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 reduce early withdrawals by 24% — as large as the effect of adverse income shocks on withdrawals during Covid-19.

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1 Introduction

Many countries have retirement saving systems with mandatory contributions, tax benefits, and substantial illiquidity. Examples include Social Security in the United States and compulsory individual retirement accounts in Australia, Chile, and Singapore (Beshears et al., 2015; OECD, 2021). One of the principal rationales for such retirement saving systems is the view that many individuals are myopic and lack the ability to save for their own retirement (Feldstein, 1985). Indeed, such saving systems play an important role in ensuring retirement adequacy, as many individuals reach retirement age with virtually no financial assets outside of the mandatory retirement system (Poterba, 2014).

During recent years, an increasing number of countries have allowed people to tap into their retirement accounts during times of aggregate stress. This is an alternative to conventional fiscal stimulus which we term 'household liquidity policy' in Schneider and Moran (2024). Some examples include Denmark in 2009, Australia in 2020, and the United States in 2020.[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. The fear is that the people who withdraw may be more likely to suffer from self-control issues or other behavioral biases, meaning that the aggregate stimulus comes at the cost of increased access by the people who most need societal help to save for retirement.

While previous research shows the importance of self-control in wealth accumulation, we know little about the degree of heterogeneity in such preferences, nor the extent to which such heterogeneity is associated with important financial decisions such as early withdrawal. The primary reason for this gap in our knowledge is due to 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. As a result, we have little understanding of the role of behavioral heterogeneity in driving decisions following the early release of retirement savings, nor their more general importance in driving household demand for liquidity in comparison to other situational factors—like resources, demographics, and recent shocks—that are better studied. 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

[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 pandemic. The authors find that individuals who withdrew spent more than 40% of the withdrawn money within the first two months.

increase in liquidity, we use individual-level data from the Household Income and Labour Dynamics in Australia (HILDA) Survey. These data are uniquely suited to our purposes as they include measures of (i) early withdrawal decisions, (ii) situational factors like income, wealth, and 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 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 heterogeneity in explaining 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. 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 heterogeneity in 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. The raw data also suggest an important role of adverse shocks and other situational factors; for instance, unemployed individuals are more than twice as likely to withdraw.

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 3+ 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).

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

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 are ultimately more important than behavioral factors when it comes to predicting which individuals extract from their retirement accounts. For instance, 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 of shocks is larger, even though they are a relatively low frequency event.

Overall, we find that self-control heterogeneity accounts for a similar share of early withdrawals as adverse income shocks. To show this, we perform a back-of-the-envelope calculation to quantify the overall share of early withdrawals that can be independently attributed to our main variables of interest.[3] While adverse income shocks are a stronger predictor of early withdrawal at the individual level, they are also much more concentrated, while self-control issues are relatively dispersed and widespread. As a result, if we could eliminate either adverse income shocks or self-control issues, both would lead to a similar reduction in the overall share of early withdrawals, 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 remains meaningful and significant even 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 effect on wealth (Attanasio et al., 2024). Second, while our baseline specification measures self-control as the principal component of the BSCS, we find that our results are robust to a 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 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; Goodman et al., 2021; Hamilton et al., 2023). These papers document that individuals are more likely to withdraw from their retirement accounts following job loss, divorce, or other adverse shocks. This empirical literature roughly mirrors the "situational view" of illiquidity highlighted by Kaplan and Violante (2014). On the other hand, while there's a growing literature documenting the

[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.

link between preference heterogeneity 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 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 attempt to bring together these two different literatures, first by providing novel evidence on the role of behavioral heterogeneity in explaining demand for liquidity, and second by evaluating the relative importance of situational vs 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.[4] 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. Second, there's growing interest in using retirement accounts to stimulate the economy. Indeed, at least 31 countries allowed early withdrawals or delayed contributions during covid as a way to support distressed households (Madeira, 2024; OECD, 2021). Third, recent research has shown that such policies have a large impact on household spending, see e.g. Kreiner et al., 2019 studying the release of retirement savings in Denmark in 2009 and 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 factors (see e.g. Bateman et al., 2023; Hamilton et al., 2023), to the best of our knowledge, no previous study has evaluated how variation in self-control issues may contribute to early withdrawal.

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 withdrew spent roughly 40% of the withdrawn funds within the first eight weeks after withdrawal. 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 rationalise the behaviour. We take a very different approach, exploiting survey-based measures of preference heterogeneity 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

[4]Similar to us, Goodman et al. (2021) show that early withdrawal is more likely following job separation or other income shocks. We build upon their analysis by also investigating the importance of psychological factors, such as self-control, something which cannot be observed in tax data.

early withdrawals, supporting the interpretation by Hamilton et al. (2023).

Our analysis also complements two recent papers that study the determinants of early withdrawal in Australia. Bateman et al. (2023) conduct a real-time survey and find that self–reported reasons for withdrawal were generally about consumption smoothing: either replacing lost income or precautionary purposes. Respondents to their survey reported that they were *not* motivated by impatience. Preston (2022) documents the importance of numerous factors that contribute to early withdrawal, with a particular emphasis on situational factors (e.g. income or job loss), financial literacy, and gender. She finds that job loss and low financial literacy are important predictors of early withdrawal, similar to our results. We build upon the above studies by evaluating a wide range of behavioral factors that may influence demand for liquidity, documenting which of these factors are most important, and then comparing them to the situational determinants which have already received substantial attention. To the best of our knowledge, we are the first to evaluate the role of self-control issues for demand for liquidity.

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 the degree of heterogeneity in present–bias, nor how this heterogeneity drives differences in early withdrawal decisions. 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 future models. Further, our survey-based approach is complementary to the growing literature that estimates present-bias in life-cycle consumption saving models (Kovacs et al., 2021; Laibson et al., 2024) which generally needs to assume homogeneous preferences to identify the average level of present-bias. We take a very different approach, directly measuring self-control issues using a popular instrument from the psychological literature, then evaluating the implications for observed financial decisions.

Finally, our paper builds upon a large literature that uses survey-based measures of preferences to evaluate the relationship between preferences and wealth. For instance, Ameriks et al. (2003) show that households' propensity to plan is correlated with wealth. Banks et al. (2010) show that individual measures of numeracy and cognitive ability are associated with greater wealth both before and after retirement. Goda et al. (2019) show that survey-based 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 heterogeneity in self-control issues makes a substantial contribution 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. For example, 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) under certain conditions, 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 31 countries implemented policies that allowed for early withdrawal or delayed contributions to retirement accounts during the covid pandemic (Madeira, 2024; OECD, 2021).[5]

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 31 different countries that have implemented such policies. Furthermore, Australia's early withdrawal policy was one of the larger programs of this kind that has already attracted considerable attention in the recent literature.

2.1 Institutional Setting

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). The policy was controversial. Critics, including some personal financial experts and asset management firms, argued that it could undermine retirement security and deplete essential savings. Supporters, such as the government and various consumer advocacy groups, saw it as a necessary measure for immediate financial relief.

Australia's system of mandatory retirement savings, known as superannuation, began

[5] While such policies exploded in popularity during the covid 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).

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 long-term plans to eventually reach 12% by 2025. Superannuation accounts receive substantial tax benefits and are almost entirely illiquid before 'preservation age' (65 for most current workers), with only a few specific exceptions (e.g., financial hardship, compassionate grounds, and terminal illness.) Australia's approach is similar to other countries with mandatory defined contribution systems, such as Canada, with its Registered Retirement Savings Plan (RRSP) and Pension Plan (CPP), and Sweden, which has a Premium Pension scheme.[6]

During the pandemic, 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,[7] the eligibility conditions were relatively broad and covered more than 70% of the working age population (Hamilton et al., 2023). Further, eligibility was entirely self–reported with no independent governmental verification.[8]

While the United States also has mandatory retirement savings in the form of Social Security, the Australian system differs in a few key regards. First, Australia's superannuation scheme is a defined–contribution rather than defined–benefit pension system, meaning that assets and their returns are directly earmarked to individuals, rather than pooled across society. Second, since contributions are mandatory and more uniform across the income distribution, Australia's superannuation 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 income distribution, meaning that voluntary savings are more important for the top of the distribution. Additionally, Australia's version of social security, known as the Age Pension, provides a safety net for retirees based on means testing, complementing the superannuation system. This contrasts with the U.S. Social Security system, which is based on payroll taxes and provides a more uniform benefit level based on earnings history.

[6]While the United States also has mandatory retirement savings, it occurs through Social Security, which is a defined-benefit scheme. In contrast, Australia and many other countries have mandatory retirement savings in defined-contribution accounts (see e.g. Bateman et al., 2001; Beshears et al., 2015).

[7]See Fact Sheet: Early access to superannuation.

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

2.2 Data

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a long-running longitudinal study that collects annual data on income, employment, and wealth from a large sample of Australian households. Initiated in 2001, the HILDA Survey follows a panel structure similar to the Panel Study of Income Dynamics (PSID) in the United States, but with a substantially larger sample size: approximately 17,000 individuals across more than 8,000 households in the most recent wave. The survey collects detailed data on a wide range of variables, including demographics, family structure, employment, income, and wealth holdings. In addition, the HILDA Survey is relatively unique among nationally representative longitudinal surveys in its collection of detailed psychological traits, which have been used by a variety of past studies (see e.g. Todd and Zhang, 2020). We use data from waves 18 to 21 of the HILDA Survey, which was collected between 2018 and 2021. Information on early withdrawals was collected in waves 20 and 21. The Brief Self-Control Survey was conducted in wave 19, between July 2019 and February 2020. In our empirical analysis, we weight using responding person longitudinal weights balanced between waves 18 to 21.

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 superannuation accounts become partially liquid regardless of retirement status.[9] We restrict the sample to individuals who were interviewed in all four waves of the HILDA Survey 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.[10]

Throughout our analysis, we focus on individual level data, given that superannuation accounts in Australia are individually owned and controlled, and the decision to withdraw during covid is an individual decision. Almost all of our variables of interest are mea-

[9] 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.

[10] The SCQ is a 20 page survey consisting of questions that are difficult to administer in a time-effective manner in a personal interview, or which respondents may feel slightly uncomfortable answering in a face-to-face interview. Conditional on meeting our other sample requirements, we find that 94.4% of individuals complete the SCQ. Conditional on completing the SCQ, response rates to the BSCS are quite high, with 97.4% of SCQ respondents in our sample answering all 13 questions of the BSCS.

sured at the individual level, including including self-control and the other psychological variables, with the exception of wealth which is measured at the household level.

Demographics. We 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. We measure income in logs and include a dummy for any individual with missing or zero income.

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, weighted estimates show that 13.8 percent of working-age individuals withdrew from their retirement accounts. 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, in our baseline analysis, we focus on the discrete decision to withdraw, rather than the continuous decision of how much to withdraw.[11]

Self-Control. There are two distinct approaches to measuring self-control. 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 which relies upon survey-based measurement. One of the main benefits of this approach is that it can be embedded in large-scale household panel surveys which 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.

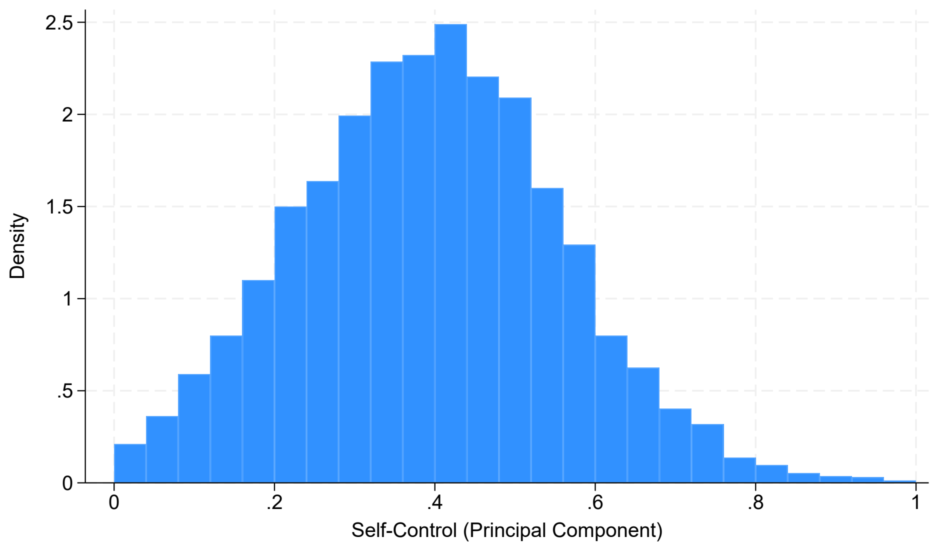
In 2019, HILDA survey participants were asked to complete the well-established Brief Self-Control Scale (BSCS), which is widely used in the psychological literature, and consists of 13 targeted questions on impulse control and goal adherence. Established by Tangney et al. (2004), the scale is designed to measure self-control—"the capacity to regulate attention, emotion, and behavior in the presence of temptation"—by asking respondents to score on a Likert scale of 1 to 5 how much a series of 13 statements applies

[11] Analysis using the amount withdrawn yields similar results to our baseline analysis.

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 found that this scale shows good internal consistency and retest reliability (Tangney et al., 2004; Bertrams and Dickhäuser, 2009). Further, research using this scale has shown 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 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.[12] 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 correspond to full self-control issues. Appendix A.1 shows the full list of items, the distribution of responses, and the estimated factor loadings. Figure 1 shows the distribution of the first principal component 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 and standard deviation of 0.16. The distribution is positively skewed (0.15) with a long right tail.

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. We do not assume ex-ante which of the psychological traits are most

[12]We experimented with including an additional factor in our empirical analysis, but found that it did not meaningfully change the results, and that only the first factor had a significant correlation with early withdrawal.

important; instead, we include all traits in our empirical analysis and test which have significant explanatory power.

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, Extraversion, Agreeableness, and Neuroticism – are measured through a series of standardized questions. Recent research 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).[13]

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 has the option of choosing: (1) next week; (2) next few months; (3) next year; (4) next two to four years; (5) next five to ten years; and (6) more than ten years ahead. While planning horizon is not a perfect proxy for time preference, planning horizon is often used as a proxy for time preference when a direct measure does not exist in the data (see e.g. Barsky et al., 1997; Brown and Van der Pol, 2015; Samwick, 1998), and past research has shown that planning horizon is correlated with time preference (Adams and Nettle, 2009).[14]

Wealth. The HILDA Survey collects detailed data on household wealth through approximately 20 to 30 specific questions, covering a wide range of asset and liability categories. This includes information on real estate, financial assets, vehicles, business investments, and various 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, collected in 2018.

In our analysis, we divide wealth between three categories: liquid, illiquid excluding superannuation, and superannuation. Liquid wealth is defined as the sum of household cash holdings, equity investments, own bank accounts, joint bank accounts, and children's bank accounts, net of credit card debt and overdue bills. Illiquid wealth is defined as the sum of housing, other property, businesses, vehicles, and collectibles, net of mortgages and

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

[14] Adams and Nettle (2009) show that planning horizon and discount rate, measured using hypothetical trade-offs over time, 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 to be associated with length of planning horizon. We therefore control for income, wealth, and age in our empirical analysis.

other debt. Superannuation wealth includes all wealth held in superannuation accounts. Since wealth is measured at household level, while all other variables of interest are measured at the individual level, we cluster our standard errors at the household level.

In our full specification, 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 individuals with higher mortgage payments. That said, we find no evidence of such an effect.

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 the 2020 or 2021 waves of the survey.[15] Based on this measure, roughly 14 percent of our sample experienced unemployment during this period, which is slightly higher than usual given the pandemic. Second, we measure pandemic-induced negative 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 who were in paid employment as of March 2020. In our sample, 17.6 percent of individuals reported a decrease in income due to the pandemic.

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 different observable characteristics, such as self-control or adverse shocks. We then explore the marginal effect of each of these variables in a regression specification in Sections 3.2 and 3.3, and quantify their relative 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, which shows all these relationships are in the directions one would expect—early withdrawal is more common among people with greater self–control issues, shorter planning horizon, fewer assets, and lower income, as well as those who suffered adverse shocks during the pandemic.

[15] We also experimented with a more granular measure of unemployment based on the percent of the year unemployed, but found it did not substantially alter our results.

Focusing first on the behavioural 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. Similarly, Figure 2b shows that shorter planning horizons are also correlated with a higher probability of early withdrawal, with individuals with shorter planning horizons much more likely to withdraw. Both of these behavioural measures are likely correlated with other variables—shorter planning horizons and less self–control could both, for example, lead to less wealth accumulation or different labour market decision. It's therefore difficult to draw strong conclusions based on the unconditional correlations alone, and we investigate the conditional relationships in Section 3.3.

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).

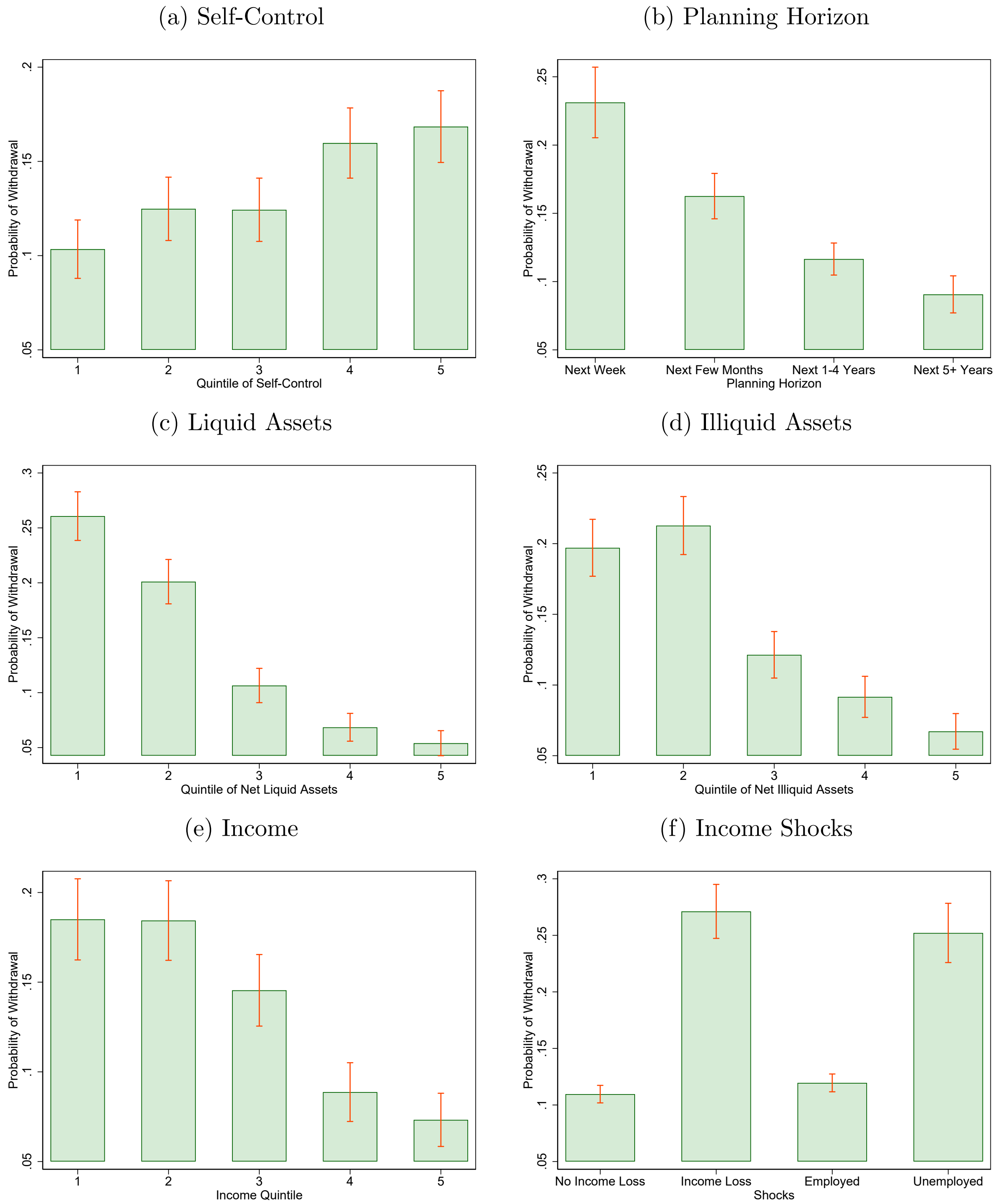
Figures 2e and 2f show how early withdrawal varies with income and income shocks. The probability of early withdrawal is highest for individuals in the bottom 40 percent of the income distribution, adjusted for age, and declines gradually for higher income individuals. Further, the probability of early withdrawal is substantially higher for those who have experienced adverse shocks, such as a pandemic related loss of income or unemployment. Such shocks, while relatively rare in the population, appear to be strongly correlated with early withdrawal.[16] Such correlation should not be a complete surprise, since eligibility for early withdrawal was technically limited to individuals who had suffered a reduction in work hours, loss of employment, or reduction in turnover, although past research shows that this policy did not have a binding effect on early withdrawal behavior.[17] The importance of income shocks broadly lines up with the existing literature, e.g. Choukhmane et al. (2023) who find that those who experience larger income declines are more likely to take a withdrawal.

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 Hamilton et al. (2023), which may reflect the fact that these individuals have already had a few years to accumulate wealth in their retirement

[16] In our sample, 17.6 percent of individuals suffered a pandemic related loss of income, while 14.0 percent of individuals suffered unemployment in 2020, substantially higher than usual due to the pandemic.

[17] As noted in Section 2.1, eligibility was widespread, self-reported, and not verified. The presence of such rules, however, may still have deterred some individuals from withdrawing.

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



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.

account, but are still relatively constrained compared to their older counterparts. Turning to financial literacy, we see that individuals with high financial literacy are substantially less likely to withdraw, similar to Preston (2022). More specifically, individuals who have correctly answered all of the “Big 3” financial literacy questions are 8 percentage points less likely to withdraw than those who have not.

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 the 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 13 question Brief Self-Control Scale discussed in Section 2.2, 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. Finally, 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.

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). Overall, we find that both situational and behavioral factors are significantly correlated with early withdrawal. Further, self-control is the most important of the different behavioral factors we consider.

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, even when controlling for demographics, shocks, personality, and wealth. 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.[18] As we move through the specifications, adding controls for adverse shocks (2), then be-

[18]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.

havioral factors (3), and then 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.[19]

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 (the latter of which are left to Appendix A.3 for brevity.) We find that financial literacy is correlated with a 4.2 percentage point reduction in the probability of early withdrawal, although this relationship is nearly halved once we control for wealth in Column 4.[20] Further, we find that individuals with longer planning horizons have a lower probability of early withdrawal. This effect disappears when we control for wealth, however, suggesting that the effect of shorter planning horizons on early withdrawal is mediated mainly through reduced wealth. Finally, we also evaluate the role of the big five personality traits, which have been shown to be important in various other areas of economic behavior (see e.g. Almlund et al., 2011; Borghans et al., 2008; Heckman et al., 2021; Todd and Zhang, 2020). We find that greater emotional stability reduces the probability of early withdrawal, but that none of the other big five traits have a significant effect on early withdrawal. Overall, of all the psychological measures we consider, self-control remains the most important determinant of early withdrawal.

In line with the existing literature, we also find that situational factors play an important role in predicting early withdrawal. More specifically, unemployment and pandemic-related negative income shocks increase the probability of early withdrawal by 5.8 and 19.0 percentage points respectively. We find that the average marginal effect of self-control lies somewhere between these two estimates, at 8.6 percentage points in specification 4. 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.

[19] 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.

[20] 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, we also find that wealth is an important predictor of early 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, with the latter having a smaller and less precise AME (in line with 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 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 of wealthy hand-to-mouth behavior driven by standard preferences, where the MPC declines rapidly with the size of the transfer, 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 which 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 early withdrawal, 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 support recent analysis by Goda et al. (2019), who predict individual retirement wealth 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 and more withdrawals. While the setting in that paper differs from ours—contributions in the US are not mandatory, nor are withdrawals banned (they simply attract a 10% withdrawal penalty)—our results support the idea that present–bias is likely to contribute to greater leakage from retirement accounts (Goodman et al., 2021).

Our results on financial literacy also complement recent work by Preston (2022), who explores the determinants of early withdrawal in Australia. That study explores the relationship between early withdrawal and measures of situational factors, financial literacy, as well as a battery of demographic controls, and breaks these estimates out by the respondent's sex. The paper establishes great importance of situational factors—people were more likely to withdraw if they were financially fragile, in insecure employment, lone parents, lower income and in rental accommodation. And it explores explores the role of financial literacy, finding that illiteracy was associated with a higher propensity to withdraw. Our work complements this by broadening the scope of behavioural determinants to include self–control and other measures. We show that of these behavioral determinants, only self–control measures are robustly and directly related to withdrawal propensities. That is, whilst things like financial literacy are likely important for wealth accumulation and other choices, they drive demand for liquidity only indirectly.

3.4 Aggregate Implications

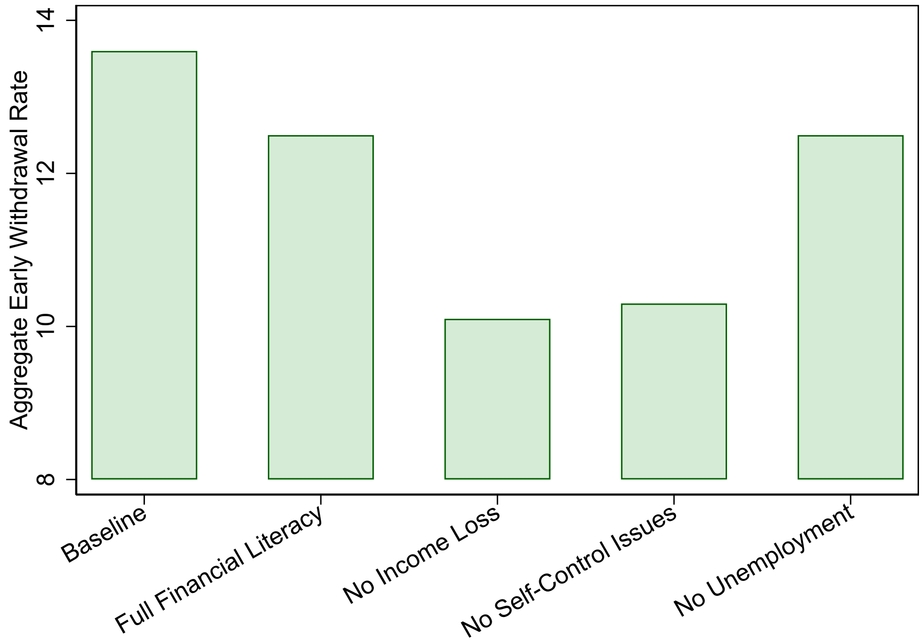
What do the individual level results in Table 1 imply at the societal level? To what extent is the aggregate propensity to withdraw from retirement accounts driven by psychological vs situational factors? To estimate the aggregate importance of these different factors, we need to think about how the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

Figure 3 shows the overall share 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 contribution to early withdrawal. 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.

Overall, we find that self-control accounts for a similar share of early withdrawals as pandemic-related negative income shocks. While negative shocks have a much stronger AME, they are relatively concentrated among a few households; by contrast, self-control issues cause smaller effects but are much more widespread across households, and the net effect is about the same. Roughly 17.6 percent of individuals in our sample were affected by negative income shocks from Covid–19. If we were to eliminate such income losses, 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 households, while holding all other covariates fixed, we would predict the early withdrawal rate to decline by 3.3 percentage points.

In contrast, we see that self-control and negative income shocks both account for

Figure 3: Aggregate Implications



a larger share of early withdrawals than unemployment or financial illiteracy. When we eliminate all unemployment in our model, 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 assume that all households were financially literate, the predicted early withdrawal rate would only lower by 1.3 percentage points, a much smaller effect than many of our other covariates.

The relative importance of self-control compared to financial literacy is consistent with recent research by Goda et al. (2019) who predict individual retirement wealth across US households and find that present bias is a more important predictor 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 the important trade-off policymakers face: balancing the need to provide individuals with access to liquidity during adverse situations while also ensuring that those with self-control issues 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.

In this paper, we examine the 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. Further, 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 that a standard fiscal transfer might. But it is attended by the fear that people who lack self–control will be more likely to draw down their nets–eggs beyond the need that their current circumstances dictates. We find that this is indeed a well–founded fear.

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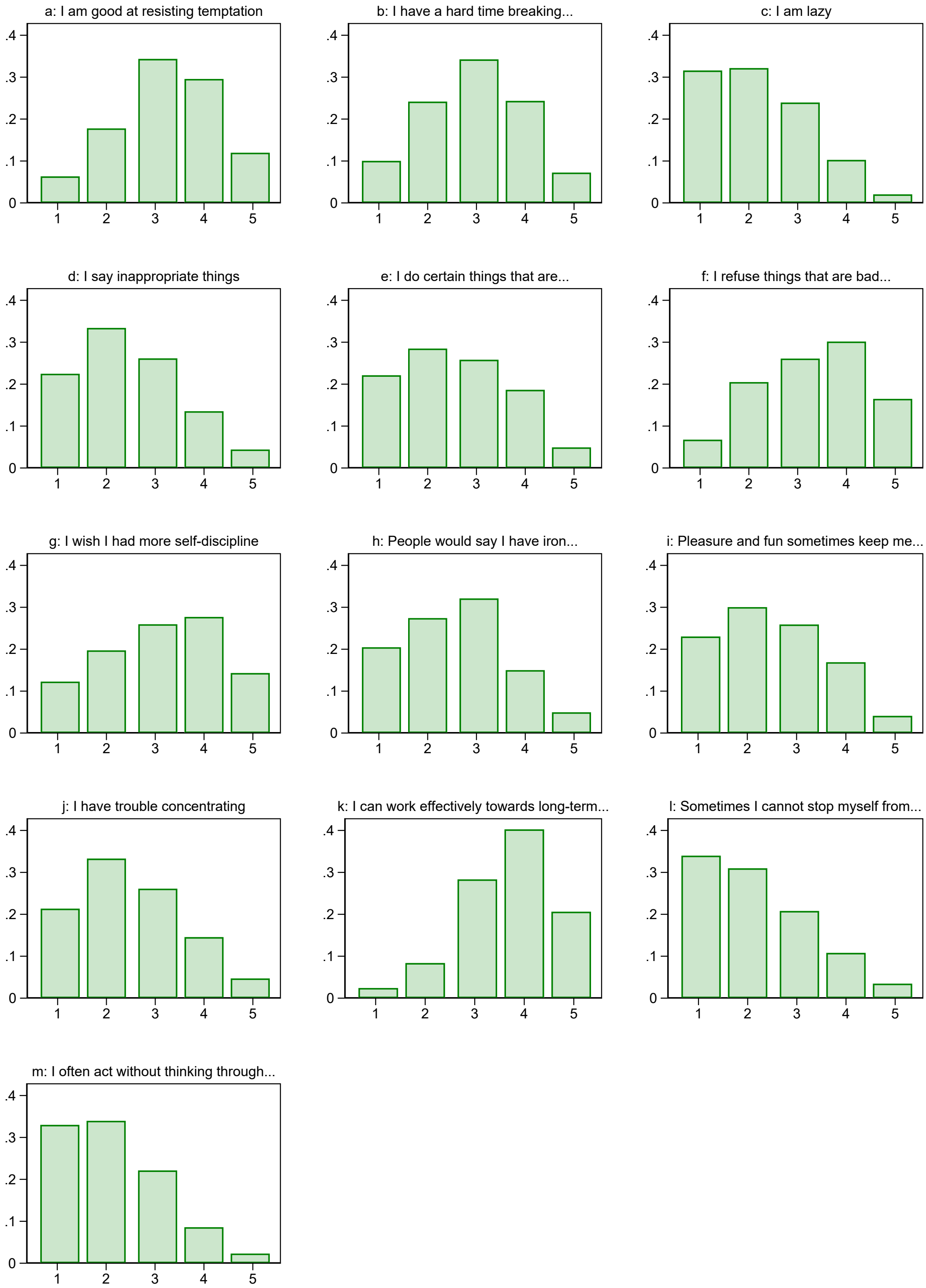
A Appendix

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").

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

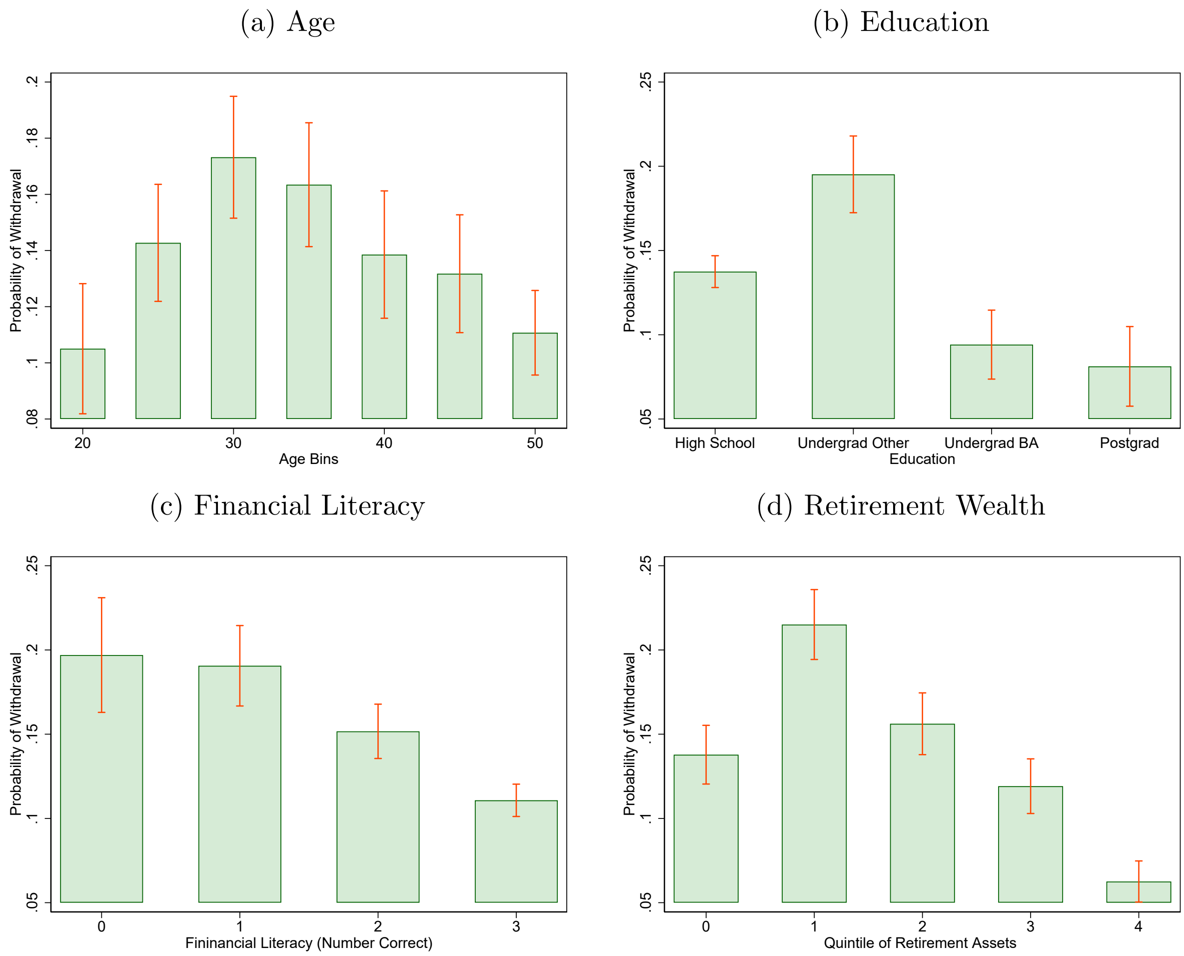
A.2 Summary Statistics

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.

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.

Figure 5: Probability of Early Withdrawal



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.

A.3 Empirical Analysis

Table 3 reports the marginal effects for the full set of covariates included in our empirical specification, including a number of covariates which were omitted from Table 1 for the sake of expositional clarity.

Education initially appears to be an important predictor of early withdrawal in specification 1, although we find that most of this effect disappears once we include additional controls for wealth in specification 4. Further, although age appeared strongly correlated with early withdrawal in Figure 5, age is not an important predictor of early withdrawal once we control for other factors.

While the "Big Five" personality traits have been shown to be an important predictor of labor market outcomes, we find that these traits are relatively unimportant for early withdrawals. Of the big five traits, only emotional stability has a significant relationship, with greater emotional stability being correlated with reduced withdrawals.

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)
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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$