)	-
Balanced Fund Product	-0.0078*	-	-0.0059	-	-0.0022	-
	(-1.84)	-	(-1.59)	-	(-0.40)	-
Ln(Fund Size)	-0.0018*	-0.0687***	-0.0013	-0.0734***	0.0011	-0.0829***
	(-1.72)	(-7.60)	(-1.14)	(-6.53)	(1.08)	(-2.96)
Lag Fund Flow	0.4487***	0.0667*	0.3845***	0.0398	0.0535	-0.0668
	(6.25)	(1.68)	(4.60)	(0.97)	(1.01)	(-1.57)
Lag 1 Quarter Return	0.3358*	0.1817	-	-	-	-
	(1.75)	(1.22)	-	-	-	-
Lag 1 Year Return	-	-	0.2212***	0.1082*	-	-
	-	-	(2.89)	(1.92)	-	-
Lag 3 Year Return	-	-	-	-	0.3168***	0.1219
	-	-	-	-	(2.72)	(0.81)
N_{obs}	2,056	2,056	1,844	1,844	1,041	1,041
R^2	0.33	0.33	0.26	0.25	0.03	0.11
Adj. R^2	0.06	0.34	-0.01	0.25	-0.03	0.13
Time FE	X	X	X	X	X	X
Fund FE	-	X	-	X	-	X

Table 3: First Stage Instrument Variables Regressions

This table reports the regressions of early release amounts normalized by total assets on our instrumental variables and control variables. Young members (middle-aged members) is the fraction of members under the age of 35 (aged between 35 and 60). Low income contribution is the amount of government co-contributions to the fund scaled by total assets. For other variables, see Table 1 and Table 2. t-statistics are in parenthesis and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Model A	Model B	Model C	Model D
Intercept	-0.0402***	-0.0389***	0.0036	-0.0090
	(-2.80)	(-2.93)	(0.13)	(-0.33)
$D_{industry}$	-	-	0.0042	0.0044
	-	-	(1.36)	(1.42)
D_{public}	-	-	0.0005	0.0012
	-	-	(0.11)	(0.29)
D_{retail}	-	-	0.0054	0.0051
	-	-	(1.60)	(1.56)
Balanced Fund Product	-	-	-0.0027	-0.0023
	-	-	(-1.57)	(-1.23)
Ln(Fund Size)	-	-	-0.0017*	-0.0013
	-	-	(-1.82)	(-1.29)
Cash to Assets Ratio	-	-	0.0127	0.0207
	-	-	(0.40)	(0.65)
Illiquid Asset Allocation	-	-	-0.0126***	-0.0115**
	-	-	(-2.66)	(-2.54)
Lag 1 Year Return	-	-	-0.0265	-0.0274
	-	-	(-0.31)	(-0.32)
Other Flow Q2	-	-	-0.1143**	-0.1031**
	-	-	(-2.17)	(-1.99)
Flow Q1	-	-	-0.0426	-0.0363
	-	-	(-1.53)	(-1.07)
Beta	-	-	-0.0436	-0.0363
	-	-	(-1.60)	(-1.36)
Young Members	0.1227***	0.0855***	0.1278***	0.1093***
	(6.78)	(3.71)	(5.68)	(3.56)
Middle-aged Members	0.0364*	0.0440**	0.0456**	0.0533**
	(1.89)	(2.44)	(2.02)	(2.46)
Low Income Contribution	-	11.671**	-	6.5302
	-	(2.27)	-	(1.06)
N_{obs}	72	72	69	69
R^2	0.60	0.64	0.70	0.72
Adj. R^2	0.59	0.62	0.63	0.64
First Stage F-statistic	33.8	22.2	24.2	16.3

Table 4: Second Stage Instrument Variables Regressions — Quarter 2 Returns

This table documents the instrumental variable regressions of the fund returns in Q2-2020 on the early release ratio and other control variables. Demog. refers to the two instrumental variables: fractions of young members and middle-aged members. LIC denotes the third instrument: low income contribution share. For detailed definition, see Table 1, Table 2, and Table 3. t-statistics are in parenthesis and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Model A	Model B	Model C	Model D	Model E	Model F
Intercept	0.0619***	0.0576***	0.0604***	-0.1043*	-0.1217*	-0.1037*
	(19.6)	(13.0)	(15.3)	(-1.90)	(-1.89)	(-1.74)
$D_{industry}$	-	-	-	0.0040	0.0003	0.0027
	-	-	-	(0.59)	(0.04)	(0.33)
D_{public}	-	-	-	-0.0009	0.0004	0.0007
	-	-	-	(-0.11)	(0.05)	(0.10)
D_{retail}	-	-	-	-0.0002	-0.0034	-0.0009
	-	-	-	(-0.03)	(-0.43)	(-0.13)
Balanced Fund Product	-	-	-	0.0017	0.0016	0.0017
	-	-	-	(0.33)	(0.34)	(0.37)
Ln(Fund Size)	-	-	-	0.0029	0.0033	0.0026
	-	-	-	(1.47)	(1.50)	(1.31)
Cash to Assets Ratio	-	-	-	0.0703	0.0915	0.0800
	-	-	-	(1.28)	(1.41)	(1.29)
Illiquid Asset Allocation	-	-	-	0.0083	0.0102	0.0072
	-	-	-	(0.89)	(1.02)	(0.79)
Lag 1 Year Return	-	-	-	0.2866	0.2863	0.3220
	-	-	-	(0.85)	(0.89)	(0.96)
Other Flow Q2	-	-	-	-0.2379	-0.2239	-0.2079
	-	-	-	(-0.85)	(-0.87)	(-0.79)
Flow Q1	-	-	-	-0.0074	-0.0019	0.0015
	-	-	-	(-0.12)	(-0.03)	(0.02)
Beta	-	-	-	0.1507*	0.1638**	0.1426*
	-	-	-	(1.96)	(2.14)	(1.94)
Early Release to Assets Ratio	-0.0043	0.2692	0.1669	0.0752	0.3165	0.2306
	(-0.03)	(1.50)	(1.01)	(0.75)	(1.42)	(1.23)
N_{obs}	71	71	71	69	69	69
R^2	0.00	-0.03	-0.02	0.51	0.49	0.50
Adj. R^2	-0.01	-0.05	-0.03	0.41	0.38	0.39
Instrumental Variables	None	Demog.	Demog. & LIC	None	Demog	Demog. & LIC.
J-test p-value	-	0.89	0.36	-	0.65	0.62

Table 5: Second Stage Instrument Variables Regressions — Quarter 1 Returns

This table presents the instrumental variable regressions of fund returns in Q1-2020 on the early release ratio and other control variables. Demog. refers to the two instrumental variables: fractions of young members and middle-aged members. LIC denotes the third instrument: low income contribution share. For detailed definition, see Table 1, Table 2, and Table 3. t-statistics are in parenthesis and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Model A	Model B	Model C	Model D	Model E	Model F
Intercept	-0.1035***	-0.0999***	-0.1006***	0.0328	0.0370	0.0435
	(-29.2)	(-23.5)	(-23.6)	(1.03)	(1.21)	(1.50)
$D_{industry}$	-	-	-	-0.0054	-0.0042	-0.0045
	-	-	-	(-1.05)	(-0.79)	(-0.86)
D_{public}	-	-	-	0.0027	0.0039	0.0038
	-	-	-	(0.29)	(0.42)	(0.41)
D_{retail}	-	-	-	-0.0050	-0.0028	-0.0033
	-	-	-	(-0.87)	(-0.49)	(-0.59)
Balanced Fund Product	-	-	-	0.0053	0.0064	0.0065
	-	-	-	(1.15)	(1.47)	(1.51)
Ln(Fund Size)	-	-	-	-0.0022	-0.0022	-0.0024*
	-	-	-	(-1.53)	(-1.63)	(-1.81)
Fund Cash to Asset Ratio	-	-	-	-0.0262	-0.0299	-0.0148
	-	-	-	(-0.53)	(-0.58)	(-0.33)
Illiquid Asset Allocation	-	-	-	-0.0082	-0.0104	-0.0118
	-	-	-	(-0.85)	(-1.14)	(-1.34)
Lag 1 Year Return	-	-	-	-0.1188	-0.1258	-0.1395
	-	-	-	(-0.71)	(-0.77)	(-0.88)
Other Flow Q2	-	-	-	0.0032	0.0080	0.0220
	-	-	-	(0.03)	(0.07)	(0.21)
Flow Q1	-	-	-	0.0671	0.0665	0.0813
	-	-	-	(0.83)	(0.83)	(1.02)
Beta	-	-	-	-0.1785***	-0.1836***	-0.1901***
	-	-	-	(-3.43)	(-3.53)	(-3.75)
Early Release to Assets Ratio	-0.0147	-0.2066	-0.1494	-0.1051	-0.1878	-0.1546
	(-0.09)	(-0.95)	(-0.69)	(-0.86)	(-1.16)	(-1.04)
N_{obs}	71	71	71	69	69	69
R^2	0.00	-0.02	-0.01	0.58	0.58	0.57
Adj. R^2	-0.01	-0.04	-0.03	0.49	0.48	0.48
Instrumental Variables	None	Demog.	Demog. & LIC	None	Demog	Demog. & LIC.
J-test p-value	-	0.46	0.31	-	0.42	0.54

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