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Gritty peers☆

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ABSTRACT

We use the National Longitudinal Study of Adolescent to Adult Health to explore how high school peers' grit, a personality trait characterized by perseverance and passion, influences long-term outcomes approximately 15 years after high school. Exploiting random variation within schools across cohorts and the longitudinal nature of our data, we find that peer grit significantly increases future earnings by 4.2%, especially for students from disadvantaged backgrounds. This implies that peer grit may help bridge socioeconomic gaps. We uncover three potential channels through which peer grit affects long-term earnings: college enrollment, job alignment with long-term career goals, and increased resilience to difficulties. Additionally, peer grit leads to higher job satisfaction and asset accumulation. Thus, peer grit's effects extend beyond short-term educational performance and persist into adulthood.

1. Introduction

A growing literature in economics, psychology, and sociology has recognized the importance of personality traits in explaining individuals' life trajectories. Traits such as patience, conscientiousness, self-control, and grit have been shown to be highly predictive of outcomes, including educational attainment, health, risky behaviors, earnings, and investment (e.g., Duckworth et al., 2007; Borghans et al., 2008; Duckworth and Quinn, 2009; Almlund et al., 2011; Golsteyn et al., 2014; Attanasio et al., 2020; Arduini et al., 2021; Lam and Zhou, 2022; Santos et al., 2022; Savelyev, 2022; Cobb-Clark et al., 2024). Additionally, research on peer effects during childhood and adolescence has demonstrated that peer characteristics such as race, gender, behaviors, and test scores influence long-term outcomes, including earnings realized during adulthood (e.g., Burke and Sass, 2013; Carrell et al., 2018; Jones and Kofoed, 2020; Lépine and Estevan, 2021; Feld and Zölitz, 2022; Denning et al., 2023).

There is little evidence on the labor market consequences of high-school peers' personality traits, specifically how peers' grit, as distinct from an individual's own grit, can shape long-term outcomes. Peer grit may influence outcomes by shaping students' behavior in school, academic engagement, and attitudes toward effort and perseverance. While peer effects estimates are difficult to translate directly into policy (Carrell et al., 2013), they remain important for understanding social spillovers. In this sense, understanding the role of peer personality traits is relevant for the broader evaluation of educational and

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personality-development interventions, as such programs may generate benefits that extend beyond the targeted individuals.

In this paper, we examine whether peer personality affects long-run labor earnings, using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health)—a longitudinal study of a nationally representative sample of adolescent students in the U.S., which provides extensive information on personality traits and long-run outcomes. Tracking individuals from high school into adulthood is challenging, which may explain why most existing literature emphasizes the influence of peer personality traits on short-term educational outcomes. However, the question of whether these peer effects extend beyond academic performance and persist into adulthood — especially in shaping economic outcomes such as earnings — remains largely unexplored. Our study fills this gap by examining whether peer personality traits during adolescence have a lasting impact on labor market outcomes in early adulthood.

We focus on one key personality trait: grit, which is characterized by perseverance and passion toward a specific goal. Own grit has been proven to be associated with improved educational attainment and economic success (Duckworth et al., 2007; Duckworth and Quinn, 2009; Alan et al., 2019). Additionally, peer persistence — an important facet of grit — has also been shown to boost educational performance (Golsteyn et al., 2021; Shure, 2021; Zou, 2024) but mainly in the short-run. Building on these insights, we investigate whether peer grit during high school (ages 12-19) affects *long-run* outcomes in early adulthood (ages 24-32) and their persistence into mid-adulthood (ages 34-43).

Identifying peer effects involves several challenges, including the reflection problem and endogenous group selection (Manski, 1993). The reflection problem arises because students and their peers can influence each other simultaneously when focusing on contemporaneous outcomes. Utilizing the longitudinal nature of our data, the reflection problem is unlikely to bias our estimates, as earnings measured in adulthood cannot influence peer or own grit during high school.

To address the issue of selection into peer groups, we leverage variation in peer grit across cohorts within schools, while controlling for school and cohort fixed effects, a well-established approach in the literature (Bifulco et al., 2011; Lavy and Schlosser, 2011; Kiessling and Norris, 2023; Merlino et al., 2024).[1] Our identification strategy exploits the fact that while parents may select a school based on the average grit level of its students, it is unlikely that within-school sorting into specific grades is influenced by the specific composition of a child's cohort. This approach builds on that of Giulietti et al. (2022), who examine the long-term effects of peer depression using Add Health data and a similar identification strategy. In our analysis, we find no evidence of sorting into school-cohorts based on grit, conditional on the leave-out mean at the school level and predetermined characteristics at both the individual and family level. Placebo tests further support our identification strategy. Moreover, by conditioning on an extensive set of average peer individual and family characteristics, we seek to isolate the specific impact of peer grit. This approach helps reduce confounding by other peer characteristics, such as socioeconomic status, family background, self-control, confidence, beauty, self-reported health status, Big Five traits, non-risky behaviors, parental expectations, or depression.

Our findings reveal a substantial effect of peer grit on annual gross earnings: a one standard deviation increase in peer grit is associated with a 4.2% increase in earnings. This effect is notable when compared to the impact of one's own grit (7.6%). Students from economically disadvantaged backgrounds, as defined by parental income or education, benefit more from peer grit. Specifically, for individuals with low-educated parents, a one standard deviation increase in peer grit leads to a 5.6% increase in future earnings, an effect that is 33% greater than in the overall sample. Additionally, individuals who were more exposed to peers with higher grit during high school tend to experience greater job satisfaction, and are more likely to hold jobs aligned with their long-term career goals. They also accumulate more assets in early adulthood. However, we do not find a significant impact of peer grit on labor supply or specific job characteristics, such as holding a supervisory role, working in non-repetitive tasks, or engaging in decision-making roles at work.

Our further analysis reveals that peer grit influences educational outcomes, personality, and attitudes in both the short and long run. Individuals who had gritty peers during high school are more likely to enroll in college. They also reported higher levels of their own grit in the follow-up survey one year later. In the long run (14-15 years after), they exhibit lower risk aversion and less frequent feelings of being unable to overcome recent difficulties in their lives. These factors may contribute to their economic success.

We uncover three potential major channels through which high school peer grit affects long-term earnings. College enrollment serves as an important mechanism, consistent with the literature that has analyzed short-term educational effects. However, this is not the only pathway explaining the long-run earnings effects. Job alignment with long-term career goals emerges as an equally important channel: individuals exposed to grittier peers are more likely to perceive their current job as aligned with their long-term career trajectory. A third channel is an increased ability to overcome difficulties: those with grittier high school peers report less frequent feelings of being unable to overcome recent challenges. Together, these three mechanisms — college enrollment, career-aligned job choices, and resilience — explain why high school peer grit continues to affect earnings well into adulthood.

Our research contributes to the literature that investigates the effects of peer characteristics on individuals' academic and other life outcomes (e.g., Marmaros and Sacerdote, 2002; Zimmerman, 2003; Stinebrickner and Stinebrickner, 2006; Aizer, 2009; Black et al., 2013; Jackson, 2013; Antecol et al., 2016; Aparicio-Fenoll and Oppedisano, 2016; Brady et al., 2017; Carrell et al., 2018; Arduini et al., 2019; Coveney and Oosterveen, 2021; Giulietti et al., 2022; Berlinski et al., 2023; Bertoni and Nisticò, 2023; Dong et al., 2023; Costas-Fernández et al., 2023; Cattan et al., 2023; Shin, 2024). In particular, we focus on the importance of peer *personality*. Previous studies have explored the effects of peer motivation (Bietenbeck, 2024), creativity (Van Lent, 2024), and the Big Five personality traits (Shure, 2021; Hancock and Hill, 2022) in the short run. Existing research demonstrates that *own* grit has consistent effects on academic achievement and earnings in a variety of countries with different cultures, namely the U.S. (Duckworth and Quinn, 2009; Eskreis-Winkler et al., 2014; Bowman et al., 2015), Germany (Lechner et al., 2019), Taiwan (Lin and Chang, 2017), and Japan (Suzuki et al., 2015). Similarly, studies examining the effects of peer grit-related personality traits — including peer perseverance, motivation, and conscientiousness — on educational and labor market outcomes show considerable consistency across different contexts, i.e., the UK, Sweden, the U.S., China, and the Netherlands (Shure, 2021; Golsteyn et al., 2021; Hancock and Hill, 2022; Bietenbeck, 2024; Zou, 2024; Shan and Zölitz, 2025), suggesting that peer personality effects operate through fundamental mechanisms that go beyond cultural differences to shape educational attainment and labor market success. Our analysis confirms this, indicating that peer grit increases the likelihood of college enrollment. Due to the difficulty of tracking individuals into adulthood, however, little is known about how peer grit affects long-run outcomes. By utilizing the unique features of the Add Health survey, which tracks individuals from high school into adulthood, we fill this gap and provide the first empirical evidence that high school peers' personality traits also influence long-term economic success in adulthood.

[1] By focusing on peers within the same cohort rather than classmates or nominated friends, we mitigate concerns related to the endogenous friendship formation, as discussed in the literature (McPherson et al., 2001; Belot and de Ven, 2011; Carrell et al., 2013; Cullen and Perez-Truglia, 2023).

Our second contribution is to the literature on the role of peer characteristics in shaping the development of individual personality traits (Gong et al., 2021; Pagani et al., 2021; Xu et al., 2022; Wu et al., 2023). In particular, Shan and Zölitz (2025) show that having conscientious peers can increase students' own conscientiousness, with effects lasting for at least three years. We extend this by demonstrating that peer grit influences short-run own grit (after one year) but also risk aversion in the long run (after 14-15 years). These long-lasting effects suggest that peer grit may influence personality beyond mere peer observation — a widely discussed potential mechanism (e.g., Buechel et al., 2018; Gerhards and Gravert, 2020) — as individuals' actions are less likely to be observed by their high school peers once they reach adulthood.

Our findings establish a link between the peer effects literature and empirical evidence on the importance of individual grit. We demonstrate that, in addition to factors like ability, gender, and race of peers, peer grit also plays a crucial role in long-term outcomes such as earnings. It is not only an individual's own grit that matters for long-run outcomes; peer grit is also important. Seminal papers highlight the positive impact of early childhood programs and classroom training on students' non-cognitive skills and personality traits, as well as their subsequent positive influence on educational and economic success (e.g., Chetty et al., 2011; Yeager and Dweck, 2012; Heckman et al., 2013; Sisk et al., 2018; Alan and Ertac, 2018, 2019; Alan et al., 2019; Sorrenti et al., 2024). Our results imply that the social returns of such interventions may be underestimated if the spillover effects of peer personality are overlooked, particularly regarding long-term outcomes like earnings.

2. Data

We use data from Add Health, a longitudinal survey of a nationally representative sample of high school students in the U.S. During the 1994–1995 school year, a selection of 80 high schools and 52 middle schools participated, with over 90,000 students from grades 7 through 12 completing an in-school survey. Approximately 20,000 of these students were then invited for in-home interviews, with data collection continuing over five waves. Add Health collected comprehensive information on a wide range of topics, including demographic characteristics, social relationships, family and socioeconomic background, health and behavioral issues, academic performance, personality traits, and labor market outcomes.

2.1. Sample and variable construction

In our analysis, we mainly focus on in-home interview data from 1994–1995 (Wave I), when respondents were aged 12 to 19; follow-up data from one year later (Wave II); data from 2001–2002 (Wave III), when participants were aged 18 to 25 and had typically completed high school; and data from 2009 (Wave IV), when participants were aged 24 to 32.[2]

Our measure of grit is constructed by selecting questions from the Wave I survey that closely align with the Short Grit Scale (Grit-S) introduced and validated by Duckworth and Quinn (2009) as the Add Health dataset does not include a direct measure of grit. To this end, all Add Health items in the "Feelings" and the "Personality and Family" sections of the Wave I questionnaire, which contain the non-cognitive measures, were systematically examined, and items corresponding to the Duckworth and Quinn (2009) Grit-S were identified. Specifically, items capturing sustained effort, task initiation, difficulty maintaining focus, avoidance of problems, and reactions to setbacks align with both the consistency of interests and perseverance of effort components of grit and are therefore included. In particular, we use the following questions from Add Health to construct the grit measure: (1) You had trouble keeping your mind on what you were doing; (2) Difficult problems make you very upset; (3) When you get what you want, it is usually because you worked hard for it; (4) It was hard to get started doing things; (5) You felt that you were too tired to do things; (6) You usually go out of your way to avoid having to deal with problems in your life; and (7) You feel like you are doing everything just about right. The remaining items in these sections measure depression, self-esteem, parenting dynamics, sexual knowledge, or physical health, none of which correspond conceptually to grit. As such, our selection is intended to be comprehensive given the information available in Add Health, while avoiding the exclusion of relevant items or the inclusion of conceptually unrelated ones.

Based on the responses to the selected items, we use factor analysis to construct a single "grit" variable.[3] For a similar approach, see Fernández-Villaverde et al. (2014) who construct a "shame" factor using Add Health data. Factor analysis helps identify or confirm the latent factor structure among a group of measured variables (Harman, 1967). Latent factors are unobserved variables that cannot be directly measured but are assumed to influence observed outcomes. In this context, the latent factor is "grit", which is presumed to influence individuals' responses to certain questions in the Add Health survey. The selected items load strongly on a single latent factor, which explains more than 58% of the total variance, indicating that the items primarily reflect one underlying trait. The strongest factor loadings correspond to items directly related to effort, task initiation, and sustained persistence—core elements of the Duckworth and Quinn (2009) scale. In Section 2.2 we assess the validity of our grit measure, while we provide further details on the factor analysis employed in Online Appendix A. Our variable of interest, peer grit, is constructed at the school-cohort level using the Add Health school and grade identifiers. Specifically, for each respondent, we calculate the leave-out-mean of grit among their peers in the same school and grade, excluding the respondent.[4]

Add Health includes information on other personality traits potentially related to grit, such as self-control, self-confidence, and depression, as well as information on non-risky behavior and parental expectations. In our sensitivity analysis, by controlling for these factors (both for the individuals and their peers), we ensure that our grit measure does not capture their effects (see Section 4).

In our analysis, we examine the effects of peer grit on respondents' long-term outcomes using several (self-reported) measures from Wave IV. Our main outcome of interest is annual gross earnings (in U.S. dollars).[5] Additional outcomes we consider include total value of assets (categorized from 1 less than $5000 to 9 for $1,000,000 or more), labor supply (measured as the probability of being non-employed and the probability of working at least 10 h a week), occupation characteristics (such as having a supervisory role, performing non-repetitive tasks, and having freedom in decision making at work), job satisfaction (categorized from 1 for extremely dissatisfied to 5 for extremely satisfied), whether the respondent describes their primary job as part of their long-term career or work goals, and how often the respondent felt

[2] In our further analysis, we also utilize data from 2016–2018 (Wave V), when the respondents were aged 34–43 (see Section 4.4).

[3] In our further analysis, we also utilize data from 2016–2018 (Wave V), when the respondents were aged 34-43 (see Section 4.4).

[4] In U.S. high schools, students are not assigned to fixed classrooms but select individual courses, so daily interactions typically span a broad share of the school cohort rather than a single classroom. This makes the school–grade level the appropriate unit for defining peer groups. For respondents with fewer than three peers within their school-grade, we treat cohort-level variables as missing.

[5] This information comes from the Add Health question: "In 2006/2007/2008, how much income did you receive from personal earnings before taxes, that is, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment?".

Table 1
Descriptive statistics.

Variables	N (1)	Mean (2)	SD (3)	Min (4)	Max (5)
	Grit measure (Wave I)				
Own grit	5773	0	1.000	−4.358	1.489
Peer grit	5773	0	1.000	−4.542	3.197
	Demographic characteristics				
% Male	5773	0.510	0.500	0	1
Age	5773	28.15	1.770	24	32
% White	5768	0.782	0.413	0	1
% Black	5768	0.130	0.336	0	1
% Hispanic	5762	0.114	0.318	0	1
% Asian	5768	0.0380	0.191	0	1
% Foreign born	5773	0.0494	0.217	0	1
	Ability proxy and family of origin char.				
AHPVT standardized score	5773	102.6	13.71	10	137
Parental educational level	5773	1.676	0.994	0	3
Gross HH Income in 000 $	5773	47.49	46.68	0	999
% Two-parent family	5773	0.686	0.464	0	1
Number of siblings	5773	1.397	1.132	0	10
% First-born	5773	0.430	0.495	0	1
	Wave I outcomes				
GPA	5740	2.854	0.767	1	4
Math grade	5428	2.744	1.025	1	4
English grade	5681	2.875	0.959	1	4
	Wave II outcomes				
Own grit in Wave II	4510	0	1.000	−4.293	1.416
	Wave III outcomes				
% Enrolled in college by Wave III	5770	0.607	0.489	0	1
	Wave IV outcomes				
Log(earnings)	5773	10.20	0.844	6.620	11.92
Asset tiers	5321	3.718	1.912	1	9
Not employed	6308	2748	1642	20.57	10,688
Hours ≥ 10	5466	0.792	0.406	0	1
% Managerial position	5738	0.389	0.488	0	1
% Non-repetitive tasks	5737	0.373	0.484	0	1
Decision making at work	5737	1.943	0.933	0	3
Job satisfaction	5738	2.880	0.917	0	4
Job aligned with career goals	5736	0.670	0.470	0	1
	Wave IV traits				
Risk aversion	5770	2.990	0.999	1	5
Overcome difficulties	5772	2.840	1.007	0	4
Extraversion	5770	13.41	3.023	4	20
Neuroticism	5770	10.36	2.736	4	20
Agreeableness	5770	15.32	2.399	4	20
Conscientiousness	5770	14.60	2.669	5	20
Openness	5745	14.61	2.437	4	20

Note: See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Corrected for the design effects of the Add Health sampling process.

overwhelmed by difficulties (ranging from 0 for very often to 4 for never).[6,7] Following the literature, we also consider academic performance measured as college enrollment from Wave III. In our analysis we also consider personality traits and attitudes measured in Wave IV, including risk aversion, and Big Five Personality traits (Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness). Additionally, we construct a grit measure in Wave II using the same method (factor analysis) and the same set of questions as in Wave I.[8] Online Appendix Table B1 provides further details for all the variables included in our analysis.

Table 1 reports the summary statistics of our benchmark sample.[9] To allow for a more direct interpretation and comparison of magnitudes between own and peer grit, we have standardized both measures so that they have mean zero and unit variance in the benchmark sample.[10,11] Approximately 51% of the sample are males, with ages ranging from

[6] We use the question from Wave IV, "In the last 30 days, how often have you felt that difficulties were piling up so high that you could not overcome them?" to construct the variable related to feelings about difficulties. We recode the variable so higher values correspond to a lower frequency of experiencing difficulties.

[7] The Add Health data set does not provide continuous information on hours of work.

[8] Note that the questions used to construct the grit measures in Waves I and II were not asked again in the subsequent waves.

[9] In Wave IV, we observe a total of 6307 individuals. Since our analysis focuses on individuals with positive earnings, we exclude those with zero or negative earnings. To reduce the influence of outliers and ensure that our estimates are not driven by extreme values, we further trim the bottom and top 1% of the positive earnings distribution. Our final sample consists of 5773 observations. Moreover, we have examined whether individual grit predicts inclusion in the final estimation sample. Specifically, we regressed an indicator variable equal to one if the observation is included in the final sample on the baseline grit score. As shown in Online Appendix Table B2, the coefficient on grit is very small (0.003) and statistically insignificant. Therefore, grit has no meaningful predictive power for sample inclusion, suggesting that sample selection bias due to grit is unlikely to be a concern.

[10] In Section 3, we demonstrate that there is sufficient variation in peer grit at the level of identification—that is, within schools across cohorts.

[11] According to Appendix Fig. A.1(a), most individuals have a grit score between −1 and 1 both in the initial and final sample used in the analysis, but there is also a non-negligible number of students with low scores. The distribution of our grit measure after accounting for baseline covariates displays a pronounced left tail (see Appendix Fig. A.1(b)), similar to the distribution

Table 2
Validation of grit measure.

Panel A: Big Five Personality Traits	(1) Openness	(2) Conscientiousness	(3) Extraversion	(4) Agreeableness	(5) Neuroticism
Grit	0.060	0.404***	0.132**	0.076*	−0.449***
	(0.043)	(0.057)	(0.063)	(0.040)	(0.044)
Observations	5745	5770	5770	5770	5770
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	14.61	14.60	13.41	15.32	10.36

Panel B: Labor Market Outcomes	(1) Log(earnings)	(2) Job satisfaction	(3) Decision making	(4) Non-repetitive tasks	(5) Supervisory role
Grit	0.074***	0.054***	0.044**	0.025***	0.022**
	(0.016)	(0.017)	(0.018)	(0.009)	(0.009)
Observations	5773	5738	5737	5737	5738
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	10.20	2.880	1.943	0.373	0.389

Panel C: Educational Outcomes	(1) GPA	(2) Math grade	(3) English grade	(4) College enrollment
Grit	0.131***	0.141***	0.135***	0.033***
	(0.013)	(0.018)	(0.017)	(0.008)
Observations	5740	5428	5681	5770
Demographic Controls	Yes	Yes	Yes	Yes
Parental Income Control	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.854	2.744	2.875	0.607

Note: Corrected for the design effects of the Add Health sampling process. Standard errors in parentheses are clustered at the school level. All models include demographic controls (age, gender, race, and foreign-born status) as in Lechner et al. (2019). Panel C additionally includes a control for parental income as in Zamarro et al. (2020). *p < 0.10; **p < 0.05; ***p < 0.01.

24 to 32. The table also includes summary statistics for other potential determinants of earnings, such as race, high school Add Health Picture Vocabulary Test (AHPVT) standardized score (as often considered a proxy for ability when taken at an early age—see, for example, Bifulco et al. (2011)), birthplace (whether the respondent was born in the U.S.), parental education, parental income, number of siblings, first-born status within the family, and whether the respondent was living with both parents during Wave I, as well as outcomes of interest considered in the subsequent empirical analysis.[12]

2.2. Validation of the grit measure

As the Add Health data do not include a direct measure of grit, it is not possible to replicate the Duckworth and Quinn (2009) Grit-S exactly. While our grit measure is constructed to closely align with the Grit-S, we nevertheless validate it in this section by examining whether it predicts a range of outcomes in a manner consistent with established grit measures used in the literature, before turning to the main empirical analysis. This validation exercise is intended to assess whether the measure captures behavioral patterns commonly associated with grit, rather than to provide causal estimates. For this purpose, we use regression models conditional on basic demographic characteristics (age, gender, race, and foreign-born status), where the choice of controls is guided by the existing literature (Lechner et al., 2019; Zamarro et al., 2020) to facilitate comparison with prior studies.[13] These estimates are presented in Table 2.

In Panel A, we examine the relationship between *own* grit and each of the Big Five personality traits, and find that grit is strongly and positively associated with conscientiousness, consistent with the psychology literature that views conscientiousness as the Big Five dimension most closely related to grit (Duckworth et al., 2007; Duckworth and Quinn, 2009). Grit is also negatively associated with neuroticism, which is also consistent with existing evidence (Duckworth et al., 2007).

In Panels B and C, we follow the approaches in Lechner et al. (2019) for labor market outcomes and Zamarro et al. (2020) for educational outcomes, by estimating regressions in which *own* grit predicts (i) labor market outcomes and (ii) educational outcomes using comparable sets of controls. Our estimates align closely with the magnitudes documented in studies using standard grit scales. For example, Lechner et al. (2019) find that a one–standard deviation increase in grit predicts an 8.3% increase in monthly income of German adults in Programme for the International Assessment of Adult Competencies (PIAAC) survey, which is remarkably similar to our estimate of approximately 7.6% for annual earnings among American adults in Add Health.[14]

Lechner et al. (2019) also document positive correlations of grit with job satisfaction and job prestige, measured using Treiman's Standard International Occupational Prestige Scale scores generated from

of the residuals of the grit measure in Alan et al. (2019) (see their Figure III, control group).

[12] A parent or guardian was interviewed during Wave I, providing further information about family characteristics, including the highest level of education attained and the gross total family income. More than 90.5% of the parent interview respondents were mothers (biological, step, adoptive, or foster).

[13] Results are qualitatively similar when additional controls used in the main empirical analysis (see Section 3) are included, indicating that the predictive patterns of the grit measure are not sensitive to richer control sets.

[14] In the Add Health sample, the average annual income from personal earnings before taxes is around 35,000 U.S. dollars, which translates to a monthly figure of approximately 2900 U.S. dollars. In the German PIAAC sample, the average monthly income is 2956 euro. Despite differences in income definitions, the income levels in the two samples are therefore broadly comparable.

respondents' current occupations. In our sample, we confirm the positive correlation with self-reported job satisfaction (Panel B, column 2). While we do not have direct information on occupational prestige for the Add Health respondents, we use self-reported decision-making at work, supervisory role, and non-repetitive tasks (Panel B, columns 3–5) as proxies and find positive associations.

Similarly, our results for GPA, subject-specific grades, and probability of college enrollment reproduce the predictive patterns found in Zamarro et al. (2020). They find that a one-standard deviation increase in grit is associated with a 0.266 increase in high school GPA. Given that the mean GPA in their sample is 85, this corresponds to about 2.7% of the mean. In the Add Health sample, a one-unit increase in our grit measure predicts a 0.131 increase in self-reported GPA in Wave I (Panel C, column 1), relative to a mean GPA of 2.854, which corresponds to approximately 4.6% of the mean. Thus, the magnitude of our estimate is comparable to that found in Zamarro et al. (2020), even though the sample and the outcomes are not identical. For instance, our estimate is based on the most recent self-reported GPA for a nationally representative sample of U.S. high school students, whereas theirs reflects cumulative GPA at the end of high school for a single high school. In addition, Zamarro et al. (2020) document positive associations with end-of-year math and reading test scores. While we do not have comparable test score information in Add Health, we use self-reported math and English grades as proxies and confirm positive associations (Panel C, columns 2–3). We also confirm the positive association with college enrollment (Panel C, column 4), although our correlation is somewhat smaller. This likely reflects the sample differences noted above. Indeed, the mean college enrollment rate in our data is 61%, compared to 64% in their sample.

Taken together, while we acknowledge that our measure does not replicate the exact (Duckworth and Quinn, 2009) Grit-S, these correlations support the construct validity of the grit measure used in our analysis.

3. Empirical strategy

Understanding peer effects poses significant challenges, particularly due to issues such as the reflection problem and endogenous group selection (Manski, 1993). The reflection problem arises when students and their peers influence each other simultaneously, complicating the analysis of contemporaneous outcomes. To overcome this, we take advantage of the longitudinal structure of our data, which allows us to investigate how peer grit affects long-term adult outcomes, approximately 15 years post-high school.[15]

To address the issue of selection into peer groups, we utilize the unique design of the Add Health survey, which tracks multiple cohorts within the same school. Our approach leverages differences in the distribution of grit among peers across cohorts, assuming that families select schools based on general information about the average student composition in the school rather than the specific composition of their child's cohort (which is in principle not known, making cohort-based sorting unlikely). This approach is widely used in the literature (Hoxby, 2000; Bifulco et al., 2011; Lavy and Schlosser, 2011; Cools et al., 2022; Kiessling and Norris, 2023; Adamopoulou and Kaya, 2024; Merlino et al., 2024).

The success of our identification strategy relies on two factors. First, we need sufficient variation within schools across cohorts to obtain precise estimates. Following Ammermueller and Pischke (2009), we perform a variance decomposition by first calculating the school-cohort average of our grit measure. We then decompose the total variance in the cohort-level average grit into within-school and between-school components.[16] As Table 3 shows, approximately two-thirds of the variation in peer grit (66.6%) arises from differences across cohorts within the same school, with the remaining one-third (33.4%) stemming from differences between schools. This indicates substantial within-school, across-cohort variation, which is precisely the source of identifying variation in our empirical strategy.[17]

Table 3
Variance decomposition.

Variable	Within	Between	Total
Grit	0.104 (66.60%)	0.052 (33.4%)	0.156

Note: The variance decomposition is performed following Ammermueller and Pischke (2009) by first computing the cohort average of grit, and then decomposing the total variance in the cohort-level average of grit into within school and between school variances. Percentages are a proportion of total variance. There are 130 different schools and 462 different school-cohorts in the final sample. See text for sample restrictions.

Second, the assumption that students are randomly assigned to cohorts within schools needs to be credible. By defining the peer group based on all students in a given cohort, rather than friendship nominations, we mitigate potential concerns regarding "homophily"—the tendency of individuals to select friends similar to themselves (McPherson et al., 2001; Belot and de Ven, 2011; Carrell et al., 2013; Graham, 2015; Cullen and Perez-Truglia, 2023). Furthermore, we formally test for sorting in our setting using the correction method proposed by Guryan et al. (2009). Specifically, we regress peer grit (leave-out-mean at the cohort-school level) on the individual's own grit, conditional on the leave-out mean at the school level, as well as school and cohort fixed effects. We then include predetermined characteristics as additional controls. As Table 4 shows, there is no evidence of sorting based on grit. The coefficient estimate for own grit is negligible and not statistically significant, regardless of whether we control for other predetermined characteristics. Reassuringly, the individual coefficients on predetermined characteristics are also small and statistically insignificant, except for household income, which is positive and significant at the 5% level but economically negligible in magnitude (0.001 per \$1000). Moreover, these predetermined characteristics are not jointly statistically significant, as indicated by the p-value presented in the last row of column 2. This provides further support for the view that the composition of peer groups with respect to grit is plausibly random, which is essential for the internal validity of our identification strategy. The absence of a significant relationship between an individual's characteristics and the average grit of their peers suggests that peer group formation is not influenced by sorting on observable traits, which supports a causal interpretation of the estimated peer effects rather than one driven by selection.

[15] Giulietti et al. (2022) study the long-term effects of peer depression also using Add Health and an identification strategy similar to ours. Specifically, they use a set of questions from Add Health to define peer depression in Wave I and examine its impact on individuals' own depression and, subsequently, their earnings in Wave IV.

[16] Formally, the total variance in school-cohort average of variable x is decomposed into its within and between school components using the relationship: $\frac{1}{C}\sum_{s=1}^{S}\sum_{c=1}^{C_s}(x_{cs}-\bar{x})^2 = \frac{1}{C}\sum_{s=1}^{S}\sum_{c=1}^{C_s}(x_{cs}-\bar{x}_s)^2 + \frac{1}{C}\sum_{s=1}^{S} C_s(\bar{x}_s-\bar{x})^2$, where $s = 1, 2, \dots, S$ and $c = 1, 2, \dots, C_s$ denote school and school-cohort indicators, respectively, and C is the total number of cohorts in the sample.

[17] For comparison, Ammermueller and Pischke (2009) report within-school variance shares ranging from about 7% to 46% across different background and achievement characteristics in European primary schools, noting that even within-school shares of 30% or less constitute "non-negligible" variation for peer-effects estimation. Calsamiglia and Loviglio (2019) find within-school shares of 29%–44% for evaluated grades in Catalonian public schools, which they interpret as "reasonable" variation. Studies using Add Health also document substantial within-school variation; for example, Adamopoulou and Kaya (2024) report within-school shares of 45%–52% for peer attractiveness.

Table 4
Balancing test: Coefficient estimates of the pre-determined characteristics.

	Dep. var.: Peer grit$_{-i}$	
	(1)	(2)
Own grit	0.001	0.003
	(0.016)	(0.016)
Male		0.010
		(0.017)
Age		0.008
		(0.015)
Black		−0.026
		(0.037)
Hispanic		−0.000
		(0.035)
Asian		0.022
		(0.044)
Foreign born		0.050
		(0.043)
AHPVT standardized score		0.000
		(0.001)
Parental education: High school or similar		−0.026
		(0.030)
Parental education: More than high school		−0.024
		(0.030)
Parental education: college or more		−0.012
		(0.033)
Gross HH income in $000		0.001**
		(0.000)
Number of siblings		0.007
		(0.007)
Firstborn		0.013
		(0.019)
Two-parent family		−0.030
		(0.019)
Observations	5773	5773
School FE	Yes	Yes
Cohort FE	Yes	Yes
Leave-out school average	No	Yes
p-value	–	0.543

Note: The Table shows the unweighted balancing test results following the correction procedure outlined in Guryan et al. (2009). Peer grit is the average grit of peers in the same school-cohort, excluding individual i. Leave-out school average is the average grit of peers in the same school, excluding individual i. The p-value represents the joint significance of predetermined characteristics controls. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

Our baseline specification applies the linear-in-means (LIM) peer effects model as follows:

$$\begin{aligned} \text{Outcome}_{ics} &= \beta_1(\text{own grit})_{ics} + \beta_2(\text{peer grit})_{-ics} \\ &\quad + \beta_3 X_{ics} + \eta_c + \kappa_s + u_{ics} \end{aligned} \tag{1}$$

where $Outcome_{ics}$ of individual i within grade (i.e., cohort) c and school s, representing the (log) annual gross earnings in Wave IV in our baseline, is regressed on individual's i own grit and the average peer grit within the same school and grade excluding the individual i (i.e., leave-out-means denoted by subindex $-i$), grade (i.e., cohort) fixed effects η_c, and school fixed effects κ_s. The benchmark specification also includes a set of observable characteristics X_{ics} that are potential determinants of earnings such as gender, age, race, whether the respondent was born in the U.S., AHPVT standardized score, parental education and income, number of siblings, whether the respondent is the first-born child, and whether the respondent was living with both parents in Wave I.[18]

Although unobserved correlated peer characteristics cannot be fully ruled out, we leverage the richness of the Add Health data to conduct extensive robustness checks with a comprehensive set of peer-level controls. These include individual and peer measures of self-control, confidence, physical attractiveness, self-perceived health, the Big Five personality traits, depression, non-risky behavior, parental expectations, cohort size, and peer contextual characteristics (averages of all baseline controls; see Section 4).

Our primary outcome of interest is earnings but we also examine the effects on medium-term outcomes related to college enrollment and individual grit, as well as long-term outcomes associated with job characteristics and personality traits. By focusing on future outcomes, we also mitigate concerns related to reverse causality, as it ensures that our key variables (own and peer grit) are measured in Wave I, and are not influenced by adulthood outcomes (measured in later waves). In our benchmark models, we cluster standard errors at the school level; however, we also conduct sensitivity analyses using clustering at various levels (see Section 4).

4. Results

4.1. Benchmark estimates

Our benchmark analysis focuses on estimating the effects of peer grit on long-term earnings (reported in Wave IV). Table 5 column 1 reports the estimated coefficients for peer grit and own grit from a parsimonious specification that includes cohort and school fixed effects but excludes control variables. We find a positive and statistically significant effect of peer grit on long-term earnings. In column 2, we gradually add control variables, beginning with demographic characteristics including age, gender, race, foreign-born status, and the AHPVT standardized score (used as an ability proxy). In column 3, we further incorporate family background variables such as parental education, gross household income in Wave I, number of siblings, birth order (i.e., whether the respondent is first-born), and whether the respondent grew up in a two-parent family. The estimated coefficient on peer grit remains robust to the inclusion of these additional controls, decreasing only slightly in magnitude and remaining statistically significant across specifications.

Our estimates show that own grit during high school is positively and significantly associated with (log) annual gross earnings when individuals are aged between 24 and 32. In the most comprehensive specification (column 3), a one standard deviation increase in own grit is associated with a 0.073 log points or 7.6% increase in earnings.[19] This is similar to the findings of Fletcher (2013), who reports that a one standard deviation increase in conscientiousness results in a 3%–6% increase in earnings.

Turning to the role of peer grit — which is the main focus of our paper — our estimates show a strong, positive, causal effect of the average grit of high school peers on earnings. In our benchmark specification (column 3), a one standard deviation increase in peer grit is associated with a 4.2% increase in earnings. This effect is substantial when compared to the impact of one's own grit (7.6%), or gross household income during high school (4.8%) as reported in the Online Appendix Table B3. Therefore, it is not only an individual's own grit but also the grit of their peers that can positively influence long-term economic success in the labor market.[20]

[18] Our benchmark specification includes pre-determined characteristics measured prior to, the formation of peer groups. The AHPVT standardized score captures cognitive ability measured at Wave I, prior to the outcomes of interest. Vocabulary tests are consistently found to be among the strongest measures of overall cognitive ability (Beaujean et al., 2013), and cognitive ability measured in adolescence exhibits high rank-order stability into adulthood (Breit et al., 2024). The AHPVT score is widely used for this purpose in the Add Health literature (Halpern et al., 2000). Moreover, we also explore the sensitivity of our results to its exclusion (see Section 4).

[19] Throughout, percentages are calculated as exp(log points) – 1.

Table 5
Effect of peer grit on log earnings.

	Dep. var.: Log(earnings)		
	(1)	(2)	(3)
Peer grit	0.043**	0.043**	0.041**
	(0.018)	(0.017)	(0.017)
Own grit	0.092***	0.076***	0.073***
	(0.017)	(0.016)	(0.016)
Observations	5773	5773	5773
School FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Controls	No	Demo	Demo and Family
Dep. Var. Mean	10.20	10.20	10.20
p(Own=Peer)	0.075	0.208	0.224

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls , as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. The *p*-value from a test of equality between the own and peer grit coefficient estimates is reported in the last row. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

4.2. Other outcomes

Does peer grit affect other outcomes in the medium- to long-run beyond earnings? If so, do any of these outcomes serve as underlying channels through which gritty peers influence future earnings?

To shed light on these key questions, we begin by estimating a version of Eq. (1) to explore whether peer grit enhances students' medium-term educational outcomes, specifically college enrollment as reported in Wave III.[21] We find that peer grit increases the likelihood of college enrollment: a one standard deviation increase raises enrollment probability by 2.6 percentage points—a sizable effect compared to the 3.8 percentage point increase associated with a one standard deviation increase in one's own grit.

Our finding that peer grit increases the probability of college enrollment aligns with findings from Golsteyn et al. (2021), Shure (2021), and Zou (2024), who exploit random allocation of peer groups and demonstrate that peer persistence, a facet of grit, positively affects student performance across different countries and age groups.[22] Moreover, we extend the insights from Zou (2024), who document that peer persistence correlates with higher self-reported aspirations for obtaining a college degree in China. Our results demonstrate that students exposed to higher peer grit also have a greater probability of actually enrolling in college. The consistency of findings across two large economies (China and the U.S.) with distinct labor market institutions and educational systems strengthens the external validity of peer grit's role in shaping educational attainment and subsequent labor market outcomes.

Next, Table 6 reports the estimates of own and peer grit on additional economic and labor market outcomes, such as the probability of being employed, working 10 or more hours per week, probability of employment in a job aligned with long-term career goals, job satisfaction, other job characteristics (such as probability of having a supervisory role, working in non-repetitive tasks, and participating in decision-making roles at work), and accumulated assets. We do not find any statistically significant impact of peer grit on the probability of being employed (column 2) or working 10 or more hours per week (column 3), suggesting that peer grit is not likely to have a meaningful relationship with labor supply. However, those with gritty peers report higher job satisfaction (column 4), are more likely to be employed in jobs aligned with their long-term career goals (column 5), and accumulate more assets (column 9). These findings highlight the lasting influence of a gritty peer environment during adolescence on career planning and financial stability. By contrast, we find no significant effect of peer grit on other job characteristics, such as the likelihood of holding a supervisory role (column 6), working in non-repetitive tasks (column 7), or participating in decision-making roles at work (column 8).[23]

What about the impact of peer grit on non-cognitive skills in both short- and long-run? To address this question, Table 7 examines whether gritty peers during high school shape own grit in later high school years as well as the Big Five personality traits and attitudes (risk aversion and perceived inability in overcoming difficulties) in adulthood. Column 1 assesses the impact of peer grit on an individual's own grit measured one year later (in Wave II), and confirms that peer grit can increase students' own grit. A one standard deviation increase in peer grit increases own grit one year later by 0.054 standard deviations.[24] Despite the differences in data sources, samples, and country contexts, our estimated peer effect on grit (0.054 standard deviation) is comparable to the estimate in Shan and Zölitz (2025), who find that peers who are one standard deviation more conscientious increase students' own conscientiousness by 0.048 standard deviations. Our findings indicate that the effect of peer personality traits on the development of one's own traits starts already during adolescence, that is, during high school.

Furthermore, as reported in Table 7, peer grit reduces risk aversion (column 2) and decreases the frequency of feeling overwhelmed by difficulties (column 3). These results imply that students surrounded by gritty peers may develop a greater willingness to take risks. Moreover, gritty peers appear to reduce individuals' perceived inability to overcome difficulties. However, we do not find evidence that the average grit of high-school peers affects any of the Big Five personality traits (columns 4–7), including Openness, Conscientiousness, Extraversion, Agreeableness, or Neuroticism.

[20] In Table 5 we formally test whether the coefficient estimates on own and peer grit differ significantly. The p-values, presented in the bottom row, show that we cannot reject the null hypothesis that the coefficient estimates on own grit and peer grit are equal. This is consistent with the findings of Zou (2024), who reports own and peer effects of persistence of similar magnitude on academic performance.

[21] An alternative educational outcome to consider is high school GPA. However, because GPA is measured in the same wave as peer grit, we do not use it as a benchmark outcome due to simultaneity concerns, but explore it in supplementary analysis. In the full sample, peer grit is not significantly associated with GPA, potentially reflecting the fact that peer networks are already well established among older cohorts. In a subsample of younger students (grades 7–9), peer grit is positively associated with GPA. Given the concurrent measurement, however, these results are interpreted cautiously and are available upon request.

[22] Golsteyn et al. (2021) study the impact of peer persistence on student academic performance using data from a Dutch business school. Shure (2021) uses data from Flanders, Belgium, focusing on pupils who began secondary school in 1990. Zou (2024) analyzes data from Chinese middle school students from grades 7 and 8.

[23] We do not find any effect of peer grit on the probability of being self-employed either (results available upon request). Unlike the other economic outcomes we examine here, which are measured in Wave IV, self-employment is observed only in Wave V, during later adulthood.

[24] In Table 6, column 1, the coefficient estimate on *own* grit (0.434) reflects a reasonable degree of stability for grit in adolescence. While non-cognitive traits tend to be more stable in adulthood (Cobb-Clark and Schurer, 2012), evidence shows that they change during adolescence. For instance, Hoeschler et al. (2018) report a correlation of 0.30 for grit measured six years apart using the standard (Duckworth and Quinn, 2009) Grit-S in a panel of adolescents, concluding that grit and other non-cognitive traits are changeable during these years. Similarly, Southwick et al. (2019) emphasize that personality traits evolve over time, consistent with evidence from the psychology literature showing that older adults tend to score higher in grit than younger adults (Credé et al., 2017; Duckworth et al., 2007).

Table 6
Effect of peer grit on other outcomes.

	(1) College enrollment (Wave III)	(2) Not employed	(3) Hours ≥ 10	(4) Job satisfaction	(5) Job aligned with career goals	(6) Supervisory role	(7) Non repetitive tasks	(8) Decision-making job	(9) Assets tier
Peer grit	0.026**	−0.009	0.019	0.039*	0.023**	0.003	0.020	−0.001	0.084**
	(0.013)	(0.005)	(0.013)	(0.022)	(0.010)	(0.013)	(0.012)	(0.024)	(0.040)
Own grit	0.038***	−0.001	0.013*	0.056***	0.034***	0.021**	0.025***	0.042**	0.156***
	(0.007)	(0.004)	(0.008)	(0.017)	(0.008)	(0.009)	(0.009)	(0.017)	(0.036)
Observations	5770	6308	5466	5738	5736	5738	5737	5737	5321
Dep. Var. Mean	0.607	0.0661	0.792	2.880	0.670	0.389	0.373	1.943	3.718
p(Own=Peer)	0.417	0.220	0.648	0.507	0.428	0.225	0.767	0.149	0.213

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls, as well as school and cohort fixed effects. The asset tiers are: less than \$5000, \$5000 to \$9999, \$10,000 to \$24,999, \$25,000 to \$49,999, \$50,000 to \$99,999, \$100,000 to \$249,999, \$250,000 to \$499,999, \$500,000 to \$999,999, \$1,000,000 or more. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. The *p*-value from a test of equality between the own and peer grit coefficient estimates is reported in the last row. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table 7
Effect of peer grit on personality and attitudes in early adulthood.

	(1) Grit (Wave II)	(2) Risk aversion	(3) Overcome difficulties	(4) Openness	(5) Conscien-tiousness	(6) Extra-version	(7) Agreeable-ness	(8) Neuroticism
Peer grit	0.054*	−0.049**	0.043*	−0.012	0.030	−0.087	0.004	0.001
	(0.030)	(0.024)	(0.024)	(0.059)	(0.063)	(0.080)	(0.057)	(0.064)
Own grit	0.434***	0.026	0.151***	0.040	0.386***	0.132**	0.063	−0.444***
	(0.021)	(0.018)	(0.019)	(0.043)	(0.057)	(0.063)	(0.040)	(0.045)
Observations	4510	5770	5772	5745	5770	5770	5770	5770
Dep. Var. Mean	0	2.990	2.840	14.61	14.60	13.41	15.32	10.36

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

Taken together, the results presented in Tables 6 and 7 suggest that while peer grit does not significantly influence labor supply outcomes, it plays an important role in shaping college enrollment, career-oriented decisions, financial outcomes, own grit, risk attitudes and resilience in overcoming difficulties. In Section 4.4, we build on these findings by examining the potential mechanisms in explaining the observed relationship between peer grit and long-term earnings.

4.3. Robustness checks

Our benchmark specification includes a rich set of controls that are likely determinants of earnings, such as gender, age, race, AHPVT standardized score, whether the respondent was born in the U.S., parental education and income, number of siblings, whether the respondent is the first-born child in the family, and whether the respondent was living with both parents in Wave I. In a first set of robustness checks, we explore whether our baseline results (presented in Table 5 column 3) are robust to the inclusion of non-standard own and peer controls, which may affect earnings but are also potentially related to own and peer grit.[25]

As shown in Table 8, our benchmark results are robust to the inclusion of own and peer self-control (column 1), self-confidence in Wave I (column 2), physical attractiveness (column 3), depression (column 4), non-risky behavior (column 5), health status in Wave IV (column 6), and Big Five traits in Wave IV (column 7).[26,27] In addition, the coefficient of peer grit is robust to the inclusion of parental expectations in Wave I (column 8). Including high school cohort size to assess whether variability in peer grit reflects the number of peers in the cohort, does not affect our estimates either (column 9). Importantly, controlling for contextual characteristics, i.e., the full set of peer socioeconomic and family characteristics that may be correlated with peer grit, leaves our conclusions unchanged (column 10). While we cannot fully rule out the influence of unobserved correlated peer traits, the stability of the peer grit coefficient across these specifications is reassuring.

In our benchmark model, we include the AHPVT standardized score as a proxy for cognitive ability, as is standard in the literature (e.g., Bifulco et al., 2011). Nevertheless, because AHPVT score is measured in Wave I alongside grit, we also conduct sensitivity checks that exclude it from the control set. The coefficient on peer grit remains virtually unchanged relative to the benchmark specification when AHPVT score is excluded (Appendix Table A.1).

To understand whether peer interactions prior to Wave I may affect our results, as a robustness check, we re-estimate our benchmark model

[25] See Online Appendix Table B4 for sample statistics for these additional variables.

[26] We construct a self-control measure similar to our grit measure, using the first factor derived from factor analysis applied to the following variables: (1) When making decisions, you usually go with your "gut feeling" without thinking too much about the consequences of each alternative; (2) When you have a problem to solve, one of the first things you do is get as many facts about the problem as possible; (3) When you are attempting to find a solution to a problem, you usually try to think of as many different ways to approach the problem as possible; (4) When making decisions, you generally use a systematic method for judging and comparing alternatives; and (5) After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong. See Online Appendix Table B1 for definitions of other non-standard controls.

[27] Self reported health status and Big Five personality traits measured in Wave IV may be endogenous and therefore constitute "bad controls". However, our benchmark results remain stable even when we include them, suggesting that peer grit is not merely a proxy for these later-life traits. Although grit and conscientiousness are positively correlated, grit emphasizes long-term perseverance and consistency in goal pursuit, whereas conscientiousness captures traits such as orderliness and self-control (Duckworth et al., 2007; Duckworth and Quinn, 2009), which are related to but do not fully overlap with grit. Accordingly, when we control for conscientiousness, the coefficient on *own* grit decreases but remains statistically significant (Table 8, column 7), suggesting that grit captures distinct information than conscientiousness.

Table 8
Effects of peer grit on log earnings – robustness checks with additional controls.

	Dep. var.: Log(earnings)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer grit	0.043**	0.041**	0.041**	0.044**	0.045**	0.040**	0.043***	0.042**	0.041**	0.046**
	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.019)
Own grit	0.067***	0.073***	0.071***	0.072***	0.065***	0.063***	0.054***	0.071***	0.073***	0.074***
	(0.017)	(0.016)	(0.016)	(0.018)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)
Observations	5738	5773	5764	5717	5744	5763	5689	5723	5773	5742
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Own and peer self-control in Wave I	Own and peer self-confidence in Wave I	Own and peer attractiveness in Wave I	Own and peer depression in Wave I	Own and peer non-risky behavior in Wave I	Own and peer health status in Wave IV	Own and peer Big Five in Wave IV	Own and peer parental expect. in Wave I	Cohort size in Wave I	Contextual characteristics in Wave I
Dep. Var. Mean	10.20	10.20	10.20	10.20	10.20	10.20	10.20	10.20	10.20	10.20

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls, as well as school and cohort fixed effects. Baseline controls: age, gender, race, foreign-born status, AHPVT standardized score, parental education, parental income, number of siblings, birth order (first child), and whether the respondent lived with both parents in Wave I. Additional controls: Col. (1) Own and peer self-control in Wave I; Col. (2) Own and peer self-confidence in Wave I; Col. (3) Own and peer physical attractiveness in Wave I; Col. (4) Own and peer depression in Wave I; Col. (5) Own and peer non-risky behavior (no smoking, no alcohol, no fights) in Wave I; Col. (6) Own and peer self-reported health status in Wave IV; Col. (7) Own and peer Big Five traits in Wave IV; Col. (8) Own and peer parental expectations in Wave I; Col. (9) Cohort size in Wave I; Col. (10) Peer contextual characteristics (average of all baseline controls). See text for sample restrictions and Online Appendix Table B1 for variable definitions. Standard errors are clustered at the school level. *p < 0.10; **p < 0.05; ***p < 0.01.

using a subsample of younger students—those in grades 7 to 9. This approach allows us to focus on students who were at an earlier stage of forming peer connections. Appendix A2 confirms that our results remain robust for this younger group, who were likely in the early stages of forming connections with their cohorts by Wave I.

We also experiment with alternative methods for clustering standard errors beyond the school level, which serves as our baseline. As Appendix Table A.3 shows, the results are robust if we cluster at the grade level (column 1), school, grade level (column 2), or school×grade level (column 3).

Our next exercise examines the validity of the assumption that peer comparisons in terms of grit are mainly made within the same cohort and among students with whom respondents are likely to interact the most. To validate this assumption, we run a series of placebo regressions by randomly assigning each respondent to a different cohort within their school. Specifically, we retain the same school but define placebo peers as students from higher or lower grades than the respondent's, repeating this procedure for a total of 1000 placebo cohorts.[28] Appendix Fig. A.2 presents the distribution of the coefficients of placebo peer grit on (log) earnings for the 1000 estimates. The vertical line in Appendix Fig. A.2 represents our benchmark coefficient estimate (presented in Table 5 column 3), which stands as a clear outlier in the distribution of the placebo estimates. This indicates that our estimated effects are unlikely to be driven by chance.

4.4. Mechanisms

What drives the impact of average peer grit on future earnings? To shed light on potential mechanisms, we extend our main specification (Eq. (1)) by sequentially including candidate mechanism variables as additional controls.[29] Table 9 presents the results, with column 1 reproducing our benchmark estimates for comparison.

First, college enrollment is a natural mechanism to consider, consistent with the literature documenting short-term educational effects. Including college enrollment (column 2) reduces the magnitude of the coefficient on peer grit by approximately 20 percent.[30]

Another potential mechanism is that exposure to gritty peers may affect an individual's own grit, which could in turn influence future earnings. To examine this channel, we use own grit measured in Wave II, one year after Wave I (column 3).[31] Controlling for own grit measured one year later leads to a modest reduction in the estimated effect of peer grit relative to the benchmark specification in column 1, suggesting that changes in own grit over this period are unlikely to be the primary channel through which peer grit affects earnings.

Risk aversion is also a plausible mechanism. However, comparing columns 1 and 4 shows that the estimated effect of peer grit remains largely unchanged after controlling for risk aversion, indicating that this channel does not appear to play a central role.

The following two columns of Table 9 point to two additional channels that appear to be relevant: job alignment with long-term career goals (column 5) and the ability to overcome difficulties (column 6). Individuals exposed to grittier peers are more likely to perceive their current job as part of their long-term career trajectory, suggesting that having gritty peers in high school may lead individuals to prioritize long-term career goals when making job and career decisions. Similarly, exposure to gritty peers is associated with lower perceived inability to overcome obstacles, suggesting that peer grit may foster greater resilience.

When all mechanisms are included simultaneously (column 7), the peer grit coefficient falls to 0.019 and becomes statistically insignificant. These findings suggest that peer grit influences long-term earnings through multiple channels: educational attainment, career-focused job choices, and enhanced resilience in overcoming difficulties.[32]

[28] See, for example, Merlino et al. (2019) and Adamopoulou and Kaya (2024) for a similar approach.

[29] We do not consider job satisfaction as a potential mechanism, as it is likely to be simultaneously determined with pay, making it more appropriate to treat as an outcome rather than an intermediate channel from peer grit to earnings.

[30] We focus on college enrollment rather than highest educational attainment because it is measured earlier (Wave III) and therefore precedes the earnings outcome. This temporal ordering is consistent with the requirements for mediation analysis (Imai et al., 2010), whereas completed educational achievement may itself be influenced by later labor market experiences.

[31] Information on own grit is missing for individuals who had completed high school by Wave II. To maintain a consistent sample size across specifications, column 3 includes an indicator for missing Wave II grit.

Table 9
Underlying mechanisms.

	Dep. var.: Log(earnings)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer grit	0.041**	0.033*	0.039**	0.040**	0.030*	0.036**	0.019
	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.015)
Own grit	0.073***	0.063***	0.056***	0.072***	0.057***	0.054***	0.022
	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.018)	(0.015)
College enrollment		0.307***					0.234***
		(0.035)					(0.038)
Grit(Wave II)			0.047***				0.036**
			(0.018)				(0.017)
Risk aversion				−0.001			0.004
				(0.013)			(0.012)
Job aligned with career goals					0.455***		0.411***
					(0.036)		(0.036)
Overcome difficulties						0.126***	0.104***
						(0.016)	(0.016)
Observations	5773	5773	5773	5773	5773	5773	5773
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	10.20	10.20	10.20	10.20	10.20	10.20	10.20
p(Own=Peer)	0.224	0.235	0.509	0.215	0.266	0.493	0.896

Note: Corrected for the design effects of the Add Health sampling process. To maintain a consistent sample size across all mediation factors, we incorporate missing-value indicators to handle missing data within each mediator. All specifications include baseline controls, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

It is worth noting that the results presented in Table 9 provide suggestive evidence on the potential mechanisms rather than a formal causal mediation analysis, which would require additional identifying assumptions. According to Imai et al. (2010), there are four conditions that are generally required for a causal mediation analysis. First, because the mediator lies on the causal pathway between the treatment and the outcome, it must be a post-treatment variable that occurs prior to the realization of the outcome. In our context, a plausible causal chain would run from peer grit to intermediate outcomes and ultimately to adult earnings. Second, the potential outcome is assumed to depend only on the realized values of the treatment and mediators, and not on the process by which these values were generated. The observed attenuation of the peer-grit coefficient when potential mechanism variables are included is consistent with this condition being reasonably satisfied. Third, the *sequential ignorability* assumption requires that (i) conditional on pre-treatment covariates, exposure to peer grit is "as good as random" with respect to future earnings; and (ii) conditional on peer-grit exposure and pre-treatment covariates, the mediators are "as good as random" with respect to earnings. As we do not attempt a formal decomposition of total effects, these assumptions are invoked as a conceptual benchmark rather than conditions we formally test. The fourth condition discussed in Imai et al. (2010), concerning the absence of interaction between the treatment and the average causal mediation effect, is less central for our purposes for the same reason.

Given this background, some of the mechanisms considered in Table 9 are measured contemporaneously with earnings in Wave IV. As a supplementary analysis, Appendix Table A.4 presents a robustness check using earnings measured in Wave V and mechanism variables measured only in earlier waves. This provides a clearer temporal ordering that runs from peer grit to intermediate outcomes and ultimately to adult earnings and strengthens the plausibility of the proposed mechanisms. The drawback is that earnings in Wave V are reported in categories rather than as a continuous measure, as in Wave IV. We therefore use midpoints of the earnings brackets to convert the categorical measure into a continuous variable for estimation. Including the underlying potential mechanisms identified above — college enrollment measured in Wave III (column 2), and job alignment with career goals and the ability to overcome difficulties measured in Wave IV (columns 5 and 6) — in the regressions reduces the magnitude of the peer-grit coefficient, rendering it statistically insignificant also when all are included together (column 7). These patterns are consistent with the potential ordering in which peer grit influences these factors, which in turn may lead to higher earnings in Wave V and they confirm the patterns observed in the analysis using Wave IV earnings.

4.5. Heterogeneity analysis

As emphasized by seminal research on long run educational, health and labor market outcomes, considering heterogeneity in family background is crucial (e.g., Lundberg, 2013; Papageorge and Thom, 2020; Bolyard and Savelyev, 2024). Socioeconomic factors affect access to resources and opportunities. Students from higher-income or more educated households may benefit from environments that already foster traits like resilience and persistence, meaning that the additional influence of peer grit could be less pronounced. Conversely, for students from lower-income or less educated backgrounds, exposure to high-grit peers may play an important role in shaping their long-term outcomes.

[32] According to Zou (2024) and Golsteyn et al. (2021), students with more persistent peers are more likely to form friendship with persistent students. Consistent with this, we find that students in cohorts with higher average peer grit are more likely to nominate friends who exhibit higher levels of grit. We also find that friends' grit is positively associated with individual labor market outcomes, with an estimated magnitude of approximately 87% of the effect of own grit. We, however, interpret these results cautiously, given the endogeneity of friendship formation due to homophily. Additionally, students exposed to grittier peers report having more friends in early adulthood, although neither friendship nominations nor the number of adulthood friends appears to operate as an underlying mechanism in our analysis. These results are available upon request.

Table 10
Effect of peer grit on log annual earnings: by socio-economic background.

	Dep. var.: Log(earnings)				
	(1)	(2)	(3)	(4)	(5)
		By parental education		By parental income	
	All	Low	High	Low	High
Peer grit	0.041**	0.056**	0.015	0.049	0.019
	(0.017)	(0.022)	(0.028)	(0.031)	(0.024)
Own grit	0.073***	0.071***	0.071***	0.072***	0.077***
	(0.016)	(0.022)	(0.021)	(0.025)	(0.022)
Observations	5773	2459	3314	2809	2963
Dep. Var. Mean	10.20	10.11	10.27	10.03	10.36

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls , as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

We examine whether the impact of peer grit varies by students' socioeconomic background, specifically parental education and income. In particular, we classify students based on their parents' education and income levels, identifying them as having either low- or high-educated parents and low- or high-income parents. We then re-estimate Eq. (1) for each subgroup.[33]

Table 10 presents the results. A comparison of columns 2 and 3, as well as columns 4 and 5, indicates that, in fact, students with less-educated and low-income parents are the ones who benefit a lot from higher peer grit. In other words, having gritty peers during high school significantly supports students from disadvantaged backgrounds, leading to increased earnings in the future. More specifically, for individuals with low-educated parents, a one standard deviation increase in peer grit increases future earnings by 5.8% (column 2). This effect is 38% greater than in the overall sample (4.2%–reproduced in column 1). According to Sharafi (2023), poverty has a large and significant negative effect on perseverance, a facet of grit, causing students from economically disadvantaged backgrounds to exert less effort than their peers from wealthier backgrounds. Our results suggest that exposure to high school peers with higher grit can help bridge the gap in opportunities and resources for students from economically disadvantaged backgrounds.

We also estimate the heterogeneous effects of peer grit based on students' own grit levels. To do this, we divide the students into two groups based on the median value of their own grit. As shown in Online Appendix Table B5 columns 1 and 2, students with high levels of grit benefit more from having gritty high school peers, achieving higher earnings in adulthood. This finding aligns with the results of Zou (2024), who demonstrates that students with higher persistence levels gain significantly from having persistent peers in academic performance. Furthermore, our analysis reveals stronger effects for boys than girls (see Online Appendix Table B6), likely because boys exhibit higher average grit levels. However, a comparison of Online Appendix Table B5 columns 3 and 4 with columns 5 and 6, indicates that the low socioeconomic background continues to play an important role, irrespective of the level of one's own grit.

[33] The information on parental education and income comes from the parent questionnaire in Wave I (see Section 2). We define as low-income those with a parental household income below the median ($40,000). A low-educated parent is defined as someone whose highest level of education is high school or less.

5. Conclusion

Using data from the Add Health survey, this paper explores the effect of peer grit on long-term outcomes. By shifting the focus from more commonly studied peer effects (e.g., the influence of peer gender or race on academic achievement in the short run) to peer personality traits that are not easily observed and their long-term effects, we contribute to the established literature by demonstrating that peer grit affects long-term earnings in early adulthood.

In our analysis, we leverage the unique features of the Add Health survey, which tracks multiple cohorts within the same school and provides rich data on respondents' personalities and long-term economic and labor market outcomes. We identify the effect of peer grit during high school on future earnings by utilizing the variation in peer grit across cohorts within the same school. We confirm the findings of the existing literature, which suggest that peer grit increases the probability of enrolling in college. Furthermore, we find that students exposed to peers with higher grit during high school achieve higher earnings in early adulthood. Students from disadvantaged family backgrounds — those with low-educated or low-income parents — benefit significantly more from exposure to peers with higher grit. This increased exposure enhances their opportunities for long-term economic success, as measured by future earnings, and may help bridge socioeconomic gaps.

Exposure to gritty peers in high school also affects other long-term outcomes. In particular, it leads to greater accumulated assets, increased job satisfaction, and a higher likelihood of being employed at a job that is aligned with one's long-term career goals. The impact of peer grit also extends beyond economic outcomes, shaping personality and attitudes in adulthood. Exposure to gritty peers tends to increase one's own grit one year later. We also find that peer grit reduces risk aversion in early adulthood and decreases the likelihood of feeling unable to overcome difficulties in life.

Our further analysis reveals three plausible channels through which exposure to gritty peers in high school leads to higher earnings in early adulthood: college enrollment, a higher likelihood of perceiving one's current job as aligned with long-term career goals, and a decreased likelihood of feeling unable to overcome difficulties.

Our findings suggest that personality interventions in schools may generate benefits that extend beyond targeted individuals. Evaluations focusing solely on direct effects and short-run educational outcomes may therefore understate the total benefits of such programs if peer spillovers and longer-term labor market effects are overlooked.

Future work could investigate whether the magnitude of peer grit and the specific mechanisms through which it operates vary across institutional and cultural contexts, providing further insight into the generalizability and policy relevance of these findings.

CRediT authorship contribution statement

Effrosyni Adamopoulou: Writing – review & editing, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Yaming Cao:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ezgi Kaya:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Claude in order to check for spelling and grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A

See Figs. A.1–A.2 and Tables A.1–A.4.

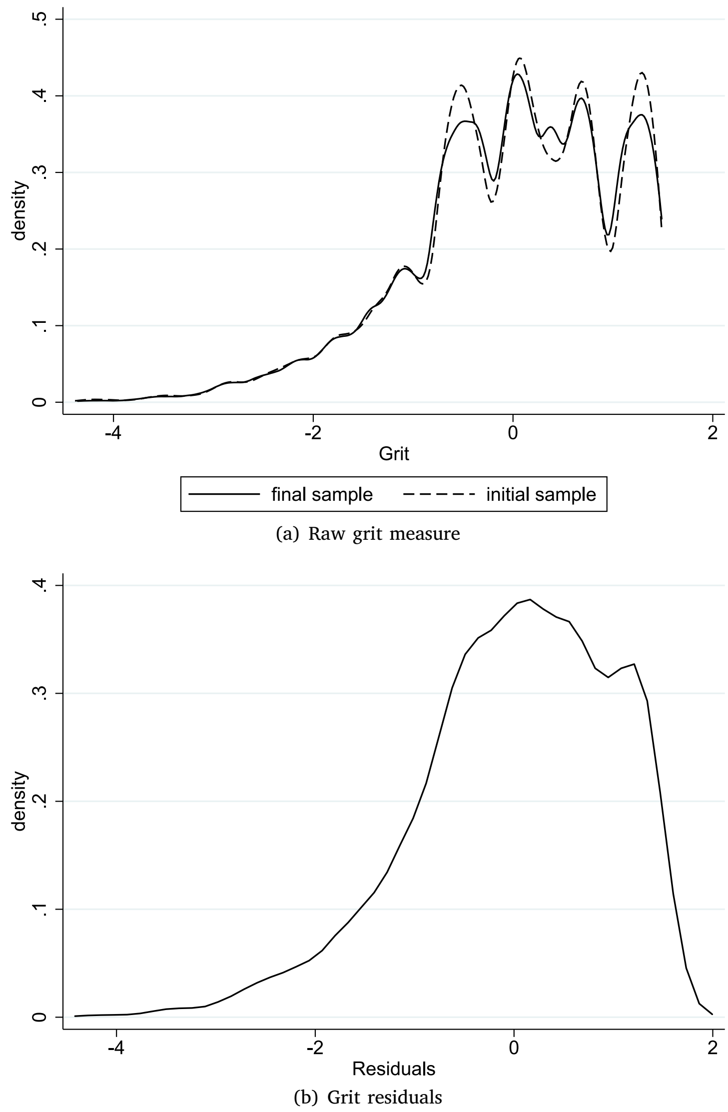

Fig. A.1. Distribution of grit measure.

Note: Figure (a) plots the distribution of grit measure, constructed using Add Health questions described in the text. The initial sample represents the original dataset, while final sample refers to the sample used in the main analysis. Figure (b) displays the distribution of grit in the final sample that cannot be explained by baseline controls. A lower number indicates a lower grit value.

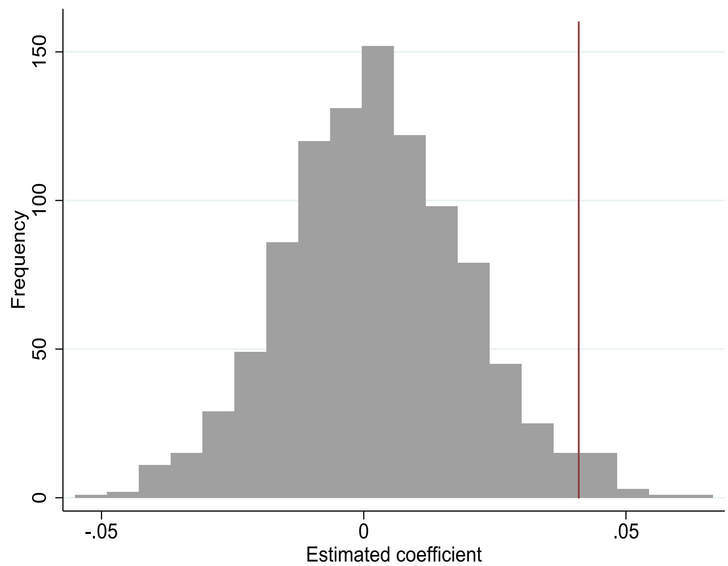

Fig. A.2. Placebo estimates.
Note: Figure shows the estimated coefficients of the (log) earnings equation when the placebo peers are used, and the procedure is repeated 1000 times. Placebo peers are students from the same school as the respondent but from a different (randomly assigned) cohort. The regressions include baseline controls, as well as school and cohort fixed effects. The vertical line represents the benchmark coefficient estimate presented in Table 5 column 3.

Table A.1
Effects of peer grit on earnings - robustness checks excluding AHPVT score.

	Dep. var.: Log(earnings) (1)
Peer grit	0.040**
	(0.017)
Own grit	0.076***
	(0.016)
Observations	5773
School FE	Yes
Cohort FE	Yes
Controls	Exclude AHPVT
Dep. Var. Mean	10.20

Note: Corrected for the design effects of the Add Health sampling process. The specification includes baseline controls with the exception of AHPVT standardized score, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for variable definitions. Standard errors are clustered at the school level. *p < 0.10; **p < 0.05; ***p < 0.01.

Table A.2
Effects of peer grit - robustness checks with a sample of students from grade 7 to 9.

	Dep. var.: Log(earnings) (1)
Peer grit	0.063*
	(0.032)
Own grit	0.087***
	(0.024)
Observations	2762
School FE	Yes
Cohort FE	Yes
Controls	Yes
Dep. Var. Mean	10.08

Note: Corrected for the design effects of the Add Health sampling process. The specification includes baseline controls, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Presented are based on an analysis of a subsample of students from grades 7 to 9. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A.3
Effects of peer grit on earnings - robustness checks with alternative clustering.

	Dep. var.: Log(earnings)		
	(1)	(2)	(3)
Peer grit	0.044**	0.044*	0.044***
	(0.014)	(0.019)	(0.017)
Own grit	0.061***	0.061**	0.061***
	(0.012)	(0.016)	(0.015)
Observations	5741	5741	5741
School FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
SE Cluster	Grade	School, Grade	School×Grade
No. Cluster	6	130, 6	453
Dep. Var. Mean	10.20	10.20	10.20

Note: Corrected for the design effects of the Add Health sampling process. All specifications include baseline controls, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the level indicated within each column are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A.4
Underlying mechanisms, wave V earnings.

	Dep. var.: Log(earnings in Wave V)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer grit (Wave I)	0.048*	0.037	0.047	0.048*	0.036	0.039	0.021
	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)	(0.028)
Own grit (Wave I)	0.115***	0.102***	0.108***	0.116***	0.094***	0.093***	0.069**
	(0.024)	(0.024)	(0.027)	(0.023)	(0.023)	(0.025)	(0.026)
College enrollment (Wave III)		0.463***					0.379***
		(0.052)					(0.050)
Own Grit (Wave II)			0.023				0.002
			(0.033)				(0.033)
Risk aversion (Wave IV)				−0.016			−0.005
				(0.024)			(0.023)
Job aligned with career goals (Wave IV)					0.514***		0.444***
					(0.054)		(0.053)
Overcome difficulties (Wave IV)						0.144***	0.110***
						(0.024)	(0.024)
Observations	4135	4135	4135	4135	4135	4135	4135
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	10.54	10.54	10.54	10.54	10.54	10.54	10.54

Note: Corrected for the design effects of the Add Health sampling process. Earnings are reported in tiers in Wave V of Add Health, rather than as a continuous variable as in Wave IV. The earnings tiers are: less than $5000, $5000 to $9999, $10,000 to $14,999, $15,000 to $19,999, $20,000 to $24,999, $25,000 to $29,999, $30,000 to $39,999, $40,000 to $49,999, $50,000 to $74,999, $75,000 to $99,999, $100,000 to $149,999, $150,000 to $199,999, and $200,000 or more. We use midpoints in the estimation. To maintain a consistent sample size across all mediation factors, we include missing-value indicators to account for missing data in each mediator. All specifications include baseline controls, as well as school and cohort fixed effects. See text for sample restrictions and Online Appendix Table B1 for the definitions of all variables. Standard errors clustered at the school level are in parentheses. *p < .10; **p < .05; ***p < .01.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.labeco.2026.102870.

Data availability

The authors do not have permission to share data.

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