Supplemental Materials

Math-Related Career Aspirations and Choices Within Eccles et al. Expectancy-Value Theory of Achievement-Related Behaviors

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Appendix 1. Self-report measures from the Childhood and Beyond Study used in the present research

CAB surveys are available here: http://www.rcgd.isr.umich.edu/cab

Teacher-evaluated math aptitude in elementary school

1. Compared to other children, how much innate ability or talent does this child have in math?
   (1 = "Very little" to 7 = "A lot").
2. How well do you expect this child to do next year in math?
   (1 = "Very poorly" to 7 = "Exceptionally well")

Self-concept of math ability and expected success

1. How good at math are you?
   (1 = "Not at all good" to 7 = "Very good")
2. If you were to list all the students in your grade from the worst to the best in math, where would you put yourself?
   (1 = "One of the worst" to 7 = "The best")
3. Some students find that they are better at one subject or activity than another. Compared to most of your other activities, how good are you at math?
   (1 = "Not as good as other activities" to 7 = "A lot better than other activities")
4. How well do you expect to do in math next year?
   (1 = "Not at all well" to 7 = "Very well")
5. How good would you be at learning something new in math?
   (1 = "Not at all good" to 7 = "Very good")

Math utility

1. In general, how useful is what you learn in math?
   (1 = "Not at all useful" to 7 = "Very useful")
2. For me, being good in math is…
   (1 = "Not at all important" to 7 = "Very important")
3. Some students find what they learn in one subject or activity more useful than what they learn in another. Compared to most of your other activities, how useful is what you learn in math?
   (1 = "Not as useful as what I learn in other activities" to 7 = "A lot more useful than what I learn in other activities")
4. Some students believe that it is more important to be better at one subject or activity than another. Compared to most of your other activities, how important is it to you to be good at math?
   (1 = "Not as important as being good in other activities" to 7 = "A lot more important than being good in other activities")

Intrinsic interest in math

1. How much do you like math?
   (1 = "A little" to 7 = "A lot")
2. In general, you find working on math assignments…
   (1 = "Very boring" to 7 = "Very interesting")
3. Some students find that they like one subject or activity much more than another. Compared to most of your other activities, how much do you like math?
   (1 = "Not as much as other activities" to 7 = "A lot more than other activities")

Career plans for math- or science-related occupations

1. Look at the following list and rate how likely you would consider entering each of these kinds of jobs.
   Science or math related field (like engineer, architect)
   (1 = "Very unlikely" to 7 = "Very likely")

Career attainment (open-ended questions)

Please answer [the following questions] with your *current* or *most recent* occupation information

1. What is/was your occupation? For example: Electrical Engineer, Stock Clerk, Typist.
   ____

2. What are/were the most important activities or duties at this job (Ex. typing, keeping account books, filing, selling cars, operating printing press, laying bricks)
   ____

3. What is/was the official title of your job?
   ____

4. What kind of business or industry do/did you work in? That is, what do they make or do at the place where you work? (Ex. TV and radio manufacturing, retail shoe store, farm)
   ____

Appendix 2. Product Terms Computed for Tests of Latent Interactions in Models B5-B6, and B9-B10

Table S2.1. Product terms for the latent interactions tested in Models B5 and B6

	Four product terms were computed between the following pairs of items in Models B5 and B6:	
	Utility	**Self-Concept**
1.	For me, being good in math is… (1 = "Not at all important" to 7 = "Very important")	How good at math are you? (1 = "Not at all good" to 7 = "Very good")
2.	In general, how useful is what you learn in math? (1 = "Not at all useful" to 7 = "Very useful")	The average of: How well do you expect to do in math next year? (1 = "Not at all well" to 7 = "Very well") and How good would you be at learning something new in math? (1 = "Not at all good" to 7 = "Very good")
3.	Some students find what they learn in one subject or activity more useful than what they learn in another. Compared to most of your other activities, how useful is what you learn in math? (1 = "Not as useful as what I learn in other activities" to 7 = "A lot more useful than what I learn in other activities")	Some students find that they are better at one subject or activity than another. Compared to most of your other activities, how good are you at math? (1 = "Not as good as other activities" to 7 = "A lot better than other activities")
4.	Some students believe that it is more important to be better at one subject or activity than another. Compared to most of your other activities, how important is it to you to be good at math? (1 = "Not as important as being good in other activities" to 7 = "A lot more important than being good in other activities")	If you were to list all the students in your grade from the worst to the best in math, where would you put yourself? (1 = "One of the worst" to 7 = "The best")

Table S2.2. Product terms for the latent interactions tested in Models B9 and B10

	Three product terms were computed between the following pairs of items in Models B9 and B10:	
	Intrinsic Interest	**Self-Concept**
1.	In general, you find working on math assignments… (1 = "Very boring" to 7 = "Very interesting")	How good at math are you? (1 = "Not at all good" to 7 = "Very good")
2.	How much do you like math? (1 = "A little" to 7 = "A lot")	The average of: How well do you expect to do in math next year? (1 = "Not at all well" to 7 = "Very well") and How good would you be at learning something new in math? (1 = "Not at all good" to 7 = "Very good")
3.	Some students find that they like one subject or activity much more than another. Compared to most of your other activities, how much do you like math? (1 = "Not as much as other activities" to 7 = "A lot more than other activities")	The average of: If you were to list all the students in your grade from the worst to the best in math, where would you put yourself? (1 = "One of the worst" to 7 = "The best") and Some students find that they are better at one subject or activity than another. Compared to most of your other activities, how good are you at math? (1 = "Not as good as other activities" to 7 = "A lot better than other activities")

Appendix 3. Standardized Path Coefficients Estimated in Models A1-A4 (n = 980)

Table S3.1 Standardized Path Coefficients Estimated in Models A1-A4 (n = 980; see Figures 1-4 in the manuscript)

Predictors of Math Aptitude	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.07 †	.08 †	.08 †	.07 †
Parent education	.24 ***	.24 ***	.24 ***	.24 ***
Cohort 2	.03	.03	.03	.03
Cohort 3	-.01	-.01	-.01	-.01
Predictors of Cognitive Ability	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.13 ***	.13 ***	.13 ***	.13 ***
Parent education	.19 ***	.20 ***	.20 ***	.19 ***
Cohort 2	.04	-.04	-.04	-.04
Cohort 3	-.23 ***	-.23 ***	-.23 ***	-.23 ***
Predictors of Self-Concept – Grade 9	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.04			.04
Parent education	.08			.07
Cohort 2	.15 **			.16 **
Cohort 3				
Cognitive ability	.08			.10
Math aptitude	.34 ***			.33 ***
Predictors of Utility– Grade 9	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male		-.02		-.01
Parent education		.03		.02
Cohort 2		.16 *		.17 **
Cohort 3				
Cognitive ability		-.04		-.02
Math aptitude		.04		.03
Predictors of Interest – Grade 9	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male			.01	.01
Parent education			-.01	-.01
Cohort 2			.14 *	.13 *
Cohort 3				
Cognitive ability			-.04	-.03
Math aptitude			.14 †	.14 †
Predictors of Career Plans – Grade 9	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.20 **	.20 **	.20 **	.20 **
Parent education	.01	.01	.00	.01
Cohort 2	.11 †	.12 *	.12 *	.12 †
Cohort 3				
Cognitive ability	.11 †	.09	.11 †	.10 †
Math aptitude	.00	.10	.10	.03
Predictors of Self-Concept – Grade 12	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	-.03			-.03
Parent education	.04			.05
Cohort 2	-.03			-.03
Cohort 3	.10 †			.10 †
Cognitive ability	.06			.05
Math aptitude	.13 *			.13 *
Self-concept – Grade 9	.60 ***			.61 ***
Utility – Grade 9				-.06
Interest – Grade 9				.05
Career plans– Grade 9	.15 *			.15 †

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Predictors of Utility– Grade 12	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male		-.04		-.04
Parent education		-.02		.00
Cohort 2		-.08		-.07
Cohort 3		.07		.08
Cognitive ability		.02		.02
Math aptitude		.12 †		.11
Self-concept – Grade 9				-.06
Utility – Grade 9		.48 ***		.35 **
Interest – Grade 9				.29 *
Career plans– Grade 9		.20 *		.16 *
Predictors of Interest – Grade 12	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male			-.05	-.04
Parent education			.03	.01
Cohort 2			.02	-.01
Cohort 3			.11 †	.10 †
Cognitive ability			.06	.03
Math aptitude			.04	.00
Self-concept – Grade 9				.21 *
Utility – Grade 9				.00
Interest – Grade 9			.68 ***	.54 ***
Career plans– Grade 9			.09	.05
Predictors of Career Plans – Grade 12	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.15 **	.16 **	.15 **	.16 **
Parent education	.05	.06	.07	.06
Cohort 2	-.03	-.02	-.02	-.02
Cohort 3	.13 *	.14 *	.13 *	.14 *
Cognitive ability	.08	.12 *	.10 *	.10 †
Math aptitude	.08	.12 †	.11 †	.10
Self-concept – Grade 9	.13 †			.06 * *a.*
Utility – Grade 9		.14 *		.04 * *a.*
Interest – Grade 9			.10	.06 * *a.*
Career plans– Grade 9	.47 ***	.47 ***	.49 ***	.46 ***
Predictors of Adult Career Attainment	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.13 *	.14 *	.12 *	.14 *
Parent education	.00	.00	.01	.01
Cohort 2	.07	.06	.07	.07
Cohort 3	.09	.09	.10	.11
Cognitive ability	.02	.03	.02	.03
Math aptitude	.07	.08	.08	.07
Self-concept – Grade 9	.09			.07
Utility – Grade 9		.13		.09
Interest – Grade 9			.13	.08
Career plans– Grade 9	.07	.06	.05	.03
Self-concept – Grade 12	-.06			-.02
Utility – Grade 12		-.02		.16
Interest – Grade 12			-.10	-.24
Career plans– Grade 12	.31 **	.28 **	.34 **	.30 **

a. The unstandardized path coefficients for grade 9 (*Time 2*) math self-concept, math utility, and intrinsic interest predicting grade 12 (*Time 3*) career plans were fixed to be the same in Model A4.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

Appendix 4. Model A4 without Equality Constraints for the Predictive Paths of Grade 9 (Time 2) Expectancy/Value Constructs Predicting Grade 12 (Time 3) Career Plans

The following Figure S4.1 presents Model A4 without equality constraints for grade 9 expectancy/value constructs (math self-concept of ability, math utility, and intrinsic interest in math) predicting math/ science-related career plans in grade 12.

Model A4.

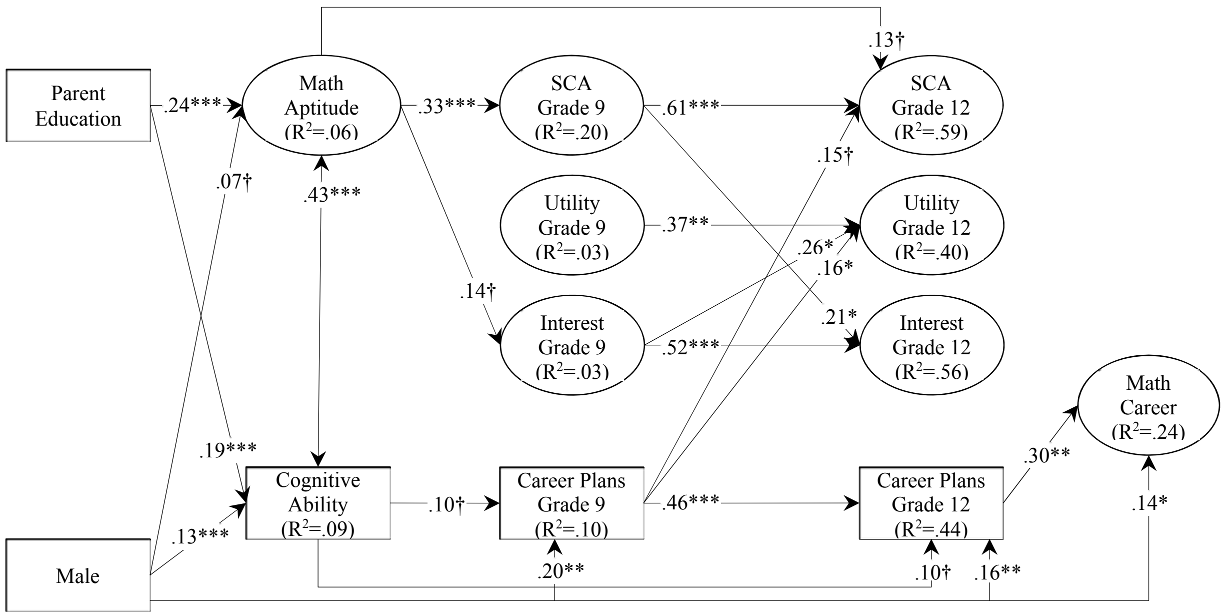

Figure S4.1. Reciprocal relations between math-related self-concept of ability (SCA), utility, intrinsic interest, and career plans, and long-term predictive effects on math-related career attainment. Residual correlations between constructs assessed in grade 9 and residual correlations between constructs assessed in grade 12 were estimated, but are not shown (these correlations were positive and significant ρ=[.30,.78], *p*s ≤ .001). Cohort was included as a control variable, but is not shown for the sake of clarity. Only paths with $p < .10$ are shown. The overall model fit was acceptable, χ^2=1129.99, *df*=462, CFI=0.936, TLI=0.917, RMSEA=0.038, 90%CI=[0.036,0.041], SRMR=0.078. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

Appendix 5. Tests of Measurement Invariance Across Gender in Models A1-A4

The following analyses show the overall model fit for Models A1-A4 in which different sets of model parameters were either freely estimated across gender or fixed to be the same. As shown in Table S5.1, measurement invariance was supported for models in which all factor loadings and all predictive paths were fixed to be the same across gender. We would like to note, however, that we have insufficient statistical power to adequately test our models within each subgroup of participants; for instance, the ratio of male participants who had data in grade 9 (only Cohort 2 and Cohort 3 were available for this time point) to the number of freely estimated parameters ranged from 0.64 to 1.31 across Models A1-A4. Thus, although we provide suggestive evidence in support of measurement invariance, further analyses with a larger sample are needed to examine the potential moderating role of gender.

Table S5.1. *Multigroup Analyses by Gender in Models A1-A4*

Estimated Models	χ^2	df	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
Model A1								
Freely estimated parameters [a]	466.885	258	0.964	0.948	0.041	0.064	-	-
Fixed loadings and predictive paths	470.596	268	0.966	0.951	0.039	0.063	-.002	-.002
Model A2								
Freely estimated parameters [a]	296.262	186	0.974	0.957	0.035	0.064	-	-
Fixed loadings and predictive paths	347.132	231	0.973	0.964	0.032	0.080	.001	-.003
Model A3								
Freely estimated parameters [a]	185.107	130	0.987	0.976	0.029	0.073	-	-
Fixed loadings and predictive paths	233.874	173	0.986	0.980	0.027	0.085	.001	-.002
Model A4								
Freely estimated parameters [a]	1533.651	866	0.936	0.917	0.040	0.075	-	-
Fixed loadings and predictive paths	1636.216	953	0.934	0.923	0.038	0.083	.002	-.002

Note. See Figure 1 for Model A1, Figure 2 for Model A2, Figure 3 for Model A3, and Figure 4 for Model A4 in the manuscript.

a. One factor loading per construct was fixed at 1.0 for model identification purposes.

Tests of Measurement Invariance Across Gender in Models B5-B6 and B9-B10

The following analyses show the overall model fit for Models B5-B6 and B9-B10 in which different sets of model parameters were either freely estimated across gender or fixed to be the same. As shown in Table S5.2 below, measurement invariance was supported for models in which all factor loadings and predictive paths were fixed to be the same across gender. All variables were group-mean centered prior to the analyses (for males and for females).

Table S5.2. *Multigroup Analyses by Gender in Models B5-B6 and B9-B10*

Estimated Models	χ^2	df	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
Model B5								
Freely estimated parameters [a]	673.69	314	0.944	0.925	0.048	0.049	-	-
Fixed loadings and predictive paths	689.62	334	0.945	0.930	0.047	0.051	-.001	-.001
Model B6								
Freely estimated parameters [a]	700.86	338	0.945	0.925	0.047	0.047	-	-
Fixed loadings and predictive paths	719.17	359	0.945	0.930	0.045	0.050	.000	-.002
Model B9								
Freely estimated parameters [a]	653.81	242	0.937	0.911	0.059	0.046	-	-
Fixed loadings and predictive paths	669.77	260	0.937	0.917	0.057	0.051	.000	-.002
Model B10								
Freely estimated parameters [a]	675.53	262	0.938	0.910	0.057	0.044	-	-
Fixed loadings and predictive paths	692.51	281	0.938	0.917	0.055	0.049	.000	-.002

a. One factor loading per construct was fixed at 1.0 for model identification purposes. All variables were group-mean centered prior to the analyses (for males and for females).

Appendix 6. Tests of Models A1-A4 and Model B10 in Subsets of the Full Sample

Due to the high percentage of missing data for selected variables and time points (e.g., in grade 9, for which only two cohorts were available; see Table 1 and Table 2), we tested the robustness of our results (a) using data only from participants who had at least one observation in high school and adulthood (n = 596, Table S6.2), (b) using only observed variables so that the ratio of estimated parameters to available data is reduced (n = 596, Table S6.3), and (c) using only observed variables and data only from Cohort 1 and Cohort 2 with at least one observation in high school or adulthood (n = 361, Table S6.4). Only cross-lagged effects were tested with n = 361 due to insufficient statistical power for testing interactive associations. These analyses corroborate all of our findings regarding cross-lagged effects, interactive effects, and significant predictors of career attainment.

For the sake of comparison, Table S6.1 presents selected predictive coefficients for the full sample of n = 980, as reported in the main manuscript.

Table S6.1 Standardized path coefficients estimated in Models A1-A4 using latent constructs and data from all participants, as reported in the main manuscript (n = 980)

Stability Coefficients	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Self-Concept Grade 12 on Self-concept Grade 9	.60 ***			.61 ***
Utility Grade 12 on Utility Grade 9		.48 ***		.35 **
Interest Grade 12 on Interest Grade 9			.68 ***	.54 ***
Career Plans Grade 12 on Career Plans Grade 9	.47 ***	.47 ***	.49 ***	.46 ***
Cross-Lagged Effects	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Career Plans Grade 12 on Self-concept Grade 9	.13 †			.06 * *a.*
Self-concept Grade 12 on Career Plans Grade 9	.15 *			.15 †
Career Plans Grade 12 on Utility Grade 9		.14 *		.04 * *a.*
Utility Grade 12 on Career Plans Grade 9		.20 *		.16 *
Career Plans Grade 12 on Interest Grade 9			.10	.06 * *a.*
Interest Grade 12 on Career Plans Grade 9			.09	.05
Significant Predictors of Adult Career Attainment	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.13 *	.14 *	.12 *	.14 *
Career plans– Grade 12	.31 **	.28 **	.34 **	.30 **

a. The unstandardized path coefficients for grade 9 (*Time 2*) math self-concept, math utility, and intrinsic interest predicting grade 12 (*Time 3*) career plans were fixed to be the same in Model A4.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

Table S6.2 Standardized path coefficients estimated in Models A1-A4 using latent constructs and data from participants with at least one observation in high school or adulthood (n = 596)

Stability Coefficients	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Self-Concept Grade 12 on Self-concept Grade 9	.60 ***			.61 ***
Utility Grade 12 on Utility Grade 9		.49 ***		.35 **
Interest Grade 12 on Interest Grade 9			.68 ***	.54 ***
Career Plans Grade 12 on Career Plans Grade 9	.47 ***	.47 ***	.49 ***	.46 ***
Cross-Lagged Effects	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Career Plans Grade 12 on Self-concept Grade 9	.13 †			.06 * *a.*
Self-concept Grade 12 on Career Plans Grade 9	.15 *			.15 *
Career Plans Grade 12 on Utility Grade 9		.14 *		.04 * *a.*
Utility Grade 12 on Career Plans Grade 9		.20 *		.16 *
Career Plans Grade 12 on Interest Grade 9			.10	.06 * *a.*
Interest Grade 12 on Career Plans Grade 9			.09	.05
Significant Predictors of Adult Career Attainment	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.12 *	.13 *	.12 *	.14 *
Career plans– Grade 12	.32 **	.29 **	.34 **	.30 **

a. The unstandardized path coefficients for grade 9 (*Time 2*) math self-concept, math utility, and intrinsic interest predicting grade 12 (*Time 3*) career plans were fixed to be the same in Model A4.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

Table S6.3 Standardized path coefficients estimated in Models A1-A4 using observed variables (mean scores) and data from participants with at least one observation in high school or adulthood (n = 596)

Stability Coefficients	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Self-Concept Grade 12 on Self-concept Grade 9	.58 ***			.54 ***
Utility Grade 12 on Utility Grade 9		.47 ***		.35 **
Interest Grade 12 on Interest Grade 9			.64 ***	.38 ***
Career Plans Grade 12 on Career Plans Grade 9	.48 ***	.47 ***	.49 ***	.46 ***
Cross-Lagged Effects	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Career Plans Grade 12 on Self-concept Grade 9	.12 †			.06 ** *a.*
Self-concept Grade 12 on Career Plans Grade 9	.16 **			.16 *
Career Plans Grade 12 on Utility Grade 9		.15 **		.05 ** *a.*
Utility Grade 12 on Career Plans Grade 9		.20 **		.16 *
Career Plans Grade 12 on Interest Grade 9			.10	.07 ** *a.*
Interest Grade 12 on Career Plans Grade 9			.08	.04
Significant Predictors of Adult Career Attainment	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.10 †	.10 †	.10 †	.10 †
Career plans– Grade 12	.31 **	.29 **	.33 **	.31 **

a. The unstandardized path coefficients for grade 9 (*Time 2*) math self-concept, math utility, and intrinsic interest predicting grade 12 (*Time 3*) career plans were fixed to be the same in Model A4.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

Table S6.4 Standardized path coefficients estimated in Models A1-A4 using observed variables (mean scores) and data from participants with at least one observation in high school or adulthood and only coming from the two younger cohorts, Cohort 1 and Cohort 2 (n = 361; no data were collected for Cohort 3 in grade 9)

Stability Coefficients	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Self-Concept Grade 12 on Self-concept Grade 9	.57 ***			.51 ***
Utility Grade 12 on Utility Grade 9		.48 ***		.36 ***
Interest Grade 12 on Interest Grade 9			.64 ***	.50 ***
Career Plans Grade 12 on Career Plans Grade 9	.46 ***	.45 ***	.47 ***	.44 ***
Cross-Lagged Effects	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Career Plans Grade 12 on Self-concept Grade 9	.13 *			.06 ** *a.*
Self-concept Grade 12 on Career Plans Grade 9	.17 **			.16 *
Career Plans Grade 12 on Utility Grade 9		.16 **		.06 ** *a.*
Utility Grade 12 on Career Plans Grade 9		.21 **		.18 *
Career Plans Grade 12 on Interest Grade 9			.11 †	.08 ** *a.*
Interest Grade 12 on Career Plans Grade 9			.09	.05
Significant Predictors of Adult Career Attainment	*Model A1*	*Model A2*	*Model A3*	*Model A4*
Male	.17 *	.16 *	.16 *	.17 *
Career plans– Grade 12	.22 †	.24 †	.28 *	.23 †

a. The unstandardized path coefficients for grade 9 (*Time 2*) math self-concept, math utility, and intrinsic interest predicting grade 12 (*Time 3*) career plans were fixed to be the same in Model A4.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (two-sided)

In addition to Models A1-A4, we tested one of our most complex models including interaction terms, Model B10, with subsamples of the data. The interaction between math self-concept and intrinsic interest remained significant in these analyses: (a) using latent variables and data only from individuals with at least one observation in adolescence or adulthood (n = 596; β = .16, b = 0.770, p = .026) and (b) using observed variables (mean scores) and data only from individuals with at least one observation in adolescence or adulthood (n = 596; β = .14, b = 0.789, p = .023). Gender and career plans also remained significant or marginally significant predictors of career attainment in this subsample using latent variables (n = 596): (a) gender: β = .12, b = 3.037, p = .034; and career plans: β = .35, b = 1.866, p < .001 predicting career attainment; vs. observed variables (n = 596): (b) gender: β = .10, b = 2.462, p = .072; and career plans: β = 35, b = 1.927, p < .001 predicting career attainment. Model B10 could not be tested with individuals who came only from Cohorts 1 and 2 and who had at least one observation in adolescence or adulthood due to insufficient sample size and statistical power (n = 361).

In sum, these analyses demonstrate that findings reported in our main manuscript are robust when we analyze only subsets of the data with smaller proportions of missing information, as well as when we used observed variables (in which case the proportion of missing data to the number of estimated parameters is smaller than in models using latent variables).

Appendix 7. Supplemental Analyses Using High School Achievement Data

A set of additional analyses was conducted to test the robustness of our results reported in the main manuscript. Of particular relevance for our analyses is the fact that high school achievement data are available in CAB, but due to the amount of missing information for these variables, they could not be included in our main analyses. Nevertheless, we describe and report these data here as online supplemental material.

Two math-specific achievement indicators are available in the CAB data set at the end of high school: school records data for grade 12 math grades and standardized math scores, which serve as indicators of college readiness (most students had reported ACT [American College Testing] math scores, but some students also reported SAT [Scholastic Aptitude Test] or PSAT [Preliminary SAT] math scores). Unfortunately, the amount of missing data for both measures (grade 12 school records data and standardized math scores) caused some of our main models to fail to converge due to insufficient covariance coverage of less than 10% (e.g., Models A1-A4). It is possible to run analyses with less than 10% covariance coverage (in Mplus 7.11, which is the software we use), but the obtained estimates may not be trustworthy due to insufficient data. In the following section, we describe these two achievement measures and report correlational patterns with key variables of interest, namely math-related career attainment and gender.

Grade 12 math grades. Grade 12 math grades were obtained from school records and are recorded on a 16-point scale ranging from 1 = "F" (minimum) to 16 = "A+" (maximum). Unfortunately, only 114 individuals in our sample had data for both grade 12 math school grades and adult career attainment. More importantly, these grade 12 math grades were not significantly correlated with our outcome measure of math-related career attainment (r=.14, p=.131, n = 114), whereas both of the ability/aptitude indicators used in our analyses from elementary school are significantly correlated with career attainment (see Measures, as well as Table 2 in the manuscript). This difference might be due, at least in part, to the amount of missing data in grade 12 math grades; in contrast, we have very little missing data for the elementary school ability/aptitude indicators used in our analyses. In addition, a possible reason for the lack of significant association is that the participating students could be taking vastly different math classes (e.g., basic or advanced math classes), so that their grades are not easily comparable.

Using all available math grades for grade 12, we found that female participants had slightly higher math grades in grade 12 than male participants (r= –.15, p=.026, n = 222). This result suggests that the reported differences between male and female participants in preferences for math/science-related careers (favoring males, see Results) are unlikely to be attributable to differences in math grades at the end of high school (which slightly favor females).

ACT Math Scores. The ACT math scores are an assessment of college readiness that can be used for college applications. Most students take the ACT in their junior or senior year. The

ACT scores in our sample ranged from 10 to 36. [1] These ACT math scores were significantly correlated with our measure of math-related career attainment (r = .23, p=.009, n = 131). Notably, the correlation between our measure of teacher-rated math aptitude used in the manuscript (see Measures) and these high school ACT math scores is relatively high, at r=.64, p<.001, n = 245, which supports the predictive validity of our elementary school math aptitude assessment.

We found no significant association between these ACT scores and gender (r=.07, p=.293, n = 245). Accordingly, although the amount of missing data is problematic, using all available information about end-of-high school achievement, we do not find evidence that females' lower likelihood of pursuing math-related careers, relative to males' likelihood of pursuing such careers, might be attributable to achievement differences in math. As noted in the manuscript, this result is consistent with the preponderance of available evidence, according to which achievement differences in math explain very little of the variance in gendered educational and occupational choices.

[1] There was one implausible value of 47 (the maximum possible ACT score is 36). Fortunately, PSAT scores were available for this individual, so that we could transform this individual's PSAT score of 600 into an ACT score of 27 (see Dorans, N. J. (1999). Correspondences between ACT and SAT I Scores. College Board Report No. 99-1. New York: College Entrance Examination Board.). This correction does not change our results and conclusions.