Situational and Behavioral Determinants of Early Withdrawal from Retirement Accounts*

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Abstract

Using a survey-elicited measure of psychological self–control and a policy change in Australia during COVID–19, we find that self–control issues significantly predict early withdrawals from retirement accounts. Individuals in the top quintile of self–control issues are 60% more likely to withdraw than those in the bottom quintile. Self–control is a stronger predictor of early withdrawal than other behavioral factors such as financial literacy, planning horizons, or personality traits. The effects are economically meaningful: eliminating self–control issues could have reduced early withdrawals by 24%—as large as the effect of adverse income shocks on withdrawals during COVID–19.

*The views expressed in this paper are solely those of the authors and do not represent the views of the Federal Reserve Board or the Federal Reserve System. This paper uses data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute. Patrick Schneider: London School of Economics (p.schneider4@lse.ac.uk). Patrick Moran: Federal Reserve Board, IFS, and CEBI (patrick.e.donnellymoran@frb.gov).

1 Introduction

Many countries encourage households to save in individual retirement accounts. One of the principal rationales for such retirement saving systems is the view that many people are myopic and lack the ability to save for retirement on their own (Feldstein, 1985). Indeed, such systems play an important role in ensuring retirement adequacy, as many individuals end their working lives with virtually no financial assets outside of the formal retirement system (Poterba, 2014). The defining feature of these accounts is that they are illiquid before retirement—where early withdrawals are either prohibited or attract substantial tax penalties (Beshears et al., 2015).

In recent years, however, an increasing number of countries have relaxed the illiquidity of these accounts during periods of aggregate distress. This represents a novel approach to supporting households and stimulating the economy, which we term 'household liquidity policy' in Schneider and Moran (2024). Some examples include Denmark in 2009, and Australia, the United States, and many others in 2020 (OECD, 2021).[1] These policies have attracted substantial controversy. The hope is that such policies can help liquidity constrained households who have been hit by adverse shocks, while also stimulating the economy in a downturn. But the fear is that the people who withdraw may be more likely to suffer from self–control issues or other behavioral biases.

We have little evidence on the role of behavioral biases in driving retirement leakage and demand for liquidity, relative to better studied situational factors like resources, demographics, and adverse shocks. This is largely driven by data limitations that impede simultaneous observation of self–control issues and real–world financial decisions. To the best of our knowledge, no previous study has combined individual measures of preference heterogeneity with observed early withdrawal decisions, nor a policy change giving people greater access to liquidity. This paper seeks to fill that gap.

We study an unexpected policy change in Australia that gave working-age individuals the ability to withdraw up to $20,000 AUD from their individual retirement accounts during the COVID–19 pandemic. To evaluate who takes advantage of the unexpected increase in liquidity, we use individual-level data from the Household Income and Labour Dynamics in Australia (HILDA) Survey. This survey is uniquely suited to our purposes as it includes measures of (i) early withdrawal decisions, (ii) situational factors like income, wealth, and adverse shocks, and (iii) various psychological traits, including self–control, financial literacy, planning horizons, and personality. The self–control measure comes from the 13 question Brief self–control Scale (BSCS), which is well-established in the

[1] Recent evidence shows that early access to retirement wealth can have a substantial impact on consumer spending. Hamilton et al. (2023) study the Australian policy that gave individuals the ability to tap into their individual retirement accounts during the COVID–19 pandemic. The authors find that individuals who withdrew spent more than 40% of the withdrawn money within the first two months.

psychology literature, and in a particular stroke of luck, was added to the HILDA survey in 2019.[2] Taken together, the HILDA survey gives us a unique opportunity to evaluate the role of behavioral versus situational factors in explaining differences in demand for liquidity following an unexpected increase in access to retirement wealth.

Among working age Australians, we find that one in seven (roughly 14%) took advantage of the opportunity to withdraw from their retirement account during COVID–19. In line with the existing literature, we find that those who withdrew were on average younger and had lower income, fewer liquid resources, and more children (Hamilton et al., 2023; Bateman et al., 2023). Building on the existing literature, we provide the first evaluation of the role of self–control issues and other behavioral factors. In the raw data, we see that individuals in the top quintile of self–control issues are about 60 percent more likely to withdraw from their retirement account than those in the bottom quintile. The results are similarly stark for planning horizons and financial literacy.

To investigate which of the potential factors have the most explanatory power for predicting early withdrawal, we estimate a series of regressions where we include a growing set of situational and behavioral characteristics. While we do not assume ex-ante which of the behavioral characteristics are most important, we ultimately find that self–control issues have the most explanatory power. self–control issues are significantly and meaningfully correlated with early withdrawal when controlling for demographics, income, adverse shocks, planning horizon, financial literacy, personality traits, and wealth. In contrast, planning horizons cease to be a significant predictor after we control for wealth, indicating that their effect is not direct. The relationship between self–control and early withdrawal is economically meaningful. High self–control issues are associated with an 8.6 percentage point higher probability of early withdrawal, which is similar to the marginal effect of having more than three children (associated with an increase of 8.5 percentage points) and substantially stronger than financial illiteracy (associated with an increase of 2.8 percentage points).

We also document an important role for situational factors, in line with Coyne et al. (2022) and Andersen et al. (2024). To the best of our knowledge, we are the first to evaluate the relative importance of situational versus behavior determinants of demand for liquidity. We find that situational factors – in particular, adverse shocks – are ultimately more important than behavioral factors when it comes to predicting which individuals extract from their retirement accounts. Unemployed individuals are 5.8 percentage points more likely to withdraw, while individuals who have suffered a pandemic-related negative income shock are 19.0 percentage points more likely. Thus, while both personality traits and adverse shocks are correlated with early withdrawal, we find that the marginal effect

[2] Developed by Tangney et al. (2004), this measure has become popular in the psychological literature, and has been increasingly used in economic studies (e.g. Cobb-Clark et al., 2022). See Section 2.2.

of adverse shocks is larger, even though they are a relatively low frequency event.

How do these individual–level factors contribute to the aggregate share of early withdrawals? Overall, we find that self–control issues account for a similar share of aggregate withdrawals as adverse income shocks. More specifically, we perform a back-of-the-envelope calculation to quantify the overall share of withdrawals that can be independently attributed to our main variables of interest.[3] While adverse income shocks are a stronger predictor of withdrawal at the individual level, they are also much less common, while self–control issues are relatively dispersed and widespread. As a result, eliminating either adverse income shocks or self–control issues would reduce the share of early withdrawals by about a quarter in both cases, all else equal.

We evaluate the sensitivity of our results to a number of different assumptions. First, we find that the importance of self–control is meaningful and precisely estimated when controlling for liquid and illiquid wealth, despite the fact that wealth is endogenous and may also be influenced by self–control issues. As a result, self–control issues matter above and beyond their documented effect on wealth (Attanasio et al., 2024). Second, while our baseline specification measures self–control as the first principal component of the BSCS, we find that our results are robust to an orthogonalized two–factor version of the BSCS, generally termed impulsivity and restraint by the existing literature (Maloney et al., 2012). In this case, we find that only the first factor (impulsivity) is significantly correlated with early withdrawal.

Related literature. Our analysis contributes to a growing empirical literature that evaluates demand for liquidity in retirement systems. In doing so, we bring together two separate strands of literature. On one hand, there's a large and growing literature documenting situational demand for liquidity (Amromin and Smith, 2003; Andersen et al., 2024; Bateman et al., 2023; Coyne et al., 2022; Goda et al., 2022; Goodman et al., 2021; Hamilton et al., 2023). These papers document that individuals are more likely to withdraw from their retirement accounts (if allowed) following job loss, divorce, or other adverse shocks. This empirical literature roughly mirrors the "situational view" of illiquidity highlighted by Kaplan and Violante (2014, 2022). On the other hand, while there's a growing literature documenting the link between preferences and wealth accumulation (Ameriks et al., 2003; Banks et al., 2010; Epper et al., 2020; Goda et al., 2019; Stango and Zinman, 2023), we know of no studies evaluating the empirical link between preference heterogeneity and differences in the demand for liquidity. This latter mechanism roughly mirrors the "behavioral view" of illiquidity highlighted by Laibson (1997), Attanasio et al. (2024), and Maxted et al. (2024). We bring together these two different literatures, first by providing novel evidence on the role of behavioral heterogeneity in explaining

[3] We should note that this should be viewed as a lower bound estimate, as we also control for wealth and other factors that may be correlated with either self–control or adverse shocks.

demand for liquidity, and second by evaluating the relative importance of situational and behavioral factors.

Understanding demand for liquidity and the determinants of early withdrawal is important for numerous reasons. First, given the growing prevalence of defined contribution retirement accounts, there's widespread concern about leakage from these accounts and the potential consequences for retirement adequacy. Goodman et al. (2021) find that for every dollar put into the US retirement system, 22 cents come out as early withdrawals. Choukhmane et al. (2023) show that early withdrawals are common, especially among low-income and minority savers, with almost one-quarter of Black savers making an early withdrawal each year. Goda et al. (2022) show that penalized withdrawals are more common among recent claimants of unemployment insurance. Second, there's growing interest in using retirement accounts to stimulate the economy. Indeed, at least 30 countries allowed early withdrawals or delayed contributions during COVID–19 as a way to support distressed households (Madeira, 2024; OECD, 2021). Third, recent research shows that such policies have a large impact on household spending, such as Kreiner et al., 2019 studying the release of retirement savings in Denmark in 2009 or Hamilton et al., 2023 studying the release of retirement savings in Australia in 2020. And while a growing literature mentions the potential role of behavioral biases (e.g. Bosch et al., 2020; Hamilton et al., 2023; Bateman et al., 2023), to the best of our knowledge, no previous study has evaluated how variation in such biases may contribute to differences in early withdrawal decisions.

Our analysis complements an influential recent paper by Hamilton et al. (2023) who also evaluate the early release of retirement wealth in Australia. The authors analyze the situational determinants of early withdrawal, then study how the policy affects consumer spending. Using high frequency spending data, the authors find that individuals who withdraw spend roughly 40% of the withdrawn funds within the first eight weeks. The authors argue that this indicates a sensitivity of consumption to income that is far greater than traditional models can predict, even with liquidity constraints, and show that the addition of present–bias is able to rationalize the behavior. We take a very different approach, exploiting survey–based measures of preferences to evaluate how early withdrawal varies with behavioral versus situational factors. Our results provide new, direct evidence that self–control issues played an important role in early withdrawals, supporting the interpretation by Hamilton et al. (2023).

Our analysis also complements recent papers that study the determinants of early withdrawal following the relaxation of withdrawal restrictions, a concept that we term "household liquidity policy" in Schneider and Moran (2024). In the Australian setting, Bateman et al. (2023) conduct a real-time survey and find that self–reported reasons for withdrawal were generally related to consumption smoothing. Preston (2022) documents the importance of numerous factors that contribute to early withdrawal, with a particular emphasis on income, job loss, financial literacy, and gender. They find that job loss and low financial literacy are important predictors of early withdrawal, a result that we confirm as well. In the US, Goda et al. (2022) evaluate the change in withdrawals at the age when the early withdrawal penalty is lifted, finding an important role for liquidity constraints and unemployment. We build upon the above studies by evaluating a wide range of behavioral factors that may influence demand for liquidity and then comparing such factors to the situational determinants that have already received substantial attention.

Our results highlight the complex trade-offs faced by policy makers that are interested in giving immediate financial relief to households, while also ensuring adequate resources for retirement. As such, our results are informative for the growing literature that uses quantitative models to evaluate the design of retirement account when agents suffer from present-bias (Beshears et al., 2020; Andersen et al., 2024; Choukhmane and Palmer, 2024; Schneider and Moran, 2024). One challenge facing this literature is that we have little empirical evidence on how heterogeneity in present–bias drives differences in behavior. Our analysis provides the first empirical evidence on how self–control heterogeneity affects demand for liquidity and, as such, may serve as important evidence to discipline such heterogeneity in models. Further, our survey-based approach is complementary to the studies that estimate present-bias in life-cycle consumption saving models (Kovacs et al., 2021; Laibson et al., 2024) which generally assume homogeneous preferences to identify the average level of present-bias. We take a very different approach, directly measuring self–control using a popular instrument from the psychological literature, then evaluating the implications for observed financial decisions.

Finally, our paper builds upon a large literature using survey-based preference measures to evaluate the relationship between preferences and wealth. Ameriks et al. (2003) show that one's propensity to plan is correlated with wealth. Banks et al. (2010) show that measures of numeracy and cognitive ability are associated with greater wealth both before and after retirement. Goda et al. (2019) show that survey measures of present-bias and exponential-growth bias are both meaningful predictors of retirement wealth. Epper et al. (2020) document a strong correlation between time discounting and individuals' position in the wealth distribution. Stango and Zinman (2023) measure a wide range of behavioral biases and document that present-bias is negatively correlated with wealth and other financial conditions. Relative to the existing literature, we believe we are the first to evaluate the relationship between preferences and demand for liquidity. Our results indicate that self–control issues contribute meaningfully to retirement leakage.

2 Setting and Data

During the COVID–19 pandemic, many countries implemented policies allowing individuals to access their retirement savings to provide financial relief during the economic crisis. In the United States, the CARES Act permitted individuals to withdraw up to $100,000 from their retirement accounts without the usual penalties. Similarly, Canada allowed withdrawals from the Registered Retirement Savings Plan (RRSP), Australia allowed individuals to withdraw up to $20,000 AUD from superannuation funds, and Chile permitted withdrawals from their mandatory individual retirement accounts up to 10% of accumulated savings. Overall, at least 30 countries implemented policies that allowed for early withdrawal or delayed contributions to retirement accounts during the pandemic (Madeira, 2024; OECD, 2021).[4]

In this paper, we focus on the Australian experience. The presence of high quality data on the situational and behavioral characteristics helping us predict early withdrawal is a unique opportunity across the countries that have implemented such policies. Further, Australia's early withdrawal policy was one of the larger programs of this kind, and has already attracted considerable attention in the recent literature.

2.1 Institutional Setting

Australia's system of mandatory retirement savings, known as superannuation, began in 1992 with the introduction of the Superannuation Guarantee (SG) scheme. Initially, the SG required employers to contribute 3% of employees' earnings into a superannuation fund. This rate increased incrementally over the years: to 6% by 1999, 9% by 2002, and 9.25% by 2013, with plans to eventually reach 12% by 2025. Superannuation accounts receive substantial tax benefits and are almost entirely illiquid before 'preservation age' (60 for most current workers), with only a few exceptions (e.g., financial hardship, compassionate grounds, and terminal illness). Australia's approach is similar to numerous other countries with mandatory defined-contribution (DC) systems.[5]

While the U.S. also has mandatory retirement contributions in the form of Social Security, the Australian system differs in a few key regards. First, Australia's SG scheme is a defined–contribution rather than defined–benefit pension system, as assets are directly earmarked to individuals, rather than pooled across society. Second, since contributions are mandatory and more uniform across the income distribution, Australia's superannua-

[4] While such policies exploded in popularity during the COVID–19 pandemic, there were some pre-pandemic instances as well. For instance, Denmark in 2009 implemented a policy to stimulate the economy by allowing individuals to tap into their previously illiquid retirement accounts (Kreiner et al., 2019).

[5] Bateman et al. (2001) and Beshears et al. (2015) discuss mandatory saving in DC accounts. Countries with similar policies include Canada, Chile, Denmark, Peru, Vietnam, Singapore, and Sweden.

tion system is designed to provide a close–to flat replacement rate of working–life income. In contrast, the U.S. system of mandatory social security contributions provides a higher replacement rate for those at the bottom of the distribution.

COVID–19 Early Release of Super program. In 2020, Australia introduced a policy allowing individuals to access up to $10,000 AUD from their individual retirement accounts by July 1, 2020, and an additional $10,000 AUD by December 31, 2020. The policy was widely publicized and saw significant uptake, with millions of Australians withdrawing funds. Most individuals who withdrew decided to withdraw the maximum of $20,000 AUD (Hamilton et al., 2023). Despite its popularity, the policy was controversial. Critics argued that it could undermine retirement security, while supporters saw it as a necessary measure for immediate financial relief.

Applications for early withdrawal from superannuation accounts were made online and required minimal supporting documentation (Bateman et al., 2023). While eligibility was supposed to be limited to individuals who had been financially affected by the pandemic,the conditions were relatively broad and covered more than 70% of the working age population (Hamilton et al., 2023).[6] Further, eligibility was entirely self–reported with no independent governmental verification.[7]

2.2 Data

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a long-running longitudinal study that collects annual data on employment, income, and wealth from a large sample of Australian households. Initiated in 2001, HILDA follows a panel structure similar to the U.S. Panel Study of Income Dynamics (PSID), but with a substantially larger sample size: roughly 17,000 individuals across more than 8,000 households in the most recent wave. The survey collects detailed data on demographics, family structure, employment, income, and wealth. Further, HILDA is relatively unique among nationally representative longitudinal surveys in its collection of detailed psychological traits, used by a variety of past studies (see e.g. Todd and Zhang, 2020). We use data from waves 18 to 21, collected between 2018 and 2021. The Brief self–control Survey was conducted in wave 19, between July 2019 and February 2020.

Sample selection. We restrict attention to individuals between the ages of 21 and 58 in 2020. The upper limit is motivated by the fact that 58 is the 'preservation age' at which

[6] Residents needed to meet one of three criteria: (1) unemployment, (2) eligibility for a range of other government benefits, or (3) had been made redundant, working hours reduced by more than 20% or, if a sole trader, business suspended or revenue reduced by more than 20%.

[7] Despite not binding in practice, the presence of these rules may have deterred people who could have withdrawn, and wanted to, due to a perception that they would be punished for doing so.

superannuation accounts became partially liquid regardless of retirement status.[8] We further restrict the sample to individuals who were interviewed in all four survey waves between 2018 and 2021, given our desire to measure wealth (recorded every 4 years, last measured before the pandemic in 2018), personality traits (measured in 2019), and early withdrawals (measured in 2020 and 2021). Among this group, we further restrict our sample to individuals who responded to the 2019 self-completion questionnaire (SCQ), which measures personality traits and a host of other factors, and who did not miss 3 or more questions on the Brief self–control Survey.[9] Together, these restrictions leave us with a sample of 7,214 individuals, with observations spanning the 2018-21 waves of the survey.

Throughout our analysis, we focus on individual level data, as superannuation accounts are individually owned and controlled, and the decision to withdraw during COVID–19 was an individual decision. Almost all of our variables of interest are measured at the individual level, including self–control, and the other psychological variables with the exception of wealth, which is measured at the household level.

Early Withdrawal. HILDA respondents were asked "Did you withdraw money from any of your superannuation [pension] funds because of the coronavirus crisis?" and, if yes, "What was the amount withdrawn?" In our data, 13.8 percent of working-age individuals withdrew early, matching estimates from other papers (Bateman et al., 2023; Hamilton et al., 2023) and official statistics. [10]

Self–control. In 2019, HILDA survey participants were asked to complete the Brief self–control Scale (BSCS), which is widely used in the psychological literature, and consists of 13 targeted questions on impulse control and goal adherence. Established by Tangney et al. (2004), the scale is designed to measure self–control—"the capacity to regulate attention, emotion, and behavior in the presence of temptation"—by asking respondents to score on a scale of 1 to 5 how much a series of 13 statements applies to them. The statements include "I am good at resisting temptation," "I often act without thinking," and "I am able to work effectively toward long-term goals." Previous work has

[8] At the time of the policy change in 2020, anyone aged 58 and above was allowed to implement a 'Transition To Retirement' strategy, moving any existing superannuation balance into a 'pension' account, exempting it from all taxes and imposing minimum and maximum withdrawal limits; people in this age group are still allowed to work and so have a tax arbitrage—they can withdraw the maximum from their pension account, and voluntarily contribute more into their superannuation account, reducing the tax liability to 15% on any earned income, up to the limit on concessional contributions.

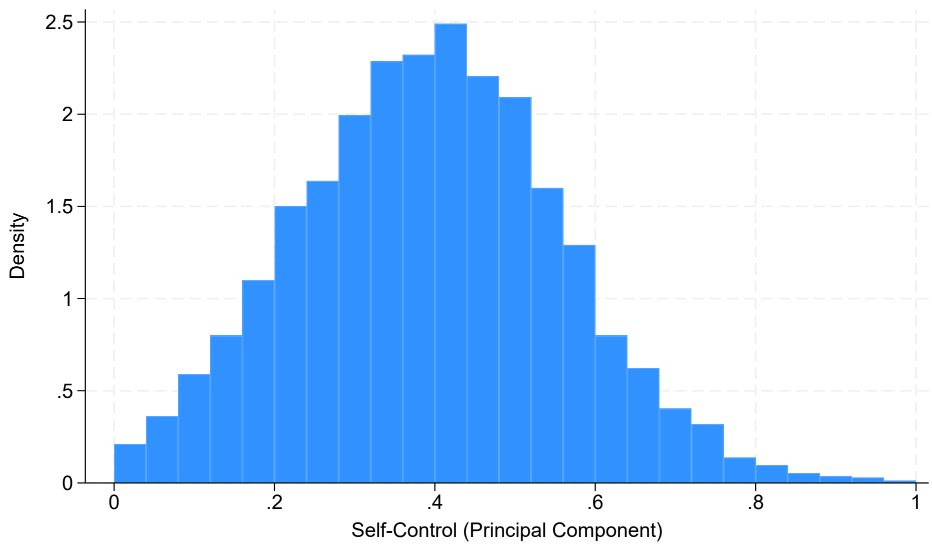
[9] The SCQ is a 20 page survey consisting of questions that are difficult to administer in time-effectively in a personal interview. Conditional on meeting our other sample requirements, 94.4% of individuals complete the SCQ, and 97.4% of SCQ respondents answer all 13 questions of the BSCS.

[10] Previous research has shown that the vast majority of individuals who withdrew decided to withdraw the maximum amount permitted each round (Bateman et al., 2023; Hamilton et al., 2023). As a result, we focus on the discrete decision to withdraw, rather than the continuous decision of how much to withdraw. Indeed, analysis using the amount withdrawn (not reported) yields similar qualitative results to our baseline analysis.

found that this scale shows good internal consistency and retest reliability (Bertrams and Dickhäuser, 2009; Tangney et al., 2004), and that higher self–control is linked to better financial outcomes and disciplined behavior (Cobb-Clark et al., 2022).

We use Principal Components Analysis (PCA) to reduce variation in the 13 BSCS items to one dimension, a standard approach in the psychology literature (e.g. Manapat et al., 2021). We find that the first principal component explains roughly one-third of the variation across the standardized 13 item scale, and that the sign of each loading is as we would expect given the direction of phrasing.[11] We rescale the first principal component so that it ranges between zero and one, where zero represents no self–control issues on all 13 items, while one corresponds to full self–control issues. Figure 1 shows the distribution of self–control issues. Overall, we see that self–control issues are relatively widespread and feature substantial variation across individuals, with an average of 0.39, standard deviation of 0.16, and a long right tail to the distribution.

Figure 1: Distribution of self–control Issues



Other Psychological Traits. We augment our measure of self–control with other psychological measures including financial literacy, the Big Five personality traits, and planning horizon.

Financial Literacy is measured using the well-established "Big-3" measure of Lusardi and Mitchell (2014), which is a binary measure equal to one if the respondent correctly answered all three questions related to interest rates, inflation, and diversification. The Big Five personality traits – Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism – are measured through a series of standardized questions. Past research

[11] Appendix A.1 shows the full list of items, the distribution of responses, and the factor loadings. We experimented with an additional factor in our empirical analysis, but found that it did not meaningfully change the results, and that only the first factor was significantly correlated with withdrawal.

has used HILDA data to document the importance of the Big Five personality traits for schooling and labor market outcomes (Flinn et al., 2018; Todd and Zhang, 2020).[12]

Planning horizon is measured based on individuals' response to the question "In planning your savings and spending which of the following time periods is most important to you?" The respondent can choose: next week; next few months; next year; next 2-4 years; next 5-10 years; or 10+ years ahead. While planning horizon is not a perfect measure of time preference, it is often used as a proxy when a direct measure does not exist in the data (e.g. Barsky et al., 1997; Samwick, 1998; Brown and Van der Pol, 2015). Past research has shown that planning horizon is correlated with time preference.[13]

Wealth. The HILDA Survey collects detailed data on household wealth through approximately 20 to 30 questions, covering a wide range of asset and liability categories. This includes information on real estate, financial assets, vehicles, business investments, and liabilities such as mortgages and personal loans. Given the reporting burden, the wealth module is only administered every four years. We use the most recent wave of wealth data prior to COVID–19, collected in 2018.

We divide wealth between three categories. The first is liquid wealth: the sum of cash holdings, equity investments, and bank accounts, net of credit card debt and overdue bills. Second is illiquid wealth: the sum of housing, other property, businesses, vehicles, and collectibles, net of mortgages and other debt. And third is superannuation wealth, which includes all superannuation accounts. Wealth is measured at the household level, and because of this we cluster standard errors by household.

Adverse shocks. We collect two important measures of adverse labor market shocks: unemployment and pandemic-induced negative income shocks. We record an individual as experiencing unemployment if they report unemployment in either 2020 or 2021.[14] Roughly 14 percent of our sample experienced unemployment during this period, much higher than usual. Second, we measure pandemic-related income shocks based on individuals' response to the question "Did the income you normally receive from paid employment increase or decrease because of the coronavirus? Or did it not change much?" which was asked to all individuals employed as of March 2020. In our sample, 17.6 percent of individuals reported a decrease in income due to the pandemic.

[12] While the use of the Big Five traits in explaining economic outcomes is now well-established among economists (Almlund et al., 2011; Borghans et al., 2008; Heckman et al., 2021), there is much less evidence on self–control, perhaps because it has only recently been incorporated into large-scale surveys.

[13] Adams and Nettle (2009) show that planning horizon and discount rate are correlated, -0.19, with a p value < 0.001. While individuals with a higher time preference rate are likely to have a shorter planning horizon, socio-economic status and life expectancy are also likely associated with planning horizon. We thus control for income, wealth, and age in our empirical analysis.

[14] We found that a more granular measure (time unemployed) did not substantially alter our results.

Demographics. We also collect a rich set of demographics for each individual. These include age, gender, education, marital status, number of children, and income (defined as financial year wages and salaries). All demographic variables are measured in 2020, the time when individuals were allowed early access to retirement wealth.

3 Analysis

In this section, we evaluate the psychological and situational determinants of early withdrawal. To set the stage, we first show how the probability of early withdrawal varies based on observable characteristics, such as self–control or adverse shocks. We then explore the marginal effect of each variable in a regression specification in Section 3.3 and quantify their aggregate importance in Section 3.4.

3.1 Descriptive Statistics

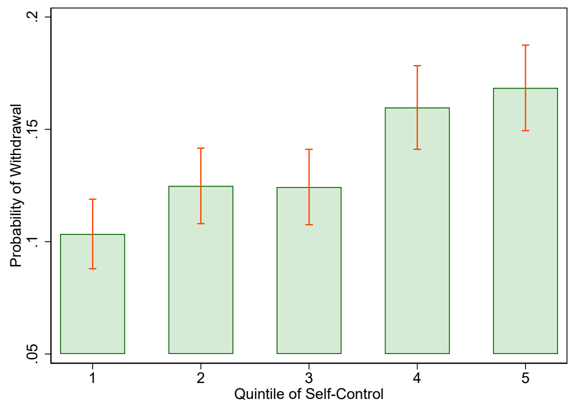
Overall, we find that around one in six (13.8%) working age individuals withdrew from their retirement account during the pandemic, in line with other papers that measure participation in alternative datasets (e.g. Bateman et al., 2023; Hamilton et al., 2023). This aggregate statistic masks meaningful heterogeneity in various behavioural and situational dimensions, some of which are plotted in Figure 2. We see that early withdrawal is more common among people with greater self–control issues, shorter planning horizons, fewer assets, and lower income.

Focusing first on the behavioral factors, we explore how early withdrawal varies with our measures of self–control and planning horizon. Figure 2a shows that the probability of early withdrawal increases markedly with self–control issues. In the bottom quintile of self–control issues, around 10 percent of individuals withdraw, while in the top quintile, roughly 17 percent withdraw, with a statistically significant difference. Figure 2b shows that shorter planning horizons are also correlated with a higher probability of early withdrawal.

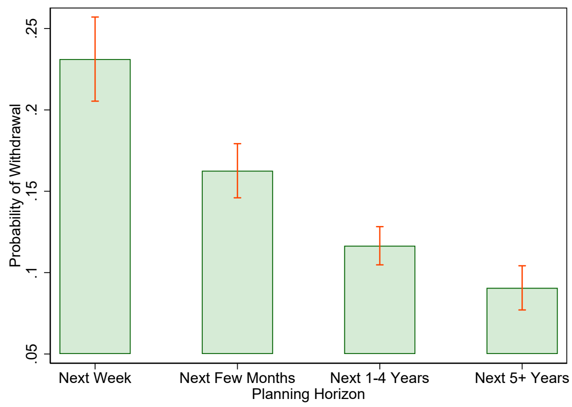
Turning now to situational factors, we have measures of households' financial position and incomes, as well as adverse shocks suffered during the pandemic. Figures 2c and 2d show that the probability of early withdrawal is decreasing with wealth, whether liquid or illiquid, although the relationship with the former is slightly stronger, in line with the literature showing the primacy of liquid wealth in determining household spending (Kaplan and Violante, 2014). Figures 2e and 2f show how withdrawal varies with income and income shocks. The probability of early withdrawal is highest for individuals in the bottom two quintiles of the income distribution, adjusted for age, and declines gradually for higher income individuals. Further, the probability of withdrawal is much higher for

Figure 2: Probability of Early Withdrawal based on Situational and Behavioral Factors

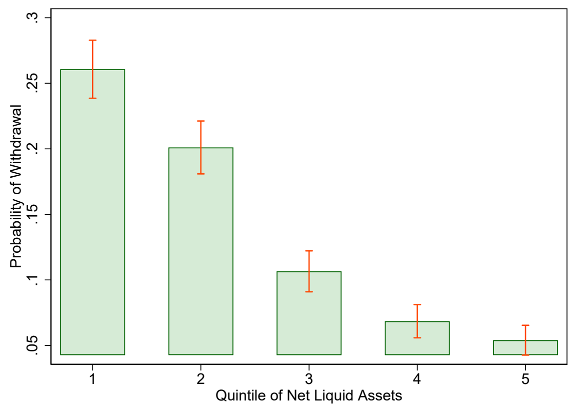
(a) Self–control



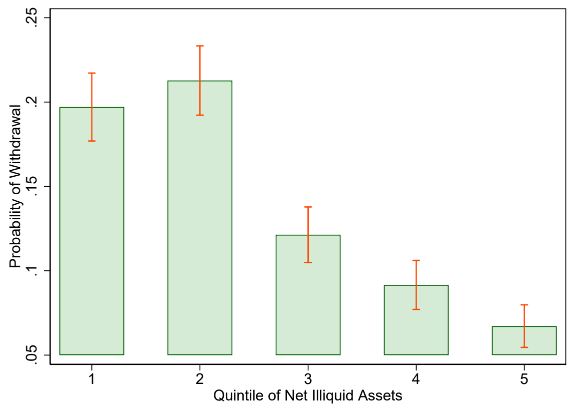
(b) Planning Horizon



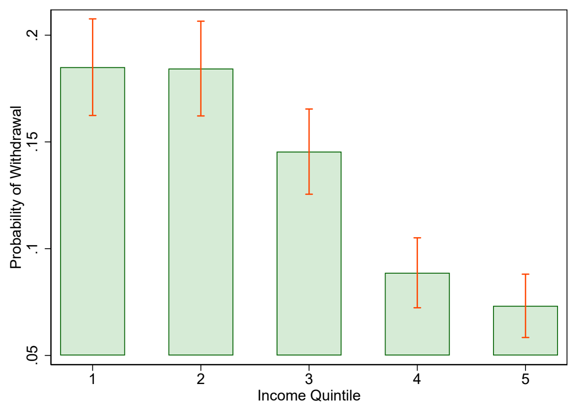
(c) Liquid Assets



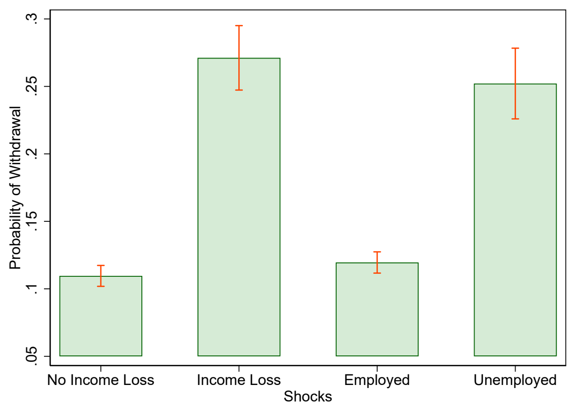
(d) Illiquid Assets



(e) Income



(f) Income Shocks



Note: Each figure shows the probability of early withdrawal based on a different observable characteristic. Income quintiles are computed within age group, since otherwise the income results are mostly driven by age effects.

those who have experienced adverse shocks, such as unemployment or pandemic related loss of income. Such shocks, while relatively rare, are strongly correlated with early withdrawal.[15] The importance of such shocks broadly lines up with the existing literature,

[15]Such correlation is not a complete surprise, since eligibility was technically limited to individuals who had a reduction in work hours, loss of employment, or reduction in turnover. As noted in Section

such as Goda et al. (2022) who show that penalized withdrawals are more common among recent claimants of unemployment insurance and Choukhmane et al. (2023) who find that those who experience larger income declines are more likely to withdraw.

There are various other forms of heterogeneity which we report in Appendix A.2, such as age and financial literacy. Looking at age, individuals in their thirties are the most likely to withdraw, similar to the finding in Hamilton et al. (2023), which may reflect the fact that these individuals have already had a few years to accumulate wealth in their retirement account, but are still relatively constrained compared to their older counterparts. Turning to financial literacy, we see that financially literate individuals are substantially less likely to withdraw, as in Preston (2022).

3.2 Empirical Specification

While the above section shows the unconditional probability of withdrawal for each of our main variables of interest, there are likely to be meaningful correlations between these variables. Issues with self–control, for instance, might be related to other psychological measures, such as planning horizon or financial literacy. Further, wealth may be greatly affected by psychological factors. Rather than assume ex-ante which of the potential determinants are most important, we include them all in a regression and test which have significant explanatory power.

To investigate the marginal relationships between self–control and each of the situational and behavioral factors we consider, we estimate the following logistic regression

$$\ln\left(\frac{p_i^{ew}}{1-p_i^{ew}}\right) = \beta_0+\beta_1\cdot\text{self–control}_i+\beta_2\cdot\text{demog}_i+\beta_3\cdot\text{shocks}_i+\beta_4\cdot\text{psych}_i+\beta_4\cdot\text{wealth}_i+\epsilon_i \tag{1}$$

where p_i^{ew} is the probability of early withdrawal for individual i, self–control is the first principal component of the Brief self–control Scale, demog is a vector of demographic controls including education, children, age, sex, relationship status, log income, and a dummy for missing income, shocks is a vector containing unemployment and negative income shocks during COVID–19, psych is a vector containing financial literacy, planning horizon, and the big five personality traits. Wealth is a vector containing liquid, illiquid, and Superannuation asset quartiles, as well as mortgage debt and mortgage payments. We weight using responding person longitudinal weights balanced between waves 18 to 21 and cluster standard errors at the household level.

2.1, however, eligibility was widespread, self-reported, and not verified. Past research shows that such rules did not have a binding effect, although it may still have deterred some withdrawals.

3.3 Individual-Level Results

Table 1 reports the average marginal effects (AME) in a series of specifications, which build toward the full set of controls outlined in Equation (1). We find that both situational and behavioral factors are significantly correlated with early withdrawal, and that self–control is the most important of the behavioral factors we consider.

Self–control and other psychological traits. Our first object of interest is the marginal effect of self–control issues, shown in the top row of Table 1. We find that self–control issues have an economically meaningful and significant relationship with early withdrawal. In specification (1), which controls just for demographics, we find that individuals with the highest level of self–control issues are 16 percentage points more likely to withdraw relative to those with no self–control issues, all else equal.[16] As we move through the specifications, adding controls for adverse shocks (2), behavioral factors (3), and wealth (4), we find that the AME of self–control diminishes but still remains economically meaningful. In specification (4), which includes all of our controls, we estimate an AME of 8.6 percentage points, which is similar to the effect of having 3 or more children. Based on this estimate, a one standard deviation increase in self–control issues (0.16) translates to a 1.4 percentage point increase in the probability of early withdrawal, while moving from the bottom to top quintile of self–control issues (i.e. from 0.17 to 0.63) translates to a 3.9 percentage point increase in the probability of early withdrawal, all else equal. This effect may be viewed as a lower bound if we believe that self–control issues also lead to lower wealth accumulation.[17]

While other psychological factors also play a role in predicting early withdrawal, we find that the estimated effects are weaker and less robust than that of self–control issues. Column 3 of Table 1 shows the marginal effects once we control for the full battery of psychological factors including financial literacy, planning horizon, and the big five personality traits. We find that financial literacy is correlated with a 4.2 percentage point reduction in the probability of withdrawal, although this relationship is nearly halved once we control for wealth in Column 4.[18] Further, we find that individuals with longer planning horizons have a lower probability of withdrawal. This effect disappears when we control for wealth, however, suggesting that the effect of shorter planning horizons on withdrawal is mediated mainly through wealth. Finally, we also evaluate the role of the big five personality traits (reported in Appendix A.3). We find that greater emotional stability reduces the probability of withdrawal, but that none of the other big five traits

[16]Recall that our measure of self–control issues ranges between zero and one, so the AME tells us the implied impact, all else equal, of moving from no self–control issues to the maximum.

[17]If wealth is a mediator for self–control issues, then it is a bad control, absorbing variation that should rightly be attributed to self–control.

[18]Similarly, when predicting individual retirement wealth in the US, Goda et al. (2019) find that present bias and financial literacy are both important, with present-bias being the stronger predictor.

Table 1: Marginal Effects

	(1)	(2)	(3)	(4)
Self-Control Issues	0.16***	0.13***	0.11***	0.086**
	(0.036)	(0.034)	(0.036)	(0.034)
Log Income	−0.035***	−0.022***	−0.016***	−0.0097
	(0.007)	(0.006)	(0.006)	(0.006)
Children: 1	0.070***	0.078***	0.069***	0.060**
	(0.024)	(0.025)	(0.024)	(0.023)
Children: 2	0.067***	0.067***	0.064***	0.055***
	(0.020)	(0.020)	(0.020)	(0.019)
Children: 3+	0.11***	0.11***	0.10***	0.085***
	(0.022)	(0.021)	(0.020)	(0.019)
Income Loss from Covid		0.19***	0.18***	0.19***
		(0.023)	(0.021)	(0.021)
Unemployed		0.068***	0.066***	0.058***
		(0.016)	(0.015)	(0.016)
Financial Literacy			−0.042***	−0.028**
			(0.013)	(0.012)
Planning Horizon: Few Months			−0.031*	−0.012
			(0.018)	(0.017)
Planning Horizon: 1-4 Years			−0.058***	−0.023
			(0.018)	(0.016)
Planning Horizon: 5+ Years			−0.065***	−0.023
			(0.020)	(0.019)
Liquid Assets: 2nd Quartile				−0.079***
				(0.017)
Liquid Assets: 3rd Quartile				−0.12***
				(0.017)
Liquid Assets: Top Quartile				−0.11***
				(0.022)
Illiquid Assets: 2nd Quartile				0.017
				(0.018)
Illiquid Assets: 3rd Quartile				−0.032*
				(0.020)
Illiquid Assets: Top Quartile				−0.049**
				(0.020)
Observations	7214	7214	7214	7214
Demographics	*Yes*	*Yes*	*Yes*	*Yes*
Adverse Shocks		*Yes*	*Yes*	*Yes*
Psych Controls			*Yes*	*Yes*
Wealth Controls				*Yes*

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

have a significant effect. Overall, of all the psychological measures we consider, self–control remains the most important determinant.

Adverse shocks. In line with the existing literature, we also find that adverse shocks play an important role in predicting early withdrawal. Unemployment and pandemic-related negative income shocks increase the probability of early withdrawal by 5.8 and 19.0 percentage points respectively. Our results indicate that negative income shocks are a stronger predictor of early withdrawal than self–control at the individual level. That said, it's important to note that the incidence of self–control issues is higher than either of these adverse shocks, a topic that we return to when evaluating the aggregate implications in Section 3.4.

Wealth. Finally, we also find that wealth is an important predictor of withdrawal. Individuals with low liquid assets are much more likely to tap into their retirement account, and liquid wealth plays a more important role than illiquid wealth in the spirit of Kaplan and Violante (2014). Of course, wealth is likely endogenous to personality traits such as self–control. Even when we control for wealth, however, we still see a significant and meaningful relationship between self–control and early withdrawal. This finding lends support to theories of present-bias contributing to high MPCs, above and beyond the effects of situationally low liquidity (Attanasio et al., 2024). In contrast, planning horizons cease to be important after controlling for wealth.

Our results complement recent analysis by Hamilton et al. (2023), who find that Australians who withdrew from their retirement accounts during COVID–19 spent around 40% of the money within the first two months, despite the modal withdrawal being the maximum $20,000 AUD. The authors state that this high MPC out of such a large amount is inconsistent with traditional models, where the MPC declines rapidly with shock size, and argue that early withdrawal is better rationalized by models with present-bias. We complement the above paper by evaluating the psychological determinants of early withdrawal using individual-level data on self–control issues, something the above authors do not observe. Our results provide clear evidence that self–control matters for early withdrawal. Further, our results show that heterogeneity in self–control is an important determinant of behavior, lending support to recent models of retirement savings that explicitly model this form of heterogeneity (see e.g. Choukhmane and Palmer, 2024).

Our results also complement Goda et al. (2019), who predict retirement wealth in the US using a survey based measure of present-bias. The authors find that a one standard deviation increase in present-bias is associated with approximately $19,000 (10%) less retirement wealth at age 65. Two channels could cause this lower level of savings: fewer contributions or more withdrawals. While the setting in that paper differs from ours (namely, contributions are optional in the US and withdrawals are generally permitted), our results support the idea that present–bias is likely to contribute to greater leakage from retirement accounts.

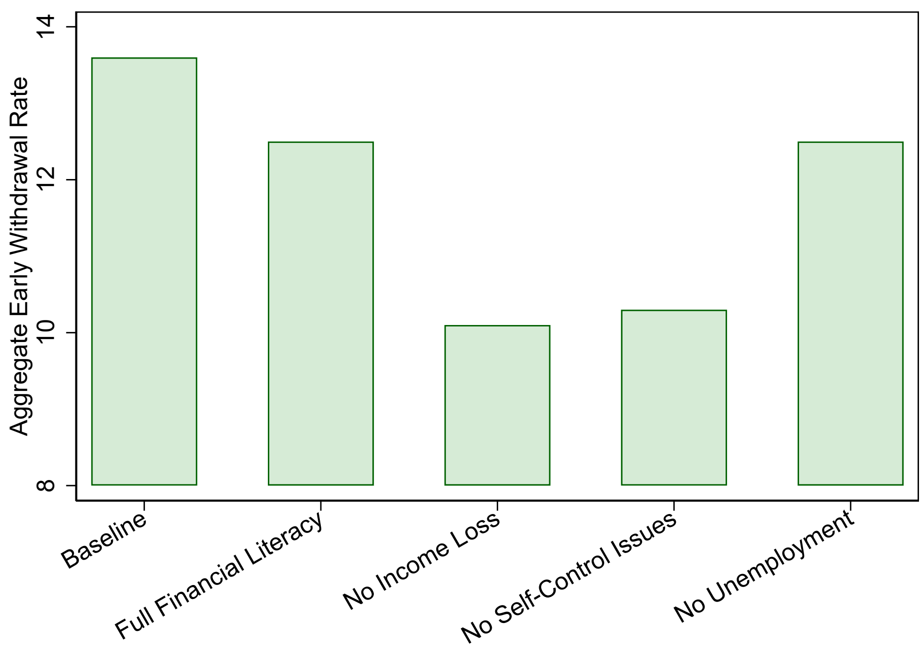
3.4 Aggregate Implications

What do the individual level results in Table 1 imply at the societal level? To what extent is the aggregate propensity to withdraw from retirement accounts driven by psychological vs situational factors? To estimate the aggregate importance of these different factors, we need to think about how the composition of each varies across the population.

Figure 3 shows the overall rate of early withdrawals in the data (Bar 1) and under various counterfactuals (Bars 2 to 5) where we eliminate unemployment, pandemic related negative income shocks, self–control issues, and financial illiteracy. The counterfactuals are computed by setting each of these explanatory variables to zero in Equation (1), in effect turning off their direct influence on early withdrawal.[19] We then aggregate the fitted values to estimate the share of individuals that perform early withdrawal under each alternative assumption. This approach gives a lower bound of the effect of each of these factors because the traits are likely to have direct effects, as well as indirect ones mediated through income, wealth, or other controls; because we are only turning off the former, the aggregate importance we estimate does not include any indirect effects.

Remake this figure so it's all relative to some baseline. Also relabel No unemp as full employment

Figure 3: Implications for Aggregate Early Withdrawals



Overall, we find that self–control accounts for a similar share of withdrawals as negative income shocks. While negative income shocks have a larger AME, they are relatively

[19]We use the full specification, i.e. the estimates in column 4 of Table 1, for this exercise.

concentrated; by contrast, self–control issues have a smaller AME but are much more widespread, and the net effect is about the same. More specifically, 17.6 percent of individuals in our sample were affected by pandemic-related negative income shocks. If we were to eliminate such shocks, the predicted early withdrawal rate would decline by 3.5 percentage points. In contrast, in our baseline sample, our measure of self–control has a mean value of 0.39. If we were to eliminate self–control issues by setting this value to zero for all individuals, while holding all other covariates fixed, we would predict the early withdrawal rate to decline by 3.3 percentage points.

Further, we see that self–control and negative income shocks both account for a larger share of early withdrawals than unemployment or financial illiteracy. If we were to eliminate the direct effects of unemployment, we predict the early withdrawal rate to fall by 1.1 percentage points. This is despite the fact that the unemployment rate was unusually high during the pandemic, with 14 percent of our sample being unemployed during COVID–19. Similarly, if we were to eliminate financial illiteracy, the predicted early withdrawal rate would only lower by 1.3 percentage points. The relative importance of self–control compared to financial literacy is consistent with Goda et al. (2019), who find that present bias is a more important predictor of retirement wealth than financial literacy. While the above authors evaluate the behavioral determinants of wealth accumulation, we believe we are the first to evaluate the behavioral determinants of demand for liquidity.

4 Conclusion

Our results highlight an important trade-off faced by policymakers: providing liquidity during economic distress while also ensuring that individuals with limited self–control can still build sufficient wealth for retirement. The recent trend of allowing households to withdraw from retirement accounts in times of aggregate economic distress amplifies the urgency of addressing this trade-off.[20]

In this paper, we examine the various factors influencing demand for liquidity, distinguishing between situational needs versus behavioral desires. Our results indicate that self–control issues do contribute substantially to early withdrawal. And while situational factors are generally a stronger predictor of early withdrawal at the individual level, situational and behavioral factors are similarly important at the societal level.

Early access to retirement funds satisfies the need for short–term liquidity in the same way as traditional debt-financed fiscal stimulus payments. But it is attended by the fear

[20]While a full welfare analysis of this trade-off is outside the scope of the current paper, we return to this question in Schneider and Moran (2024), where we develop a heterogeneous agent model to evaluate the distributional welfare implications of 'household liquidity policy' relative to traditional fiscal stimulus.

that people who lack self–control will be more likely to tap into their retirement accounts and draw down their nest egg. We find that this is indeed a well–founded fear.

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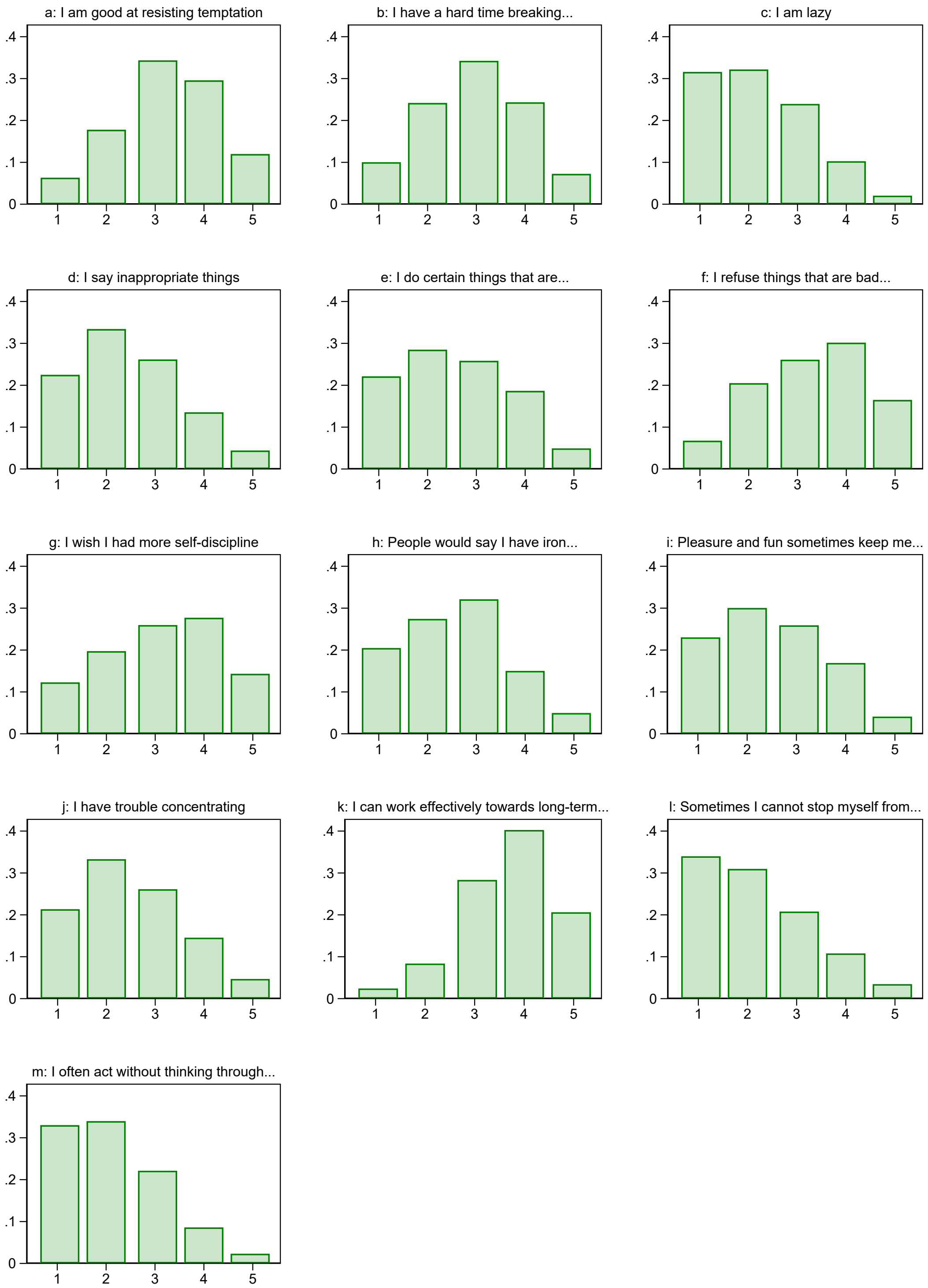
A Appendix

A.1 Brief self–control Scale

Figure 4: Brief self–control scale questions and answers



Note: Respondents are asked to rate how well each statement describes them, with responses ranging from 1 ("not at all") to 5 ("very well").

Figure 4 shows the distribution of responses to the 13 items included in the Brief self–control Scale. Table A.1 shows the estimated factor loadings for each of the 13 items. Overall, we see that the factor loadings go in the directions that we would expect based on the wording of each item. Further, we see that the estimated factor loadings, while relatively broad-based, are largest for items related to temptation and impulsive behavior.

Table 2: PCA Factor Loadings

	Question	Loading
a	I am good at resisting temptation	-0.2772
b	I have a hard time breaking bad habits	0.2916
c	I am lazy	0.2702
d	I say inappropriate things	0.2674
e	I do certain things that are bad for me, if they are fun	0.3185
f	I refuse things that are bad for me	-0.2331
g	I wish I had more self-discipline	0.3185
h	People would say I have iron self-discipline	-0.2100
i	Pleasure and fun sometimes keep me from getting work done	0.2656
j	I have trouble concentrating	0.2930
k	I can work effectively towards long-term goals	-0.2143
l	Sometimes I cannot stop myself from doing something, even if I know it is wrong	0.3247
m	I often act without thinking through all the alternatives	0.2907

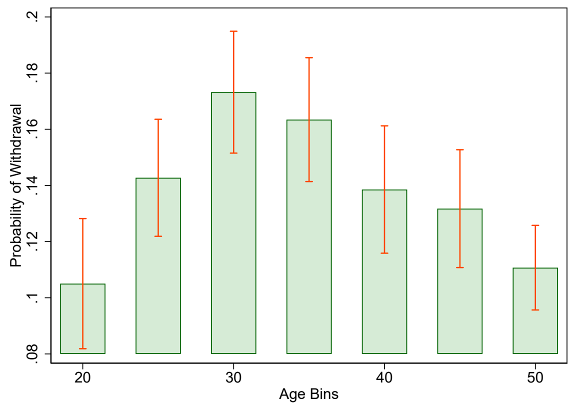
Of course, the Brief self–control Scale is not the only way to measure self–control issues. In general, there are two distinct approaches to measuring self–control, summarized by Cobb-Clark et al. (2022). The first relies upon responses to validated batteries of questions, following the canonical approach for measuring personality traits in the literature on personality psychology and economics (e.g. Almlund et al., 2011; Borghans et al., 2008; Heckman et al., 2021). The second approach is based on experimental economics, often measured on university students, which structurally estimates an individual's level of self–control based on their present-bias parameter β when estimating a $\beta - \delta$ model based on incentivized tasks (e.g. Andreoni and Sprenger, 2012; Andreoni et al., 2015; Augenblick and Rabin, 2019; Augenblick et al., 2015). In the present paper, we adopt the former approach using survey-based measurement. One benefit of this approach is that it can be embedded in large-scale household panel surveys that are nationally-representative and record a range of important economic outcomes. Both the Australian HILDA and German SOEP have recently incorporated such survey-based measurement of self–control into their large-scale panel surveys using the Brief self–control Scale.

A.2 Summary Statistics

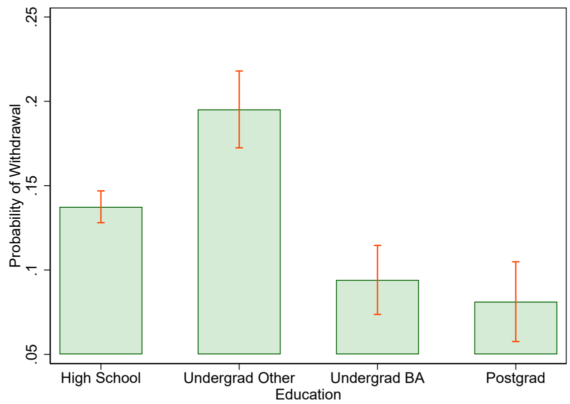
Figure 5 shows the probability of early withdrawal conditional on various observable characteristics not shown in the main text. The probability of early withdrawal is highest for individuals in their thirties, which likely owes to the fact that these individuals have had time to accumulate wealth in their superannuation account, but still are early in their life-cycle and therefore may be more exposed to other shocks. Turning towards education, we see that the probability of early withdrawal is lower for those who have completed a bachelors or postgraduate degree. The highest probability of early withdrawal is for those classified as "Undergrad Other," which reflects a number of undergraduate degrees including diplomas, certificates, and associate degrees, but not bachelor degrees.

Figure 5: Probability of Early Withdrawal

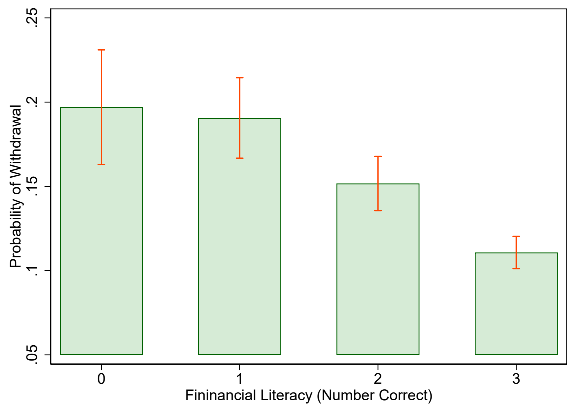
(a) Age



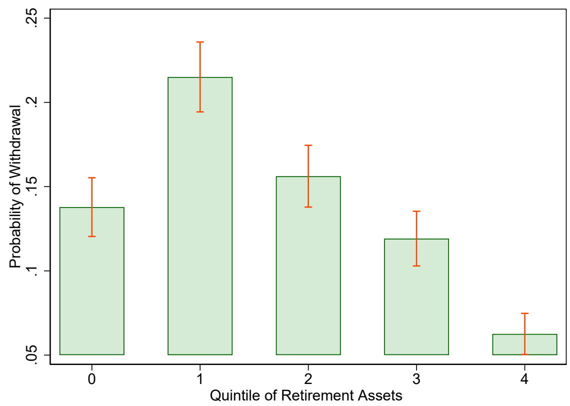
(b) Education



(c) Financial Literacy



(d) Retirement Wealth



Note: Each figure shows the probability of early withdrawal based on a different observable characteristic. Retirement wealth is defined as the wealth held in one's superannuation account.

Turning towards financial literacy, we see that the probability of early withdrawal is declining with the number of correct answers to the "big three" financial literacy questionnaire. Finally, turning towards wealth held in superannuation accounts, we see that the probability of early withdrawal is highest for those in the low-middle part of the distribution. Individuals in the bottom quintile have very little money to withdraw. Individuals in the top quintile are relatively wealthy and may have other forms of wealth that they can draw on before turning to retirement assets.

Motivated by these results, we include all of these variables as additional explanatory factors in our empirical specification discussed in Section 3.2.

A.3 Empirical Analysis

Table 3 reports the marginal effects for the full set of covariates included in our empirical specifications, including those omitted from Table 1 for the sake of expositional clarity.

Education initially appears to be an important predictor of withdrawal, although we find that most of this effect disappears once we control for wealth in specification (4). Further, although age appears strongly correlated with withdrawal in Figure 5, we find it is not an important predictor of withdrawal once we control for other factors.

We investigate the importance of the "Big Five" personality traits, which have been shown to be an important predictor of labor market outcomes (see e.g. Almlund et al., 2011; Borghans et al., 2008; Heckman et al., 2021; Todd and Zhang, 2020).[21] Overall, we find that most of these traits are unimportant when it comes to predicting early withdrawals. Of the big five traits, only emotional stability has a significant relationship, with greater emotional stability being correlated with reduced withdrawals. That said, none of the other traits have any significant relationship with withdrawal.

In specification (4), we also control for the presence of a mortgage and the size of mortgage payments, given the possibility that early withdrawal might be more likely for mortgagors. We find no evidence of such an effect conditional on our other controls.

Table 3: Marginal Effects

	(1)	(2)	(3)	(4)
Self-Control Issues	0.16***	0.13***	0.11***	0.086**
	(0.036)	(0.034)	(0.036)	(0.034)
Log Income	−0.035***	−0.022***	−0.016***	−0.0097
	(0.007)	(0.006)	(0.006)	(0.006)
Postgraduate	−0.055***	−0.052***	−0.041**	−0.034
	(0.020)	(0.018)	(0.019)	(0.022)
Undergraduate Bachelor	−0.051***	−0.046***	−0.038**	−0.031*
	(0.017)	(0.017)	(0.017)	(0.017)

[21]While the use of the Big Five personality traits in explaining economic outcomes is now well-established among economists, there is much less evidence on the role of self–control, perhaps because self–control has only recently been incorporated into large-scale household surveys.

Undergraduate Other	0.035*	0.033*	0.031*	0.019
	(0.019)	(0.019)	(0.018)	(0.017)
Children: 1	0.070***	0.078***	0.069***	0.060**
	(0.024)	(0.025)	(0.024)	(0.023)
Children: 2	0.067***	0.067***	0.064***	0.055***
	(0.020)	(0.020)	(0.020)	(0.019)
Children: 3+	0.11***	0.11***	0.10***	0.085***
	(0.022)	(0.021)	(0.020)	(0.019)
agebins=30	0.016	0.015	0.019	−0.00085
	(0.027)	(0.027)	(0.025)	(0.025)
agebins=40	−0.021	−0.020	−0.0074	−0.012
	(0.024)	(0.025)	(0.023)	(0.023)
agebins=50	−0.043*	−0.042*	−0.025	−0.017
	(0.023)	(0.024)	(0.023)	(0.023)
male	0.033**	0.027**	0.033**	0.033***
	(0.013)	(0.013)	(0.013)	(0.013)
hasPartner	−0.028*	−0.021	−0.017	−0.0034
	(0.016)	(0.016)	(0.015)	(0.015)
incomeMissing	−0.41***	−0.27***	−0.21***	−0.15**
	(0.076)	(0.070)	(0.064)	(0.064)
Income Loss from Covid		0.19***	0.18***	0.19***
		(0.023)	(0.021)	(0.021)
Unemployed		0.068***	0.066***	0.058***
		(0.016)	(0.015)	(0.016)
Financial Literacy			−0.042***	−0.028**
			(0.013)	(0.012)
Planning Horizon: Few Months			−0.031*	−0.012
			(0.018)	(0.017)
Planning Horizon: 1-4 Years			−0.058***	−0.023
			(0.018)	(0.016)
Planning Horizon: 5+ Years			−0.065***	−0.023
			(0.020)	(0.019)
Big Five: Extroversion			0.016	0.016
			(0.014)	(0.014)
Big Five: Agreeableness			0.0082	0.014
			(0.018)	(0.018)
Big Five: Conscientiousness			0.014	0.021
			(0.017)	(0.017)
Big Five: Emotional stability			−0.033**	−0.033**
			(0.017)	(0.017)
Big Five: Openness			−0.0035	−0.015
			(0.015)	(0.015)
Liquid Assets: 2nd Quartile				−0.079***
				(0.017)
Liquid Assets: 3rd Quartile				−0.12***
				(0.017)

Liquid Assets: Top Quartile				-0.11^{***}
				(0.022)
Illiquid Assets: 2nd Quartile				0.017
				(0.018)
Illiquid Assets: 3rd Quartile				-0.032^{*}
				(0.020)
Illiquid Assets: Top Quartile				-0.049^{**}
				(0.020)
Super Assets: 2nd Quartile				0.039^{**}
				(0.018)
Super Assets: 3rd Quartile				0.023
				(0.019)
Super Assets: Top Quartile				-0.013
				(0.019)
mortgagePositive				0.12
				(0.090)
logMortgagePayment				-0.018
				(0.012)
Observations	7214	7214	7214	7214
Demographics	*Yes*	*Yes*	*Yes*	*Yes*
Adverse Shocks		*Yes*	*Yes*	*Yes*
Psych Controls			*Yes*	*Yes*
Wealth Controls				*Yes*

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$