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The intergenerational transmission of future-orientedness

Abstract

Knowles and Postlewaite (2023) construct an index of an individual's future-orientedness that has statistically significant effects on savings and nonfinancial choices. We extend that work to investigate transmission of parental future-orientedness to offspring. We show that the index predicts wealth accumulation of offspring and grandchild wealth accumulation. We also identify several channels through which household future orientedness affects grandchildren's future orientedness.

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1. Introduction

Knowles and Postlewaite (2023) define *future-orientedness* as the collection of personality traits that contribute to observed variation across individuals in intertemporal decisions, whether due to preferences or other personality traits related to planning. To distinguish the effects of future-orientedness from other potential explanations of savings inequality, they rely on survey questions about planning for the future. They exploit data from a series of questions related to attitudes about the future that the Panel Study on 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 PSID data include many married couples, with separate responses for each spouse. In this paper, we ask whether future-orientedness is transmitted from parents to children and grandchildren.

The inclusion of all offspring of PSID respondents in the sample frame allows us to examine the intergenerational transmission of future-orientedness by estimating the relationship between parental attitude index (AI) and the savings behavior of adult offspring since 2001. The results suggest that offspring inherit at least some degree of their parents' future-orientedness. One might argue, however, that what is being transmitted is the parents' financial acumen. Our findings show that the parental AI also has nonfinancial effects: offspring of high-AI parents are less likely to marry as teenagers, less likely to have children before the age of 21, and, among those who do marry, those with higher maternal AI are less likely to divorce, even after controlling for age at marriage. We interpret these results as offspring of more future-oriented couples behave in a more future-oriented way.

While these results demonstrate a link between parents and children, they're not informative about the mechanism of transmission. The structure of the PSID confines attention to the offspring as adults. Starting in 1997, however, the Child Development Survey of the PSID allows us to analyze the interactions between children aged 0 to 18 and the parents. This sample is too young to allow observation of wealth in middle age or savings behavior.

We demonstrate that this intergenerational link extends beyond the immediate offspring to the grandchildren as well. The predicted wealth of grandchildren in their 40s is influenced by their grandparent's future-orientedness. A higher grandparent AI predicts greater wealth for the grandchild as they approach middle age, controlling for factors such as age and predicted income.[1] Similar to these findings for the children of the first generation, we provide evidence that this grandchild effect is not solely attributable to financial acumen. Some nonfinancial aspects of the grandchild's upbringing, such as religious participation, contribute to greater predicted wealth accumulation. Notably, a higher grandparent AI is associated with a greater likelihood of religious participation.

2. Related literature

Parent-child transmission of future-orientedness is a plausible mechanism for explaining intergenerational 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) find 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.[2]

Clark and Cummins (2015) argue for similar wealth elasticities, around 0.6, based on U.K. 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 United Kingdom. Benhabib et al. (2021) argue that to explain such high persistence of wealth across generations requires transmission of a family-specific effect, probably cultural, that allows some families to obtain higher rates of return on wealth. 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) find that, despite having parents who were no more prosperous or educated than average, the grandchildren of China's prerevolutionary

1 Grandchild income is forecast based on parents' education and wealth.

2 In an earlier attempt at uncovering intergenerational links in savings we analyzed the intergenerational correlation of the regression residual in household savings rates (Knowles & Postlewaite, 2005). This current paper builds 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.

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.[3] Our paper doesn't 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.[4]

3. PSID attitude survey

Each year from 1968 through 1972, the PSID asked the household head a series of questions concerning efficacy and planning.[5] The responses are coded as five-point Likert scales, which reflect the degree of agreement with one or another of five alternatives.

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 his life ahead, or 5, that they are not.

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 future?" Again, most people answer 1 or 5, but this time 17% of the sample indicate they "want to do both." To avoid issues related to nonlinearity in the response, we recode the raw responses to each question into a binary variable: one if the response is above the PSID average, zero otherwise. In the case of household heads, for whom there were as many as four 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. To ensure consistency of interpretation, we further recode the variables so that a 1 indicates more future-orientedness.[6] 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%.

3 Dynastic savings were also important in Castaneda et al. (2003), who further argued that the U.S. 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 degree of income inequality among the richest households falls far short of what the model needs to explain wealth inequality.

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

5 Details of the choice of these questions can be found in Veroff et al. (1971).

6 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 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.

4. Empirical strategy

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, individuals' attitude index, or AI, defined by the total estimated contribution 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.

Foremost among the estimations are regressions that show how an individual's future-orientedness affects descendants' decisions and outcomes—that is, intergenerational transmission.

Our estimation equation is derived from a simple and standard neoclassical model of lifecycle savings. Our model is described formally in the Appendix; in this section we explain how the model equation can be estimated with data on attitudes and household wealth.

In our basic model, variation in future-orientedness takes the form of variation in the discount factor, which governs the choice of savings. The model relates the unobservable discount-factor variation to noisy indicators, such as the attitude responses. For simplicity, much of our theoretical description treats each household as a person, but after developing our main ideas, we extend our analysis to married-couple households, which will be the focus of much of our empirical analysis.

In our model, agents discount their future utility at rate β_i per period. They begin each period t with wealth level $a_{i,t}$ and receive nonfinancial income $y_{i,t}$, which grows (deterministically) over time at a constant, agent-specific rate $\gamma_{i,t}$. 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:

$$w_{i,t} = \lambda_o + \lambda_1 w_{i,t-1} + \lambda_2 \gamma_{i,t} + \cdots + v_{i,t}$$

where

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

and $\lambda 2 < 0$. The ellipsis acknowledges that savings may differ for other reasons—such as family composition and health status—that aren't included in the model but will be included in the empirical analysis.[7] We refer the reader to Knowles and Postlewaite (2023) for a discussion of this equation.

5. Attitudes and saving

5.1 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 (1), 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:

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

The attitude-response variables act collectively as a proxy for future-orientedness. Given a set of estimates for equation (5.1), 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 nonlinear 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.)

The method resembles a fixed-effect regression equation. 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.

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 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.

6. 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 (5.1), and analysis of the attitude index constructed from those estimates.

6.1. 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 five years.[8] The sample consists of each wealth observation of 1,714 married people who are observed at least twice during this period.[9]

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

7 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..

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

9 Our wealth-estimation sample includes 18.4% of the 9,323 people who answered the attitude questions in the 1970s. Of the respondents who were excluded, all but 2,452 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 the wealth variables were recorded or were missing variables for prediction of education or were outliers in our income-prediction exercise.

Table 2 shows the results of the regression. We see that, across the board, the attitude responses often have a statistically significant effect on saving for both husbands and wives, even for the maximum set of controls. We use those estimates to construct individuals' AI, as described above, and regress household wealth on AI. Table 3 shows the results of three specifications of the regression. Table 21 shows the full regression results.

For all three of the models, both the husband's AI and the wife's AI are large and significant. In all three models, lagged W/Y is positive and significant, as it should be: Our model predicts that higher initial wealth should result in higher ending wealth. Our model also predicts that higher income growth should result in lower current saving, which is confirmed in all three specifications. We turn next to intergenerational future-orientedness.

TABLE 2. 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
R2	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. Education 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.

TABLE 3. 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	0.68
	0.006	0.006	0.006
Future Income Growth	-0.65	-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 attitude-wealth PSID sample of observations for years 1984–2001. Dependent variable is W/Y. Other controls are included; see Table 21 in the Appendix for complete estimates.

7. The effect of parents' attitudes on offspring

To summarize, we have shown that an individual's constructed AI captures a general notion of future-orientedness. It's predictive of both their future financial outcomes and nonfinancial choices. We move on to our primary interest in this paper: the intergenerational transmission of future-orientedness. Our goal is to show that the offspring of more future-oriented parents are themselves more future oriented.

We begin by investigating the impact of parental AI on demographics and pecuniary characteristics of their offspring.

7.1. Offspring demographics and parental AI

Table 4 shows offspring demographics by quartile (lowest-quarter parents AI, middle half, and highest AI quartile) for sons and daughters. The average age of the husband in the offspring sample, as shown in the top panel of Table 4 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. The age effect is likely related to retirement, as we show below in Table 5 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.[10] A connection between husband's parental AI quartile and education is also evident in the table.

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

TABLE 4. OFFSPRING DEMOGRAPHICS BY PARENTAL AI

Household Sample	Percentile HH AI	Hub's Age	Hub.-Wife 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 2.

TABLE 5. 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 2.

7.2. Offspring affluence and parental AI

In Table 5, it is 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 5 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.

Considering the estimation results in Table 2, 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.

7.3. 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 doesn't have attitude questions that are many years prior to the attitudes reports, so we can't apply our method to compute the AI directly.[11] The attitude variables we use instead are the parents' AIs. These are available for only one of the spouses in each couple, because the other spouse's parents aren't PSID members. The sample consists of all the married offspring of the attitudes sample, regardless of whether the parents were also present in the attitude-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 1,382 couples, 628 sons, and 754 daughters.

7.4. Parents' attitudes and offspring savings

Our married-offspring sample pools the initial-wealth observations every two years for 2003–2021 treating householder-year as the unit of observation. For the analysis of offspring wealth, we consider adult sons and daughters of respondents in the attitude-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 6 we report the attitude estimates from our benchmark specification (model 3), which controls for education of both parents and offspring, along with several alternate versions with a nested set of the explanatory variables consisting of the AI from our attitude-wealth sample as estimated in Table 2, along with control variables.[12]

We identify several robust features of these estimates. The basic message in Table 6 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 the controls are included. For sons, the AI effects 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, 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 mothers 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.

11 For this generation, the attitude questions were only asked in 2016, so it's not possible to replicate the analysis of the attitude-wealth sample, as most wealth observations are now prior to the attitudes reports.

12 In the Appendix (see Table 14) 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 6. 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 14.

8. Timing of family choices and parental attitudes

Knowles and Postlewaite (2023) show that the effect of an individual's attitude index is not restricted to the financial sphere—it affects whether an individual is likely to smoke and is related to frequency of exercise among other things. We 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.

8.1. Offspring age at first child

Individuals who are more future-oriented would plausibly be more willing to wait to start a family and prepare for it. Table 7 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.[13]

13 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.

TABLE 7. 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

*** for $p < 0.01$ ** for $p < 0.05$ * for $p < 0.1$

Notes: 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.

8.2. Premarital birth

It may not be that delaying first births is unambiguously a sign of being future oriented. To reduce the ambiguity, we repeat our exercise for having a premarital birth, which is clearly associated with lower economic outcomes in empirical studies (Nock, 1998). In the probit results shown in Table 8, the dependent variable is 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 is negligible with or without education controls, but strongly negative on daughters, despite a 40% reduction, from -.74 years to -.44 years, when controlling for education (column W2).

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.

In summary, these results support the view that the children of more future oriented parents are more future oriented themselves.

TABLE 8. PROBABILITY OF OFFSPRING'S PREMARITAL 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). Education2= (Years/10)^2.

8.3 Early marriage

Early marriages are another sign associated with low outcomes, perhaps driven by accidental pregnancies (Uecker & Stokes, 2008). Consider a binary variable equal to one if the offspring marries at age 21 or less. Table 9 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 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.

TABLE 9. 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).

8.4 Divorce

One might consider a 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 logistic 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 10 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 much 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 fathers' AI on selection into marriage.[14]

14 It is well known that earlier marriages (before age 22) result in a high rate of divorce, and to avoid simply restating a result therefore implied by Table 9, we need to control for age at marriage. This control variable has a negative effect in all the models of Table 10 but is not shown in the table.

TABLE 10. 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

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.

9. Grandchildren

The results in the previous section demonstrate that there is a significant relationship between parental AI and offspring choices and outcomes many years later. The choices and outcomes that are affected are both financial and nonfinancial. We turn next to an investigation of the relationship between a couple's AI and their grandchild's choices and outcomes.

9.1. CDS

We focus on CDS sample for 1997. This sample of kids aged 0–14 in 1997 was followed in successive waves of the CDS, and then as they aged out of CDS, they were followed in the TAS (Transition into Adulthood Supplement). In this paper we restrict analysis to the 2002 wave because the questions we're interested in concern school-age children.

Table D.1 shows that the initial wave of the CDS in 1997 covers 3,563 children, of whom 2,907 are also covered in the 2002 wave; most of those who are not have aged out of CDS and will be present in TA 2005, the 2005 wave of TAS. The table also shows that by 2021, most of these children (2,416) have become respondents in the PSID, meaning that they are now either a household reference person or spouse thereof. This, in turn, implies that the regular PSID questions will be asked of either head or spouse. By 2021, we have 1,913 CDS respondents.

The sample of interest for our analysis is the intersection of the CDS sample with the attitude sample (that is, the grandparent generation respondents for whom we have computed AI's) we studied in our earlier project. That sample consists of household heads in 1968–72 and spouses in 1976; in these years the respondents reported their attitudes toward planning for the future. The overlap between the samples is because many of the CDS 1997 individuals are grandchildren of the respondents in the attitude sample. Table 2 shows that almost all (3,494) CDS children have the mother's mother in the attitude sample; the father's father is present in only 825 cases.

TABLE 11. PREDICTED WEALTH FOR EARLY COHORT

Variable	Men	Women
Intercept	22.85*** (38.01)	-167.33*** (40.18)
Wealth	0.17*** (0.01)	0.54*** (0.02)
Own a Business	10.69** (3.73)	24.08** (3.93)
Non-Asset Income	-0.0004 (0.0001)	0.0006* (0.0001)
Married	31.39*** (2.06)	15.30*** (2.16)
Working	-16.30*** (4.42)	-4.76* (2.87)
Unemployed	-38.67*** (5.95)	-17.13** (5.16)
Health Good	30.73*** (3.87)	24.40*** (4.10)
PreSchool	-18.39*** (1.58)	-18.47*** (1.35)
Occupation Income	0.08 (0.06)	0.44* (0.10)
High School	9.71*** (2.91)	10.51** (3.61)
College	4.31* (2.22)	4.87* (2.35)
Bachelor Degree	-61.25*** (7.50)	-64.36*** (6.50)
Dad has Bachelor Degree	46.22*** (2.61)	13.53** (2.79)
Dad Attend College	0.19 (2.86)	17.12***(3.01)
Dad Attend High School	17.19*** (3.42)	-2.47 (3.62)
Mom Attend College	10.43*** (2.74)	-23.99*** (2.84)
Mom Attend High School	-15.95*** (4.22)	7.46* (3.82)
Both Parents	-4.04*** (0.44)	-0.50 (0.48)
Parents Poor	-7.74*** (1.84)	2.68 (1.98)
Parents Rich	-5.01** (1.96)	5.96* (2.07)
Black	-27.47*** (4.30)	-24.64*** (4.28)
White	-10.96*** (3.62)	-20.22*** (3.46)
Age	-2.31 (2.68)	11.83** (2.88)
Age Squared	7.67 (4.70)	-19.39*** (5.06)
Income × Bachelor	0.0040*** (0.0003)	-0.0023*** (0.0002)
occ_BA	1.31*** (0.08)	1.48*** (0.11)
Black × Bachelor Degree	-4.62 (7.17)	15.33* (6.85)
White × Bachelor Degree	17.39*** (5.54)	58.49*** (5.43)
R-Square	0.2439	0.2139
N_used	932	1360

Notes: Sample of PSID householders aged 20–30 in 2003. Wealth variable is household net worth, in units of $1,000. All variables are averages over 2001–2003. Occupation income consists of mean income of age 40–50 workers in same two-digit occupation in U.S. Census of year 2000.

Ideally, we would exploit the PSID structure to measure the grandchildren's adult outcomes, as we did with two generations. However, the restriction to CDS1997 means that the age range of the sample, as of 2024, lies between 27 and 42. This presents a problem. For both the initial generation and their offspring, we had their midlife wealth, and we could estimate the effect of their AI on this wealth. Given the age range in CDS1997, it's likely that many of the sample are not household heads or spouses. Some of the outcomes of interest that we used in our earlier work—wealth, in particular—are missing for some respondents.

To deal with this problem, we predict grandchildren's wealth at age 40 by looking at an earlier cohort for which PSID includes realized wealth. On this cohort, we estimate midlife wealth on many variables that are included in CDS1997 as well as in the PSID for the earlier cohort. We use the coefficients from this regression on the earlier cohort to compute grandchildren's predicted 2041 wealth. The assumption here is that the relationship between explanatory variables and savings behavior of the grandchildren is the same as it was for the earlier cohort.[15]

There is one variable, occupation, that is difficult to deal with because it takes on many values with no obvious way to order them. For the current exercise, we rank occupations by income, which we take to be the average income of a job using census data.[16]

Once we have occupations ranked by average income, we separate them into deciles and regress wealth at age 40 for the earlier cohort on the LHS with explanatory variables, including indicator variables for each decile of occupation rank. Table 11 shows the predicted wealth the early cohort.

As we described above, we want to predict grandchildren's wealth given the information in CDS1997. Table 12 shows the results of predicting grandchildren's 2041 wealth in five models. All models use the coefficients on variables from the regression on the earlier cohort.[17] Model M1 in this table uses only the average of the two grandparents' AIs, GPAI, and the respondents' region. GPAI has a substantial and highly significant effect on predicted year 2041 grandchild wealth, which holds for the other specifications, suggesting that there is something about grandparents' future-orientedness that affects not only their children's financial decisions, but also their grandchildren's. Thus, we have achieved our first goal—establishing a link between future-orientedness of the grandparent generation and the future-orientedness of the grandchildren.

15 There may, of course, be differences in the relationship between explanatory variables and accumulated wealth for the earlier and later cohorts, for example, differences in mortgage interest rates.

16 An obvious problem with this is that high-prestige low-income occupations, such as 'writer' or 'artist' would be ranked relatively low. Consequently, ranking by income is inherently a noisy measure of an occupation's status.

17 Table 15 gives the statistics for Table 12.

TABLE 12. SUMMARY OF PREDICTED CHILD WEALTH ON CDS

Variable	M1	M2	M3	M4	M5
Household AI	63.61***	31.75***	122.07***	39.62***	87.22***
	(23.32)	(22.14)	(41.95)	(22.85)	(42.01)
AI × Female			-69.47		-43.04
			(43.31)		(43.18)
AI× Black			7.72		21.59
			(62.51)		(61.65)
AI × Latino			-135.77		-148.70
			(117.10)		(116.71)
Child Obedience × Female			-1.35		-7.82
			(11.60)		(15.55)
Desired Education × Female			49.04**		61.73**
			(21.15)		(27.03)
On School Athletic Teams × Female			45.77***		9.82
			(8.59)		(12.35)
AI x In-Sample			-109.69***		-99.53**
			(43.94)		(43.61)
Parents Desired Schooling for Kids*				-60.89	-25.77
				(70.46)	(75.51)
On School Athletic Teams				36.88***	24.55***
				(7.11)	(9.28)
Takes Lessons				4.04	7.43
				(7.07)	(6.64)
Played Sports Last Summer				22.25***	21.41***
				(8.03)	(7.51)
Member of Community or Group				12.54*	10.30
				(7.11)	(6.70)
Attends Religious Services				18.58**	21.96**
				(7.37)	(6.93)
Child Obeys Parents*				-1.87	4.37
				(8.74)	(11.22)
Female		-67.15	-81.29		-103.15**
		(69.57)	(77.24)		(29.86)
Black		-70.41***	-68.26***		-71.98***
		(9.22)	(16.92)		(16.78)
Latino		0.00	0.00		0.00
In-Sample		3.05	31.15		26.63
		(6.29)	(13.74)		(13.66)

TABLE 12. SUMMARY OF PREDICTED CHILD WEALTH ON CDS (CONTINUED)

Variable	M1	M2	M3	M4	M5
Age	8.66***	8.58***	8.25***	8.84***	8.38***
	(1.18)	(1.12)	(1.13)	(1.22)	(1.16)
Age squared	-0.21***	-0.18***	-0.15***	-0.18***	-0.13***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
R-Squared	0.10	0.22	0.26	0.16	0.28
N used	1008	1008	1008	1008	1008

Notes: Dependent variable is predicted grandchild wealth in 2041, in units of $1K. M1 includes intercept not shown, M2 adds sex and race and in/out of sample, M3 adds interactions with M2 controls. M4 adds to M1 controls for behavior reported in CDS. Variables marked with * were classed as 1 if response value was above average, zero otherwise. Controls not shown: Regions 1 through 4, respectively Northeast, North Central, South and West.

9.2. Mediating variables

In addition to estimating the effect (if any) of GPAI on grandchildren predicted wealth, we want to "unpack" GPAI to get a more granular view of the influences on grandchildren outcomes.

For a respondent in the AI sample, we defined their AI essentially as the amount by which their answers to the six attitude questions affect future accumulated wealth. We think of there being a latent variable, future-orientedness, that affects an individual's choices today in situations in which there are future consequences of their choice. This is, of course, a "reduced form" measure, meaning the answers to the attitude questions don't *directly* affect choices; we don't expect an individual to choose differently in future problems (e.g., save more) if they claim, incorrectly, that they Carry Out Plans. This contrasts with *consequential* variables, by which we mean variables that have direct welfare consequences, such as age at (first) marriage, age at first birth, income, occupation, whether to smoke, wealth, etc.

The basic idea is to run two regressions: first, estimate grandchild predicted wealth on GPAI, and second, estimate grandchild predicted wealth on a sample with GPAI and a mediating variable in CDS1997 such as a parent's response to a question about whether the child is obedient.

If, for example, there is no connection between a variable like obedience and predicted wealth, the effect of GPAI will be the same for the two regressions. If there is a connection, it may be that the effects of GPAI and the obedience variable are independent, in which case the effect of GPAI will again be the same in the two regressions. Lastly, we might see a drop in the coefficient on GPAI, indicating that AI was picking up part of the effect of obedience. One can add more than a single mediating variable, where a drop in the effect of GPAI indicates that GPAI overlaps with the set of added variables in prediction.

A mediating variable may be a parental choice, such as setting rules about a child's screen time, or it may be that the child controls, at least partially, a variable—such as whether the child regularly finishes their homework. The coefficient on a mediating variable tells us something about how the added variable affects predicted grandchild future wealth. One can then estimate the variable on grandparents' future-orientedness to see the degree to which grandparents affect the variable. We regress (observable) midlife wealth of the earlier cohort using only variables we have for the younger respondents of interest, including grandparents' GPAI. If GPAI has a positive impact on predicted wealth, we can investigate the channels that connect GPAI and grandchildren's upbringing and predicted wealth.

The idea is that if the GPAI effect is due to GPAI inducing differences in environment or treatment in the parental household, then the effect of GPAI will be reduced when these mediating variables are included. If the grandparent AI works by shifting one of the mediating variables x_{ik}, then the coefficient γ_2 will fall relative to γ_1. We use this as a metric of the relative importance of each variable x_{ik}.[18]

18 This is strictly true only under the orthogonality assumption, the plausibility of which depends on the variables involved.

TABLE 13. SUMMARY OF ALL GROUPS BY DEPENDENT VARIABLE

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Grandparent Effect			Separate Effects		
School Sports						
Total GP Index	0.111	0.0288	-0.0114			
Grandmother				-0.0436	-0.0263	-0.0378
Grandfather				0.276*	0.169	0.142
Observations	1907	1890	1890	1183	1174	1174
R-Squared	0.0234	0.0420	0.0495	0.0245	0.0445	0.0515
Attends Religious Services						
Total GP Index	0.304***	0.358***	0.301***			
Grandmother				0.0161	0.0153	0.00153
Grandfather				0.155	0.237*	0.204
Observations	1907	1890	1890	1182	1173	1173
R-Squared	0.00896	0.0502	0.0688	0.00749	0.0361	0.0489
Member of Community Group						
Total GP Index	0.224**	0.128	0.0980			
Grandmother				-0.0180	-0.0242	-0.0303
Grandfather				0.381***	0.319**	0.305**
Observations	1908	1891	1891	1183	1174	1174
R-Squared	0.00969	0.0310	0.0359	0.0152	0.0358	0.0382
Take Lessons						
Total GP Index	0.314***	0.303***	0.265***			
Grandmother				0.343***	0.367***	0.357***
Grandfather				0.0339	-0.0408	-0.0652
Observations	1908	1891	1891	1183	1174	1174
R-Squared	0.0627	0.0752	0.0828	0.0696	0.082	0.0882
Desired Education						
Total GP Index	0.169***	0.122**	0.0868			
Grandmother				0.000276	0.00387	-0.00723
Grandfather				0.190**	0.170**	0.142*
Observations	1971	1954	1954	1209	1200	1200
R-Squared	0.00883	0.0255	0.0457	0.0111	0.0357	0.0606

Notes: Total GP index is the summation of grandmother and grandfather index. Models 1 and 4 control for child's age and gender only. Models 2 and 5 also for Black. Latino. Region and Metropolis. Model 3 controls add household income of parents. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

9.3. The prediction variables

Model M2 adds controls for gender of respondent and race. Grandchild gender doesn't have a significant effect, but race does: GPAI has a significantly lower on predicted wealth for Blacks. Model M3 of Table 12 shows that there is no significant difference in the GPAI effect on predicted wealth by race or gender of the grandparent.

Parents in CDS respond to numerous questions that are potentially connected to the grandchild's future-orientedness latent variable. To illustrate, consider model M4 in Table 12. M4 differs from M1 only in that we have added seven CDS mediating variables in CDS1997: Parent's Desired Level of Schooling, Takes Lessons, Played Sports Last Summer, Member of a Community or Group, Attends Religious Services and Obeys Parents.

When these variables are included, the coefficient on grandparents' AI drops markedly but is still highly significant. This means that much of the effect of GPAI on predicted grandchild wealth reflects the effect of the mediating variables on predicted wealth. For example, Played Sports Last Summer has a large and significant effect on the grandchild wealth prediction, even when it "competes" with other possible connections. Note that the contributions of both sports variables (On School Athletic Teams and Played Sports Last Summer) are essentially unchanged if we move from M4 to M5, where all controls are included. This is more or less the case for the other mediating variables that are included.

To summarize, the collection of the seven mediating variables accounts for a substantial part of the GPAI. Of the seven variables, those that have a statistically significant effect on accumulated wealth are the two sport variables (On School Athletic Teams and Played Sports Last Summer), Takes Lessons, Member of a Community Group and Attends Religious Services.[19]

We remind the reader that our interest in this paper is the intergenerational transmission of future-orientedness. Consequently, it's not enough to predict that a child who played baseball is, or will be, more future-oriented. Her parents may be lazy layabouts who spend all their time and money pursuing their passion, going to baseball games. We have to drill down further to know if playing sports is a channel through which *future-orientedness* is transmitted from parents to offspring.

To investigate whether grandparents' attitude index is being passed on to grandchildren through sports, we run simple regressions to estimate the grandparents' AI effect on whether the grandchild played on school athletic teams. Table 17 shows the results of these regressions.

We used the CDS question: "Was the child a member of any school athletic or sports teams in the last 12 months?" We coded this as one for yes and zero for no. To maximize comparability across birth years, we use the response for the last wave that the child appears in the CDS: 2002 for the older children and 2007 for the younger. We run separate regressions for grandparents' AI for grandparents of mothers and fathers, for male and female grandchildren, and with different sets of controls.

Table 17 shows there's essentially no impact of Total GP on the likelihood of the grandchild playing school sports for both the maternal and paternal side. We see, however, that the paternal grandfather AI is significant in predicting school sport participation. This doesn't mean parental attributes *don't* affect the probability that their children engage in school sports, only that whatever affects this probability is not future-orientedness. For example, it may be that a child who is on a sports team becomes well known in the community, which leads to higher-paying jobs after graduating, and higher midlife wealth. This may easily be, however, someone who saves an above-average amount of that salary.

Before going on, it's worthwhile discussing this exercise a bit further. A positive response to the question "Did the child play school sports?" might correlate with larger wealth accumulation in various ways: it could be that playing sports builds discipline in participants; it could be that playing sports *requires* discipline, and only disciplined children play sports; there may (or may not) be any change in the child's discipline. It could also be that playing sports teaches teamwork, etc. We're agnostic about *why* an activity or attribute predicts greater wealth accumulation; our aim is to identify channels underlying intergenerational correlation of future-orientedness.

We ask which of the mediating variables in Table 12 are affected by GPAI—that is, which mediating variables would one predict are related to more future-oriented grandparents? Table 13 gives a condensed list of the mediating variables and the effect of GPAI, without separating the sex of the grandchild or separating whether the grandparent was maternal or paternal. The table shows that GPAI has a large and significant effect on Attends Religious Services and Takes Lessons, and a slightly less significant effect on (Parents response to) Desired Education.

19 It isn't obvious when a parent responds to a survey question whether the activity is a choice of the child or of the parent. One might surmise that Attends Religious Services is the parent's choice, while Playing Sports Last Summer is more likely the child's choice. We intend to address this question in subsequent work to better understand family dynamics.

Table 18 provides interesting detail about the GPAI effect on religious participation. First, the grandparent effect comes from the mother's parents' side, not the father's—the maternal Total GP effect is large and highly significant, while the paternal Total GP effect is essentially zero. Second, the GP effect is much stronger and more significant for boys than for girls.

Contrast this with the other significant mediating variable, Takes Lessons. We see from Table 20 that GPAI is again large and very significant, but this time the effect is essentially the same for boys and girls. In addition, for Takes Lessons the effect comes almost entirely from grandmothers, both maternal and paternal.

To summarize, Higher Religious Attendance and Takes Lessons are both associated with predicted grandchild wealth, as is the case with school sports. However, higher GPAI is more likely to be associated with Higher religious attendance and Takes Lessons than is the case with school sports.

Numerous channels could be behind this connection. For example, there may be a genetic aspect (that is, a "future-orientedness gene"); alternatively, it could be that children of parents who are more future-oriented learn future-orientedness through observation or through choices that parents make about how to raise their children. As an illustration of our method, compare M1 and M4. M4 differs from M1 only in the additional mediating variables (Desired Level of Education through Obedience). When these behavior variables are included, the coefficient on grandparents' AI drops significantly. This means that much of the effect of GPAI on predicted wealth reflects the effect of the mediating variables on predicted wealth. For example, Sports at School has a large effect on the wealth prediction, even when it "competes" with a number of other possible connections. Note that the contribution of both sports variables (On School Athletic Teams and Played Sports Last Summer) is essentially unchanged if we move from M4 to M5, where all controls are included. This is more or less the case for the other mediating variables that are included.

10. Conclusion

We have shown that our measure of future-orientedness, attitude index, has predictive power about future decisions and outcomes. Most importantly, a couple's AI predicts realized wealth accumulation of their offspring.

We used the measure to predict future wealth accumulation of couple's grandchildren and identified possible channels through which the intergenerational connection is effected. Interestingly, the effect of a channel can depend on the gender of the child and the genders of both the maternal and paternal grandparents. The difference between, say, the maternal grandmother and the maternal grandfather suggests that the transmissions we identify have a nontrivial cultural component since this is contrary to the standard genetic model.

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A. Life cycle savings model

In this section we present a basic neoclassical model of household savings across generations. We need 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 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 doesn't permit a distinction between preferences and rate of return; for that, other intertemporal tradeoffs, unrelated to rate of return, must be estimated. Third, education and income growth rates aren't suitable control variables for our wealth regression because they're 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.

A.1. Life cycle savings

We begin by thinking of agents as unitary households, indexed by i, who live for three periods , $t \in \{1, 2, 3\}$. In each period t, agents in life stage t receive nonfinancial income $y_{i,t}$, which grows exogenously over time at a constant rate = g_i. Each agent stores wealth in a risk-free asset a_i with a rate of return r_i that may vary by household. 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 then die.

Preferences are represented by a utility flow each period, which we specialize to equal the log of consumption: $U(c_{i,t}) = \ln c_{i,t}$. Agents discount their future utility at rate β_i per period. 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:

$$\mathrm{U}(\mathrm{c_i}) = \left[\mathrm{u}(\mathrm{c_{i,1}}) + \beta_\mathrm{i}\, \mathrm{u}(\mathrm{c_{i,2}}) + \beta_i^2 u(c_{i,3})\right] = log(c_{i,1}) + \beta_i\, log(c_{i,2}) + \beta_i^2 log(c_{i,3})$$

We focus below on savings at t = 2, taking this as a stand-in for all intermediate periods of a hypothetical model that is otherwise identical but with a longer lifecycle.

Optimal savings behavior in period 2 implies a linear equation

$$w_{i,2} = \alpha_{0,i} + \alpha_{1,i} a_{i,t-1}/y_{i,t} + \alpha_{2,i} g_i + \upsilon_i \tag{4}$$

where $w_{i,t} \equiv a_{i,t} / y_{i,t}$ represents the wealth/income ratio at the end of period t.

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

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

and

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

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 will be reflected in the coefficient of $w_{i,1}$ in a linear regression equation with two observable control variables.

It seems like one should be able to distinguish β_i and r_i using equations for $\alpha_{1,i}$ and $\alpha_{2,i}$. However, this involves taking our simple model very seriously indeed, as the functional forms of the reduced-form coefficients are likely highly model dependent.

B. Attitude sample wealth ratio estimates

The 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.

TABLE 14. OFFSPRING SAMPLE WEALTH-RATIO REGRESSION ESTIMATES

Variable	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)					0.014	0.006	0.014	0.014
					(0.07)	(0.00)	(0.05)	(0.04)
Number of Kids					-0.070***	0.000		
					(0.016)	(0.005)		
Kids Squared					-0.030**	-0.070***		
					(0.009)	(0.012)		
Num. Kids Aged 3-13					0.030***	0.090***		
					(0.010)	(0.013)		
Num. Kids Aged 14-17								
Hub. Self Employed							0.060	0.330***
							(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)

TABLE 14. OFFSPRING SAMPLE WEALTH-RATIO REGRESSION ESTIMATES (CONTINUED)

Variable	Model 1		Model 2		Model 3		Model 4	
	Son	Daughter	Son	Daughter	Son	Daughter	Son	Daughter
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							0.056***	0.045***
							(0.03)	(0.01)
Black			-0.300***	-0.100*			-0.290***	-0.090*
			(0.063)	(0.078)			(0.061)	(0.078)
White			-0.160***	0.140***			-0.170***	0.120**
			(0.048)	(0.062)			(0.048)	(0.061)
Age of Husband	0.050***	0.000	0.070***	0.000			0.080***	0.000
	(0.05)	(0.00)	(0.07)	(0.00)			(0.08)	(0.00)
Age Hub. Squared	-0.040***	0.000	-0.060***	0.000			-0.070***	0.000
	0.016	0.005	(0.016)	(0.005)			(0.015)	(0.005)
Age of Wife	-0.010	-0.080***	-0.030**	-0.070***			-0.040**	-0.070***
	0.009	0.012	(0.009)	(0.012)			(0.009)	(0.012)
Age Wife Squared	0.020	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

C. Home equity

Throughout the empirical analysis we have relied on a measure of net worth ("Wealth1" in the PSID) that excludes equity in the principal home. We were concerned that changes in home equity are largely unrelated to planning for the future, since they may be driven by homeownership and location decisions outside the scope of this paper. There is also a potentially large conjectural element in the market value of owner-occupied housing that introduces additional noise into the wealth measure; it's essential for our interpretation of AI that attitude responses are not correlated with bias in this conjectural element.

D. Predictions method

D.1. AI-CDS sample

Out of 3,563 kids in CDS97, we have 2,416 in PSID 2021. The useful sample consists of 1,700 heads and wives with at least one grandparent in our AI data (recall there is a max of 2% grandparents, since (typically) only one couple will be in the PSID sample). Of the 1,700, about 1,000 are heads, the rest spouses. A portion (25%) of the married participants are cohabiting, not legally married. Of the missing 800, 500 are not present in 2021; the rest (287) are mostly listed as co-resident offspring of household head or spouse.

TABLE 15. GRANDCHILD PREDICTED WEALTH STATISTICS

Variable	Mean	StdD
Predicted Wealth	107.060	(116.530)
Grandparent's Attitude Index	.214	(.110)
GP AI x Female	.090	(.129)
GP AI x Black	.026	(.082)
GP AI x White	.181	(.126)
GP AI x In-Sample	.117	(.132)
Parents Desired Schooling for Kids∗	.932	(.251)
On School Athletic Teams	.409	(.492)
Takes Lessons	.340	(.474)
Played Sports Last Summer	.273	(.445)
Member of Community Group	.30	(.46)
Attends Religious Services	.73	(.44)
Child obeys Parents∗	.80	(.40)
Female	.42	(.49)
Black	.14	(.35)
White	.83	(.38)
GP In Sample	.53	(.50)
Region	2.47	(1.00)
Age	31.98	(3.66)
Age Squared	10.36	(2.41)

Variables marked with ∗ were classed as 1 if response value was above average, zero otherwise

TABLE 16. PARENTAL ATTENDANCE DATA IN CDS/TA SURVEYS

(a) Kids in CDS1997 Covered in Later CDS/TA (Mom's Parents)

Survey	All	Mom's Mom	Mom's Dad	Both Mom's Parents
CDS97	3563	1494	1224	1053
CDS02	2907	1256	1037	899
CDS07	1623	695	565	493
TA05	745	341	291	254
TA07	1115	501	418	362
TA09	1554	708	591	514
TA11	1907	858	712	610
TA13	1804	797	644	571
PSID2021	2416	1054	868	755

(b) Kids in CDS1997 Covered in Later CDS/TA (Dad's Parents)

Survey	Dad's Mom	Dad's Dad	Both Dad's Parents	Any Grandparents
CDS97	950	825	719	1772
CDS02	813	712	621	1520
CDS07	433	377	329	822
TA05	233	206	184	438
TA07	335	291	256	618
TA09	443	379	334	848
TA11	530	453	400	1010
TA13	486	429	373	944
PSID2021	648	565	492	1247

D.2. Mediating variables

Formally, we settle on two status variables: predicted household wealth S_i^W, and a predicted- status index, S_i^{NDX}. We then implement a second regression to analyze the relationship between the predicted status and the grandparent's attitude index. Then, assuming there's a strong connection, we augment this second regression with CDS/TAS variables relating to the treatment of kids by their parents. The idea is that if the AI effect is due to AI inducing differences in environment or treatment in the parental household, then the effect of AI will be reduced when these mediating variables are included.

The first status variable S_i^W is conceptually very standard: we use regression methods to predict wealth on a middle-aged sample (ages 40–70, taking as explanatory variables selections from the set of variables that are also available for the younger (CDS) sample. This means if we include income, or marital status, then it will be as of age 30 or so, allowing us to apply the estimates to the CDS1997 sample in 2023 (not yet released, but we can use 2021 until it is).

The second status variable S_i^{NDX} is conceptually less straightforward. It deals with the problem of multiplicity of the possible variables that potentially affect wealth in a logical way. The idea is to find the basket of status variables in the CDS 1997 sample that is best predicted by the grandparent's AI. One can think about this as there being primitive status variables, which, even if perfectly measured, are incomplete. What matters is that there is some underlying status variable ("success") that is correlated with each of the primitives. It is this underlying variable that is most strongly correlated with the grandparent attitudes.

This view is close to that of Clark (2021)—although he argues that, in the end, the underlying variable is genetic. In Bidner-Knowles (2019), people construct a variable similar to this by forming Bayesian posteriors of the genetic ability of potential spouses, combining the family status of the potential spouse's parents with the signals from the observed primitive variables of the spouse (e.g., education).

Implementing this second variable can be seen as a way of summarizing the multiplicity of variants of our approach. Given a set of primitive estimated-status variables S_i , where $j \in \{1, 2, \ldots J\}$ references wealth, income, education etc., we construct the index by estimating an equation that predicts the grandparent AI

$$AI_i^G = \alpha_0 + \sum_{j \in \{1,2,\ldots J\}} \beta_j S_i^j + \epsilon_i^G$$

We then use the estimate to assess the role of the mediating variables from CDS/TAS, x_{ik}, where $k \in \{1, 2, \ldots K\}$, by comparing the coefficients γ_1 and γ_2 in estimates of the following two equations

$$S_i^{NDX} = \gamma_0 + \gamma_1 AI_i^G + \epsilon_i^{N1}$$

$$\mathrm{S}_\mathrm{i}^{\mathrm{NDX}} = \gamma_0 + \gamma_2 \, \mathrm{AI}_\mathrm{i}^\mathrm{G} + \sum_{k \in \{1,2,\ldots,K\}} \delta_\mathrm{k} \;\; \mathrm{x}_{\mathrm{ik}} + \epsilon_\mathrm{i}^{\mathrm{N1}}$$

The idea is that if the grandparent AI works by shifting one of the mediating variables x_{ik}, then the coefficient γ_2 will fall relative to γ_1. We use this as a metric of the relative importance of each variable x_{ik}. This is strictly true only under the orthogonality assumption, the plausibility of which depends on the variables involved.

D.4. GPAI prediction of mediating variables

TABLE 17. SCHOOL SPORTS

Did child play school sports?		(1)	(2)	(3)	(4)	(5)	(6)
		Total Grandparent Effect			Separate effects		
Dad GP	Total GP Index	0.0294	-0.0227	-0.0970			
	Grandmother				-0.247	-0.183	-0.211
	Grandfather				0.643***	0.519**	0.475*
	Observations	727	718	718	475	471	471
	R-Squared	0.0291	0.0535	0.0761	0.0455	0.0687	0.0806
Mom GP	Total GP Index	0.164	0.0714	0.0527			
	Grandmother				0.0826	0.0999	0.0956
	Grandfather				0.0168	-0.0921	-0.111
	Observations	1181	1173	1173	709	704	704
	R-Squared	0.0233	0.0451	0.0467	0.0298	0.0568	0.0625
Girls	Total GP Index	0.183	0.0888	0.0422			
	Grandmother				-0.0240	-0.00915	-0.0432
	Grandfather				0.309	0.208	0.197
	Observations	927	921	921	578	576	576
	R-Squared	0.0116	0.0309	0.0408	0.0178	0.0462	0.0601
Boys	Total GP Index	0.0205	-0.0247	-0.0575			
	Grandmother				-0.0727	-0.0295	-0.0288
	Grandfather				0.230	0.107	0.0742
	Observations	980	969	969	605	598	598
	R-Squared	0.0103	0.0371	0.0432	0.0131	0.0487	0.0526
All	Total GP Index	0.111	0.0288	-0.0114			
	Grandmother				-0.0436	-0.0263	-0.0378
	Grandfather				0.276*	0.169	0.142
	Observations	1907	1890	1890	1183	1174	1174
	R-Squared	0.0234	0.0420	0.0495	0.0245	0.0445	0.0515

Notes: Dependent Variable: Was CHILD a member of any school athletic or sports teams? Models 1 and 4 control for child's age and gender only. Models 2 and 5 also control for Black, Latino, Region and Metropolis. Model 3 controls add household income of parents. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE 18. DID CHILD ATTEND RELIGIOUS SERVICES

Attend Religious Service		(1)	(2)	(3)	(4)	(5)	(6)
		Total grandparents effect			Separate effects		
Dad GP	Total GP Index	0.175	0.218	0.125			
	Grandmother				-0.162	-0.186	-0.224
	Grandfather				0.334	0.444^{*}	0.387^{*}
	Observations	726	717	717	474	470	470
	R-Squared	0.00418	0.0396	0.0806	0.00724	0.0495	0.0738
Mom GP	Total GP Index	0.397^{***}	0.448^{***}	0.412^{***}			
	Grandmother				0.111	0.148	0.144
	Grandfather				0.0408	0.107	0.0881
	Observations	1182	1174	1174	709	704	704
	R-Squared	0.0211	0.0798	0.0872	0.0220	0.0554	0.0626
Girls	Total GP Index	0.199	0.307^{**}	0.232^{*}			
	Grandmother				-0.106	-0.0663	-0.0978
	Grandfather				0.0686	0.134	0.124
	Observations	927	921	921	577	575	575
	R-Squared	0.00745	0.0552	0.0855	0.0132	0.0320	0.0469
Boys	Total GP Index	0.417^{***}	0.410^{***}	0.372^{***}			
	Grandmother				0.125	0.0676	0.0686
	Grandfather				0.233	0.328	0.281
	Observations	980	969	969	605	598	598
	R-Squared	0.0130	0.0491	0.0595	0.00896	0.0453	0.0558
All	Total GP Index	0.304^{***}	0.358^{***}	0.301^{***}			
	Grandmother				0.0161	0.0153	0.00153
	Grandfather				0.155	0.237^{*}	0.204
	Observations	1907	1890	1890	1182	1173	1173
	R-Squared	0.00896	0.0502	0.0688	0.00749	0.0361	0.0489

Notes: Dependent variable: Attends Religious Services. Models 1 and 4 control for child's age and gender only. Models 2 and 5 also control for Black, Latino, Region and Metropolis. Model 3 controls add household income of parents. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE 19. CHILD WAS A MEMBER OF A COMMUNITY GROUP

Member of Community and Group		(1)	(2)	(3)	(4)	(5)	(6)
		Total grandparents effect			Separate effects		
Dad GP	Total GP Index	0.0517	0.00601	-0.0459			
	Grandmother				-0.159	-0.164	-0.183
	Grandfather				0.561**	0.512**	0.482**
	Observations	727	718	718	475	471	471
	R-Squared	0.0248	0.0566	0.0695	0.0348	0.0695	0.0760
Mom GP	Total GP Index	0.333***	0.199*	0.182			
	Grandmother				0.0816	0.0622	0.0609
	Grandfather				0.247	0.169	0.164
	Observations	1182	1174	1174	709	704	704
	R-Squared	0.00911	0.0359	0.0376	0.00742	0.0290	0.0296
Girls	Total GP Index	0.136	0.0327	0.000985			
	Grandmother				-0.149	-0.144	-0.155
	Grandfather				0.329*	0.292	0.288
	Observations	928	922	922	578	576	576
	R-Squared	0.0102	0.0329	0.0380	0.0172	0.0361	0.0377
Boys	Total GP Index	0.324**	0.244*	0.217			
	Grandmother				0.109	0.0947	0.0952
	Grandfather				0.430**	0.340*	0.313
	Observations	980	969	969	605	598	598
	R-Squared	0.00871	0.0328	0.0379	0.0160	0.0419	0.0452
All	Total GP Index	0.224**	0.128	0.0980			
	Grandmother				-0.0180	-0.0242	-0.0303
	Grandfather				0.381***	0.319**	0.305**
	Observations	1908	1891	1891	1183	1174	1174
	R-Squared	0.00969	0.0310	0.0359	0.0152	0.0358	0.0382

Notes: Dependent variable: Member of Community or Group. Models 1 and 4 control for child's age and gender only. Models 2 and 5 also control for Black, Latino, Region and Metropolis. Model 3 controls add household income of parents. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE 20. DID CHILD TAKE LESSONS?

Did Child take lessons?		(1)	(2)	(3)	(4)	(5)	(6)
		Total grandparents effect			Separate effects		
Dad GP	Total GP Index	0.272*	0.21	0.158		0.272*	0.21
	Grandmother				0.373***		
	Grandfather				0.342		
	Observations	727	718	718	475	727	718
	R-Squared	0.0465	0.0641	0.0777	0.0713	0.0465	0.0641
Mom GP	Total GP Index	0.341***	0.352***	0.320***		0.341***	0.352***
	Grandmother				0.286**		
	Grandfather				-0.156		
	Observations	1182	1174	1174	709	1182	1174
	R-Squared	0.0834	0.105	0.11	0.0795	0.0834	0.105
Girls	Total GP Index	0.314**	0.322**	0.257*		0.314**	0.322**
	Grandmother				0.450***		
	Grandfather				-0.0037		
	Observations	928	922	922	578	928	922
	R-Squared	0.06	0.0759	0.095	0.0845	0.06	0.0759
Boys	Total GP Index	0.323**	0.289**	0.275**		0.323**	0.289**
	Grandmother				0.252**		
	Grandfather				0.092		
	Observations	980	969	969	605	980	969
	R-Squared	0.0336	0.0547	0.0561	0.0242	0.0336	0.0547
All	Total GP Index	0.314***	0.303***	0.265***		0.314***	0.303***
	Grandmother				0.343***		
	Grandfather				0.0339		
	Observations	1908	1891	1891	1183	1908	1891
	R-Squared	0.0627	0.0752	0.0828	0.0696	0.0627	0.0752

Notes: Dependent variable: Did Child Take Lessons? Models 1 and 4 control for child's age and gender only. Models 2 and 5 also control for Black, Latino, Region and Metropolis. Model 3 controls add household income of parents. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE 21. HUSBAND AI VERSUS WIFE'S AI: FULL ESTIMATES

Variable	Model 1	Model 2	Model 3
Intercept	-2.131	-2.957	-0.784
	(0.760)	(0.779)	(0.793)
Husband's AI	0.645***	0.956***	1.030***
	(0.039)	(0.064)	(0.079)
Wife's AI	0.311***	0.806***	0.884***
	(0.040)	(0.087)	(0.106)
Lagged W/Y	0.687***	0.680***	0.617***
	(0.006)	(0.006)	(0.007)
Income Growth	-0.650***	-1.21***	-0.650***
	(0.156)	(0.171)	(0.252)
Wife's Education		0.040***	0.041***
		(0.010)	(0.010)
Husband's Education		0.045***	0.034***
		(0.009)	(0.009)
Income (log)		-0.012	0.010
		(0.013)	(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			0.603***
			(0.044)
Hub. Working			0.164***
			(0.047)
Hub retired			0.518***
			(0.051)
Hub Unemployed			-0.033
			(0.074)
Owns Business			-0.163***
			(0.039)
Incorp. Business			-0.09***
			(0.036)
Wife Working			0.069***
			(0.020)
Wife Retired			1.037***
			(0.059)

TABLE 21. HUSBAND AI VERSUS WIFE'S AI: FULL ESTIMATES (CONTINUED)

Variable	Model 1	Model 2	Model 3
Wife Unemployed			-0.32***
			(0.052)
Black		-0.020	-0.127
		(0.088)	(0.086)
White		0.171	0.034
		(0.076)	(0.075)
Husband's Age	-0.013	-0.013	-0.071
	(0.038)	(0.038)	(0.037)
Husb.'s $(Age/10)^2$	0.020	0.020	0.071
	(0.037)	(0.037)	(0.037)
Wife's Age	0.119***	0.110***	0.078***
	(0.033)	(0.033)	(0.033)
Wife's $(Age/10)^2$	-0.13***	-0.12***	-0.087***
	(0.034)	(0.034)	(0.033)
Year-1970	-0.11***	-0.11***	-0.09***
	(0.013)	(0.013)	(0.012)
$(Year-1970)^2$	0.421***	0.410***	0.348***
	(0.042)	(0.042)	(0.041)
R^2	0.445	0.449	0.479
N	929	929	929

Notes: Dependent variable is W/Y. Estimated on the attitude-wealth sample. AI = attitude index from model 3 (benchmark) in Table 2.

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