

# Supplemental Appendix to: Self-Control and Early Withdrawal from Retirement Accounts

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## A Supplemental Appendix

### A.1 Brief self-control Scale

Figure 1 shows the distribution of responses to the 13 items included in the Brief Self-Control Scale. Respondents are asked to rate how well each statement describes them, with responses ranging from 1 (“not at all”) to 5 (“very well”).

We use Principal Components Analysis (PCA) to reduce variation in the 13 BSCS items to one dimension. 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, the estimated factor loadings, while relatively broad-based, are largest for items related to temptation and impulsive behavior.

Table 1: 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

Response rates for the Brief Self-Control Scale are high. The 13 questions are included in HILDA’s self-completion questionnaire (SCQ), which is a 20 page survey consisting of a variety of questions that are difficult to administer quickly 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.

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  $\beta$  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

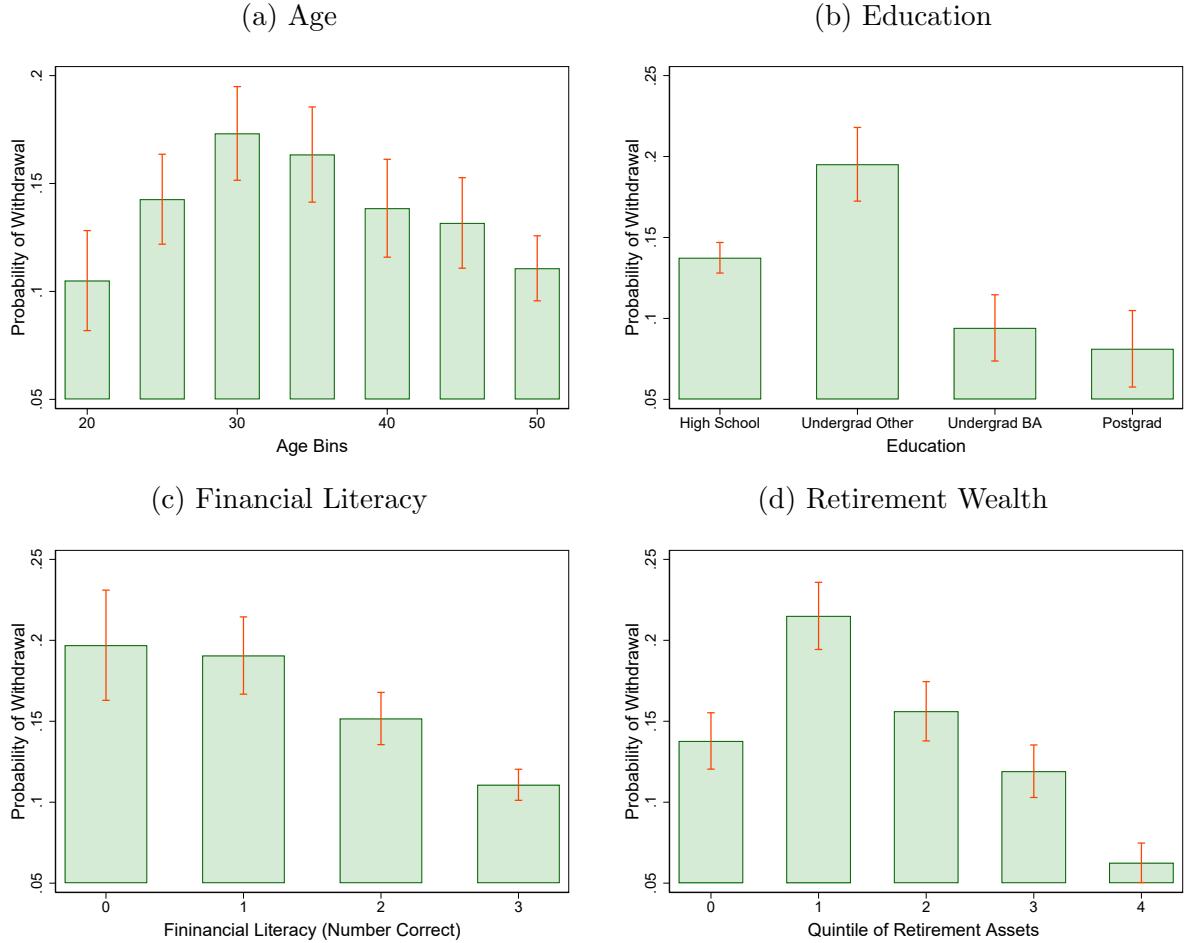
Table 2 reports averages for all of our control variables in aggregate, and comparing withdrawing and non-withdrawing respondents.

Table 2: Summary Statistics

	No Withdrawal 6,538 (86.2%)	Early Withdrawal 1,047 (13.8%)	Total 7,585 (100.0%)
Unemployed			
0	87.9%	74.5%	86.0%
1	12.1%	25.5%	14.0%
incomeChangeCovidTrunc			
Not Decreased	85.1%	65.4%	82.4%
Income Loss from Covid	14.9%	34.6%	17.6%
Financial Literacy			
0	44.1%	56.5%	45.8%
1	55.9%	43.5%	54.2%
Self-Control Issues	0.390	0.423	0.394
bscs (standardized)	-0.003	0.213	0.027
Scores for component 1 (standardized)	-0.001	0.204	0.027
Age	39.210	38.305	39.085
educBins			
High School	67.5%	67.1%	67.4%
Postgraduate	7.3%	4.0%	6.8%
Undergraduate Bachelor	10.9%	7.1%	10.4%
Undergraduate Other	14.4%	21.8%	15.4%
male	0.450	0.489	0.455
Income	77,625.840	58,345.173	75,021.767
netLiquidWealth	79,730.663	29,160.334	72,750.158
netIlliquidWealth	608,484.840	309,511.091	567,215.820

Figure 2 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 2: 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.

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.

### 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 the paper 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 2, 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).<sup>1</sup> 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*** (0.036)	0.13*** (0.034)	0.11*** (0.036)	0.086** (0.034)
Log Income	-0.035*** (0.007)	-0.022*** (0.006)	-0.016*** (0.006)	-0.0097 (0.006)
Postgraduate	-0.055*** (0.020)	-0.052*** (0.018)	-0.041** (0.019)	-0.034 (0.022)
Undergraduate Bachelor	-0.051*** (0.017)	-0.046*** (0.017)	-0.038** (0.017)	-0.031* (0.017)
Undergraduate Other	0.035* (0.019)	0.033* (0.019)	0.031* (0.018)	0.019 (0.017)
Children: 1	0.070*** (0.024)	0.078*** (0.025)	0.069*** (0.024)	0.060** (0.023)
Children: 2	0.067*** (0.020)	0.067*** (0.020)	0.064*** (0.020)	0.055*** (0.019)
Children: 3+	0.11*** (0.022)	0.11*** (0.021)	0.10*** (0.020)	0.085*** (0.019)
agebins=30	0.016 (0.027)	0.015 (0.027)	0.019 (0.025)	-0.00085 (0.025)
agebins=40	-0.021 (0.024)	-0.020 (0.025)	-0.0074 (0.023)	-0.012 (0.023)
agebins=50	-0.043* (0.023)	-0.042* (0.024)	-0.025 (0.023)	-0.017 (0.023)
male	0.033** (0.013)	0.027** (0.013)	0.033** (0.013)	0.033*** (0.013)
hasPartner	-0.028* (0.016)	-0.021 (0.016)	-0.017 (0.015)	-0.0034 (0.015)
incomeMissing	-0.41*** (0.076)	-0.27*** (0.070)	-0.21*** (0.064)	-0.15** (0.064)

<sup>1</sup>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.

Income Loss from Covid	0.19*** (0.023)	0.18*** (0.021)	0.19*** (0.021)
Unemployed	0.068*** (0.016)	0.066*** (0.015)	0.058*** (0.016)
Financial Literacy		-0.042*** (0.013)	-0.028** (0.012)
Planning Horizon: Few Months		-0.031* (0.018)	-0.012 (0.017)
Planning Horizon: 1-4 Years		-0.058*** (0.018)	-0.023 (0.016)
Planning Horizon: 5+ Years		-0.065*** (0.020)	-0.023 (0.019)
Big Five: Extroversion	0.016 (0.014)	0.016 (0.014)	
Big Five: Agreeableness	0.0082 (0.018)	0.014 (0.018)	
Big Five: Conscientiousness	0.014 (0.017)	0.021 (0.017)	
Big Five: Emotional stability	-0.033** (0.017)	-0.033** (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
Demographics	Yes	Yes	Yes
Adverse Shocks		Yes	Yes
Psych Controls			Yes
Wealth Controls			Yes

Standard errors in parentheses

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

## References

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Figure 1: Brief self-control scale questions and answers

