PIER
PENN INSTITUTE *for* ECONOMIC RESEARCH
UNIVERSITY *of* PENNSYLVANIA

The Ronald O. Perelman Center for Political Science and Economics (PCPSE)
133 South 36th Street
Philadelphia, PA 19104-6297

pier@econ.upenn.edu
http://economics.sas.upenn.edu/pier

PIER Working Paper
23-019

Future Orientedness

JOHN KNOWLES
Simon Fraser University

ANDREW POSTLEWAITE
University of Pennsylvania

October 2023

Future Orientedness*

John Knowles† Andrew Postlewaite‡

October 2023

Abstract

We develop an index of "future orientedness" based on how an individual's attitudes to planning for the future, reported in the PSID in the 1970s, predict the growth rate of household wealth many years later. Our results suggest that variation in future orientedness is more about effective planning than about discounting the future. Wives appear to have much less influence than husbands over household savings but transmit future orientedness to offspring more reliably. Variation in future orientedness is distinct from financial sophistication or opportunity, as it also helps to predict non-financial choices, such as smoking, health and the timing of children. Simulation of the cumulative effects over the lifetime suggests that variation in future orientedness increases inequality of wealth at retirement, boosting the Gini coefficient by 10-20%.

Keywords: Family Economics, Inequality, Household Formation, Household Economics.
JEL Classification: D10, D19, D31, D80, D83, H31, H52, I24, J11, J12, J18

*This is an update of an earlier TIAA-institute working paper with the title "Do Children Learn to Save From Their Parents?". Knowles gratefully acknowledges support from Social Sciences and Humanities Research Council (SSHRC) Grant # 435-2018-0111. Postlewaite gratefully acknowledges support from National Science Foundation Grant #SES 0095768. We are also grateful for funding from the Boettner Center for Pensions and Retirement Security at the University of Pennsylvania. We wish to thank Jess Benhabib, Bertille Antoine, Joachim Hubmer, Jerry Jacobs, Dirk Krueger and Petra Todd for helpful conversations and Lucie L'Heudé for excellent research assistance.

†Department of Economics, Simon Fraser University, 8888 University Drive, Burnaby, B.C. Canada V5A 1S6. jaknowle@sfu.ca

‡Department of Economics, University of Pennsylvania, Perelman Centre, Philadelphia, PA. apostlew@upenn.edu

1 Introduction

To arrive at retirement age with the optimal amount of savings requires a household to both formulate a long-term consumption/savings plan and also to stick to that plan over many years. While standard neo-classical models assume that agents costlessly implement the optimal savings/consumption program, various models of time-inconsistent behaviour have been proposed to explain why households might not stick to a plan. However, it is difficult empirically to distinguish such deviations from a long list of standard reasons that the optimal amount savings might vary across households and over time.

Furthermore, it is possible that the sources of both types of variation lie deeper in the psyche; variation in parameters as well as deviations from optimality may well arise from the attitudes of different personality types with regards to trade-offs between the present and the future. Recently the literature on social mobility has argued for the role of innate differences arising from family culture or genetics as contributing to inequality of various forms. Empirical studies discussed below suggest that such innate differences contribute to wealth inequality that may persist across many generations.

In this paper, we loosely define "Future-Orientedness" as the collection of personality traits that contribute to observed variation across individuals in inter-temporal decisions, whether due to preferences or other personality traits. This of course raises a well-known empirical problem: how to distinguish the effects of an unobservable quality such as future-orientedness from other potential explanations of savings inequality? This is impossible on the basis of observed behavior alone, the preferred method of the economics literature, so we take a more sociological approach that relies on survey questions about planning for the future.

We exploit a series of questions related to attitudes about the future that the Panel Study of Income Dynamics (PSID) asked householders in the early 1970s. Examples of the questions are "Would you rather save more for the future or spend your money and enjoy life today?" and "Are you the kind of person that plans his life ahead all the time, or do you live more from day to day?" The data include many married couples with separate responses for each spouse. It is not clear, however, whether these responses reflect permanent personality characteristics, or whether they are related to savings behaviour.

Fortunately, the PSID has continued to follow these individuals, and since the 1980s has regularly measured household net worth and its constituent assets and debt. This allows us to measure the predictive power of the attitude responses for the growth rate of each household's savings, using regression analysis to control for income, initial wealth and other relevant variables, such as education and employment status. This exceptionally large time lag between the attitude responses and the wealth measurement is a key feature of our empirical strategy as it rules out the possibility that attitude reports are tainted by the individual's recent financial experiences.

We find statistically-significant effects of the responses to the questions on household savings of married couples a decade or more later (between 1984 and 1999)[1]. We use the resulting coefficient estimates to create a single-digit Attitude Index (AI) for each spouse, equal to the predicted effect of the attitude responses on the household savings rate.

We use this index to show that the attitudes of husbands have roughly twice the effect on savings as that of their wives, and that the effects of each spouse are close to additive. We take this latter point as evidence against the view that the effect of the AI is driven by financial acumen or opportunities; that would suggest a Leontieff-type effect where only the spouse with the highest AI matters for savings. In fact, we find no systematic difference in the strength of the smaller AI from that of the larger AI of each couple. This suggests that AI variation is not simply a reflection of variation in financial opportunities, whether due to sophistication or to personal networks.

We then compute the household AI, from the joint effects of both spouse's responses. We find that this household index is strongly related to the attitudes to planning but not to the questions that relate most closely to economic theories of savings differences, such as "Do you prefer to spend now or save for the future?", which we consider to reflect variation in inter-temporal discounting, or "Do You Finish Things", which suggests variation in time consistency of preferences. The effects of these latter variables are essentially unrelated to our measure of savings. We infer from this that variation in future-orientedness is more about variation in planning for the future than about preferences.

We also propose a more direct way to distinguish the effects of future-orientedness from those of associated differences in financial sophistication: by asking whether AI also helps to explain other inter-temporal outcomes, where financial sophistication does not play a role.[2] We find that married people with low AI are more likely have been smokers, and that among men who smoke, those with low AI are less likely to quit smoking. We also show that AI predicts a higher rate of physical exercise, but even controlling for this, as well as for education, smoking history and for BMI years earlier, we find that AI is strongly predictive for the health of both men and women, with similar magnitudes of the effect by sex. We take these results as supportive of the hypothesis that our measure of future-orientedness reflects variation in permanent and deep-seated personality traits that govern a wide range of inter-temporal behavior.

We use two methods to measure the effect of our estimates of heterogeneity in future-orientedness on inequality of wealth at retirement. First, we consider two otherwise-identical households, above and below the mean of household AI by one standard-deviation. By compounding over 40 years the effect of the AI on savings, we show that the terminal wealth of the high-AI household is higher by the amount of one-year's income than that of the low-AI household. Second, we simulate a cohort of married households whose distribution

[1]We restrict the sample to married couples in order to avoid dealing with potentially confounding differences in household structure and marital histories.

[2]For non-savings results, we use a broader sample consisting of everyone who answered the attitude questions in the 1970s.

over income matches both the Gini coefficient and the Markovian transition matrix for US income, as reported by Diaz-Gimenez et al. [2011]. We compare the Gini coefficient for wealth at retirement for an economy with permanent heterogeneity in household AI to one without. We find that the effect of AI on savings alone generates an increase on the order of 10-20% in the wealth Gini.

The presence in the PSID sample frame of all offspring of PSID respondents allows us to measure transmission of future-orientedness across generations by estimating the association between the parental AI and the savings of the adult offspring in the years since 2001. Our results suggest that offspring inherit at least some of their parent's future-orientedness. One might argue, however, that it is the parent's financial acumen that is being shared with offspring households. However we find that the parental AI also has non-financial effects: offspring of high-AI parents are less likely to marry as teenagers, are less likely to have children before age 21, and, among those who marry, those with higher maternal AI are less likely to divorce (even after controlling for age at marriage). The likelihoods of self-employment and business-ownership both appear to be increasing in household AI: we find that households in the top AI quartile are 50% more likely to own a business than those in the bottom quartile, and the husbands twice as likely to be self-employed. Parental AI however does not present any clear pattern with respect to the offspring's self-employment or business-ownership. But when controlling for other variables, a statistically significant effect of parental AI becomes apparent; the effect of maternal AI on the son's ownership of an incorporated business is large (about 1/4 of the effect of parental business ownership), while the smaller effect of paternal AI is entirely explained by parental business ownership. For daughter's business ownership, there is no robust effect of parental AI. These results suggest both weaker effects of wive's AI on business ownership and stronger transmission of maternal than paternal AI to succeeding generations.

2 Related Literature

Our work contributes to a thriving macroeconomics literature on the sources of household wealth inequality, dating back to the seminal finding, by Aiyagari [1994], that the neoclassical model of savings could not explain why the US wealth distribution was so much more skewed than the income distribution: the wealthiest households save too much, the median (and poorer) households not enough. In an early attempt to resolve this problem, Krusell and Smith [1998] showed that the concentration of wealth could be explained by dynastic wealth accumulation in the presence of discount-factor heterogeneity that was transmitted imperfectly to offspring. The problem was that empirical micro studies did not offer much support for the view that discount-factor heterogeneity explains variation in savings.[3]

[3]Dynastic savings were also important in Castaneda et al. [2003], who further argued that the US wealth distribution could be replicated by the model with more accurate measurement of earnings uncertainty among the richest households. However Benhabib et al. [2019] showed, using administrative data, that the

For example, Ameriks et al. [2003] designed survey questions to measure individuals' discount rates, risk aversion and planning. They found that the standard discounting model did not predict well the wealth accumulation for their sample. They found instead that planning-related differences did better in predicting saving.

Our results reconcile these views: our estimates satisfy the basic restrictions implied by a generic neo-classical model of savings with discount-factor variation, but with the caveat that the parameter is better interpreted as planning-related heterogeneity outside the model.

More recent papers have focused on models in which business ownership generates extreme wealth concentration among the richest households. Benhabib et al. [2019] and Hubmer et al. [2021] stress the importance of stochastic idiosyncratic returns to wealth, while De Nardi and Fella [2017] emphasizes the contribution of the correlation of entrepreneurship across generations. We have little to say about the very rich since they are not in our data, but we show that our measured effects of future-orientedness are not explained away by business ownership. Moreover, we also find that the offspring of highly future-oriented people are more likely to become business owners, even after controlling for education and parent's business ownership.

Much of the apparent under-saving by US households with below-median wealth could also be explained within the model, by accounting for the incentives implied by government programs or by medical insurance, as shown, respectively, by Scholz et al. [2006] and Hubbard et al. [1995]. However, the most influential approach consists of attributing under-saving to households either failing to devise an (ex ante) optimal savings plans or, alternatively, deviating from such plans. The first case may arise due to a lack of financial expertise or acumen, as argued by the papers reviewed in Lusardi et al. [2017], or due to inconsistent preferences, as in Choi et al. [2014], who find a strong positive association between wealth and rationality. Our results are consistent with variation in financial expertise or acumen, but suggest that this is itself the effect of deeper personality differences, perhaps related to rationality. Barth et al. [2020] uses genome data to argue a genetic basis for financial sophistication, but this does not rule out a genetic basis for personality differences that in turn generate financial sophistication.[4]

In contrast, it is often argued that households that plan, often have trouble sticking to the plan. Laibson [2015] argues that it is often costly for people to commit to plans they might make, and Bernheim et al. [2001] argue that "rules of thumb" or other less than

degree of income inequality among the richest households falls far short of what the model needs to explain wealth inequality.

[4]Like our paper, much of this literature relies on survey data to identify personality differences in householders. For instance, Lusardi [2000], using survey data from HRS finds that households differ in the degree to which they have thought about retirement, and that those households that think more about retirement have substantially higher wealth than those that have given less thought. A problem with this approach may be endogeneity: lack of wealth causes people not to think about the future. Our paper is relatively robust to this issue because we rely on saving rates measured many years after the attitudes are reported.

fully rational decision processes, including behavioral rules, are more consistent with their findings. See Cronqvist and Siegel [2014] for a survey of the literature on behavioral biases in finance. Twin studies have shown that genes play a nontrivial role in explaining financial behavior such as savings and portfolio choices (Cesarini et al. [2010] Cronqvist and Siegel [2014], Cronqvist and Siegel [2015]).

Flechtner [2023] surveys the literature on "under saving," and argues that much of the empirical literature mistakenly categorizes some observed behaviors as "under saving" that may in reality be optimal. Since saving is a household outcome, it's possible that married couples, though fully rational individually, fail to follow the optimal joint savings program when their interests conflict, perhaps due to the threat of divorce. In theoretical terms, married couples may be unable to commit to a complete state-contingent dynamic contract.

This view is supported by the empirical analysis of Voena [2015], who finds that switching from equal-division to unilateral divorce laws affects both the savings rates of married couples and the allocation of resources between spouses. The PSID attitudes survey allows us to bypass this issue because it identifies planning issues at the individual spouse level.

Our finding that attitudes can help to explain savings rate variation is closely related to Hurst [2003], who uses the PSID attitude responses to measure the connection between being a planning type of person and household savings. He notes that householders with lower pre-retirement wealth are much less likely to report themselves to be planners. Almenberg et al. [2021] provides a novel survey that includes attitudes toward debt, and relate those attitudes to savings behavior. Interestingly, they also study intergenerational transmission of debt attitudes by asking survey respondents about their parents' attitudes toward debt. We view these attitudes as being related to the personality characteristics captured by our AI.

Parent-child transmission of future-orientedness is a plausible mechanism for explaining inter-generational wealth correlations. On the basis of PSID wealth data for 1984-1999, Charles and Hurst [2003] find the elasticity of child wealth with respect to parental wealth to be 0.37. Using Norwegian data, Fagereng et al. [2021] finds a wealth elasticity of 0.57 for biological offspring, and 0.25 for adoptees, suggesting an important role for genetic transmission but also for other influences, perhaps cultural or financial.[5]

Clark and Cummins [2015] argues for similar wealth elasticities, around 0.6, on the basis of UK family trees and probate data. But Clark [2014] argues for a significantly higher number, around 0.8, on the basis of the surprising persistence of wealth observed across multiple generations in the UK. Benhabib et al. [2022] argues that to explain such high persistence of wealth across generations requires transmission of a family-specific effect,

[5] In an earlier attempt at uncovering inter-generational links in savings Knowles and Postlewaite [2005], we analyzed the inter-generational correlation of the regression residual in household savings rates. Our current paper can be seen as building on the previous paper by focusing on the role of personality as evidenced by the attitude responses, and by reliance of the estimation on an additional 20 years of wealth data.

probably cultural, that allows some families to obtain higher rates of return on wealth.[6] However the importance of family-specific effects is also apparent in the absence of such material advantages. For instance, Clark [2014] finds that descendants of the Swedish aristocracy are more likely to be professionals today, even though they lost most of their legally-enshrined advantages as of 1680, and the remainder by 1860. Similarly, Alesina et al. [2020] finds that, despite having parents who were no more prosperous or educated than average, the grandchildren of China's pre-revolutionary elite are not only more prosperous today than their peers, but also more likely than their peers to attribute economic success to working long and hard.

The mechanism underlying these long-term family effects may be cultural, as suggested by the results of Fuchs-Schündeln et al. [2020], which finds second-generation immigrants from countries that put strong emphasis on thrift or wealth accumulation tend to save more, or genetic, as implied by the findings of Barth et al. [2020] regarding financial acumen. Our paper does not take a stand on this, but our results suggest that at least some of the transmission is cultural, as we reject the symmetry by sex implied by the linear genetic model.[7]

In closing this section, we note that some agents with high AI may not behave as one would expect. For example, agents, particularly those with low income, may not choose what seem to be good investments (e.g., health expenditures) because of liquidity constraints, and not an absence of future orientedness.[8] This essentially just adds noise to the predictions one makes on the basis of AI. Robson et al. [2020], shows how children's "self-regulation", a compendium of personality traits, of which self-control is an important ingredient, is predictive of outcomes at later ages.

3 PSID Attitude Survey

Each year from 1968 through 1972, the PSID asked the household head a series of questions concerning efficacy and planning.[9] The responses are coded as five-point Likert scales, which reflect the degree of agreement with one or the other of two

We isolate six attitude questions that are plausibly pertinent to savings decisions. For instance, the text of one question, shown in Table 1 as "Plans Ahead", reads "Are you the kind of person that plans his life ahead all the time, or do you live more from day to day?". Almost all respondents answered either 1, indicating they strongly agree that they are the kind of person that plans ahead, or 5.

Similarly, another question, shown in Table 1 as "Prefers to Spend Rather than Save", asks "Would you rather spend your money and enjoy life today, or save more for the

[6] See also the references in this paper.

[7] An alternative interpretation of the asymmetry we find is that issues of intra-household allocation generate sex-specific biases in parent-child correlations.

[8] Kremer and Glennerster [2011] surveys this issue.

[9] Details of the choice of these questions can be found in Veroff et al. [1971]

future?". Again, most people answer 1 or 5, but this time there are 17% of the sample who "want to do both". To avoid issues related to non-linearity in the response, we re-code the raw responses to each question into a binary variable: one if the response is above the PSID average, zero otherwise. In the cases of household heads, for whom there were as many as 4 years of responses, we took as the response the individual's average for the question.

Note that for "Prefers to Spend Rather than Save", an answer of 1 indicates less interest in saving for the future, and thus less future-orientedness, while for "Plans Ahead" an answer of 1 indicates a higher tendency to plan, and thus more future-orientedness. To ensure consistency of interpretation, we further re-code the variables so that a 1 indicates more future orientedness[10]. As Table 1 shows, most people consider themselves better described by the future-oriented option, except that people are evenly split on whether they prefer to save. However, the share of the sample who consider themselves better described by the other option is above 20% in each case, typically above 35%.

Table 1: Attitude Questions and Responses

Life Works Out		
1	45.48	Usually been pretty sure.
5	38.4	More times when not very sure about it.
Plans Ahead		
1	41.48	Plan ahead.
5	45.48	Live more from day to day.
Carries Out Plans		
1	47.86	Usually get to carry out things the way expected.
5	34.53	Things usually come up to make me change plans.
Finishes Things		
1	67.99	Nearly always finish things.
5	20.89	Sometimes have to give up before they are finished.
Prefers to Spend rather than Save		
1	35.51	Would rather spend money and enjoy life today.
5	36.44	Save more for the future.
Thinks About the Future		
1	37.46	Think a lot about things that might happen.
5	20.89	Usually just take things as they come.

Source: PSID Heads of household in 1968, N=4,802.

3.1 Correlations

The responses to the six questions are generally correlated with each other suggesting that the responses reflect underlying personality traits. Tables 2 and 3 show that the correlation of the attitude responses to each other, for wives and husbands respectively, is generally positive but quite low, in the 0.2 range. Table 4 shows for each question, the correlation of the husbands responses with those of the wives is also positive, and again fairly low. The

[10] For "Life Works Out" the interpretation is less clear; we coded "Usually been pretty sure" as a 1, on the basis of correlation with other variables.

Table 2: Husbands' Correlations

Attitude Question	Life Works Out	Plans Ahead	Carries Out Plans	Finishes Things	Prefers to Save	Thinks About the Future
Mean	0.35	0.65	0.64	0.82	0.63	0.55
Life Works Out	1					
Plans Ahead	0.168	1				
Carries Out Plans	0.281	0.214	1			
Finishes Things	0.148	0.122	0.164	1		
Prefers to Save	0.030	0.207	0.047	0.073	1	
Thinks About the Future	0.039	0.275	0.055	0.056	0.134	1

Note: Based on binary version. Source: PSID 1972-76, and authors' calculations.

Table 3: Wives' Correlations

Attitude Question	Life Works Out	Plans Ahead	Carries Out Plans	Finishes Things	Prefers to Save	Thinks About the Future
Mean	0.33	0.47	0.6	0.77	0.55	0.44
Life Works Out	1					
Plans Ahead	0.138	1				
Carries Out Plans	0.258	0.178	1			
Finishes Things	0.118	0.101	0.138	1		
Prefers to Save	0.013	0.169	-0.012	0.027	1	
Thinks About the Future	-0.086	0.254	-0.032	-0.053	0.148	1

Note: Based on binary version. Source: PSID 1972-76, and authors' calculations.

sample for these tables consists of people who answered the attitude questions at any of the 1968-76 PSID waves and in 1976 were in a marriage to a spouse who had also answered the questions. The positive correlation suggests that the responses do reflect some underlying characteristics and even suggests some positive assortment into marriage, but the weakness of the correlation justifies treating each question as an independent variable in our regression analysis below.

Columns 2-5 of Table 5 show the correlation of both husband (sex 1) and wife (sex 2) responses and demographic information. Of particular interest is the positive correlation of both Plans Ahead and Carries Out Plans with Wealth, Income and Education for both wives and husbands. Intuitively, we would expect higher education for individuals who are future-oriented, and, *ceteris paribus*, greater wealth.[11] It should be kept in mind that wealth

[11] Of course there may be other forces unconnected with future orientedness. For example, more educated individuals might be better at identifying profitable investments and to understand better compound returns

Table 4: Husband-Wife Correlations

	Attitude Question	Husband: Life Works Out	Plans Ahead	Carries Out Plans	Finishes Things	Prefers to Save	Thinks About the Future
Wife	Life Works Out	0.178	0.104	0.111	0.091	0.048	0.011
	Plans Ahead	0.096	0.177	0.078	0.041	0.023	0.112
	Carries Out Plans	0.097	0.112	0.162	0.109	0.030	0.018
	Finishes Things	0.071	0.013	0.075	0.024	-0.015	-0.074
	Prefers to Save	0.012	0.091	0.035	0.024	0.080	0.031
	Thinks About the Future	0.009	0.110	0.029	0.001	0.031	0.116

Note: Based on binary version. Source: PSID 1972-76, and authors' calculations.

and income in the table are measured decades after the survey questions were answered; it is not the case that it is simply that successful people decide *ex post* that they are clever and diligent. Most people answering these questions answered before they had made the decisions that resulted in their subsequent financial situation, suggesting that there was heterogeneity in personality in the late 1960's and early 1970's that is correlated with success in accumulating wealth over the following decades.[12]

Table 5: Individual Responses and Demographics

Attitude Question	Sex	Education: Husband's	Education: Wife's	Household Income	Self Employed, Owns a Business	Self Employed, Owns a Corporation	Household Wealth
Life Works Out	Men	0.167	0.099	0.101	0.112	0.060	0.063
	Women	0.176	0.160	0.101	-0.005	0.035	0.015
Plans Ahead	Men	0.195	0.062	0.073	0.030	-0.022	0.046
	Women	0.163	0.239	0.108	0.093	0.055	0.073
Carries Out Plans	Men	0.169	0.121	0.077	0.027	-0.009	0.028
	Women	0.198	0.159	0.100	0.015	0.032	0.068
Finishes Things	Men	0.075	0.022	0.034	0.019	0.025	0.026
	Women	0.044	0.098	0.025	-0.027	-0.009	0.045
Prefers to Save	Men	0.059	0.012	-0.041	0.020	0.061	-0.067
	Women	0.003	0.020	0.004	0.017	0.023	0.020
Thinks About the Future	Men	0.233	0.132	0.076	0.077	0.090	0.021
	Women	0.080	0.119	0.051	0.091	-0.004	0.042

Source: PSID 1972-76, and authors' calculations.

4 Empirical Strategy

In this section, we explain how we rely on a linear equation for optimal saving to estimate on a representative sample of married couples the contributions of future-orientedness, as embodied in respondents' survey responses. We summarize these effects for each person by a single number, their "Attitude Index", or AI, defined by the total predicted contribution

regardless of their future-orientedness.

[12]See Poterba et al. [2009] for a discussion of retirement planning.

to the household savings rate of the person's reported attitudes. This AI, which is computed separately for husband and wife is then used as an indicator of a person's future orientedness in further regression estimations of other outcomes.

Our estimation equation is derived from a very simple, albeit standard, neoclassical model of lifecycle savings. We rely on the model to provide a coherent framework for the empirical analysis without recourse to numerical solutions. This requires the simplest possible model of savings that admits choices over education and savings rate. To achieve this, we abstract from many of the important concerns of the savings literature, including, *inter alia*, uncertainty, parental altruism, mortality risk and business ownership. The deterministic life-cycle assumption allows us to carry out our analysis in terms of savings instead of consumption, because our data includes wealth variables but relatively little about consumption.

The model allows us to make a few basic points. First, we show that, when the dependent variable is the wealth/income ratio, discount-factor variation will enter a linear regression equation as a level effect. This is a convenient property not only for the sake of keeping the regression analysis simple and easy to interpret, but also because it allows us to extend the analysis across generations. Second, the savings equation does not permit a distinction between preferences and rate of return; for that other inter-temporal tradeoffs, unrelated to rate of return, must be estimated. Third, education and income growth rates are not suitable control variables for our wealth regression as they are influenced by the same sort of variation in discount factor that generates variation in savings behavior. Thus we rely in the empirical analysis on instruments to proxy for education and income growth.

4.1 A Model of Life-cycle Savings

We begin by thinking of agents as unitary households, indexed by i, who live for three periods , $t \in \{1, 2, 3\}$. There is no uncertainty and no borrowing constraint. In the first two periods, $t = 1, 2$, agents choose consumption $c_{i,t}$ and savings $a_{i,t}$. In the third period agents consume $c_{i,3}$ and die. The household begins each period t with wealth level $a_{i,t}$ and receives non-financial income $y_{i,t}$, which grows (deterministically) over time at a constant, agent-specific, rate $\gamma_{i,t}$. Each agent stores its wealth in a risk-free asset a_i with a fixed rate of return r_i that may vary by household.

Preferences are represented by a utility flow each period, which we specialize to equal the log of consumption: $u(c_{i,t}) = \ln c_{i,t}$. Household i discounts its future utility at rate β_i per period, so preferences over the consumption stream $c_i = [c_{i,1}, c_{i,2}, c_{i,3}]$ are given by the discounted sum of the utility flow each period:

$$U(c_i) = u(c_{i,1}) + \beta_i u(c_{i,2}) + \beta_i^2 u(c_{i,3}) = \log(c_{i,1}) + \beta_i \log(c_{i,2}) + \beta_i^2 \log(c_{i,3}). \quad (1)$$

In the absence of binding borrowing contraints, optimal consumption is a function of lifetime wealth, which is defined as :

$$W\left(a_{0i}, r_i\right) = a_{0i} + y_{i,1} + \frac{y_{i,2}}{1+r_i} + \frac{y_{i,3}}{\left(1+r_i\right)^2}$$

where a_{0i} denotes initial wealth.

For an unconstrained agent, taking $W\left(a_{0i}, r_i\right)$ as given, the optimal consumption sequence in period t satisfies the constant-expenditure share property:

$$\frac{c_{i,t}}{\left(1+r\right)^{t-1}} = \frac{\beta_i^{t-1}}{1+\beta_i+\beta_i^2} W\left(a_{0i}, r_i\right)$$

or

$$c_{i,t} = \frac{\left[\beta_i\left(1+r_i\right)\right]^{t-1}}{1+\beta_i+\beta_i^2} W\left(a_{0i}, r_i\right)$$

Let $a_{i,2}$ denote savings in period 2. In Appendix section A we derive an expression for the period-2 savings out of current income: the wealth-income ratio is

$$\frac{a_{i,2}}{y_{i,2}} = \kappa_i + \kappa_i \frac{s_{i,2}}{y_{i,2}} + \left[\frac{\kappa_i - 1}{1+r_i}\right] g_i \tag{2}$$

where

$$s_{i,2} \equiv a_{i,1}\left(1+r_i\right)$$

represents the household's net worth at the start of period 2, $g_i \equiv \frac{y_{i,3}}{y_{i,2}}$ and $\kappa_i \equiv \frac{\beta_i}{(1+r_i)(1+\beta_i)} < 1$.

4.2 Optimal savings

Equation (2) suggests that we can write optimal savings behavior in period 2 in the form of a linear equation:

$$w_{i,t+1} = \alpha_{0,i} + \alpha_{1,i}\frac{s_{i,t}}{y_{i,t}} + \alpha_{2,i} g_i + \upsilon_i \tag{3}$$

, where $w_{i,t} \equiv s_{i,t+1}/y_{i,t}$ represents the savings/income ratio at the end of period t.

The reduced-form parameters in this equation can be written as:

$$\alpha_{1,i} = \alpha_{0,i} \equiv \frac{\beta_i}{1+\beta_i}\left[1+r_i\right] < 1 \tag{4}$$

and

$$\alpha_{2,i} \equiv \left[\frac{\alpha_{0,i} - 1}{1+r_i}\right] < 0 \tag{5}$$

. The error term υ_i, assumed to be white noise, reflects the contributions of unobserved variations across sample members in other factors that affect savings. The significance of this result is that it suggests that variation in β_i will be reflected in the coefficient of $w_{i,1}$ in a linear regression equation with two observable control variables.

We focus below on savings at $t = 2$, taking this as a stand-in for all intermediate periods of a hypothetical extension of the 3-period model to a T-period finite life-cycle model.

Optimal savings behavior implies a linear equation for $w_{i,t} \equiv a_{i,t}/y_{,it}$, the wealth/income ratio at the end of period t, as a function of the wealth-income ratio at the start of the period:

$$w_{i,t} = \lambda_0 + \lambda_1 w_{i,t-1} + \lambda_2 \gamma_{i,t} + ... + \upsilon_{i,t} \tag{6}$$

where

$$\lambda \equiv \lambda_0 = \lambda_1 = \frac{\beta}{1+\beta}[1+r] < 1 \tag{7}$$

and $\lambda_2 < 0$. The ellipsis refers to the fact that in reality savings may differ for other reasons, such as family composition and health status that are not included in the model, but will be included in the empirical analysis.[13]

This equation implies that, given repeated observations, household-level variation in λ can be measured as a level effect in a linear regression equation. The key features of this equation, as elucidated by the model, are that the dependent variable should be the ratio of terminal wealth to income earned during the period, and that it is essential to control for initial wealth and the expected income-growth rate. The model also implies that it will be difficult to distinguish between household variation in rate of return and variation in future-orientedness. It is also very helpful that estimation does not require measures of consumption expenditure over time.

Since we are controlling for the wealth-income ratio at the start of the period, the predicted value of $w_{i,t}$ can be interpreted as the change in net worth, divided by income earned during the period; in other words, the savings rate. So variation in λ across agents relates directly to savings-rate variation, rather than to whether agents are rich or poor.

As we do not observe an individual's rate of return, the agent's fixed effect λ_i would reflect idiosyncratic variation in both rate of return and β. It is not possible in models in this class (CES preferences) to distinguish, on the basis of savings behavior alone, between future-orientedness and rate of return.

One way to deal with this is to consider other intertemporal trade-offs unrelated (or at least less-related) to the rate of return in asset markets. Non-pecuniary outcomes of other intertemporal trade-offs, such as those relating to health and marriage/births, would help make this distinction (to the extent that the optimal response to these other trade-offs reflects future orientedness but is unrelated to rate of return on financial assets). In

[13]This equation is admittedly literally valid only in a world fully described by our very rudimentary model, which abstracts from many important features of real-life savings problems. We will partially remedy this in the estimation stage by supplying control variables to absorb the effects of observables that are outside the model. For instance, Euler-equation methods, as in Attanasio and Browning [1995] might incorporate discounting via a stochastic kernel that reflects uncertainty over both rate of return and future marginal utility. However such models would still suffer from the issues of omitted variables, and bring their own baggage, such as time-aggregation bias and the need to measure consumption. See Alan et al. [2019] for a recent assessment of some of these issues in simulated populations.

a more general model, however, the optimal savings will also depend on any other factor that shifts the (expected) marginal rate of substitution between the present and the future, such as anticipated medical expenses, making it harder to identify savings variation driven by future orientedness.

A direct measure of β would therefore be very helpful by providing an alternative way of distinguishing future-orientedness from other factors that affect saving. It would, in addition, be very helpful if such a measure could permit some decomposition of future-orientedness. We would like to assess the extent to which discounting or planning is the more plausible interpretation of β. In the neo-classical model, β refers strictly to a preference parameter, the agent's valuation of future utility relative to utility today. Empirically, however, even after controlling for other factors as described above, β could be any fixed unobservable characteristic of the agent that shifts the mapping between $w_{i,t}$ and a set of control variables that includes rate of return and $w_{i,t-1}$.

4.3 Role of Attitude Responses

Our approach to this problem is to exploit data on attitudes from The Panel Study of Income Dynamics (PSID), which simply asked people in the 1970s how they felt about planning. Suppose people reported both their discount factor and the degree to which their actions were determined by planning for the future. Setting aside for now the question of the reliability of such self reports, it would in principle be possible to use these responses to deal with both of the above issues: to distinguish variation in β from variation in r and to identify whether the variation in β is more plausibly related to discounting or planning ability.

In practice there are a host of issues that would arise from taking such responses at face value. There is no guarantee that survey respondents interpret the questions as intended by the survey or that it is possible to elicit theoretically meaningful parameter variation from the responses. Responses may be biased by aspirations and delusions (e.g., the "Lake Woebegone Effect"). Thus, the answers might be shaped by the outcomes we want to explain. A particularly relevant example of this is ex post rationalization: people who have accumulated a lot of wealth, relative to their income, may as a result revise upwards their opinion of their planning ability or patience, while those with low wealth may revise their opinion downwards, thus rationalizing their outcomes. In this light, it would be more useful to have responses that were made before planning-related outcomes such as wealth accumulation were realized.

Fortunately, the PSID sample in the 1970s included many relatively young householders, who continued to participate for many years. The PSID reports household wealth every 5 years for 1984-1999, and every 2 years for 2001-2019. Many of the people in the attitudes sample remained in the PSID in these years when wealth was measured. To validate use of the attitude responses as measures of λ, we estimate how well these responses in the 1970s predict the growth rate of the household's wealth/income ratio in the 1990s and beyond. This allows us to bypass to some extent the issue of what people had in mind when they answered these questions, or the extent to which the questions meant something different for men than for women.

4.4 Our Empirical Measure: the Attitude index

Suppose that for each person, there are N_r attitude responses $R_{ij} \in \{0, 1\}$, where $j = 1...N_r$ is the number of questions answered. We want to examine how these attitude responses are related to future outcomes.

We estimate a linear regression equation based on model equation (6), augmented with control variables and responses to the N_r attitude questions. The main regression equation, with N_c control variables C_{ij} added, can be written as:

$$w_{1,it} = \lambda_0 + \alpha w_{0,it} + \sum_{j=1}^{N_r} \gamma_j R_{ij} + \sum_{j=1}^{N_c} \phi j C_{ij} + \upsilon_i \tag{8}$$

The attitude-response variables act collectively as a proxy for future-orientedness. Given a set of estimates for equation (8), we can then construct an Attitude Index (AI) for each person, Ψ_i, based on the estimated effects of the response variables. In general, the relation to savings will be a non-linear function of the responses; interactions among the response variables may be important. We will assume for now that the function is linear, so that estimated coefficients indicate the relative importance of each response for explaining $w_{1,it}$.

$$\Psi_i \equiv \sum_{j=1}^{6} \gamma_j R_{ij},$$

where the γ_j are unknown parameters.

This effectively decomposes the intercept into a household-specific fixed effect Ψ_i and a general fixed term shared by all. In this sense the method resembles a fixed-effect regression equation (see Knowles and Postlewaite [2005]). However the key difference is that Ψ_i excludes the effect of unobservables: only effects related to attitude responses contribute to Ψ_i. Additionally, since the responses were made many years before, Ψ_i is unlikely to reflect the myriad other factors that might shift the savings function, as discussed above. Finally, because Ψ_i is measured using actual wealth accumulation, it does not matter so much how respondents differ in how they interpret the questions.[14]

The control variables include variables required by the model: the wealth-income ratio at the start of the period, $w_{i,t-1}/y_{i,t-1}$, and the future income-growth rate, $\gamma_{i,t}$, which is endogenous. Additionally, some variables are included as controls to represent heterogeneity

[14] Note that this procedure effectively excludes from consideration any component of the attitude responses that does not demonstrably relate to savings behavior.

that is not accounted for by the model. These include age, race, number of children, and self-reported health. Recall that the model implies a positive coefficient less than one on $w_{i,t-1}/y_{i,t-1}$ and a negative coefficient for $\gamma_{i,t}$, the expected income-growth rate. These are useful restrictions for informally validating the model.

4.5 Husbands and Wives

Wealth is observed at the household level; attitudes are measured at the level of individual householders. To deal with this mismatch in unit of observation, we restrict our empirical analysis to married couples and compare the effects of the attitude index of husbands and wives. Equation (8) is estimated twice on the married sample: once using the attitude reports of the wives and once using those of the husbands. We then carry out a third estimation on the sample, this time using both attitude indices as explanatory variables rather than using the response variables, but keeping the specification as for household i, this equation can be written as:

$$w_{1,it} = \alpha_0 + \alpha_1 w_{0,it} + \alpha_H \Psi_{iH} + \alpha_W \Psi_{iW} + \sum_{j=1}^{N_c} \phi j C_{ij} + \upsilon_i.$$

4.6 Endogeneity

A basic econometric issue with our approach is that the income process is likely to be endogenous: being future-oriented may mean you choose more education, or careers with higher income growth, or that you invest more in job search or on-the-job skills.

Consider, for example, higher education and business startups, both of which typically involve an investment phase that can last a long time before economic profits are realized. To the extent that either of these is associated with a higher rate of wealth accumulation, it would be difficult to disentangle the effects of the income process on wealth from that of being future-oriented. Controlling for higher education may also allow us to distinguish between possible effects of education on future-orientedness and innate personality characteristics.

Our approach to these issues is to apply a basic IV method: we compute average income growth as a function of predicted years of education, in lieu of actual years. The education prediction is based on parental (education, occupation) and demographic (race, sex, birth year) variables. This in principle solves the problem provided that being future-oriented is not a characteristic shared with parents. That is not entirely satisfying however because it is likely, as we argue below, that future-orientedness is in fact correlated with that of parents. So long as this correlation is imperfect, however, our method is likely to attenuate the endogeneity issue.

5 Results: Savings and the Attitude Index

In this section we report our analysis of savings in the Attitudes sample. This consists of two main parts: estimation of our empirical wealth model, equation (8), and analysis of the Attitude Index constructed from those estimates.

5.1 Attitude Responses and Household Wealth

We define our "Attitude-Wealth Sample" as those respondents who answered the attitude questions in the 1970s and, at the time wealth was measured, were married, were either household head or spouse of the head, and were between ages 40 and 70. This sample covers the years 1984, 1989, 1994 and 1999, the period when the PSID was measuring wealth every 5 years.[15] The sample consists of each wealth observation of 1714 married people who are observed at least twice during this period.[16]

The dependent variable is the household W/Y (wealth/income) ratio, where wealth is measured as household's net worth, and income as "non-asset" income, i.e., labor income and transfers, summed over both spouses. (The detailed description is in Appendix B). The model equation is estimated separately for husbands and wives, by OLS with standard errors clustered at the household level.

Table 6: Wealth Regression Samples Descriptive Statistics

	Attitudes Sample		Offspring Sample	
	Husbands	Wives	Sons	Daughters
W/Y Ratio	0.813 (1.488)	0.719 (1.330)	0.706 (1.251)	0.673 (1.224)
Life Works Out	0.732 (0.443)	0.693 (0.461)		
Plans Ahead	0.696 (0.460)	0.534 (0.499)		
Carries Out Plans	0.671 (0.470)	0.611 (0.487)		
Finishes Things	0.847 (0.360)	0.760 (0.427)		
Prefers to Save for Later Consumption	0.633 (0.482)	0.581 (0.493)		
Thinks About the Future	0.631 (0.483)	0.519 (0.500)		
Mom's Attitude Index			0.131 (0.102)	0.129 (0.102)
Dad's Attitude Index			0.243 (0.134)	0.222 (0.139)
Initial Wealth	0.696 (1.297)	0.624 (1.223)	0.656 (1.396)	0.683 (1.332)
Future Income Growth	-0.029 (0.060)	-0.018 (0.060)	0.004 (0.054)	-0.002 (0.055)
Husband's Age	51.432 (5.463)	49.409 (6.528)	47.244 (6.316)	49.902 (7.697)
Wife's Age	48.593 (6.507)	47.842 (6.185)	45.490 (7.629)	47.705 (6.308)
Observations	1,443	1,575	545	531

Source: PSID 1972-76, and authors' calculations. Note: Attitudes Sample consists of all those who responded to the attitude questions in 1968-76 and were present in married couples who reported wealth in PSID in 1984 or later

The complete results of our estimation for four specifications of the regression model

[15] After 1999, wealth is measured every two years, so 1999 represents a logical break in the series.

[16] Our wealth wealth-estimation sample includes 18.4% of the 9323 people who answered the attitude questions in the 1970s. Of the respondents who were excluded, all but 2452 had aged out of our sample frame; of the excluded remainder, 80% were unmarried at the time wealth was measured. The rest were no longer in the PSID at the time that the wealth variables were recorded or were missing variables for prediction of education or were outliers in our income-prediction exercise.

are shown in Table 32 in the Appendix. An excerpt of those estimates, for our preferred ("Benchmark") specification (specification 2), is shown in Table 7. This table displays the estimated coefficients for each of the attitude responses and the two control variables, initial wealth and income growth, required by the theoretical model, equation (6). Also included among the controls, but not shown, is our "Standard" controls set, which includes quadratics in year and ages of the spouses.

Initial wealth is given by the previous PSID wealth measurement, five years earlier. Income growth is computed by regression methods from the full PSID sample, including controls for predicted education and race, sex and health. See Table 31 in Appendix Section C.2 for a complete description of our treatment of education and income growth.

Table 7 shows that that estimation yields the model-predicted signs for expected income and initial wealth for both spouses, and a coefficient less than one in the latter case, as implied by the model. This provides some validation for the specification. The R-squared indicates that the model explains about 40% of the variation for each spouse, but further regressions (not shown) imply that most of this is due to covariates, not the attitudes themselves, which account for 1 to 2% of the variation.[17]

Before going on, we also note that the attitudes are not essentially disguised wealth, as the regressions control for initial wealth. While initial wealth has a substantial and significant effect on W/Y ratio, the attitudes still have a significant effect.[18]

Table 7 also shows that the estimates for the Attitude variables are, with few exceptions, statistically significant at the 0.01 level. This is quite remarkable: the savings behavior represented by wealth estimates 10-20 years after the attitude responses were recorded is strongly associated with the responses. Our interpretation is that the PSID attitude responses reflect heterogeneity (i.e., individual fixed effects) in persistent personal characteristics that affect intertemporal behavior. Since this association holds after controlling for past wealth, it is unlikely to be the result of attitudes responding to early financial success.

Plans Ahead has a relatively large expected effect for both Husbands and Wives. People who in the 1970's said that they tend to plan ahead end up in the 1990s with a wealth-income ratio that is higher by 0.106 in the case of wives, and 0.142 in the case of husbands. From Table 6, the mean W/Y ratio for husbands in the sample is 0..813; agreement of the respondent with this single question is associated with an increase in the household savings rate that amounts to 84% of the standard deviation (0.76) of the W/Y ratio. Similar results hold for wives. Again, this is after controlling for the W/Y ratio at the start of each

[17] An important limitation of our method is that we cannot fully control for self-selection into high-income growth occupations. The model implies that more patient people will be more likely to choose such occupations. If this effect were to dominate in our regression model, then future-income growth would have a positive effect on the W/Y ratio; indeed, this is what happens when we leave out controls for predicted education.

[18] Table 7 also shows the results of other regression specifications. Specification 3 adds a control for Education, and specification 4 adds Income and Race. These additional controls do not substantially alter the degree to which individuals' attitudes predict wealth accumulation.

Table 7: Attitude-Sample Wealth-Ratio Estimates

	Outcome: W/Y Ratio							
	Husbands	Wives	Husbands	Wives	Husbands	Wives	Husbands	Wives
	(1)		(2)		(3)		(4)	
Life Works Out	0.362***	0.062***	0.225***	0.022	0.225***	-0.001	0.214***	-0.012
	(0.019)	(0.017)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Plans Ahead	0.187***	0.215***	0.142***	0.106***	0.130***	0.096***	0.119***	0.093***
	(0.019)	(0.016)	(0.016)	(0.013)	(0.016)	(0.013)	(0.016)	(0.013)
Carries Out Plans	-0.061***	0.128***	-0.058***	0.037***	-0.070***	0.028**	-0.075***	0.020
	(0.018)	(0.016)	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)
Finishes Things	0.131***	-0.025	0.034*	-0.044***	0.018	-0.052***	0.012	-0.055***
	(0.023)	(0.018)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)
Prefers to Save for Later Consumption	-0.027	0.058***	-0.080***	0.049***	-0.075***	0.047***	-0.065***	0.054***
	(0.018)	(0.015)	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)
Thinks About the Future	0.062***	0.239***	0.068***	0.124***	0.059***	0.118***	0.058***	0.114***
	(0.018)	(0.016)	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)
Initial Wealth			0.702***	0.634***	0.698***	0.630***	0.702***	0.634***
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Future Income Growth			-0.251*	-0.389***	-0.616***	-0.991***	-0.476***	-0.866***
			(0.135)	(0.125)	(0.143)	(0.130)	(0.153)	(0.137)
Observations	1,478	1,609	1,443	1,575	1,443	1,575	1,443	1,575
R^2	0.050	0.058	0.404	0.379	0.405	0.384	0.406	0.386
Controls:								
Standard	Y		Y		Y		Y	
Model			Y		Y		Y	
Education					Y		Y	
Income							Y	
Race							Y	

Source: Estimates parental W/I on Attitudes sample. Standard controls include year, year squared, husband's age, husband's age squared, wife's age, and wife's age squared. Model controls include the initial wealth income ratio and future income growth. Educ controls consist of the wife's predicted education and the husband's predicted education. Income control is Log Inc1. Race controls are Black and White. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

period, which, the model implies, is itself influenced by attitudes variation. We think that heterogeneity in this response reflects differences in the ability or tendency to plan for the future. This kind of heterogeneity typically does not play a role in standard neo-classical models such as ours, but could be represented by a cost of planning, analogous to that in Caplin et al. [2022].

A notable result in Table 7 is the negative effect of Prefers to Save for Husbands - .08 - statistically significant at the 0.01 level. This is the only Attitude question that directly asks about intertemporal preferences, so it is surprising to see a negative effect. Our interpretation of this result is that heterogeneity in discounting is not very important for explaining residual variation in W/Y. This could be because such heterogeneity is not very large, or because the effects of it on W/Y are already accounted for by the other controls. The estimates for the other attitude variables are both smaller and less similar across the sexes. In this group, Life Works Out is the largest effect for Husbands. People who are more likely to answer that that Life Works Out have W/Y ratios that are larger by 0.225 for husbands and 0.022 for wives.

5.2 The Attitude Index

From the estimates in table 7 we now compute the Attitude Index for each individual who answered the attitude questions in the 1970s. As described in section 4, the Attitude Index for an individual is equal to the sum of the individual's own responses to attitude questions, weighted by the estimated coefficients. This is equivalent to the estimated contribution of those responses to the household W/Y ratio, taking as given wealth at the start of period.

A value of 0.1 for an individual's AI means that their household W/Y ratio is on average higher by 0.1 than that of an identical household in which the corresponding person has an AI of 0.0.[19]

Since we estimated the AI separately by spouse sex, it is natural to ask whether the contributions of each spouse's AI are overlapping or independent. In Model 1 of Table 8 we repeat the benchmark regression from Table 7, with the same sample, same set of controls, but this time we replace the attitude response variables with the AIs of both spouses. The main result is that the Husband's AI on average has twice the effect of the wife's AI, 0.645, versus 0.311.

Note that if we had included AI for only one sex, the estimated coefficient would be identically 1.0, so in the Table estimates of less than one indicate that there is overlap; the predicted increase from one spouse's AI coincides in part with the predicted increase from the other spouse's AI. In Model 1, this overlap reduces the total predicted contribution below 2, to 0.95. In Model 2, we add to Model 1 controls for education, as we did for

[19] Notice that this makes attitudes of men and women directly comparable no matter how differently they answer the attitude survey questions, as the AI exploits the estimated effects on household wealth, which does not differ between men and women.

Table 8: Joint Effects of Spouse AI on Married Savings

	Model 1	Model 2	Model 3
Husband's AI	0.645	0.922	0.956
	(0.039)	(0.060)	(0.064)
Wife's AI	0.311	0.635	0.806
	(0.040)	(0.080)	(0.087)
Lagged W/Y	0.687	0.683	0.680
	0.006	0.006	0.006
Future Income Growth	-0.650	-1.073	-1.209
	(0.156)	(0.163)	(0.171)
R^2	0.445	0.448	0.449
Observations	929	929	929

Source: Authors' calculations using Attitudes-Wealth PSID sample of observations for years 1984-2001. Dependent variable is W/Y. Other controls included; see Table 35 in Appendix C.2 for complete estimates.

the original regression. The basic pattern remains the same, but now the coefficients are higher; the wife's has doubled to 0.64 and the husband's is 50% higher, at 0.92. Thus, the gap between the spouses has narrowed and the total effect of AI has increased from 0.95 to 1.55. This suggests that the part of the AI that is correlated with education has much more overlap between the spouses, as one would expect if spouses resemble each other more in terms of education than in terms of AI. Adding a control for household income (Model 3) further reduces the overlap and the gap between spouses.[20]

The AI ranking of a household seems to be unrelated to the responses of each spouse to "Prefers to Save", but quite strongly related to their responses to the planning variables. Table 9 shows that the husband's mean responses to "Life Works Out", for instance, rises from 0.29 in the bottom AI quartile, to 0.70 in the middle quartiles, and peaks at 0.94 in the top AI quartile. A similar pattern is observed for the other planning variables, i.e. "Plans Ahead", "Carries out plans", and "Thinks About the Future". The pattern for Wives, shown in the bottom panel of the table is similar overall, but "Life Works Out" is more weakly related than in the Husband's case, and "Plans Ahead" much more strongly.

This relation of responses to AI ranking does not appear to hold for the other responses, which we see as more closely related to economic theories of savings inequality. We take "Finishes Things" as indicating time-consistent behavior; for husbands, this variable does increase with AI, but over a restricted range, starting at 0.68 for the bottom quartile, while for wives it is falling with AI. For "Prefers to Save" which we take as related to time-discounting, there is a slight increase for wives from 0.51 to 0.57, but a decline for husbands, from 0.64 to 0.56.

[20] In Table 32 of Appendix C.2, we report two more regression models; adding employment controls and then controls for number of children in the household. These have little impact relative to Model 3.

In summary we see this table as suggesting a simple way to distinguish among competing theories of savings inequality: by self-assessment. The results in our case seem to line up with variation in the tendencies to plan and to carry out those plans, rather than in a more general time-inconsistency or in the rates at which householders discount the future. The relationships uncovered by the table could be direct, in that the attitudes cause saving-rate variation, or indirect, as might be the case if planners develop their financial skills and achieve higher rates of return which increases the growth rate of household wealth.

Table 9: Mean Responses by AI Percentile

Husband's Responses						
Couple's Attitudes Pctile	Life Works Out	Plans Ahead	Carries Out Plans	Finishes Things	Prefers to Save	Thinks About the Future
0-25	0.294	0.240	0.356	0.678	0.635	0.249
26-75	0.696	0.702	0.710	0.882	0.644	0.580
76-100	0.941	0.984	0.856	0.934	0.558	0.742
Wife's Responses						
Couple's Attitudes Pctile	Life Works Out	Plans Ahead	Carries Out Plans	Finishes Things	Prefers to Save	Thinks About the Future
0-25	0.498	0.011	0.376	0.807	0.506	0.266
26-75	0.767	0.443	0.639	0.789	0.547	0.379
76-100	0.845	0.940	0.837	0.739	0.570	0.687

Mean value of binary recoding of responses to PSID attitude questions, ranked by household AI.
Source: Authors' calculations using Attitudes-Wealth PSID sample of observations for years 1984-2001.

5.3 Distribution of AI

We now define the household AI as the sum of the Model 3 estimates for spouses' AI in Table 8. This allows us to compare high-AI households with lower AI households and ask if there are obvious differences that suggest a different interpretation of our results. Table 10 shows that the husband tends to be slightly younger in the top AI quartile, 57.9 years on average, compared to 58.6 years for the mid-range households and 60.4 for the bottom quartile. The average age gap between spouses is also larger at the top quartile, 2.9 years, versus 2.6 in the mid-range, but smaller than the age gap at the lowest quartile (3.2). Age is of course relevant for savings, but the differences here are small. We also see a small advantage in education, as the top quartile averages 13 years for wives and 13.5 for husbands, compared to 12.4 for both husbands and wives in the mid-range and 11.6 and 11.3, respectively at the bottom quartile. Both of these may suggest effects of employment or occupation, and consequently, it is reassuring that our results in Models 4 and 5 of Table 35 include controls for these latter variables.

Table 10 also shows that differences are negligible for the fraction reporting White race (91%), and while there are more co-resident Kids at the top (0.72) vs the bottom (0.59), this does not suggest an alternative interpretation of the AI. The differences across high, medium and low AI households are somewhat starker in terms of pecuniary variables. Table 11 shows that the average W/Y ratio rises from 5.9 at the bottom quartile to 10.1 at the top. Household AI of course rises too, as this is the ranking variable, from .09 and 0.47, meaning that the average AI in the top quartile raises wealth by nearly a half of accumulated income. And since average annual income is also much higher at the top quartile ($32K) than at the bottom ($19K), the effect of higher AI on wealth is magnified.

Average household net worth in the top quartile is $250K, more than 2.7 times the wealth in the bottom quartile, as shown in Table 11. The higher shares of business wealth and stocks in the top quartile (7.6% and 9.5%), versus (5.2% and 3.6% for the bottom quartile) suggest that differences in rate of return may be playing a role in the AI spread between the two quartiles, but the portfolio shares of these assets are so small that this seems unlikely to be the main interpretation of AI. We conclude from these two tables that while the AI for model 3 is likely to be picking up effects of other sorts of heterogeneity, these effects are likely small relative to overall AI. For instance, in Model 5 of Table 35, shown in the Appendix, we see that the estimates for AI are similar to those for Model 3 even controlling for business ownership and occupation.

Table 10: Demographic Means by Household AI Ranking

Percentile	Hub's	Hub.-Wif.	Grades				Health Poor	
HH AI	Age	Age Gap	Wife	Hub.	White	Kids	Wife	Hub.
0-25	60.40	3.24	11.60	11.28	0.912	0.588	0.300	0.393
25-75	58.64	2.59	12.37	12.41	0.919	0.714	0.166	0.197
75-100	57.85	2.89	12.96	13.51	0.912	0.722	0.116	0.116

Source: HH AI computed using estimates in Table 8.

Table 11: Pecuniary Means by Household AI Ranking

Percentile HH AI	W/Y Ratio	HH AI	Wif. AI Share	Annual Income	Net Worth	Busi. Share of Wealth	Stock Share of Wealth
0-25	5.87	0.090	0.796	$19,033	$91,434	0.052	0.036
25-75	8.81	0.290	0.392	$28,844	$165,061	0.060	0.062
75-100	10.09	0.468	0.397	$32,080	$249,555	0.076	0.095

Source: HH AI computed using estimates in Table 8. W/Y is the ratio of net worth to accumulated non-financial income over the last 5 years. Shares of wealth for Business and Stocks are actually share of total assets.

5.4 Max/Min AI Estimates

Is it financial acumen or future orientedeness that drives variation in the AI? One way to distinguish the two is to consider the role of knowledge or skill in a co-operative household. For married couples, we have two values of AI: the wife's and the husband's. If a higher AI is associated with greater acumen, we would expect that the financial decisions are informed mainly by the higher-AI spouse, and so the higher of the two should have a systematically larger effect on household savings. If on the other hand the AI differences between spouses reflect differences in ability, or propensity, to plan, then we would expect both to be more equally relevant, as spending and planning is shared between the spouses.

Which is more important: the larger AI of the two or the smaller? To answer this we re-run the regression of W/Y on both AIs, but this time instead we classify the AI not by the sex of the spouse but by whether it is the larger of the two ("Max"). The result is shown in Table 12. The table shows 3 different versions of AI, computed from models with more controls moving from 2 to 5, as with Table 7. In Model 2, which has the smallest set of controls, the effect of minimum AI is larger, 1.04 vs 0.85, a difference that exceeds the sum of the standard errors. Controlling for education, however, makes a difference. As we move from model 2 to model 3, the effect of minimum AI falls below that of maximum AI, but Model 5 shows that adding in controls for income reduces the effect of maximum AI below that of the smaller AI. Since we do not find any systematic difference in size between the two AI of each household, it is unlikely that AI is mainly a reflection of financial acumen or opportunities.

6 Attitudes and Non-Financial Future-Oriented Behavior

In this section we ask how the AI measures derived above are related to plausibly inter-temporal decisions related to health.[21] We think of health as a state reflecting previous investments, in the form of exercise and whether or not to smoke cigarettes Grossman [2017]. People who are more future-oriented are likely to put greater weight on their future health status.

If our constructed measure, AI, is truly a general measure of future orientedness, we should also expect that it is at least weakly predictive beyond financial choices. Since we based our estimate of future orientedness on wealth accumulation, it is possible that variation in the AI simply reflects family-level variation in the rate of return or financial sophistication, rather than general future orientedness. If so, then the AI will not be predictive of non-financial future-oriented behavior.

The health results below are based on the entire sample for whom we can compute attitude indices (AI), not just those who were in the married-wealth samples that were

[21] The models below are meant to show a relationship between individuals' AI and their behavior. They are *not* aimed to be the most sophisticated models of the particular behavior.

Table 12: Max/Min AI Estimates

	Model 2	Model 3	Model 5
Maximum AI	0.853	0.840	0.696
	(0.089)	(0.087)	(0.089)
Minimum AI	1.039	0.784	0.764
	(0.096)	(0.091)	(0.095)
Initial W/Y	0.686	0.683	0.618
	0.006	0.006	0.007
Predicted Income Growth	-0.641	-1.074	-0.818
	(0.156)	(0.163)	(0.251)
Wife's Pred. Educ		0.038	0.031
		0.009	0.010
Hub's Pred. Educ		0.051	0.034
		(0.008)	(0.009)
R-Squared	0.446	0.448	0.477
MSE	1.046	1.044	1.016
N	929	929	929

"Maximum AI" is attitudes index of spouse with higher AI, "Minimum AI" that of the other spouse. Dependent variable is wealth/income, controls not shown include age, race and year. Model 5 also controls for income.

used to estimate the AI coefficients. In this sense the non-wealth results have an out-of-sample aspect that also serves to validate the AI measure.

6.1 Smoking

Consider cigarette smoking, which provides at least two connections to future orientedness: the decisions of non-smokers to start smoking and those of smokers to quit smoking may both involve an intertemporal trade-off: the pleasure from smoking now versus the future health cost. In both cases, a future-oriented individual should be less likely to begin smoking, and of individuals who do smoke, the more future-oriented individuals should be more likely to quit should they try.

We explore these issues by Probit regression analysis by sex. We estimate two equations. In the first equation the dependent variable is whether the person was ever a cigarette smoker ($S_i = 1$) or not ($S_i = 0$). This is estimated on the sample of all respondents from the Attitudes sample. In the second equation the dependent variable is whether the person eventually quit smoking ($Q_i = 1$) or not ($Q_i = 0$). This is estimated on the sub-sample of attitude respondents with $S_i = 1$. In both cases the equation we estimate takes the same form, including as explanatory variables the previously-estimated AI Ψ_i and some covariates X_i:

$$S_i = \alpha_0 + \alpha_1 \Psi_i + \alpha_1 X_i + \epsilon_i \qquad (9)$$

Table 13: Probit Regression for Ever Smoked Cigarettes

	Men		Women	
	M1	M2	W1	W2
Attitude Index	-0.822	-0.775	-1.087	-1.137
	(0.049)	(0.051)	(0.067)	(0.069)
Predicted Education	.	0.637	.	0.982
	.	(0.058)	.	(0.060)
(Predicted Education)^2	.	-0.026	.	-0.038
	.	(0.002)	.	(0.002)
Black	-0.015	0.091	-0.021	0.087
	(0.028)	(0.035)	(0.021)	(0.025)
Parents Poor	0.235	0.242	-0.070	-0.064
	(0.014)	(0.015)	(0.013)	(0.013)
N	2154	2011	2425	2273

Note: Standard errors clustered at the family ID level are in parentheses. Other controls not shown: Parents were Poor, and year of birth.

Since 1999, each survey wave of The PSID has asked whether the head ever smoked and since 2005 whether the wife ever smoked. In 1986, for instance, 40% of respondent heads said they had never smoked and 25% said they had but no longer smoked; 35% were currently smokers. For each individual we check the latest available variable to determine smoking status.

For the first regression equation, we set $S_i = 1$ for respondents currently or previously smokers. We estimate Equation (9) separately for each sex, each in two specifications, where the X_i variables include race, year of birth, and whether parents were poor when the respondent was growing up, and in the second specification, a quadratic in predicted education.

The estimates, reported in Table 13, show a negative effect of AI on the probability of having Ever Smoked Cigarettes.[22] This effect is preserved in the second specification, falling only slightly for men, from 0.822 to 0.775 and actually increasing for women, from 1.09 to 1.14. The sign and strength of these effects support the view that the savings effect of the AI, as reported in Table 7, are driven by future orientedness.

For the second regression equation, we set $S_i = 1$ for respondents who had quit smoking and $S_i = 0$ otherwise. The equation specification and estimation procedure are the same as for the first regression, but now the sample is restricted to those who were smokers at some point. For those individuals who do smoke, columns 2 and 4 of Table 14 show that the effect of AI on whether they quit Smoking is strong for men but essentially zero for women.

The results for the first equation support the view that the AI reflects general future orientedness, as opposed to being merely the effect of variation in rate of return or some other measure of financial sophistication. The second regression equation is harder to

[22]The sample consists of 2264 men and 2597 women, but roughly 10% of each are dropped in the second specification, due to missing values for predicted education.

Table 14: Probit Regression for Whether Quit Smoking

	Men		Women	
	M1	M2	W1	W2
Attitude Index	0.869	0.697	0.013	-0.091
	(0.055)	(0.059)	(0.099)	(0.103)
Predicted Education	.	0.762	.	0.707
	.	(0.076)	.	(0.095)
(Predicted Education)^2	.	-0.018	.	-0.019
	.	(0.003)	.	(0.004)
Black	-0.192	0.495	-0.028	0.396
	(0.030)	(0.041)	(0.031)	(0.038)
Parents Poor	0.120	0.360	0.120	0.278
	(0.016)	(0.018)	(0.019)	(0.020)
N	2264	2114	2597	2433

Note: Standard errors clustered at the family ID level are in parentheses. Other controls not shown: Parents were Poor, and year of birth.

interpret, because only smokers are in the sample, and we already know that on average smokers have lower AI. The result for men appears to support the view that higher-future orientedness causes smokers to quit, but the result for women suggests that higher-future orientedness also reduces entry into smoking among women who do not intend to keep smoking; this is also consistent with the fact that the smoking rate is lower for women. In this light, women may well be behaving more time-consistently than men with respect to smoking.

6.2 Health

We argued above that if health status is the result of non-pecuniary investments in health, then people who are more future-oriented should be healthier on average, particularly after middle age, when accumulated differences in investments are greater. To test this idea we use a subjective measure of health, the respondents' self-reported health status, which PSID records for heads and spouses, from 1984 onward.[23]

The PSID recorded this health-status variable on a five-point scale: Excellent, Very Good, Good, Fair or Poor. We added to this list of health outcomes an additional code "Dead", for those respondents who the PSID reports as having died by the year we analyse. We recoded the outcome list in increasing order of healthiness; we ranked Death = 0, ranking it below Poor = 1 as the lowest-health outcome, rising by one through the other response codes to "Excellent"=6.

For this case, we estimate equation 9 as a multinomial logit regression of Health Status in 1993 on own AI, controlling for education and health behaviors. The exercise variables

[23]We abstract from the possibility that respondents who say they are good planners also report their health more optimistically. This would be a serious issue if we were taking attitude reports at face value, but since our measure of future-orientedness is based on actual wealth accumulation, we are less concerned about this issue.

are based on self-reported monthly frequency of exercise from 1986; the excluded level is zero; the value ExerDum=1 indicates a positive frequency, ExerDum=2 a frequency of at least 16 times per month and ExerDum=3 a frequency of at least 30. The eversmoke variable is identical to the dependent variable in Table 13. We also include the respondent's BMI in 1986. The specification is otherwise identical to the smoking regressions explained above. Table 15 shows the results: for both men and women, the Table shows that the effect of AI on health is positive, statistically significant and robust to inclusion of education as a control. BMI has a slightly negative effect on future health, while all three exercise levels appear to be strongly predictive of health. The magnitude of the AI effect on health is in the same ballpark as increasing exercise frequency from zero to every two days. The negative effect of "eversmoke" supports our earlier argument that not smoking could be viewed as an investment in future health. It is possible that poor health could cause people to reduce exercise, so it could be that the cause of poor health in 1993 is really poor health in 1986, which also reduces exercise frequency, undermining our argument.

In the previous table we used frequency of exercise as a control variable, in order to isolate the effect of future-orientedness. However, if we are thinking of exercise as a deliberate investment in health, then it too should be increasing in future-orientedness. Table 16 shows the results of estimating a multinomial logit model of frequency of exercise, taking as controls the same variables as in Table 13. Regardless of whether we control for education, higher AI is associated with more frequent exercise; the magnitudes are greater for men, but still positive and statistically significant for women. The attitude index contributes in two ways to future health; first by influencing observable behaviors, such as smoking or exercise, and second, after controlling for those variables. Table 16 shows the results of regressing frequency of exercise on the same variables as in Table 13. For males, higher AI is associated with more frequent exercise, while for females there is no relationship.

7 Lifetime Wealth Inequality

What do our results suggest for the contribution of AI heterogeneity to inequality of wealth at retirement? In this section we take two independent approaches to assessing the longer-run implications, i.e. the projected impact on retirement wealth if households remain married with constant AI for 40 years.

An important limitation of our results so far is that they reflect only short-term savings variation, as the regression results condition the variation in AI on the previous wealth observation. The resulting estimate of AI is the effect of attitudes on the W/Y ratio over one period. The estimation, being based on PSID wealth measurements every five years before 2001, corresponds to a period duration of five years.

Our results below suggest potentially large effects of AI on wealth inequality at retirement, but caution is required, as inequality is driven by the variance of AI, and the variance

Table 15: Regression Health Status on Attitude Index

	Men		Women	
	M1	M2	W1	W2
Attitude Index	0.8093	0.7003	0.8550	0.6182
	(0.041)	(0.043)	(0.060)	(0.063)
Predicted Education	.	1.4291	.	1.9060
	.	(0.058)	.	(0.057)
(Predicted Education)^2	.	-4.4540	.	-6.2249
	.	(0.229)	.	(0.221)
BMI86	-0.0136	-0.0151	-0.0348	-0.0338
	(0.001)	(0.002)	(0.001)	(0.001)
ExerDum1	0.5021	0.4198	0.3733	0.3356
	(0.016)	(0.017)	(0.015)	(0.016)
ExerDum2	0.3275	0.2692	0.3701	0.2770
	(0.019)	(0.019)	(0.019)	(0.020)
ExerDum3	0.3747	0.3579	0.3228	0.3408
	(0.014)	(0.014)	(0.014)	(0.014)
eversmoke	-0.0803	-0.0737	-0.1230	-0.1794
	(0.013)	(0.014)	(0.011)	(0.011)
N	2154	2011	2425	2273

Note: Standard errors clustered at the family ID level are in parentheses.
Other controls included but not shown: black race, birth year, parents poor when respondent growing up.

Table 16: Regression Exercise Frequency on Attitude Index

	Men		Women	
	M1	M2	W1	W2
Attitude Index	1.3369	1.3784	0.3092	0.3566
	(0.064)	(0.069)	(0.074)	(0.077)
Predicted Education	.	1.0574	.	0.5125
	.	(0.173)	.	(0.126)
(Predicted Education)^2	.	-3.0814	.	-1.2126
	.	(0.630)	.	(0.466)
Black	-0.5247	-0.0618	-0.4940	-0.2587
	(0.040)	(0.050)	(0.026)	(0.030)
Parents Poor	-0.0262	0.1582	-0.2865	-0.1870
	(0.017)	(0.020)	(0.014)	(0.015)
N	746	675	1280	1190

Note: Standard errors clustered at the family ID level are in parentheses. Other controls included but not shown: black race, birth year, parents poor when respondent growing up.

of our estimates will certainly be inflated by the fact that our measures of AI are inherently very noisy.

7.1 Compounding the AI

One way to see the long term implications of our measures is to compound the effects of the AI over the working lifetime.

Our model implies that, under the optimal policy, the W/Y ratio, $w_{i,t}$, can be written as a first-order difference equation:

$$w_{i,t} = \lambda_{0,i} + \frac{\lambda_1}{1+\gamma_{it}} w_{i,t-1} + \lambda_2 \gamma_{i,t} + ... + \upsilon_{i,t}$$

where $\gamma_{i,t}$ is the expected growth rate of non-financial income. Note that the first term $\lambda_{0,i}$ corresponds to the household AI effect derived in our model. To streamline the exposition, suppose that the other coefficients are unrelated to household AI and that $\gamma_{i,t} = \gamma_i$. Then we can write:

$$w_{i,t-1} = \lambda_{0,i} + \frac{\lambda_1}{1+\gamma_i} w_{i,t-2} + ...$$

Through repeated substitution as we drive back further into time to the start of life at $t = T_a$:

$$w_{i,t} = \lambda_{0,i} \sum_{s=0}^{t-T_a} x^s + w_{i,T_a} \sum_{s=0}^{T_a} x^s + ...$$

where $x \equiv \frac{\lambda_1}{1+\gamma_i}$. Since we want to assess the role of our empirical estimates of $\lambda_{0,i}$, we assume away variation in the other terms, so that γ_i and w_{i,T_a} are the same for everyone. Note that, setting $t = T_R$, a uniform age of retirement. Suppose that people work K periods and then retire at $t = T_a + K$, so that we can write the summation as:

$$\sum_{s=0}^{K} x^s = \frac{1-x^{K+1}}{1-x}.$$

Then the effect of inequality of AI is summarized by:

$$w_{i,t} = \lambda_{0,i} \frac{1-x^{K+1}}{1-x}.$$

Since we estimated the AI from regression coefficients based on measures every five years, 40 years corresponds to 8 periods, so we set $K = 8$. We found a median income growth rate of 0.02 annually. The coefficient β on W/Y was on the order of 0.66. So we set $x = 0.66/(1.02) = 0.65$. This implies $\frac{1-x^K}{1-x} = 2.8$. Our AI estimates imply that the mean household AI was 0.21 and the standard deviation 0.56.

Consider two identical households that differ only in household AI: one household is one SD above the mean, while the other is one SD below. Our AI estimates imply that the mean household AI was 0.21 and the standard deviation 0.56, so the household AI is 0.77 for the first case, and -0.35 for the second. This implies the variation in wealth due to AI alone exceeds the value of one year's income. To the extent that other correlates of the savings rate, such as income and education, are driven by variation in AI, the range of variation in savings could be significantly higher. Even if the SD were smaller by 1/2, this remains a potentially important source of wealth inequality.

7.2 Simulation: the Wealth Gini

To what extent does the measured variation in AI have an observable effect on wealth inequality, as measured by the Gini coefficient? In this section we compute the Gini coefficient for wealth, based on a simulation of a population cohort of married couples, subject to realistic constraints on the income process. The parameters are drawn both from our estimation exercises and from published empirical statistics for the US in 2007, as reported by Diaz-Gimenez et al. [2011] referred to below as DGR.

Our simulation assumes that each period, household earnings transit across quintiles of the economy according to the transition matrix:

$$P(Q', Q) = \Pr\left\{y_{t+1,i} \in Q' | y_{ti} \in Q\right\}.$$

We assume a uniform distribution within each quintile: each household is assigned income equal to the mid-point of the quintile plus a uniform iid random shock.

Having observed their income, households choose their savings by following the savings rule equation (8) with coefficients as reported estimated in Table 7:

$$\omega^1_{ti} = \overline{\omega} + \lambda_{0,i} + \beta_\omega \omega^0_{t-1,i} + \beta_g E^g_{t,i} + \epsilon_{ti} \tag{10}$$

where $\overline{\omega}$ represents the mean value of the wealth/income ratio $\frac{W_{t,i}}{y_{t,i}}$ in the PSID sample, and the expected growth rate $E^g_{t,i}$ is set equal to the household's predicted growth rate. We compare wealth inequality in this economy, with one in which all households have the mean value of the household AI, $\lambda_{0,i}$.[24]

Simulation results are shown in Table 17. Rows 2 to 4 show simulated statistics that guided the calibration of the income process. The benchmark parametrization generates a 5-year auto-correlation of income around 0.41, a Gini coefficient for income of 0.35, and a correlation of wealth with income of 0.4, all comparable to existing estimates for the economy as a whole (as per Diaz-Gimenez et al. [2011]).

When the AI is the same for all households in the simulated economy, the resulting Gini coefficient for wealth, shown in row 5, equals 0.50, which is higher than that of income,

[24] In this latter case, when the model matches the Gini coefficient for income, the calibration should yield a Gini coefficient for wealth well below the US level, simply because our analysis excludes the households in the top percentiles of wealth and income, a limitation imposed by the PSID sampling structure.

Table 17: Simulated Distribution of Retirement Wealth

Row	Simulation Statistics	Benchmark Parameters	Robustness Mean AI	Robustness Std. Dev. AI
1			0.11	0.275
2	AutoCorr. Y	0.41	0.41	0.41
3	Corr(W,Y)	0.39	0.36	0.48
4	Gini Y	0.35	0.35	0.35
5	Gini W	0.50	0.57	0.49
6	Gini W AI	0.66	0.76	0.54
7	Pct. Change	0.32	0.32	0.10

Notes: Authors' computations based on Attitude-Index estimates in Table 7 and income process from DGR. "Gini Y" is the Gini coefficient for household non-financial income, "Gini W" that for wealth at retirement with no AI variation, and "Gini W AI" with AI variation.

but significantly lower than that reported by DGR, around 0.8. Now when we impose an AI distribution with the same variance as our estimated AI, the Gini coefficient for wealth rises by about 32%, to 0.66.

In the Robustness section of Table 17 we ask how the aggregate effects of AI would change if the true moments were smaller by 50%. Lower mean, for instance, drives up the wealth Gini coefficient to 0.76 but this still represents the same 32% increase over the case with no AI variation. What if the true standard deviation of AI were smaller by 50%? In this case, the contribution of AI to wealth inequality would be considerably lower, the Gini coefficient increasing only 10%, from 0.49 to 0.54.[25]

Similar comparisons were run for the other parameters but not shown. For instance, doubling the estimated effect of income growth or of initial wealth, relative to our estimates in the main regression equation, both increase the wealth Gini coefficient, but the percent change due to AI variation falls from 32% to 27%. We infer that our main result is relatively robust to errors in these parameter values.

8 The Effect of Parents' Attitudes on Offspring

Our results so far are silent on the source of heterogeneity in future-orientedness. Taken as a whole, this is a potentially complex topic that we defer to future research. However in this section we will consider whether there is an inter-generational aspect: does future-orientedness of the attitude generation help to explain the savings behavior of their adult offspring? Recent research suggests that such linkages could be the result of at least two distinct theories of transmission of attitudes within the family; cultural transmission (Fernández [2011]) or genetic transmission (Johnson et al. [2009]. It may be impossible to distinguish the two from behavioral data, in part because the truth is likely to involve a

[25]However, changes of similar size in the wealth Gini coefficient over the last twenty years have not gone unnoticed; consider for instance the rise over time in the US wealth Gini, which grew from 0.79 in 1989 to 0.86, an increase that has been accompanied by a lot of commentary on inequality https://www.federalreserve.gov/econres/notes/feds-notes/wealth-inequality-and-the-racial-wealth-gap-20211022.html.

mix of the two. In this section we ask instead whether the data supports the restrictions implied by additive genetic transmission, the benchmark model in quantitative genetics, such as twin studies and GWAS.

The main restrictions we consider are (1) that the effects of mothers' and fathers' future-orientedness on the offspring should be equal on average, and (2) the effects of the parent's future-orientedness should be independent of the sex of the offspring, and (3) the effects of the parent's future-orientedness should be independent of the environment; controlling for exogenous differences should not change the estimated effects of future-orientedness. Violation of these restrictions may be due to more complex forms of genetic transmission, or to the presence of cultural transmission, or simply due to our variables not fully distinguishing the indirect effects of future-orientedness from those of environmental variation.

We provide in the Appendix section C a discussion of the intergenerational transmission mechanism we use in our empirical analysis. Our model implies that there is a household effect $\lambda_i \equiv \frac{\beta_i}{1+\beta_i}\frac{1}{1+r_i}$ that enters additively into the savings choices of each household. We add to our model the linear transmission of this effect from parents to offspring.

In this section we apply the same methods used in our analysis of the Attitudes sample to the analysis of their offspring. The main difference is that the attitude effect is represented by the parent's future-orientedness, as measured by the attitude indices computed from Table 7. The first part of our analysis focuses on the savings of married offspring, and the second part on non-pecuniary behavior, in this case timing of marriage and births etc.

Table 18: Offspring Demographics by Parental AI

Household Sample	Percentile HH AI	Hub's Age	Hub.-Wif. Age Gap	Hub. Retired	Grades Wife	Grades Hub.	Kids At Home	Health Poor Wife	Health Poor Hub.
Sons	0-25	55.47	2.72	0.26	14.00	14.05	0.662	0.144	0.101
	25-75	52.54	1.40	0.15	14.64	14.31	0.892	0.096	0.056
	75-100	52.02	1.48	0.09	14.79	14.79	0.661	0.069	0.079
Daughters	0-25	56.26	1.93	0.24	13.70	14.35	0.496	0.123	0.098
	25-75	55.94	1.73	0.23	14.21	14.11	0.642	0.094	0.075
	75-100	54.35	1.98	0.21	14.48	14.09	0.609	0.193	0.154

Offspring sample in 2015, ranked by parent's household AI, based on estimates of Model 3 in Table 7.

8.1 The Married-Offspring Samples

To explore the association between the attitude indices of the married couples in the Attitudes sample and the behavior of their adult offspring we construct samples from the adult offspring of the members of the Attitudes sample. For this generation, the PSID does not have attitude questions that are many years prior to the attitudes reports, so we cannot apply our method to compute the AI directly.[26] The attitude variables we use instead

[26]For this generation, the attitude questions were only asked in 2016, so it is not possible to replicate the analysis of the Attitudes-Wealth sample, as most wealth observations are now prior to the attitudes reports.

are the *parents'* AIs. These are available for only one of the spouses in each couple, as the other spouse's parents are not PSID members. The sample consists of all the married offspring of the Attitudes sample, regardless of whether the parents were also present in the Attitudes-Wealth sample that was used to estimate the AIs, subject to the husband being between 40 and 70 years old. This results in a sample size of 1382 couples, 628 sons and 754 daughters.

8.1.1 Offspring Demographics and Parental AI

In Table 10, we showed how demographic variables, such as education and health, were correlated with the household AI of the attitude sample. In the Married-Offspring sample, we see a weaker echo of these patterns among the sons of the Attitude sample, but not among the daughters, suggesting either weaker transmission to female offspring, or less influence of wives over savings.

The average age of the husband in the offspring sample, as shown in the top panel of Table 18 is slightly younger in the top parental AI quartile (52 years for sons, 54 for daughters), than the bottom (55 years for sons, 56 for daughters). The age gap between spouses decreases with the AI of the husband's parents, but not with that of the wife's parents, shown in the bottom panel. As with the Attitude sample, the age effect is likely related to retirement, as we show below in Table 19 that the fraction of husbands working rises from 66% to 82% as the AI of the husband's parents increases from the bottom to the top quartiles.[27]

A connection between husband's parental AI quartile and education is also evident in the table, but it is weaker than in Table 10 for the attitude generation. This helps to rationalize our strategy of using parental variables to instrument for education. Table 18 shows that average grades completed of both spouses increases with parental AI on the husband's side and the wife's mean grades, but not those of her husband, also increase with her parent's AI. Education is an example of an offspring characteristic that may be considered as themselves the result of parental investments motivated by family future-orientedness. We suggested above that education was likely to be a function of own future-orientedness, but it is also likely to vary according to that of the parents; our analysis is silent as to the relative strength of these two mechanisms.[28]

In the top quartile of AI of the husband's parents, each spouse is less likely to be in poor health than in the bottom quartile (50% less for wives, 20% less for husbands), while for AI of the wife's parents, both spouses in the top quartiles are 50% *more* likely to be in poor health. The self-reported good health follows a corresponding pattern(not shown). This result is not suggestive of AI transmission, given our finding, in section 6 above, that

[27] The retired fraction falls from 26% to 9% as the AI of the husband's parents increases from the bottom to the top quartiles.

[28] In our current research we try to measure how future orientedness of the parents modifies the offspring's environment while growing up.

AI is associated with both higher health and more investment in health, but does not rule out a more consistent relationship that is obfuscated by other variables, a promising topic for future research.

Table 19: Offspring Income and Wealth by Parental AI

Household Sample	Percentile HH AI	W/Y Ratio	Working Hub.	Working Wife	Annual Income	Net Worth	Busi. Share of Wealth	Stock Share of Wealth
Sons	0-25	0.22	0.66	0.68	\$30,550	\$14,370	0.007	0.044
	25-75	0.38	0.79	0.66	\$36,880	\$31,495	0.034	0.030
	75-100	0.61	0.82	0.67	\$44,221	\$76,178	0.036	0.084
Daughters	0-25	0.33	0.68	0.57	\$31,495	\$48,817	0.013	0.031
	25-75	0.47	0.69	0.61	\$28,735	\$34,802	0.083	0.030
	75-100	0.34	0.74	0.63	\$35,598	\$30,952	0.028	0.058

Offspring sample in 2015, ranked by parent's household AI, based on estimates of Model 3 in Table 7.

8.1.2 Offspring Affluence and Parental AI

In our next table, it will be immediately apparent that the married offspring of parents from the top AI quartile are more prosperous than those of parents from the bottom quartile. This raises an important issue: is the connection that AI is transmitted to offspring, or is it explained by transmission of material advantages? Table 19 shows that the median annual income of the sons' households rises by roughly 50%, from \$ 31k in the bottom AI quartile to \$ 44k in the top quartile; a weaker pattern is observed for daughters: median income in the top quartile is \$ 4k higher than in the bottom, but now the middle quartile is lower than the bottom by \$ 2.5k. For male offspring, median wealth, as measured by net worth, is much higher at the top quartile (\$76k) than at the bottom quartile (\$14k). This greater disparity is reflected in the W/Y ratio which rises from 0.22 to 0.61; in our model. In light of the estimation results in Table 7, this is strongly suggestive of AI correlation between the generations. However, the wealth of the daughters of the top quartile (\$31k) is much less than that of those from the bottom quartile (\$48k), and the W/Y ratio appears uncorrelated with parental AI, raising the question of whether AI transmission might be sex-biased. The Table also shows that for the sons the stock and business shares of assets follow similar lines to income and net worth, and for daughters both shares are higher in the top quartile than in the bottom quartile, though the median business share is higher for daughters in the middle quartiles. The differential for sons might suggest that the connection with parental AI is driven by portfolio shares, but it is also apparent that these shares are quite small, the largest being 8.4% for stocks share of sons.

It is clear that the male offspring of parents with high attitude indices tend to be quite a bit wealthier than those whose parents had low AI. A regression analysis can clarify whether this is the result of having more education and income, due to self-employment or whether the sons are also saving more like their parents.

8.2 Parent's Attitudes and Offspring Savings

Our Married-Offspring Sample pools the initial-wealth observations for the years 2003, 2007, 2011, 2015, 2017 and 2019, treating householder-year as the unit of observation. For the analysis of offspring wealth, we consider adult sons and daughters of respondents in the Attitudes-Wealth sample who were married and either head or spouse at the time their wealth is measured, and aged 40-70. This leaves us with an "Offspring-Wealth" sample consisting of 714 observations on male offspring and 716 on female.

In Table 20 we report the attitude estimates from our benchmark specification (Model 3), which controls for education of both parents and offspring, along with some alternate versions with a nested set of the explanatory variables consisting of the AI from our attitude-wealth sample as estimated in Table 7, along with control variables.[29]

We identify several robust features of these estimates. The basic result in Table 20 is that the parent's AI appears to have strong effects on the savings rate of the offspring, as measured by the W/Y ratio, even after all of the controls are included. For sons, the AI effect of both parents are strong: in our benchmark, Model 2, as well as Model 3, the mother's effect (around 0.5) is slightly stronger than the father's (around 0.4), but this is reversed in Model 4, when controls for employment of parents and offspring are included. For daughters, all of the parental AI effect is due to that of the mother.

Thus, the effect of mother and father AIs are far from equal to each other, and the transmission to the offspring appears to be stronger along same-sex lines. In Model 1 the mother's effect on daughters is 0.931; on sons only 0.555. The father's effect on daughters is statistically zero, but 0.611 on sons, higher than the mother's by one standard error. Such differences between sons and daughters could provide clues as to how future-orientedness is transmitted from parents to offspring; deviation from the equal effects predicted by the linear genetic model, could be interpreted as suggesting that at least some of the effect is cultural (that is, non-genetic).

Recall that in the joint wealth regression for the Attitude-Wealth sample, as reported in Table 8, we found that the sum of both spouse's AI coefficients was in the range of 1.6 to 1.8. For the offspring's saving rate, Table 20 shows that, for both sons and daughters, the sum of the coefficients on parent AI lies in a range of 0.8 to 1.2. This is consistent with 50% or more of the parental effect being transmitted to the offspring household. Since the effect of offspring's AI is diluted by that of the offspring spouse, the strength of transmission to individual offspring could be much higher.

Note that the model's restrictions on the effects of lagged W/Y and on future income growth, as discussed in section 4, are both supported by the estimates: the effect of predicted income growth is negative and that of lagged W/Y between 0 and 1. This suggests

[29] In the Appendix (see Table 33) we also consider various tweaks of these regressions, such as extending the offspring sample back to 1994, adding controls for number of kids, and spouse's employment and extending the offspring sample to include married offspring of parents who were in the attitude sample, but not part of the married attitude-wealth sample.

Table 20: Offspring Savings and Parental Attitudes

	Model 1		Model 2		Model 3		Model 4	
	Son	Daughter	Son	Daughter	Son	Daughter	Son	Daughter
Mother's AI	0.555	0.931	0.500	0.888	0.476	0.914	0.317	1.005
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)
Father's AI	0.611	-0.001	0.419	-0.039	0.394	-0.024	0.512	0.053
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)
Lagged W/Y	0.618	0.588	0.605	0.587	0.606	0.588	0.550	0.542
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expected Income Growth	-0.316	-0.237	-0.821	-0.368	-0.806	-0.298	-0.630	-0.603
	(0.14)	(0.16)	(0.15)	(0.17)	(0.14)	(0.17)	(0.27)	(0.24)
Wife's Education			0.080	0.031	0.080	0.031	0.067	0.000
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Husband's Education			0.061	-0.018	0.068	-0.014	0.043	-0.010
			0.008	0.007	0.007	0.007	0.008	0.007
R^2	50.8%	42.4%	52.0%	42.4%	51.9%	42.3%	54.4%	43.9%
Nobs	714	716	714	716	714	716	714	716

Household W/Y ratio in the PSID, estimated on married couples in the "offspring-wealth" sample. Standard controls include quadratics in year and ages of both parents. Model controls include the wealth income ratio and future income growth. Education controls consist of the predicted education of both parents. For the full set of estimates, see Table 33.

that the data fit the model reasonably well and the results are not driven by selection on unobservables or excluded variables.

Since we control for W/Y at the start of the period, these parental AI effects are not driven by higher initial wealth of the offspring of high AI parents. Since we control for offspring (predicted) education, differences in years of education are not driving the result either. Thus, the results suggest significant transmission of future-orientedness across generations.

9 Timing of Family Choices and Parental Attitudes

It is clear from the above that the parent's AI is strongly associated with the savings of the offspring. As with the attitude-wealth sample, one may be concerned with whether the savings effect of the AI reflects future-orientedness, or instead, financial skills or knowledge. We could repeat here the analysis we carried out for health and cigarette smoking. Instead, however, we choose to exploit the fact that the offspring of respondents in the Attitudes sample have, since the time their parents first responded to the attitude questions, mostly moved out from the parent's home and started their own families. This allows us to examine the connection between the future-orientedness of the Attitudes sample and the family decisions of their offspring.

Table 21: Offspring's Age at First Child

	Son		Daughter	
	M1	M2	W1	W2
Father's AI	3.769	1.679	4.178	1.584
	(0.225)	(0.229)	(0.226)	(0.221)
Mother's AI	2.647	0.182	5.767	3.191
	(0.377)	(0.375)	(0.363)	(0.353)
Predicted Education	.	1.941	.	3.083
	.	(0.630)	.	(0.579)
(Predicted Education)^2	.	-1.488	.	-4.752
	.	(2.254)	.	(2.058)
Black	-2.591	-1.274	-3.162	-1.943
	(0.135)	(0.136)	(0.120)	(0.119)
Parents Poor	-1.552	-0.293	-1.730	-0.748
	(0.080)	(0.084)	(0.080)	(0.079)
R-Square	0.053	0.094	0.137	0.173
N	2265	2404	2116	2256

Note: Dependent variable equals offspring age at birth of first child. Standard errors in parentheses. Other controls not shown: Birth year (quadratic). Education^2= (Years/10)^2.

Individuals who are more future-oriented would plausibly be more willing to wait to start a family and prepare for it. Table 21 shows that a higher AI for either parent is strongly associated with higher age of the offspring when the offspring's first child is born. Models M1 and W1 do not control for offspring education; Models M2 and W2 show that doing so decreases the effect of parental AI, but this remains significant except for the effect of maternal AI on daughters. [30]

Table 22: Offspring's Pre-Marital Birth

	Son		Daughter	
	M1	M2	W1	W2
Father's AI	-1.320	-1.170	-0.756	-0.398
	(0.085)	(0.091)	(0.066)	(0.070)
Mother's AI	-0.059	0.050	-0.737	-0.440
	(0.141)	(0.147)	(0.108)	(0.114)
Predicted Education	.	-0.102	.	0.535
	.	(0.252)	.	(0.188)
(Predicted Education)^2	.	-0.271	.	-2.884
	.	(0.920)	.	(0.678)
Black	1.315	1.231	1.186	1.093
	(0.032)	(0.034)	(0.027)	(0.029)
Parents Poor	-0.158	-0.234	0.374	0.236
	(0.032)	(0.034)	(0.022)	(0.024)
N	2265	2116	2404	2256

Note: Dependent variable equals 1 if offspring remains never- married a year after first child is born. Standard errors in parentheses. Other controls not shown: Birth year (quadratic). Education^2= (Years/10)^2.

It may not be true that delaying first births is unambiguously a sign of being future oriented. To reduce the ambiguity, we repeat our exercise for having a pre-marital birth, which is clearly associated with lower economic outcomes in empirical studies (Nock [1998]). In the probit results shown in Table 22, the dependent variable is a binary equal to one if the offspring remains never married for at least one year after the birth of their first child. The paternal AI is associated with lower probabilities of such births; for male offspring, the effect magnitude on sons after controlling for education is -1.32, about the same size as the Black effect (but opposite sign).For female offspring, the paternal AI effect is much smaller, about -0.76, about 60 % of the magnitude of the Black effect. These effects are reduced by controlling for education (columns M2 and W2) but remain statistically significant at the 0.01 level or more. The effect of maternal AI on sons negligible with or without education controls, but strongly negative on daughter's, despite a 40 % reduction, from -.74 years to -.44 years, when controlling for education (column W2). It may not be true that delaying first births is unambiguously a sign of being future oriented. To reduce the ambiguity, we repeat our exercise for having a pre-marital birth, which is clearly associated with lower economic outcomes in empirical studies (Nock [1998]). In the probit results shown in Table 22, the dependent variable is a binary equal to one if the offspring remains never married for at least one year after the birth of their first child. The Table shows that parental AI is associated with lower probabilities of such births; for male offspring, the paternal effect magnitude after controlling for education is -1.32, about the same size as the Black effect (but opposite sign).For female offspring, the paternal AI effect is much smaller, about -0.76,

[30] As one might have expected, the delaying effect of education on first births is very strong; the estimates for offspring with 10 years of education imply about +17 years for sons and +25 years for daughters.

about 60 % of the magnitude of the Black effect. These effects are reduced by controlling for education (columns M2 and W2) but remain statistically significant at the 0.01 level or more. The effect of maternal AI on son's teenage birth probability is negligible, with or without education controls, but strongly negative on daughter's, despite a 40 % reduction, from -.74 years to -.44 years, when controlling for education (column W2). These results fit the pattern that the parental transmission of the AI effect is stronger along same-sex lines.

Table 23: Offspring's Early Marriage

	Son		Daughter	
	M1	M2	W1	W2
Father's AI	-0.634	-0.131	-0.328	0.118
	(0.055)	(0.059)	(0.049)	(0.052)
Mother's AI	-0.140	0.476	-1.042	-0.834
	(0.094)	(0.098)	(0.079)	(0.084)
Predicted Education	.	0.808	.	0.225
	.	(0.168)	.	(0.143)
(Predicted Education)^2	.	-3.864	.	-1.834
	.	(0.613)	.	(0.513)
Black	-0.342	-0.492	-0.266	-0.502
	(0.038)	(0.040)	(0.027)	(0.030)
Parents Poor	0.322	0.190	0.357	0.233
	(0.019)	(0.020)	(0.017)	(0.019)
N	2265	2116	2404	2256

Dependent variable equals 1 if offspring married before age 21. Standard errors in parentheses. Other controls not shown: Birth year (quadratic). Education^2= (Years/10)^2.

Early marriages are another sign associated with low outcomes, perhaps driven by accidental pregnancies (Uecker and Stokes [2008]). Consider a binary variable equal to one if the offspring marries at age 21 or less. Table 23 shows the results of logistic estimation along similar lines as that for single births. Parental AI is mostly associated with a lower probability of early marriage: Column M1 shows the effect of paternal AI on sons to be -.63, about twice the effect of growing up poor; column W1 shows the the effect of maternal AI on daughters to be -1.04 nearly three times the effect of growing up poor. The cross-sex effects are inconsistent: paternal AI significantly reduces daughter's early marriage probability, but maternal AI significantly increases that of sons. In this case the effects of parental AI are significantly reduced by controlling for Education; in M2 and W2 we see that while the same sex effects are reduced, they both remain negative and statistically significant, while the cross-sex effects become positive.

One might consider as similar analysis of future-orientedness on divorce; out of the population of married people, those who are future-oriented will be less likely to disregard concerns about a potential spouse turning out to be incompatible and so more likely to avoid marriages that result in divorce. This suggests that if parental future-orientedness is transmitted to offspring, then the divorce rate will be negatively associated with the AI of either parent. We again estimate a logisitic equation similar to the previous specifications. In this case the binary dependent variable equals one if the offspring ever divorced, and the sample is restricted to offspring who married.

The results, as shown in Table 24 suggest that maternal future-orientedness consistently reduces divorce probability, with roughly equal effects on both sexes of offspring, and that the magnitude of this effect is actually increased slightly by controlling for education. The size of the maternal effects, on the order of -0.5, are mcuh larger than those of the controls for Black and growing up poor. In contrast, there is no negative effect of paternal AI on future-orientedness , and even a positive effect on the son's divorce probabilities. These contrary results could be the result of an artifact caused by the effect of Dad's AI on selection into marriage.[31]

Table 24: Parental Attitude Index and Divorce

	Son		Daughter	
	M1	M2	W1	W2
Father's AI	0.387	0.266	-0.004	-0.103
	(0.057)	(0.061)	(0.064)	(0.067)
Mother's AI	-0.583	-0.620	-0.528	-0.570
	(0.095)	(0.099)	(0.102)	(0.106)
Predicted Education	.	-0.010	.	-0.239
	.	(0.172)	.	(0.181)
(Predicted Education)^2	.	0.354	.	1.175
	.	(0.614)	.	(0.642)
Black	-0.055	0.102	0.040	0.118
	(0.035)	(0.039)	(0.038)	(0.041)
Parents Poor	0.019	0.019	0.033	0.139
	(0.021)	(0.023)	(0.024)	(0.026)
N	1832	1700	1967	1849

Note: Dependent variable equals 1 if offspring ever divorced. Standard errors in parentheses. Other controls not shown: Age at Marriage, Birth year (quadratic). Education^2= (Years/10)^2.

10 Business Ownership

The contribution of entrepreneurship appears to be very important among the wealthiest US households, as discussed in Section 2. In this section we use regression analysis to measure the extent to which AI appears to predict different measures of entrepreneurship, ranging from self-employment to owning and operating a business corporation. The PSID has included family-level business questions since inception. Over time, this has extended from binary indicators for business ownership and incorporation to actual net profit and eventually, market value of the business itself. In 1999 for instance the PSID question was whether any householder had "a financial interest in any business enterprise". In 1999 873 households answered yes, about 12% of the total sample; this fell to 8.6% of the sample in

[31] It is well known that younger marriages (before age 22) result in a high rate of divorce, and to avoid simply restating a result therefore implied by Table 23, we need to control for age at marriage. This control variable has a negative effect in all the models of Table 24 but is not shown in the table.

2017, of which 80% were owned by the household head.[32]

Table 25: Employment and Business Ownership by Household AI

HH AI Percentile	Husb. Working	Self-Employed Hub	Self-Employed Wife	Owns Busi.	Incorp. Busi.	Self -Emp. x Own	Self -Emp. x Incorp.	N
0-25	0.488	0.116	0.106	0.161	0.123	0.104	0.098	520
25-75	0.629	0.191	0.108	0.193	0.200	0.139	0.149	1044
75-100	0.643	0.213	0.085	0.246	0.154	0.176	0.114	520

Attitude sample in 1989, ranked by household AI, based on estimates of Model 3 in Table 7. Self =self-employed, Own=owns a business, Incorp. = owns an incorporated business.

Business ownership is more common in our sample than overall, as we only consider middle-aged married couples. Consider Table 25, which relates the household AI to various measures of business ownership in our Attitudes sample. The fraction of households who own a business rises from 16% in the lowest AI quartile to 25% of households in the top quartile. In most of these households, according to the table, the spouses are also self-employed, which we take to mean that the spouses also operate the business. To filter out casual self-employment, consider those who operate an incorporated business, about 12% of the low AI quartile and 15% of the top quartile (this rate is actually higher (15%) in the middle two quartiles).

Our main questions for this section are (1) does business-ownership "explain" AI and (2) does AI help to explain business ownership. The first question is easily dealt with by seeing how the estimated coefficients on attitudes or on parental AI change when including business-ownership variables in the AI regression model, equation (3). To deal with the second question we rely on the assumption that parental AI is unaffected by the business ownership of the offspring, and then estimate whether parental AI helps to predict business ownership.

Table 26: Husband's Employment and Business Ownership by Parental AI

Household	Percentile	Working	Self	Own	Incorp.	Self x Own	Self x Incorp.	N
Sons	0-25	.659	.122	.169	.093	.094	.077	157
	25-75	.785	.132	.163	.072	.100	.039	317
	75-100	.831	.124	.170	.095	.053	.035	154
Daughters	0-25	.668	.099	.080	.059	.063	.059	188
	25-75	.700	.133	.165	.063	.099	.047	378
	75-100	.728	.082	.122	.041	.052	.026	188

Offspring in 2015, ranked by household AI of parents. Self =self-employed, Own=owns a business, Incorp. = owns an incorporated business.

Table 34, in the Appendix, shows the effect of controlling for self-employment in wealth income ratio regressions. The first two columns regress wealth income ratio for husbands and wives separately. The third and fourth columns are regressions of sons and daughters.

[32]It is not clear what sort of activities are counted as a business, but in the early income questions, business appears to be distinct from owning a farm or taking in lodgers, but later documentation (e.g. by 1999) seems to suggest farms are counted as part of business wealth.

Since we don't have responses to the attitude questions for offspring, we include the AIs for parents in these regressions.

It can be seen that the computed effects of attitude responses on household savings remain strong and significant after controlling for self-employment. For instance the estimated effect of Husband's response to "life works out" is 0.17 in the table, which controls for self-employment and business ownership, compared with 0.214 in Model 4 of Table 7, which does not, while the effect of 'Prefers to save' remains negative in both cases. Table 34 also shows that the effects of parental AI are robust to controlling for self-employment of both parents and offspring. These results all support the idea that business ownership is not driving the connection between attitudes and household savings.

The big question now is whether regression analysis indicates a connection between attitudes and business ownership. This is not immediately apparent. Table 26 shows that the Household AI of the parents does not appear to be systematically correlated with measures of the offspring's business ownership.

It is quite likely that business ownership is also transmitted from parents to children, either directly by passing on the family business, or indirectly by helping to collateralize the offspring, offering expertise or network advantages. We are not interested in this kind of transmission, so it is important in the latter case to control for the business ownership of the parents.

Table 27: Regression Estimates: Offspring is Self-Employed

	Model 1		Model 2	
	Son	Daughter	Son	Daughter
Mother's AI	0.509	0.204	0.402	0.192
	(0.05)	(0.04)	(0.04)	(0.03)
Father's AI	0.059	-0.068	-0.120	-0.138
	(0.03)	(0.03)	(0.03)	(0.02)
Offspring Education			0.033	-0.005
			(0.00)	(0.00)
Mother's Education	0.015	0.003		
	(0.00)	(0.00)		
Father's Education	-0.016	-0.020		
	(0.00)	(0.00)		
Parents Own Business	0.138	0.192	0.148	0.180
	(0.01)	(0.01)	(0.01)	(0.01)
R^2	7.1%	9.0%	6.0%	8.6%
N	295	326	402	427

Source: Authors' calculation on PSID, Offspring sample. Other controls not shown include Black and year of birth and interactions of Black with the other control variables.

For any given measure of entrepreneurship, we construct a continuous variable by computing each individual's average over a number of years; 1984-2000 for the attitude sample, and 2001-2019 for the offspring sample. For example, business ownership = x if the household reported owning a business in a fraction x of the years under consideration. For both samples, we only consider years in which the individual was married, and was either household head or spouse of head, and aged between 30 and 60 years old. Finally, we drop from the offspring sample those where the AI (from Model 3 of Table 7) of either of the parents are in the 1% tails of the distribution for their sex. We are left with a sample of 829 offspring households, with a few more daughters (427) than sons (402). We estimate by OLS the effects of the parent's AI on the entrepreneurship of the offspring sample. The controls include whether the parental household owns and operates a business, predicted education and the AI of the parents of the PSID member of the offspring household, and whether the PSID offspring respondent was poor or rich growing up, along with standard controls, such as birth year, and black interacted with the latter variables.

In Table 27 we show the results for offspring's self-employment, based on separate estimations by offspring sex. The main finding is that the effect of the mother's AI is quite large; controlling for parent's education, the coefficient on sons is 0.51 and that on daughters 0.20. For comparison, the coefficient on parent's business ownership is 0.14 for sons and 0.19 for daughters. The effects of the father's AI on the other hand are much smaller, 0.06 for sons and -.07 for daughters. Controlling for the son's education reduces the effect of the maternal AI by about 20%, but not that of the daughter. Bearing in mind that the standard deviation of the maternal AI is on the order of 0.2, the effect of maternal AI being one SD above versus one SD below the mean would be about 0.20 in Model 1 of the table, comparable to the effect of parent's business ownership.

Table 28: Regression Estimates: Offspring Operates Business

	Model 1		Model 2	
	Son	Daughter	Son	Daughter
Mother's AI	0.159	0.206	0.211	0.226
	(0.04)	(0.03)	(0.03)	(0.02)
Father's AI	0.028	-0.014	-0.039	-0.075
	(0.02)	(0.02)	(0.02)	(0.02)
Offspring Education			0.004	0.002
			(0.00)	(0.00)
Mother's Education	0.547	0.068		
	(0.10)	(0.07)		
Father's Education	-0.546	-0.067		
	(0.10)	(0.07)		
Parents Own Business	0.037	0.006	0.099	0.104
	(0.00)	(0.00)	(0.01)	(0.01)
Parent Log(Wealth)	0.088	0.116	0.028	0.013
	(0.01)	(0.01)	(0.00)	(0.00)
R^2	5.4%	8.0%	5.5%	7.8%
N	329	359	402	427

Source: Authors' calculation on PSID, Offspring sample. Other controls not shown include Black and year of birth and interactions of Black with the other contol variables.

What about other measures? Table 28 shows the same exercise for offspring owning/operating a business.[33] The effect of mother's AI on offspring is again much larger than that of fathers, but this time relatively invariant to sex of offspring and to whether education of parents or offspring is in the controls. While the source of this greater stability is not clear, the table reinforces the other findings discussed for Table 27; the offspring of high AI parents are on average more entrepreneurial, consistent with the view that variation in future-orientedness contributes to variation in involvement in business.

Notice that this table also adds controls for parental wealth in 1984-2000; we find excluding this has little to no effect on the results of this table for parent's AI, except that the effect of mother's AI on sons rises to 0.24, suggesting that a half of the AI effect is indirect via the effect on parent's wealth.

We see the results of this section as a potential contribution to explaining the wealth concentration among the very wealthy. Transmission of future-orientedness across generations contributes to business ownership and thus indirectly to wealth concentration by raising persistence of business ownership across generations, as per Hubmer et al. [2021] and others.

11 Conclusion

The main contribution of this paper was to show that certain personality traits, which we called 'future-orientedness', are associated with higher rates of saving and that this contributes significantly to inequality of wealth at retirement. We used the PSID to measure variation in future-orientedness of married people as the empirical association between attitudes to saving and planning in the 1970s and household savings in the 1990s; we called this the 'Attitude index'.

Discounting appears to contribute little or nothing to variation in the AI, suggesting that ability or propensity to plan is more important than variation in preferences for explaining wealth inequality. We also noted that the effects of wife's AI on savings appears to be about half as strong as that of husbands, suggesting that wives have much less influence over savings.

The presence in the PSID sample frame of all offspring of PSID respondents allowed us to measure transmission of future-orientedness across generations by estimating the association between the parental AI and the savings of the adult offspring in the years since 2001. Our results suggest that offspring inherit at least some of their parent's future-orientedness. This is consistent with an important body of previous research which argues that persistence of family-specific effects may reduce social mobility over many generations. The particular way in which future orientedness is transmitted remains an important research question.

[33]This time the education controls are actual years of education, but we did not notice any qualitative difference from using predicted years.

We found that the Attitude index helped to predict a wide range of non-pecuniary outcomes, ranging from health and smoking to marriage and divorce, which allows us to distinguish future-orientedness from specifically financial traits that have already been well-studied, such as financial acumen, business ownership and rates of return. Since the same AI that matters for wealth matters for non-financial behavior, we interpret these results as supporting the hypothesis that both behaviors are driven by deep-seated future-orientedness, which may well in turn explain variation in financial acumen.

In addition to the above, a significant contribution of this paper is the ability to separately calculate attitude indices for both spouses. This makes it possible to investigate the effect of intra-household differences in future orientedness on financial and non-financial decisions and on the inter-generational transmission of future orientedness.

Overall, our results suggest that the connection between maternal AI and offspring future-orientedness are generally stronger than those of paternal AI. Given that wives appear to have less influence over savings, we take this as evidence against the symmetry of effects implied by linear genetic models of inter-generational transmission.

We leave a number of important issues to future research. Further work is needed to distinguish between genetic and cultural models of transmission, to explore the effect of future-orientedness on financial sophistication, and to compare the ability of theoretical models of time-inconsistency to rationalize the sort of behavior that we have attributed to future-orientedness more generally.

References

S.R. Aiyagari. Uninsured idiosyncratic risk and aggregate saving. *Quarterly Journal of Economics*, 109:659–684, 1994.

Sule Alan, Kadir Atalay, and Thomas F. Crossley. Euler equation estimation on micro data. *Macroeconomic Dynamics*, 23:3267â3292, 2019.

Alberto F Alesina, Marlon Seror, David Y Yang, Yang You, and Weihong Zeng. Persistence despite revolutions. Working Paper 27053, National Bureau of Economic Research, April 2020. URL http://www.nber.org/papers/w27053.

Johan Almenberg, Annamaria Lusardi, Jenny Säve-Söderbergh, and Roine Vestman. Attitudes towards debt and debt behavior. *The Scandinavian Journal of Economics*, 123(3): 780–809, 2021.

John Ameriks, Andrew Caplin, and John Leahy. Wealth accumulation and the propensity to plan. *The Quarterly Journal of Economics*, 118(3):1007–1047, 2003.

Orazio P. Attanasio and Martin Browning. Consumption over the life cycle and over the business cycle. *The American Economic Review*, 85(5):1118–1137, 1995. ISSN 00028282. URL `http://www.jstor.org/stable/2950978`.

Daniel Barth, Nicholas W Papageorge, and Kevin Thom. Genetic endowments and wealth inequality. *Journal of Political Economy*, 128(4):1474–1522, 2020.

Jess Benhabib, Alberto Bisin, and Mi Luo. Earnings inequality and other determinants of wealth inequality. *American Economic Review*, 107(5):593–597, May 2019.

Jess Benhabib, Alberto Bisin, and Ricardo T Fernholz. Heterogeneous dynasties and long-run mobility. *The Economic Journal*, 132(643):906–925, 2022.

B Douglas Bernheim, Jonathan Skinner, and Steven Weinberg. What accounts for the variation in retirement wealth among u.s. households? *American Economic Review*, (4): 832–57, 2001.

Andrew Caplin, Mark Dean, and John Leahy. Rationally inattentive behavior: Characterizing and generalizing shannon entropy. *Journal of Political Economy*, 130(6):1676–1715, 2022.

Ana Castaneda, Javier Diaz-Gimenez, and Jose-Victor Rios-Rull. Accounting for US earnings and wealth inequality. *Journal of Political Economy*, 111(4):818–857, 2003.

David Cesarini, M Johannesson, P Lichtenstein, Örjan Sandewall, and Björn Wallace. Genetic variation in financial decision-making. *The Journal of Finance*, 65(5):1725–54, 2010.

Kerwin Kofi Charles and Erik Hurst. The correlation of wealth across generations. *Journal of Political Economy*, 111(6):1155–1182, 2003.

Syngjoo Choi, Shachar Kariv, Wieland MÃŒller, and Dan Silverman. Who is (more) rational? *American Economic Review*, 104(6):1518–50, June 2014. doi: 10.1257/aer.104.6.1518. URL `https://www.aeaweb.org/articles?id=10.1257/aer.104.6.1518`.

Gregory Clark. *The Son Also Rises*. Princeton University Press, 2014.

Gregory Clark and Neil Cummins. Intergenerational wealth mobility in England,1858 - 2012: Surnames and social mobility. *The Economic Journal*, 125(582):61–85, 2015.

Henrik Cronqvist and Stephan Siegel. The genetics of investment biases. *Journal of Financial Economics*, 113(2):215–234, 2014.

Henrik Cronqvist and Stephan Siegel. The origins of savings behavior. *Journal of Political Economy*, 123(1):123–169, 2015.

Mariacristina De Nardi and Giulio Fella. Saving and wealth inequality. *Review of Economic Dynamics*, 26:280–300, 2017.

Javier Diaz-Gimenez, Andy Glover, and Jose-Victor Rios-Rull. Facts on the distributions of earnings, income, and wealth in the United States: 2007 update. *Quarterly Review*, 34(1), 2011.

Karen E Dynan, Jonathan Skinner, and Stephen P Zeldes. Do the rich save more? *Journal of Political Economy*, 112(2):397–444, 2004.

Andreas Fagereng, Magne Mogstad, and Marte Rønning. Why do wealthy parents have wealthy children? *Journal of Political Economy*, 129(3):703–756, 2021.

Douglas S. Falconer and Trudy F. C. Mackay. *Introduction to quantitative genetics*. Harlow Longmans Green, Harlow, UK, 1996.

Raquel Fernández. Does culture matter? *Handbook of social economics*, 1:481–510, 2011.

Svenja Flechtner. (Why) do poor households under-save? a review of the behavioral literature. *A Review of the Behavioral Literature (March 20, 2023)*, 2023.

Nicola Fuchs-Schündeln, Paolo Masella, and Hannah Paule-Paludkiewicz. Cultural determinants of household saving behavior. *Journal of Money, Credit and Banking*, 52(5): 1035–1070, 2020.

Michael Grossman. On the concept of health capital and the demand for health. In *Determinants of health: an economic perspective*, pages 6–41. Columbia University Press, 2017.

Alan L Gustman, Olivia S Mitchell, Andrew Samwick, and Thomas L Steinmeier. Pension and social security wealth in the health and retirement study, 1997.

Glenn R. Hubbard, Johnathan Skinner, and Stephen P. Zeldes. Precautionary savings and social insurance. *Journal of Political Economy*, 102(April):360–99, 1995.

Joachim Hubmer, Per Krusell, and Anthony A. Smith. Sources of us wealth inequality: Past, present, and future. *NBER Macroeconomics Annual*, 35:391–455, 2021. doi: 10.1086/712332.

Erik Hurst. Grasshoppers, ants, and pre-retirement wealth: A test of permanent income. Nber working paper no. w10098, NBER, 2003.

Wendy Johnson, Eric Turkheimer, Irving I Gottesman, and Thomas J Bouchard Jr. Beyond heritability: Twin studies in behavioral research. *Current directions in psychological science*, 18(4):217–220, 2009.

John Knowles and Andrew Postlewaite. Do children learn to save from their parents? Nber working paper no. w10098, NBER, 2005.

Michael Kremer and Rachel Glennerster. Improving health in developing countries: evidence from randomized evaluations. In *Handbook of health economics*, volume 2, pages 201–315. Elsevier, 2011.

Per Krusell and Tony Smith. Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, (5):867–96, 1998.

David Laibson. Why don't present-biased agents make commitments? *American Economic Review*, 105(5):267–72, 2015.

Annamaria Lusardi. Explaining why so many households do not save. Working Paper, Dartmouth College, 2000.

Annamaria Lusardi, Pierre-Carl Michaud, and Olivia S. Mitchell. Optimal financial knowledge and wealth inequality. *Journal of Political Economy*, 125(2):431–477, 2017.

Steven L Nock. The consequences of premarital fatherhood. *American Sociological Review*, pages 250–263, 1998.

Aysu Okbay, Jonathan P. Beauchamp, and Mark Alan Fontana. Genome-wide association study identifies 74 loci associated with educational attainment. *Nature Letters*, 533(7604): 539–542, 2016.

James M Poterba, Steven F Venti, and David A Wise. The decline of defined benefit retirement plans and asset flows. In *Social Security policy in a changing environment*, pages 333–379. University of Chicago Press, 2009.

Davina A Robson, Mark S Allen, and Steven J Howard. Self-regulation in childhood as a predictor of future outcomes: A meta-analytic review. *Psychological bulletin*, 146(4):324, 2020.

John Karl Scholz, Ananth Seshadri, and Surachai Khitatrakun. Are Americans saving "optimally" for retirement? *Journal of Political Economy*, 114(4):607–643, 2006.

Jeremy E Uecker and Charles E Stokes. Early marriage in the United States. *Journal of Marriage and Family*, 70(4):835–846, 2008.

Joseph Veroff, Lou McClelland, and Kent Marquis. Measuring intelligence and achievement motivation in surveys, 1971.

Alessandra Voena. Yours, mine, and ours: Do divorce laws affect the intertemporal behavior of married couples? *American Economic Review*, 105(8):2295–2332, August 2015. doi: 10.1257/aer.20120234. URL `https://www.aeaweb.org/articles?id=10.1257/aer.20120234`.

A A Life-Cycle Savings Model

In the absence of binding borrowing constraints, optimal consumption is a function of lifetime wealth, which is defined as:

$$W\left(a_{0i}, r_i\right) = a_{0i} + y_{i,1} + \frac{y_{i,2}}{1+r_i} + \frac{y_{i,3}}{\left(1+r_i\right)^2}$$

where a_{0i} denotes initial wealth.

For an unconstrained agent, taking $W\left(a_{0i}, r_i\right)$ as given, the optimal consumption sequence in period t satisfies the constant-expenditure share property:

$$\frac{c_{i,t}}{\left(1+r\right)^{t-1}} = \frac{\beta_i^{t-1}}{1+\beta_i+\beta_i^2} W\left(a_{0i}, r_i\right)$$

or

$$c_{i,t} = \frac{\left[\beta_i\left(1+r_i\right)\right]^{t-1}}{1+\beta_i+\beta_i^2} W\left(a_{0i}, r_i\right).$$

In period 3 there is no saving, so the budget constraint implies:

$$c_{i,3} = a_{i,2}\left(1+r\right) + y_{i,3}, \tag{11}$$

where $a_{i,2}$ denotes savings in period 2. Using this third-period equation, we now derive an expression for the period-2 savings out of current income: the wealth-income ratio is

$$\frac{a_{i,2}}{y_{i,2}} = \kappa_i + \kappa_i \frac{s_{i,2}}{y_{i,2}} + \left[\frac{\kappa_i - 1}{1+r_i}\right]\gamma_i \tag{12}$$

where

$$s_{i,2} \equiv a_{i,1}\left(1+r_i\right)$$

represents the household's net worth at the start of period 2, $\gamma_i \equiv \frac{y_{i,3}}{y_{i,2}}$ and $\kappa_i \equiv \frac{\beta_i}{(1+r_i)(1+\beta_i)} < 1$.

A.1 Education Choice

Now suppose that the income profile $[y_{i,2}, y_{i,3}]$ is a deterministic function of education $e_i \in R_+$, which is chosen at the start of life. To acquire education, agents pay a unit utility cost $1/\eta_i$; we interpret η_i as innate ability, which has no effect in later life, conditional on education. Let $W\left(e_i, r_i\right)$ represent the present value of income , discounted at rate r_i. The log-utility formulation implies that the indirect utility function on completion of education, given initial wealth a_{0i},can be written as:

$$V\left(e_i, a_{0i}, r_i\right) = \left(1+\beta_i+\beta_i^2\right)\ln\left[a_{0i} + W\left(e_i, r_i\right)\right] + X\left(\beta_i, r_i\right) \tag{13}$$

where the X term is independent of education. The agent chooses education to maximize lifetime utility.

$$\max_e \{-e/\eta_i + V(e, a_{0i})\}$$

Assume the solution is interior. The first-order condition is

$$-1/\eta_i = \left(1 + \beta_i + \beta_i^2\right) \frac{W_e(e_i, r_i)}{a_{0i} + W(e_i, r_i)}.$$

The RHS is clearly increasing in β_i. It is also decreasing in a_{0i}, as an increase in wealth reduces the marginal benefit of education. In a neighborhood of $a_{0i} = 0$, the ratio term is independent of r_i, but is increasing in r_i for $a_{0i} > 0$ and decreasing for $a_{0i} < 0$. Higher education is therefore associated with higher values of β_i and η_i. The dependence of education on β_i will give rise to an endogeneity problem that we deal with in the estimation below.

A.2 Other Intertemporal Decisions

We could easily add other intertemporal trade-offs to our model. Of particular interest is the class of trade-offs that are independent of savings, financial skills and rates of return, because this allows the model to distinguish variation in β_i from variation in r_i. For our empirical analysis, we consider the decision to become a cigarette smoker as an example of such a trade-off. The idea is that people become cigarette smokers because smoking provides immediate benefits at the cost of long-run health deterioration. We assume away any financial implications of this trade-off. To the extent that variation in α_{1i} reflects variation in β_i rather than in r_i, we should expect people with higher α_{1i} to be less likely to become cigarette smokers. A similar argument applies other non-pecuniary intertemporal trade-offs, such as effort spent on physical exercise for the sake of long-run health, or deferral of marriage and children in order pursue education or career goals. So long as it is reasonable to assume that variation in r_i is orthogonal to the implicit rates of return on these other decisions, evidence that α_{1i} influences these decisions would suggest that α_{1i} indeed reflects variation in β_i rather than in r_i.

A.3 Spouses and Household Future-orientedness

In the previous sections, we thought of future-orientedness as β_i, a trait of household i. Since our empirical analysis focuses on married-couple households and attitudes are traits, of individuals we now use the model to clarify how the future-orientedness of the spouses enters into household behavior.

We assume that all agents marry in the first period, and live thereafter as married-couple households. We suppose that each household i can be characterized by a permanent parameter value β_i. In the spirit of taking the simplest approach, we set β_i equal to the weighted average of the husband's value β_{iH} and the wife's β_{iW}:

$$\beta_i = \rho\beta_{iH} + (1-\rho)\,\beta_{iW} \tag{14}$$

Note that the intercept term in the optimal savings policy can be written as:

$$\alpha_{0,i} = \frac{\beta_i}{1+\beta_i}\,[1+r_i] \approx f(\beta_i)\,[1+r_i]\,.,$$

where $f(\beta_i)$ represents a linear approximation:

$$\frac{\beta_i}{1+\beta_i} \approx f(\beta_i) \equiv m_0 + m_1\beta_i = m_0 + m_1\left[\rho\beta_{iH} + (1-\rho)\,\beta_{iW}\right].$$

So the intercept term in the savings equation reflects both spouses. We could of course do something similar with the other coefficients in the equation, as β_i enters all of them. We focus on the intercept term because it does not interact with potentially noisy variables, unlike the other coefficients.

A.4 The Savings Regression Equation

We assume that the attitude indices based on responses of each respondent j to the PSID attitude questions are noisy indicators of her true value $\beta_{i,j}$. Letting $\hat{\beta}_{i,j}$ denote the index we can write:

$$\beta_{i,j} = \hat{\beta}_{i,j} + \epsilon_{i,j}$$

where $\epsilon_{i,j}$ is a white noise variable. Now the intercept term in the optimal savings policy can be written as

$$\begin{aligned} f(\beta_i) &= m_0 + m_1\left[\rho\left(\beta_{iH} + \epsilon_{i,H}\right) + (1-\rho)\left(\beta_{iW} + \epsilon_{i,W}\right)\right] \\ &= m_0 + m_1\left[\rho\hat{\beta}_{iH} + (1-\rho)\,\hat{\beta}_{iW}\right] + m_1\left[\epsilon_{i,H} + (1-\rho)\,\epsilon_{i,W}\right] \end{aligned}$$

so the coefficients on husband and wife's attitude index, $m_1\rho$ and $m_1(1-\rho)$ reveal the husband's share ρ in the household future-orientedness.

B Empirical Method

In this section we explain the construction of the variables we used to estimate the equations in the main body of the paper. The main issues to cover are: 1. how wealth is measured, 2. how income is aggregated over time, 3. how we compute predicted education, and 4. how we compute the growth rate of income.

B.1 Data and Sub-Samples

The PSID is an extremely well-known data set based on a representative 1968 sample of 3000 US households.[34] Information at the individual level is mainly restricted to the household head and spouse. The three key features of the PSID for our purposes are: (1) The 1968-72 waves include the responses of household heads to questions about attitudes towards planning for the future, and the 1976 wave the responses of the wives to the same questions. (2) The PSID started in 1984 collecting information permitting the calculation of household wealth; the questions were repeated every 5 years until 2001, after which the frequency increased to every two years. (3) Membership in the PSID sample frame is inherited by the PSID member's offspring when they themselves become household heads and spouses, thus perpetuating the sample frame to all future generations of the direct descendants of the original sample members.

The PSID is not the best instrument for measuring wealth at any given point in time because the survey questions do not go into much detail about the composition of debts and assets. Furthermore, the PSID does not over-sample the wealthy, which is essential for aggregate wealth analysis, due to the concentration of net worth in the right tail of the wealth distribution. In both respects, the Survey of Consumer Finance (SCF) is a far better survey instrument. Another important limitation is the PSID does not allow us to distinguish between the main sources of asset growth: active savings versus capital gains, as it does not regularly track the volume of net asset purchases or asset prices. However, the PSID is to our knowledge the only data set available for tracking the evolution of household net worth over many years and across generations.

B.2 Household Wealth

The dependent variable in our main analysis is the ratio of household net worth to non-financial income. Net worth is defined as the sum of the value of household assets, net of real estate equity and the value of all household debts. It includes business equity, financial assets and the value of automobiles, net of mortgages and other debt. We excluded home equity from our measure because we wanted to minimize the extent to which variation was driven by exogenous factors such as location-specific property value fluctuations. Previous versions with home equity included deliver similar results to those reported in the main body of the paper.[35] This means our savings measure excludes changes in the value of respondents' homes. This value is excluded for two reasons. First, we are interested in the

[34] The early PSID sample contained, in addition to the representative sample, the Survey of Economic Opportunity (SEO) sample; later the PSID added a Latino sample, eventually reducing the size of all three samples to make the weighted sample more representative of the more recent population.

[35] As with most measures used in the previous literature, our measure excludes wealth in the form of pensions and social security, which, according to Gustman et al. [1997] is as large on average as all other wealth combined. It is interesting to note, however, that empirical research finds very little, or no, "offset" of pension wealth on net worth. In fact, some empirical studies (see Dynan et al. [2004] for an example) tend to find participation in pension plans *raises* other retirement savings.

accumulation of wealth that is a consequence of active choices on individuals' choices, and much of the increase in equity in homes is passive, that is, usually not the consequence of active choice. Second, changes in equity come from self-assessed current home value that is likely a quite noisy estimate of true value.

B.3 Household Income

The relevant current-income concept in our model consists of the household's non-financial income, such as earnings and transfers, accumulated over the time since the previous wealth observation to the date of the current wealth measurement, compounded at an interest rate equal to the rate of return on household savings. To estimate our model, the ideal variable to represent period-2 income would be cumulative income to the date of wealth measurement, compounded at an interest rate equal to the household's rate of return on savings. Since we cannot measure how rate of return varies across households and over time, we approximate this variable Y_{it} as the accumulated value of household labor and transfer income from $t-1$ to the date t at which wealth is measured, compounded annually at interest rate r, which we set at 4%, to match the average rate of return on corporate equity:[36] Income measurements are taken from the annual household money income variables.[37]

B.4 Instrumental Variables

We have structured our estimations around equation 6 as suggested by our model. A problem with this is that the model suggests endogeneity of education and income growth: both are likely influenced by an individual's future orientedness. We address this problem with an instrumental-variable (IV) strategy. This consists of estimating regression equations for each of these variables, and using predicted values of the dependent variables in the main analysis. For this analysis, we don't need either wealth or attitude responses. Consequently, the samples are much larger than those used in estimating the attitude index.

B.4.1 Expected Growth Rate of Income

We estimate the growth rate of income, denoted g_{it} in our model, as the annual growth rate consistent with the household's accumulated non-asset income in the five years following each period starting from the accumulated income in the five years prior to that time. We computed this for the years 1988 to 2015 on a sample of 13,723 observations drawn from married households where the head is between ages 35 and 80. We find the growth rate to average 2.24% when the head is younger than 60, and -15% for older households. Average

[36] Poterba (1998) finds that the average rate of return on corporate equity over the time period 1950-1990 is about 4% after taxes.

[37] We observe income at annual frequencies until 1999, and every two years thereafter, so for 2001 and later, we fill in the missing year with the average of the adjacent years. These and other money quantities are deflated to 1997 values using the CPI.

annual income for the two age groups was $38.8K$ and $35.3K$, respectively. For savings decisions, it is of course the *anticipation* of the growth rate that matters. We represent this by the OLS prediction of the growth rate as a function of current income plus other variables, such as education, family size, age, health and employment status.

Table 30 shows the estimates for the full set of control variables for the income regressions. The coefficients are estimated separately for households that own a business; the R-squared is 32% for non-owners (N=8,921) and 21% for owners (N=2,137). Lower growth rates are associated with husband in poor health (-5.0% and -6.1%), husband retired (-2.5% and 0.0%), husband self-employed (-2.6% and -3.9%), wife retired (-6.2% and -9.6%) and the presence of infants (-1.1% and -1.8%), where the first estimate refers to non-business owners and the second to business owners.

The strongest positive effects are Wife working (7.2% and 5.5%) and husband working (13.2% and 13.3%). The control set also includes each spouse's occupation, broadly categorized. For husbands the excluded category is blue-collar work, and for wives, no occupation. The strongest occupational effects are wife managerial/professional (3.7% and 10.0%) and wife unskilled services (-8.6% and -1.1%).

B.4.2 Education Variables

Our main measure of education is number of grades completed, which the PSID collects in every wave for every household member. The values range from 1 grade to 16 (graduated from college). We set education equal to the value in the most recent non-missing report for the individual.[38] Our education sample is divided into two sub-samples, according to the availability of parent variables.

The "first-generation" sub-sample consists of 15,266 respondents born after 1900 who were household head or spouse before 1976 and never listed as offspring of household head. For this sample the parent variables are all retrospective: the parent was never a member of the PSID, but the respondent supplied information about his parent's education and occupation using a coarser coding than for own variables and excluding until 1997 the mother's occupation.

The "next-generation" sub-sample consists of 33,050 respondents born after 1950 who were listed at least once as offspring of household head and were themselves household head or spouse in at least one later wave. For this sample the retrospective parent variables are also available, but since the parent was also a PSID respondent, the PSID includes a more detailed coding of the parent's education and occupation.

The only retrospective variable we use for both samples is: "Were your parents poor when you were growing up, pretty well off, or what?", which we code as rich or poor. We re-code parent's education into 5 levels, and father's occupation into 9 levels. The excluded

[38]The PSID does start collecting more precise attainment measures for head and spouse in 1984, but as predicting multiple levels of education would complicate our procedure, we leave this for future work.

level of education corresponds to less than 3 years of education completed. The succeeding levels correspond to completion of 6,11,12 and 13 years. For father's occupation, we excluded managerial, officials and proprietors. Since mother's occupation was not available before 1984, we do not include it in our analysis.

The race of the respondent is assumed to be the same as that of the household head. We include an indicator for Black, as well as interactions of this variable with year of birth, parent's education and whether parents were rich or poor. The estimation is carried out separately for each sex. Table 31 shows that the R-squared is somewhat higher for the first-generation sample (31% and 34%) than for the next-generation (25% and 24%), and also that the negative effect of Black fades away from (-58% and -37%) to essentially zero (-3% and 4.6%), where the first number in parenthesis is for the male sample and the second for the female. All but one of the 32 coefficients for parent's education are positive, indicating strong additive effects, as one might expect from the linear models used in quantitative genetics.

C Inter-generational Transmission

Do parents transmit future-orientedness to their offspring? In this section we assume that variation across households in the value of β_i has an inherited component, and develop a model of exogenous inter-generational transmission that would be consistent with simple models of genetic or cultural transmission. We begin with single-person households, and then extend the analysis to two imperfectly matched parents.

Consider a parent household ip and offspring household ik. Suppose that transmission of β_i takes a linear form:

$$\beta_{ik} = \gamma_0 + \gamma_1 \beta_{ip} + \upsilon_{ip}. \tag{15}$$

This model fits equally well a world with two-parent households with parents who are clones of each other.

C.1 A Two-Parent Model

Equation (15) can be extended to accommodate sex-specific transmission. Suppose that in offspring household i the husband is iH and has parents iD and iM. The offspring's future-orientedness β_{iH} is then determined by the husband's and wife's parents' values:

$$\beta_{iH} = \gamma_0 + \gamma_{HD} \beta_{iD} + \gamma_{HM} \beta_{iM} + \upsilon_{ip}.$$

The effects of the parents need *not* sum to one; a sum less than one represents imperfect transmission. Note that while it is possible that the effect of the parents on the offspring is proportional to their contribution to the future-orientedness of their own household, this not a compelling assumption a priori. In general, the weights $(\rho, 1-\rho)$ of the spouses in the intra-household allocation may be independent of the weights in transmission to offspring. This would be the case for instance if transmission was genetic and intra-household allocation was determined by bargaining between spouses.

$$\lambda_{iH} = \gamma_{H0} + \gamma_{HD}\lambda_{iD} + \gamma_{HM}\lambda_{iM} + \upsilon_{iH}$$

Imperfect assortment on β will further weaken inter-generational transmission at the household level. The offspring household will have

$$\beta_i = \rho\beta_{iH} + (1-\rho)\,\beta_{i'W}$$

where the value $\beta_{i'W}$ would be determined by the the wife's parents.

C.2 Genetic Interpretation

The inter-generational transmission equation shares with the baseline models of quantitative genetics the key property of additivity. In quantitative genetics, which deals with the inheritance of complex traits, including personality, environmental and genetic effects on the offspring's traits are often assumed to be additively separable; see Falconer and Mackay [1996] for a standard source on this literature. Examples of recent research related to the Additive Genetic Model (AGM) include an influential study in behavioral genomics, Okbay et al. [2016], who identify dozens of genes associated with education variation within populations around the world, and Barth et al. [2020], who find an association in HRS respondents between these genes and financial sophistication.

The basic assumptions of the AGM imply that, on average, both parents have equal impact on the genetic outcomes of the offspring and that the impact of each gene on the offspring's trait is independent of the effects of other genes that may be present, and of environmental factors, such as income or initial wealth. These predictions are consistent with a special case of our model. The adaptability of our model to the AGM is therefore a helpful feature that would be lost in more sophisticated models.

To fit the AGM, it must be the case that the effect of each parent is on average the same for each sex of parent and each sex of child, independent of the effect of the other parent and independent of the effects of the environment. If the empirical results are consistent with these three features, then the transmission from parents to offspring can be fully described by the AGM. [39]

[39] That model assumes that inheritance of quantitative characteristics is explained by the additive effects of many genes, half of which are inherited from each parent. While the model assumes independence of the genetic effects in the two senses listed above, these assumptions have been frequently tested in two literatures: that relying on phenotypic variation between siblings (e.g. identical twin studies), and that linking phenotypic variation to variation in single nucleotide pairs (genomics). For behavioral outcomes, including years of education, the independence assumption is rarely rejected.

Table 29: Portfolio

			Share of Assets					
Net Worth Pctile	Net Worth	Assets	Debt	Liquid Assets	Vehicles	Home Equity	Business	Stocks
0 to 1	-$151,004	$29,111	356.630	0.282	0.415	0.148	0.042	0.016
1 to 5	-$23,596	$13,433	78.959	0.293	0.478	0.148	0.012	0.011
5 to 10	-$5,940	$7,009	77.284	0.280	0.635	0.052	0.078	0.004
10 to 50	$7,323	$14,123	1.113	0.236	0.423	0.260	0.009	0.009
50 to 90	$133,511	$150,843	0.048	0.101	0.073	0.527	0.031	0.039
90 to 95	$528,797	$570,279	0.036	0.075	0.024	0.268	0.088	0.147
95 to 99	$1,085,890	$1,133,775	0.021	0.055	0.017	0.210	0.130	0.195
99 to 100	$3,974,247	$4,273,919	0.044	0.040	0.009	0.119	0.271	0.220

Based on PSID attitude-wealth sample.

Table 30: Income-Growth Regression

	Business Owner			Business Owner	
	No	Yes		No	Yes
Intercept	2.736	4.385	Husband Managerial	0.055	0.036
	(0.075)	(0.228)		(0.007)	(0.014)
Kids Aged 1-2	-0.0107	-0.0176	Husband Professional	0.0462	-0.0039
	(0.002)	(0.005)		(0.009)	(0.017)
Kids Aged 3-5	-0.0068	-0.0166	Husband Clerical	0.0002	-0.0041
	(0.002)	(0.004)		(0.003)	(0.007)
Kids Aged 6-13	0.0109	0.0092	Husband Construction	0.0243	0.0095
	(0.001)	(0.002)		(0.004)	(0.007)
White	0.0114	0.0291	Wife's Age	-0.0015	-0.0030
	(0.003)	(0.007)		(0.000)	(0.000)
Black	-0.0083	0.0264	Wife in Poor Health	-0.0073	-0.0016
	(0.004)	(0.010)		(0.002)	(0.004)
Income (log)	-0.3287	-0.5265	Wife's Years of Educ.	-0.0867	-0.2110
	(0.007)	(0.021)		(0.010)	(0.026)
$(\text{Income})^2$	1.1904	2.0500	Wife's (Educ.)^2	0.0035	0.0071
	(0.037)	(0.101)		(0.000)	(0.001)
Husband's Age	-0.0028	-0.0017	Wife Self -Employed	-0.0283	-0.0322
	(0.000)	(0.000)		(0.002)	(0.003)
Husband's in Poor Health	-0.0499	-0.0609	Wife working	0.0723	0.0554
	(0.002)	(0.005)		(0.001)	(0.003)
Husband's Years of Educ.	-0.0304	0.0464	Wife Retired	-0.0621	-0.0964
	(0.008)	(0.022)		(0.002)	(0.005)
Husband's (Educ.)^2	0.0014	-0.0019	Educ. Wife's Dad	-0.0001	0.0007
	(0.000)	(0.001)		(0.001)	(0.002)
Husband Self-employed	-0.0263	-0.0386	Educ. Wife's Mom	0.0047	-0.0063
	(0.002)	(0.002)		(0.001)	(0.003)
Hub. Working	0.1323	0.1329	(Educ.)^2 Wife's Dad	0.0113	0.0355
	(0.002)	(0.006)		(0.004)	(0.010)
Husband's retired	-0.0256	0.0049	(Educ.)^2 Wife's Mom	-0.0302	0.0706
	(0.003)	(0.007)		(0.005)	(0.015)
Educ. Husband's Dad	0.0012	0.0105	Wife's Parents Poor	-0.0028	-0.0318
	(0.001)	(0.002)		(0.001)	(0.003)
Educ. Husband's Mom	0.0063	-0.0006	Wife's Parents Rich	-0.0070	0.0099
	(0.001)	(0.003)		(0.001)	(0.003)
(Educ.)^2 Husband's Dad	0.0053	-0.0259	Wife Man./Prof.	0.0366	0.1023
	(0.005)	(0.010)		(0.010)	(0.021)
(Educ.)^2 Husband's Mom	-0.0245	0.0202	Wife Unskilled services	-0.0856	-0.0107
	(0.005)	(0.012)		(0.016)	(0.033)
Husband's Parents Poor	0.0113	-0.0047	Wife Unskilled production	0.0106	-0.0104
	(0.001)	(0.003)		(0.007)	(0.011)
Husband's Parents Rich	0.0019	0.0126	Wife Blue-collar	-0.0084	-0.0409
	(0.002)	(0.003)		(0.007)	(0.032)
R^2	0.320	0.210			
N	8921	2137			

Dependent Variable is Growth Rate of Household non-financial income.

Table 31: Education Regression

	First Generation		Next Generation	
Variable	Men	Women	Men	Women
Intercept	-122.695	-130.554	156.433	-319.061
	(2.425)	(2.163)	(6.761)	(6.458)
Dad Occ. = Prof.	0.2662	-0.2565	-0.7624	-0.7863
	(0.048)	(0.097)	(0.058)	(0.068)
Dad's Occ. = Sales/Clerical	-0.6420	-0.2333	-1.0589	-1.0897
	(0.025)	(0.037)	(0.028)	(0.035)
Dad's Occ. = Laborer	-0.3633	-0.3316	-0.6598	-1.1602
	(0.027)	(0.042)	(0.036)	(0.042)
Dad's Occ. = Craftsman	-1.0690	-1.1170	-1.1458	-1.3874
	(0.040)	(0.052)	(0.043)	(0.051)
Dad's Occ. = Blue Collar	-1.2709	-0.6211	-0.9260	-0.8596
	(0.031)	(0.043)	(0.084)	(0.100)
Dad's Occ. = Trans./Mil.	-0.9595	-0.6684	-0.9989	-1.2534
	(0.034)	(0.055)	(0.050)	(0.051)
Parents Poor	-0.3039	-0.0262	-0.3178	-0.1792
	(0.016)	(0.015)	(0.009)	(0.009)
Parents Rich	0.0189	0.4334	-0.0452	0.0580
	(0.018)	(0.018)	(0.009)	(0.008)
Black	-57.8437	-36.8302	-2.9937	4.5712
	(2.503)	(2.090)	(2.503)	(2.447)
Year of Birth	0.0696	0.0732	-0.0741	0.1713
	(0.001)	(0.001)	(0.003)	(0.003)
(Birth Year /10)^2	-0.0712	-0.0592	0.0376	-0.1218
	(0.001)	(0.001)	(0.003)	(0.002)
Dad $\geq$ 6 Years Educ.	0.7721	0.6876	0.5269	0.3376
	(0.032)	(0.028)	(0.037)	(0.029)
Dad $\geq$ 11Years Educ.	0.4368	0.4920	0.5124	0.4570
	(0.019)	(0.017)	(0.011)	(0.011)
Dad $\geq$ 12 Years Educ.	0.6042	0.3767	0.6171	0.5638
	(0.023)	(0.020)	(0.010)	(0.010)
Dad $\geq$ 13 Years Educ.	0.8336	0.6746	0.6022	0.4746
	(0.026)	(0.023)	(0.011)	(0.010)
Mom $\geq$ 6 Years Educ.	0.6726	0.9320	-0.0672	0.2592
	(0.035)	(0.033)	(0.050)	(0.045)
Mom $\geq$ 11 Years Educ.	0.8205	0.6970	0.3227	0.5776
	(0.019)	(0.017)	(0.012)	(0.011)
Mom $\geq$ 12 Years Educ.	0.1921	0.6029	0.7461	0.4965
	(0.021)	(0.018)	(0.010)	(0.009)
Mom $\geq$ 13 Years Educ.	0.5708	0.4048	0.2877	0.4075
	(0.026)	(0.023)	(0.011)	(0.010)
Black x Parents Poor	0.1736	0.1518	0.4148	0.3081
	(0.056)	(0.047)	(0.034)	(0.033)
Black x Parents Rich	-0.2877	-0.5952	0.0518	-0.5442
	(0.062)	(0.054)	(0.035)	(0.034)
Black x EducMom	0.0318	0.0642	0.0024	-0.0451
	(0.010)	(0.009)	(0.007)	(0.006)
Black x EducDad	-0.0337	-0.0436	-0.0418	-0.0243
	(0.010)	(0.008)	(0.007)	(0.006)
Black x Birth year	0.0293	0.0186	0.0015	-0.0018
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.308	0.344	0.253	0.240
N	7577	8577	16133	18087

Author's computations from PSID sample. Dependent variable is grades of education completed.

Table 32: Attitude-Sample Wealth-Ratio Regression Estimates

	Model 1		Model 2		Model 3		Model 4	
	Men	Wom.	Men	Wom.	Men	Wom.	Men	Wom.
Intercept	0.858	-0.465	1.650	-1.154	0.923	-2.733	0.813	-2.902
	(0.695)	(0.413)	(0.571)	(0.329)	(0.578)	(0.342)	(0.583)	(0.350)
Life Works Out	0.362	0.062	0.225	0.022	0.225	-0.001	0.214	-0.012
	(0.019)	(0.017)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Plans Ahead	0.187	0.215	0.142	0.106	0.130	0.096	0.119	0.093
	0.019	0.016	0.016	0.013	0.016	0.013	0.016	0.013
Carries Out Plans	-0.061	0.128	-0.058	0.037	-0.070	0.028	-0.075	0.020
	(0.018)	(0.016)	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)
Finishes Things	0.131	-0.025	0.034	-0.044	0.018	-0.052	0.012	-0.055
	(0.023)	(0.018)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)
Prefers to Save	-0.027	0.058	-0.080	0.049	-0.075	0.047	-0.065	0.054
	(0.018)	(0.015)	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)
Thinks About the Future	0.062	0.239	0.068	0.124	0.059	0.118	0.058	0.114
	0.018	0.016	0.015	0.012	0.015	0.012	0.015	0.012
Initial Wealth			0.702	0.634	0.698	0.630	0.702	0.634
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Future Income Growth			-0.251	-0.389	-0.616	-0.991	-0.476	-0.866
			(0.135)	(0.125)	(0.143)	(0.130)	(0.153)	(0.137)
Wife's Education					0.051	0.049	0.036	0.032
					(0.008)	(0.007)	(0.008)	(0.007)
Husband's Education					0.020	0.080	0.002	0.063
					0.007	0.006	0.008	0.007
Income (log)							0.064	0.056
							(0.011)	(0.010)
Black							-0.001	0.006
							(0.075)	(0.067)
White							0.183	0.175
							0.066	0.059
Age of Husband	-0.129	-0.035	-0.122	0.010	-0.127	0.018	-0.141	0.014
	(0.032)	(0.023)	(0.026)	(0.018)	(0.026)	(0.018)	(0.026)	(0.018)
Age Hub. Squared	0.155	0.052	0.125	-0.012	0.131	-0.017	0.145	-0.013
	(0.031)	(0.023)	(0.026)	(0.019)	(0.026)	(0.019)	(0.026)	(0.019)
Age of Wife	0.081	0.020	0.062	0.028	0.061	0.018	0.058	0.011
	(0.015)	(0.024)	(0.013)	(0.019)	(0.013)	(0.019)	(0.013)	(0.019)
Age Wife Squared	-0.073	-0.001	-0.064	-0.020	-0.062	-0.008	-0.059	-0.002
	0.016	0.025	0.013	0.020	0.013	0.020	0.013	0.020
Year	-0.052	0.028	-0.029	0.015	-0.037	0.005	-0.034	0.008
	(0.013)	(0.012)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
Year Squared	0.210	-0.045	0.143	0.004	0.154	0.012	0.148	0.007
	0.043	0.038	0.036	0.030	0.036	0.030	0.036	0.030
R^2	0.050	0.058	0.404	0.379	0.405	0.384	0.406	0.386
Nobs	1478	1609	1443	1575	1443	1575	1443	1575

Author's estimates based on PSID attitude-wealth sample.

Table 33: Offspring-Sample Wealth-Ratio Regression Estimates

	Model 1		Model 2		Model 3		Model 4	
	Son	Daughter	Son	Daughter	Son	Daughter	Son	Daughter
Intercept	1.764	1.769	-0.007	1.441	-0.301	1.521	0.223	1.335
	(0.36)	(0.34)	(0.38)	(0.37)	(0.37)	(0.36)	(0.37)	(0.38)
Mother's AI	0.555	0.931	0.500	0.888	0.476	0.914	0.317	1.005
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)
Father's AI	0.611	-0.001	0.419	-0.039	0.394	-0.024	0.512	0.053
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)
Lagged W/Y	0.618	0.588	0.605	0.587	0.606	0.588	0.550	0.542
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expected Income Growth	-0.316	-0.237	-0.821	-0.368	-0.806	-0.298	-0.630	-0.603
	(0.14)	(0.16)	(0.15)	(0.17)	(0.14)	(0.17)	(0.27)	(0.24)
Wife's Education			0.080	0.031	0.080	0.031	0.067	0.000
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Husband's Education			0.061	-0.018	0.068	-0.014	0.043	-0.010
			0.008	0.007	0.007	0.007	0.008	0.007
Income (log)					(0.07)	(0.00)	(0.05)	(0.04)
					0.014	0.006	0.014	0.014
Number of Kids					-(0.07)	(0.00)		
					0.016	0.005		
Kids Squared					-(0.03)	-(0.07)		
					0.009	0.012		
Num. Kids Aged 3-13					(0.03)	(0.09)		
					0.010	0.013		
Num. Kids Aged 14-17								
Hub. Self Employed							(0.06)	(0.33)
							0.034	0.045
Hub. Working							0.212	0.127
							(0.05)	(0.05)
Hub retired							0.024	0.170
							(0.07)	(0.06)
Hub Unemployed							-0.046	-0.177
							(0.05)	(0.06)
Self Business							0.162	-0.142
							(0.04)	(0.05)
Self Limited Business							0.463	0.364
							(0.04)	(0.04)
Wife Working							-0.069	-0.023
							(0.02)	(0.02)
Wife Retired							-0.133	-0.093
							0.054	0.071
Wife Unemployed							(0.03)	(0.01)
							0.056	0.045
Black			-(0.30)	-(0.10)			-(0.29)	-(0.09)
			0.063	0.078			0.061	0.078
White			-(0.16)	(0.14)			-(0.17)	(0.12)
			0.048	0.062			0.048	0.061
Age of Husband	(0.05)	(0.00)	(0.07)	(0.00)			(0.08)	(0.00)
	0.015	0.006	0.014	0.006			0.014	0.006
Age Hub. Squared	-(0.04)	(0.00)	-(0.06)	(0.00)			-(0.07)	(0.00)
	0.016	0.005	0.016	0.005			0.015	0.005
Age of Wife	-(0.01)	-(0.08)	-(0.03)	-(0.07)			-(0.04)	-(0.07)
	0.009	0.012	0.009	0.012			0.009	0.012
Age Wife Squared	0.002	0.093	0.030	0.089			0.043	0.084
	(0.01)	(0.01)	(0.01)	(0.01)			(0.01)	(0.01)
Year	-0.207	0.000	-0.204	-0.006	-0.205	-0.002	-0.239	-0.018
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Year Squared	0.363	0.000	0.351	0.007	0.351	0.001	0.420	0.039
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	50.8%	42.4%	52.0%	42.4%	51.9%	42.3%	54.4%	43.9%
Nobs	714	716	714	716	714	716	714	716

Author's estimates based on offspring PSID attitudes sample.

Table 34: Wealth Income Ratio: Regression with Self-employment Controls

	Outcome: W/Y Ratio			
	Attitudes Sample		Offspring Sample	
	Husbands	Wives	Sons	Daughters
Intercept	1.156**	-3.023***	-4.395***	0.243
	(0.587)	(0.351)	(0.836)	(0.910)
Life Works Out	0.171***	0.001		
	(0.016)	(0.014)		
Plans Ahead	0.115***	0.059***		
	(0.016)	(0.013)		
Carries Out Plans	-0.073***	0.003		
	(0.015)	(0.013)		
Finishes Things	0.032*	-0.064***		
	(0.019)	(0.014)		
Prefers to Save	-0.074***	0.075***		
	(0.015)	(0.012)		
Thinks About the Future	0.027*	0.082***		
	(0.015)	(0.012)		
Mom's Attitude Index			0.515***	0.628***
			(0.116)	(0.114)
Dad's Attitude Index			0.979***	-0.201**
			(0.095)	(0.086)
Initial Wealth	0.697***	0.644***	0.582***	0.519***
	(0.006)	(0.005)	(0.007)	(0.007)
Future Income Growth	-0.088	0.067	-1.344***	-0.702**
	(0.216)	(0.191)	(0.344)	(0.306)
Wife's Predicted Education	0.021**	0.018**	0.118***	0.058***
	(0.009)	(0.007)	(0.011)	(0.012)
Husband's Predicted Education	-0.010	0.036***	0.038***	0.039***
	(0.008)	(0.007)	(0.011)	(0.010)
Income (log)	0.083***	0.098***	0.019	-0.110***
	(0.014)	(0.013)	(0.017)	(0.017)
Husband Self Employed	0.566***	0.439***	0.114***	-0.007
	(0.041)	(0.035)	(0.043)	(0.060)
Husband Working	0.069	0.012	0.361***	0.214***
	(0.043)	(0.037)	(0.060)	(0.063)
Husband Retired	0.304***	0.355***	0.083	0.038
	(0.049)	(0.043)	(0.080)	(0.073)
Husband Unemployed	-0.134**	0.014	-0.010	-0.208***
	(0.063)	(0.065)	(0.064)	(0.075)
Husband Owns Business	-0.089**	0.013	0.042	0.216***
	(0.037)	(0.032)	(0.053)	(0.068)
Husband Operates Ltd Business	-0.045	-0.075***	0.858***	0.588***
	(0.031)	(0.028)	(0.048)	(0.051)
Wife Working	-0.017	-0.048***	-0.112***	-0.049**
	(0.018)	(0.016)	(0.023)	(0.025)
Wife Retired	0.530***	0.757***	-0.285***	0.548***
	(0.048)	(0.047)	(0.063)	(0.076)
Wife Unemployed	-0.360***	-0.283***	0.535***	0.364***
	(0.053)	(0.041)	(0.103)	(0.077)
Black	-0.011	-0.061	-0.397***	0.056
	(0.074)	(0.066)	(0.085)	(0.099)
White	0.136**	0.066	-0.248***	0.261***
	(0.066)	(0.059)	(0.065)	(0.079)
Husband's Age	-0.181***	0.021	0.161***	0.034***
	(0.026)	(0.018)	(0.022)	(0.010)
Husband's Age Squared	0.181***	-0.021	-0.141***	-0.022**
	(0.026)	(0.018)	(0.023)	(0.009)
Wife's Age	0.089***	0.012	-0.101***	-0.174***
	(0.013)	(0.019)	(0.014)	(0.019)
Wife's Age Squared	-0.090***	-0.002	0.104***	0.177***
	(0.013)	(0.020)	(0.015)	(0.020)
Year	-0.025**	0.022**	-0.018	0.156***
	(0.011)	(0.009)	(0.049)	(0.052)
Year Squared	0.131***	-0.028	0.064	-0.233***
	(0.035)	(0.030)	(0.077)	(0.082)
Observations	1,443	1,575	545	531
R^2	0.425	0.406	0.545	0.461

Notes: Dependent variable is W/Y. Estimated separately by spouse on the Attitude-Wealth and Offspring-Wealth samples.

Table 35: Husband AI vs Wife's AI: Full Estimates

	Model 1	2.	3	4	5
Intercept	-1.685	-2.131	-2.957	-2.062	-0.784
	(0.988)	(0.760)	(0.779)	(0.772)	(0.793)
Husband's AI	2.080	0.645	0.956	0.844	1.030
	(0.102)	(0.039)	(0.064)	(0.067)	(0.079)
Wife's AI	1.827	0.311	0.806	0.674	0.884
	0.136	0.040	0.087	0.086	0.106
Lagged W/Y		0.687	0.680	0.618	0.617
		(0.006)	(0.006)	(0.007)	(0.007)
Income Growth		-0.650	-1.209	-0.809	-0.650
		(0.156)	(0.171)	(0.250)	(0.252)
Wife's Education			0.040	0.034	0.041
			(0.010)	(0.010)	(0.010)
Husband's Education			0.045	0.034	0.034
			0.009	0.009	0.009
Income (log)			-0.012	-0.002	0.010
			(0.013)	(0.017)	(0.017)
Number of Kids					-0.002
					(0.018)
Kids Squared					0.000
					(0.005)
Kids Aged 3-13					-0.112
					0.021
Kids Aged 14-17					-0.046
					(0.021)
Hub. Self Employed				0.590	0.603
				(0.044)	(0.044)
Hub. Working				0.186	0.164
				(0.047)	(0.047)
Hub retired				0.528	0.518
				0.051	0.051
Hub Unemployed				-0.033	-0.033
				(0.073)	(0.074)
Owns Business				-0.151	-0.163
				(0.039)	(0.039)
Incorp. Business				-0.095	-0.090
				(0.036)	(0.036)
Wife Working				0.088	0.069
				0.020	0.020
Wife Retired				1.039	1.037
				(0.059)	(0.059)
Wife Unemployed				-0.326	-0.324
				(0.052)	(0.052)
Black			-0.020	-0.152	-0.127
			(0.088)	(0.086)	(0.086)
White			0.171	0.031	0.034
			0.076	0.075	0.075
Husband's Age	0.049	-0.013	-0.013	-0.046	-0.071
	(0.049)	(0.038)	(0.038)	(0.037)	(0.037)
Husb.'s $(\text{Age}/10)^2$	-0.025	0.020	0.020	0.049	0.071
	(0.048)	(0.037)	(0.037)	(0.037)	(0.037)
Wife's Age	0.028	0.119	0.110	0.106	0.078
	(0.043)	(0.033)	(0.033)	(0.032)	(0.033)
Wife's $(\text{Age}/10)^2$	-0.022	-0.128	-0.118	-0.112	-0.087
	0.044	0.034	0.034	0.033	0.033
Year-1970	-0.114	-0.105	-0.107	-0.085	-0.087
	(0.017)	(0.013)	(0.013)	(0.012)	(0.012)
$(\text{Year-1970})^2$	0.462	0.421	0.410	0.342	0.348
	(0.055)	(0.042)	(0.042)	(0.041)	(0.041)
R^2	0.065	0.445	0.449	0.477	0.479
Nobs	931	929	929	929	929

Notes: Dependent variable is W/Y. Estimated on the Attitude-Wealth sample. AI = Attitude Index from model 3 (benchmark) in Table 32.