Grit and Academic Resilience During the Covid-19 Pandemic

Daniel L. Chen* Seda Ertac† Theodoros Evgeniou‡ Xin Miao§
Ali Nadaf¶ Emrah Yilmaz‖

February 27, 2022

Abstract

Grit, a non-cognitive skill that indicates perseverance and passion for long-term goals, has been shown to predict academic achievement. This paper provides evidence that grit also predicts student outcomes during the challenging period of the Covid-19 pandemic. We use a unique dataset from a digital learning platform in the United Arab Emirates to construct a behavioral measure of grit. We find that controlling for baseline ability, students who were grittier according to this measure before the pandemic, register lower declines in math and science scores during the coronavirus period. Using machine learning, behavioral data in the platform prior to the pandemic can explain 77% of the variance in academic resilience. A survey measure of grit of the same students, on the other hand, does not have significant predictive power over performance changes. Our findings have implications for interventions on non-cognitive skills, as well as how data from digital learning platforms can be used to predict student behavior and outcomes, which we expect will be increasingly relevant as AI-based learning technologies become more common.

Keywords: non-cognitive skills, remote education, academic performance, Covid-19.

*Toulouse School of Economics, Institute for Advanced Studies, 21 allée de Brienne, 31015 Toulouse cedex 6, France e-mail: daniel.li.chen@gmail.com

†Koc University Department of Economics, Sariyer, Istanbul 34450 Turkey e-mail: sertac@ku.edu.tr

‡Technology Management and Decision Sciences, INSEAD, 77300 Fontainebleau, France e-mail: theodoros.evgeniou@insead.edu

§Alef Education Building 2, TwoFour54, P.O. Box 769719 Abu Dhabi, UAE e-mail: xin@alefeducation.com

¶Alef Education Building 2, TwoFour54, P.O. Box 769719 Abu Dhabi, UAE e-mail: ali.nadaf@alefeducation.com

‖Koc University College of Administrative Sciences and Economics, Sariyer, Istanbul 34450 Turkey e-mail: emrahyilmaz@ku.edu.tr

1 Introduction

Grit is an important non-cognitive skill that has been shown to predict achievement outcomes including educational attainment, academic performance, and retention (Duckworth et al., 2011; Eskreis-Winkler et al., 2014). In the school context, grit has a significant role on outcomes over and above cognitive skills, and can have large multiplier effects, given that students who give up early have fewer chances to recover. Recognizing this, in many countries, educational policymakers and NGOs implement programs to foster grit in the school environment, especially with "growth mindset" interventions that teach students the malleability of skills through effort and perseverance (Dweck, 2006; Paunesku et al., 2015).

In addition to its association with performance at school, the non-cognitive skill of grit can also be important in predicting resilience in the distance learning context during the Covid-19 pandemic. The challenges brought about by the reduced access to teachers and peers in remote learning have likely impaired the support system for students, changed the interaction of teachers, students and learning content (City et al., 2009), and made self-regulated learning (McCombs, 1986) more central. Motivating oneself when tackling potentially difficult learning tasks can be more challenging with remote learning, in the absence of direct interactions with the teacher and peers. Indeed, recent evidence shows that even in "best-case scenario" countries with favorable conditions, students have experienced learning losses with remote instruction during the pandemic (Engzell et al., 2021).

In this paper, we use unique data from an online educational platform in the United Arab Emirates to explore whether the non-cognitive skill of grit predicts performance changes in math and science subjects during the coronavirus period, among a sample of 5th-9th graders. Specifically, we utilize pre-pandemic measures of grit, coming from a survey as well as actual behavior in the digital learning platform, to predict performance changes during the pandemic.

How to measure non-cognitive skills accurately is a major issue that has interdisciplinary relevance. In much of the literature, grit has been measured by the Duckworth grit scale (Duckworth et al., 2007). Measured this way, it has been shown to correlate with a wide range of outcomes such as retention and school performance, although there is also work that has found null effects (e.g. Zisman and Ganzach (2021)). However, survey measures tend to be prone to demand effects or social desirability effects (Bertrand and Mullainathan, 2001), which may be particularly concerning in an adolescent student sample. Experimental economists have recently sought to construct behavioral measures of grit, using external, dynamic tasks that require real effort (e.g. Alan et al. (2019)). While such measures have been shown to have strong predictive power, implementing and using them at a large scale may be difficult in the regular classroom environment, as they tend to require the use of material rewards and implementation by external researchers. In this respect, using naturally occurring data from a digital learning platform enables us to obtain a unique measure of "behavioral grit" that would be difficult to obtain in the traditional learning environment. Specifically, we are able to see "after-hours" studying and practice by the students, capturing sustained voluntary effort, which allows us to define a measure of "revealed" grit in terms of the response to performance setbacks. Using this measure along with a well-known survey measure in the same sample, we are thus able to make the contribution of comparing the predictive power of survey measures of grit, and the behavioral measure of grit from platform data, both coming from the pre-Covid period, on student performance and behavior during the pandemic.

Our data confirms that the pandemic has led to significant declines in performance in math and science subjects, in line with studies showing that learning has been disrupted during the Covid-19 period. We find that the well-known survey measure of grit (Duckworth and Quinn, 2009) has limited power in predicting performance in our sample, especially during the coronavirus period, and importantly, it does not predict the declines in performance. We hypothesize that revealed grit may instead be a better predictor of the performance response. We hypothesize that students who had higher grit before the pandemic period register lower declines in academic performance during Covid-19, controlling for baseline diagnostic scores. We indeed find that revealed grit, unlike or stronger than survey-based measures: 1) predicts both pre-Covid and after-Covid performance on the digital platform in math, 2) predicts the change in performance, with grittier students registering lower declines in performance in math and science. Finally, we show that pre-Covid behavioral data in the digital platform contains significant information to explain academic resilience: up to 77% of variance in declines in performance in math and science can be explained using machine learning.

Our findings highlight a novel effect of the well-studied skill of grit—that grit can also predict a positive response to a unique type of shock to the educational environment, coming from the switch to fully remote learning. In this sense, we provide new evidence for why fostering grit in student samples is important for achieving better learning outcomes. Another implication of our results is that digital learning platforms can provide valuable information that can be used for customizing student learning, through AI-based systems that can make use of student performance as well as revealed non-cognitive skills through platform behavior. That is, such platforms, by design, can be used, to not only deliver learning content but also to collect valuable behavioral information that can provide a foundation for customized learning for students with heterogeneous levels of non-cognitive skills.

The rest of the paper is organized as follows. In Section 2, we put forward the setup and research question, and explain our grit measure. Section 3 presents results, and Section 4 concludes.

2 Setup, Data and Research Questions

Our data come from a widely used digital learning platform in the United Arab Emirates.[1] In the pre-pandemic period, the platform was used for blended learning in K-12 public school classrooms, delivering core curriculum. After the pandemic, with the switch to complete distance learning, the platform became the sole environment for teaching and learning in the country, in conjunction with communication tools such as *Zoom*. The data-set we use in the paper comes from a subset of students, for whom survey measures of grit and performance data in out-of-platform diagnostic tests before the pandemic period are available, in addition to data coming from the digital platform.

2.1 The Behavioral Grit Measure

There are several types of activities for students to engage in on the platform. For each subject (math and science), students can watch instructional videos, study digital course materials, and take online assessments to check their understanding of the material. The platform records every activity, from when the student started the activity to when it ended, how many assessments the student attempted, as well as all other login/logout attempts etc. Here, we define two important concepts that will be used in the current paper for analysis. We define a student's "platform performance" as the average score of all assessments taken by the student within a specific period of time. These scores, and hence their averages, range from 0 to 100. We define performance metrics as above for each student and subject (math and science) in the pre/post-Covid periods separately. We also calculate the differences in score from pre- to post-Covid per subject, in order to see what might have impacted the change in performance.

The second variable we use is the number of attempts for a test made by each student. The intensity of engagement with the digital platform during school hours is usually determined by the teacher. For this reason, we focus on out-of-school hours, where it is completely up to the student to use the platform for learning or practice. Given that out-of-school hours activity is voluntary, students differ in how many times they attempt an assessment task. The number of times a student approaches an assessment task is defined as the "attempts", which we use to define gritty behavior.[2]

There are many ways to conceptualize how digital learning data can be used to measure grit. Our grit measure is based on the student's response to a performance that deviates from her earlier average performance. We interpret this fall as a "setback", and the student's positive response to

[1]The data are provided by Alef Education. Alef Education is a global K-12 education technology company that provides K12 students and teachers with core curriculum and learning analytics through blended learning settings. The platform also provides experiential learning that enables students to apply and transfer their newly-acquired skills, and practice lessons for further skill mastery, with the aim of creating an effective instructional and classroom model.

[2]In calculating the variables for the pre- and post-Covid periods, there are several assumptions we make, and related definitions, which are discussed in the Appendix.

this setback (higher effort exerted out of school hours following the setback) as "grit". Specifically, we define our main grit variable as follows. For each student and for every day in our sample ("Day t"), we calculate the difference between the student's average performance in the past week (during the days $t-7$ to $t-1$) and performance on Day t. If today's score is sizably lower than last week's average score, that is, if there is an at least 5-point score decline from the previous week, we define this incidence as a setback where a behavioral grit response may be observed.[3] We define the gritty response as an increase in effort, which we capture by the number of attempts the student made in their formative tests on the platform during out-of-school hours following the setback.[4] Specifically, for each setback event, we calculate the difference between the number of out-of-school attempts on the following day ($t+1$), and compare this with the previous week's average attempt ($t-7$ to $t-1$). The behavioral grit variable takes the value of 1 if there is an increase in attempts, and 0 otherwise. Once we have the grit measure for a given day t, we take an average over all days in our sample, for both pre- and during-Covid periods.[5] Thus, we have, for each student, what percentage of the time out-of-school attempts increased after a sizable score decline. We interpret this as a measure of behavioral grit, which we calculate separately for math and science subjects. We then compare our behavioral grit measure with the well-known survey grit measure, based on Duckworth and Quinn (2009)'s "short grit scale".[6]

2.2 Data

We use data coming from 1920 students, in 17 schools and 229 classes, out of which 1279 are female and 641 are male.[7] The students are middle- and high-schoolers, and the data include five grades: grades 5 to 9.[8] We have access to objective scores from a diagnostic test on math and science as well as a survey, which were all run before the pandemic, in Fall 2019. In addition, we

[3]If performance does not decline sizably or increases on a given day, the grit variable for that day is not defined. Also, since there is little room for performance improvement for very high performing students (whose daily score average is consistently higher than 90), these students are omitted from the analysis.

[4]We do not include weekends in the calculations as the number of attempts are significantly lower. When Thursday is day t, then Sunday becomes $t+1$.

[5]In our sample, we have 56 days of observations for the pre-Covid and 84 days of observations for the during-Covid period. Since we compare with an average from the previous week, we omit first-week observations both from pre- and during-Covid periods. Note that before the start of the "Covid period" in our data, there was a 16-day break, where average activity on the platform is 90% less than both the pre- and post-Covid periods. Therefore, we have 49 effective days for pre-Covid and 77 days for during-Covid.

[6]The questions are given in the Appendix.

[7]The sample we use in this paper reflects the set of students, out of a representative sample of all Abu Dhabi public school students, who completed both the diagnostic test (mandatory) and the grit survey (optional). There may be selection in the sample in the sense that the lower tail in terms of motivation have likely been left out, but our results on the effect of grit may be considered as conservative in this sample.

[8]We have 391, 262, 488, 600 and 179 students in grade 5 to 9, respectively. Note that during our data period, there are only two students changing school, and these have been omitted from the analysis. In case of class changes, we take the last class that the student was enrolled in in the academic year as the relevant class.

have platform data from the period January 10 to March 5, 2020 (8 weeks), which we define as the pre-Covid period. The post-Covid period goes from 22 March, 2020 to June 13, 2020 (12 weeks).[9]

In additional analysis of revealed preference data on non-cognitive skills, we implement an elastic regression using 400 variables from the digital platform. These variables come from "click data" recorded on the platform, and include a detailed set of observables about students' platform activity, such as accessing different types of instructional content for each subject (e.g. videos, reading material, exercises, tests) as well as the timing and duration of these activities. The machine-learning model reduces the size of coefficients to zero when they do not explain much variance, allowing the consideration of a wide range of potential explanatory variables. To reduce risk of confusion, we use principal components analysis (PCA), a technique for reducing dimensionality of data-sets by creating new uncorrelated variables that successively maximize variance and minimize information loss. We use PCA on all of the features from the digital platform. We then report the elastic regression including only the variables selected by elastic regression.

3 Analysis and Results

3.1 Performance Changes and Covid-19

As expected, the Covid-19 period has led to an overall decline in performance, in both math and science subjects. Table 2 shows that in math, there is an about 11 points decline in the average score on the platform, and a similar decline of 10 points in science, for both genders. These declines are significant at the 1% level ($p < .0001$ for math and science in t-tests).

3.2 Grit Measures and School Performance: Pre- and Post-Covid

Table 3 shows that there is a strong correlation between behavioral grit and student performance measured in their overall platform scores in math, controlling for baseline diagnostic test scores, which can be considered as an objective baseline performance. One standard deviation of behavioral grit is associated with 4.6 points higher math scores prior to Covid relative to an average of roughly 50, which is equivalent to 10% relative to the mean. The association is significant ($p < 0.05$). For science, grit is not strongly associated with test scores prior to Covid.[10] Girls in this sample perform 20 points higher on math tests, and 28 percent higher on science tests

[9]March 22 is the day when anti-Covid measures were taken in the UAE and home-schooling officially started. We omit the March 5 to 22, 2020 period, as the schools were closed and there were very limited attempts on the platform.

[10]Grit's stronger association with math is expected, given that students tend to find math subjects particularly difficult, and consistently with this, grit has been shown to have most relevance in math performance (e.g. Alan et al. (2019)).

($p < 0.05$). The respective diagnostic score, as expected, is also positively associated with platform performance ($p < 0.01$ for both subjects). After Covid commenced, grit is associated with both math and science test scores ($p < 0.01$) at a substantial 15 points in both subjects. Of note, the gender gap shrinks by about half and is no longer statistically significant at conventional levels.

In comparison, Table 4 shows that survey grit is only associated with one of these four measures of student performance–0.8 points in science prior to Covid ($p < 0.05$). Notably, the association with gender is no longer statistically significant in comparison to Table 2. This indicates that there may be strong gender differences in self-reported grit. Moreover, science performance may be picking up certain characteristics of students that are associated with self-reported grit, however this association is small and disappears as a significant factor in the post-period.

3.3 Grit Measures and Change in Performance Post Covid

Next, we explore non-parametrically the relationship between behavioral grit and academic resilience (change in overall test scores, as used above, during Covid-19). A significant predictive association for behavioral grit can be seen in binned scatter plots in Figures 1 (math) and 2 (science), which condense the information from a scatter plot by partitioning the x-axis into bins and calculating the mean of y within each bin.

Table 5 shows, in regression form, that surveyed grit is essentially not correlated or slightly negatively correlated with resilience during Covid-19, measured as the performance change, defined as overall test scores (as above) after Covid minus overall test scores pre-Covid. In contrast, behavioral grit change is associated with 0.1 point greater resilience for math and science, respectively.

The lack of similar predictive associations for survey grit can also be seen in Figures 3 and 4, which present the non-parametric relationship between survey grit and academic resilience in math and science test scores, respectively.

We should note that there may be other ways to define "behavioral grit" using such data. Our results are largely robust to a set of variations in the assumptions we make in the definition; for example, if we look at effort not only the day after, but two days after the setback, or if we define "setback" to be only when the student registers a "bottom 20%" performance based on his/her historic performance distribution.[11]

To examine total variance explained by behavioral grit measured in the digital platform, we use an elastic regression model in which we include all clicks recorded by the platform, preprocessed into 400 categories. The detailed set of observables we have for this test include students accessing different types of instructional content on the platform for each subject (e.g. watching

[11] Results available upon request.

a video, accessing course-related reading material, doing exercises, starting/ending tests to check understanding), number of times each content is accessed, and the time spent on the platform. To aid interpretability, we first use principal components analysis on these other variables. In Table 6, we report the multivariate regression including only the variables selected by elastic regression. The results indicate that 77% of variance in resilience is explained by the behavioral data measured in the platform. The data, while inadequate to definitively infer causality, thus show the potential for high-dimensional revealed preference measurement of non-cognitive skills. Note that before the elastic regression model, we orthogonalize each explanatory variable to behavioral grit measure by projecting each successive variable on the behavioral grit variable and taking residuals. Then the elastic regression model is run by using the uncorrelated variables (i.e. residuals).

4 Discussion

The coronavirus pandemic has brought a unique set of challenges for education. The learning loss incurred because of the pandemic by students in grades 1 to 12 is estimated to translate to about 3 percent lower income over the entire lifetime (Hanushek and Woessmann, 2020). In this paper, we show that an individual non-cognitive skill, grit, can predict how large of a performance loss students will experience due to the pandemic.

Research on the effects of Covid-19 has shown that personality traits can predict behavioral responses such as hoarding or compliance with guidelines (Zettler et al., 2022), as well as with coping responses to the pandemic (Volk et al., 2021). Johnston et al. (2021) show that Covid-19 has led to declines in mental health, and this decline is not predicted by financial resources but by the non-cognitive skill of self-efficacy. We show that in the educational setting, the non-cognitive skill of grit predicts performance declines. This finding suggests that in addition to explaining performance, grit is also relevant for response to negative shocks in the educational setting, for instance distance learning during the Covid-19 pandemic.

Our behavioral measure of grit is based on identifying performance declines, and utilizing the unique advantage offered by the data recorded in voluntary after-school hours activity on the platform to measure the revealed effort response. In this sense, our measure captures the "perseverance of effort" aspect of the construct of grit. Our results are therefore consistent with Credé et al. (2017) and Ponnock et al. (2020), who show that it is the perseverance facet of grit (in contrast to consistency of interest) that has explanatory power over academic performance.

Our findings suggest that programs that aim to build grit early on in the educational environment(e.g. through promoting growth mindset, see for example Dweck (2006) and Yeager et al. (2019)), can also have positive effects on resilience and the academic performance response in times of crisis. To the extent that such crises also exacerbate educational inequalities Murat and

Bonacini (2020), teaching grit could reduce the widening gap between students coming from different social strata. The results are also useful for designing AI-based remote learning technologies—identifying students' non-cognitive skills based on their behavior in learning software can be beneficial in creating customized/personalized content for each student and potentially improve achievement. Moreover, features that teach growth mindset and promote grit can be incorporated into digital learning environments, to support self-regulated virtual learning. We expect that such strategies will be especially relevant with the growing use of AI-based online learning technologies. Finally, our results underscore the importance of constructing revealed preference measures of non-cognitive skills and how self-reported survey data can be complemented with high-dimensional revealed preference data for predicting educational outcomes.

References

Alan, S., Boneva, T., and Ertac, S. (2019). Ever failed, try again, succeed better: Results from a randomized educational intervention on grit. *The Quarterly Journal of Economics*, 134(3):1121–1162.

Bertrand, M. and Mullainathan, S. (2001). Do people mean what they say? implications for subjective survey data. *American Economic Review*, 91(2):67–72.

City, E. A., Elmore, R. F., Fiarman, S. E., and Teitel, L. (2009). *Instructional rounds in education*, volume 30. Cambridge, MA: Harvard Education Press.

Credé, M., Tynan, M. C., and Harms, P. D. (2017). Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and social Psychology*, 113(3):492.

Duckworth, A. L., Kirby, T. A., Tsukayama, E., Berstein, H., and Ericsson, K. A. (2011). Deliberate practice spells success: Why grittier competitors triumph at the national spelling bee. *Social psychological and personality science*, 2(2):174–181.

Duckworth, A. L., Peterson, C., Matthews, M. D., and Kelly, D. R. (2007). Grit: perseverance and passion for long-term goals. *Journal of personality and social psychology*, 92(6):1087.

Duckworth, A. L. and Quinn, P. D. (2009). Development and validation of the short grit scale (grit–s). *Journal of personality assessment*, 91(2):166–174.

Dweck, C. S. (2006). *Mindset: The new psychology of success (Updated edition)*. Lulu Press, Inc.

Engzell, P., Frey, A., and Verhagen, M. D. (2021). Learning loss due to school closures during the covid-19 pandemic. *Proceedings of the National Academy of Sciences*, 118(17).

Eskreis-Winkler, L., Duckworth, A. L., Shulman, E. P., and Beal, S. (2014). The grit effect: Predicting retention in the military, the workplace, school and marriage. *Frontiers in psychology*, 5:36.

Hanushek, E. A. and Woessmann, L. (2020). The economic impacts of learning losses. oecd education working papers, no. 225. *OECD Publishing*.

Johnston, D. W., Kung, C. S., and Shields, M. A. (2021). Who is resilient in a time of crisis? the importance of financial and non-financial resources. *Health Economics*, 30(12):3051–3073.

McCombs, B. L. (1986). The role of the self-system in self-regulated learning. *Contemporary Educational Psychology*, 11(4):314–332.

Murat, M. and Bonacini, L. (2020). Coronavirus pandemic, remote learning and education inequalities. Technical report, GLO Discussion Paper.

Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., and Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological science*, 26(6):784–793.

Ponnock, A., Muenks, K., Morell, M., Yang, J. S., Gladstone, J. R., and Wigfield, A. (2020). Grit and conscientiousness: Another jangle fallacy. *Journal of Research in Personality*, 89:104021.

Volk, A. A., Brazil, K. J., Franklin-Luther, P., Dane, A. V., and Vaillancourt, T. (2021). The influence of demographics and personality on covid-19 coping in young adults. *Personality and Individual Differences*, 168:110398.

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., et al. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, 573(7774):364–369.

Zettler, I., Schild, C., Lilleholt, L., Kroencke, L., Utesch, T., Moshagen, M., Böhm, R., Back, M. D., and Geukes, K. (2022). The role of personality in covid-19-related perceptions, evaluations, and behaviors: Findings across five samples, nine traits, and 17 criteria. *Social Psychological and Personality Science*, 13(1):299–310.

Zisman, C. and Ganzach, Y. (2021). In a representative sample grit has a negligible effect on educational and economic success compared to intelligence. *Social Psychological and Personality Science*, 12(3):296–303.

Tables

TABLE 1: SCORES PRE- AND POST-COVID, BY GENDER

	(1) Average Science Score Pre-Covid	(2) Average Science Score Post-Covid	(3) Average Math Score Pre-Covid	(4) Average Math Score Post-Covid	(5) Average of Change in Science Score	(6) Average of Change in Math Score
All Students	59.7	50.0	65.4	54.6	-9.5	-10.9
Female	60.1	50.1	65.0	55.1	-9.8	-10.0
Male	58.9	49.9	66.2	53.7	-9.0	12.8

TABLE 2: AVERAGE SCORES PRE- AND POST-COVID, BY GENDER

	Math Score			Science Score		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre- Covid	Post-Covid	Change	Pre- Covid	Post-Covid	Change
All Students	59.7	50.0	-9.5	65.4	54.6	-10.9
Female	60.1	50.1	-9.8	65.0	55.1	-10.0
Male	58.9	49.9	-9.0	66.2	53.7	12.8

TABLE 3: BEHAVIORAL GRIT AND PRE- AND POST-COVID SCORES

	Pre-Covid		Post-Covid	
	(1) Math Score	(2) Science Score	(3) Math Score	(4) Science Score
Behavioral Grit	4.6**	2	15.4***	15.2***
	(0.04)	(0.41)	(0.001)	(0.001)
Male	-20.3**	-28**	-10.7	-15.2
	(0.03)	(0.02)	(0.29)	(0.11)
Diagnostic Score	0.04**	0.005***	0.04**	-0.009***
	(0.001)	(0.38)	(0.001)	(0.14)
R^2	0.48	0.54	0.38	0.43
N	1738	1714	1738	1714

Notes: Coefficients are reported from OLS regressions where the dependent variables are pre/post-Covid math and science scores. P-values are reported in parentheses. Class-school dummies and grade are added as control variables. Very high performer students (average score > 90) for each subject are excluded from the analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: SURVEY GRIT AND PRE- AND POST-COVID SCORES

	Pre-Covid		Post-Covid	
	(1) Math Score	(2) Science Score	(3) Math Score	(4) Science Score
Survey Grit	0.5	0.8**	0.5	0.5
	(0.17)	(0.04)	(0.25)	(0.26)
Male	-19.7*	-6	-8.7	-14.3
	(0.05)	(0.53)	(0.42)	(0.18)
Diagnostic Score	0.04***	0.005	0.04***	0.01*
	(<0.001)	(0.4)	(<0.001)	(0.05)
R^2	0.48	0.54	0.33	0.36
N	1738	1714	1738	1714

Notes: Coefficients are reported from OLS regressions where the dependent variables are pre/post-Covid math and science scores. P-values are reported in parentheses. Class-school dummies and grade are added as control variables. Very high performer students (average score >90) for each subject are excluded from the analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5: BEHAVIORAL GRIT, SURVEY GRIT, AND PRE- AND POST-COVID PERFORMANCE CHANGE

	(1) Change in Math Score	(2) Change in Science Score	(3) Change in Math Score	(4) Change in Science Score
Change in Behavioral Grit			0.17***	0.1**
			(<0.001)	(0.01)
Survey Grit	0.03	-0.2		
	(0.94)	(0.64)		
Male	11.1	-8.2	11	35.4**
	(0.36)	(0.49)	(0.30)	(0.01)
R^2	0.32	0.31	0.35	0.34
N	1738	1714	1738	1714

Notes: Coefficients are reported from OLS regressions where the dependent variables are changes in math and science scores. P-values are reported in parentheses. Class-school dummies and grade are added as control variables. Very high performer students (average score > 90) for each subject are excluded from the analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

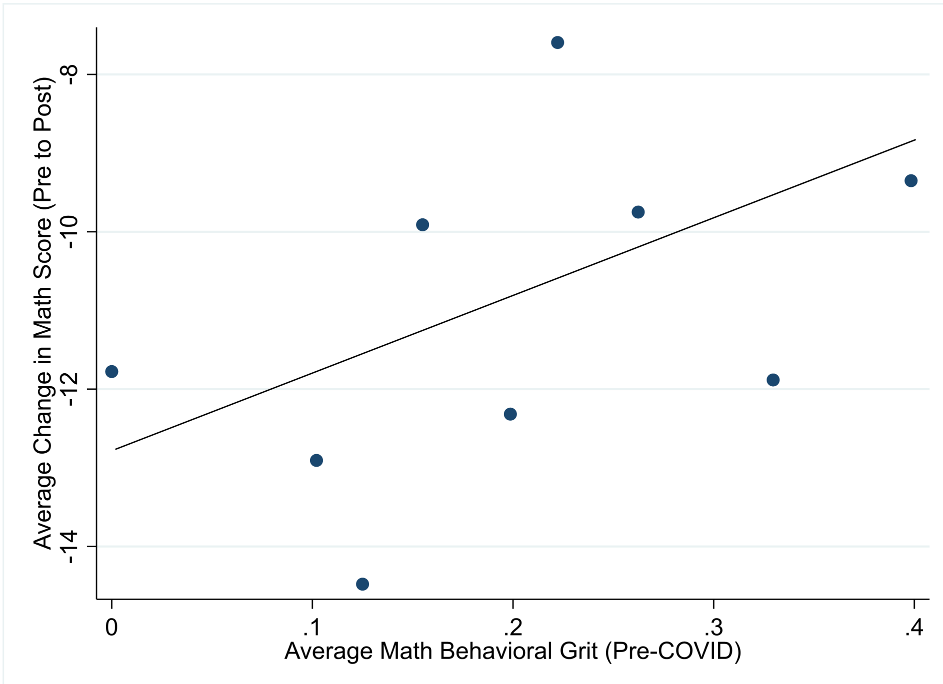
Table 6: Elastic Regression Results

	(1) Average Performance (Math and Science)
Behavioral Grit	-1.46***
	(<0.001)
pc10	-12.41***
	(<0.001)
pc1	8.863***
	(<0.001)
pc14	-5.146***
	(<0.001)
pc2	5.050***
	(<0.001)
pc9	-4.532***
	(<0.001)
pc18	4.493***
	(<0.001)
pc11	-4.077***
	(<0.001)
pc14	4.026***
	(<0.001)
pc8	3.724***
	(<0.001)
pc17	2.719***
	(<0.001)
pc13	2.552***
	(<0.001)
pc5	2.056***
	(<0.001)
pc12	1.374**
	(0.014)
pc19	-0.812
	(0.215)
pc16	-0.573
	(0.341)
pc15	0.521
	(0.377)
R^2	0.77
N	1434

Notes: Coefficients are reported from OLS regressions where the dependent variable is average score. P-values are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

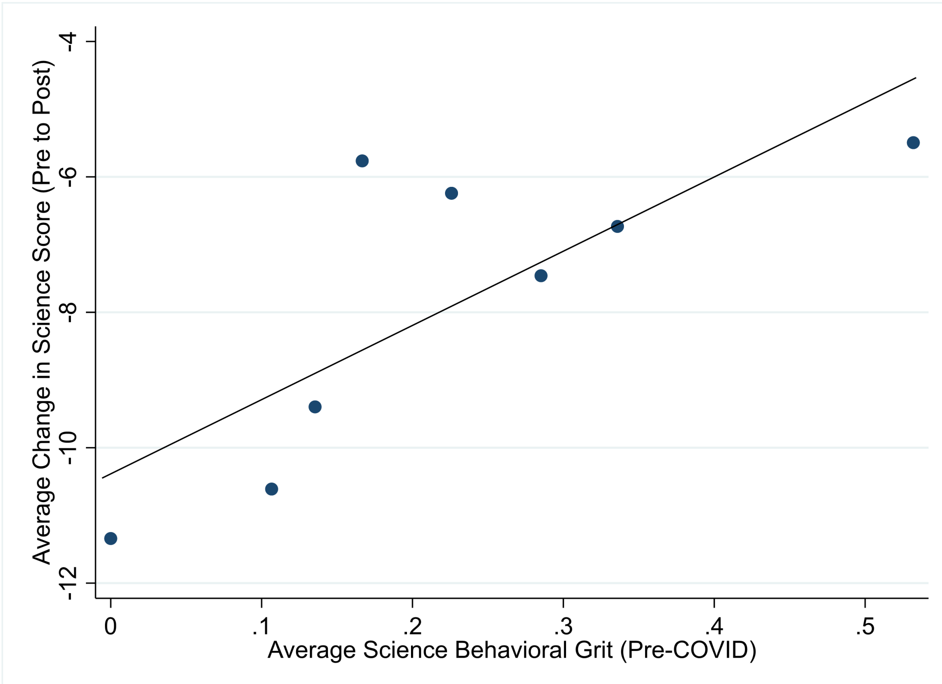
Figures

FIGURE 1: PRE-COVID BEHAVIORAL GRIT AND ACADEMIC RESILIENCE IN MATH



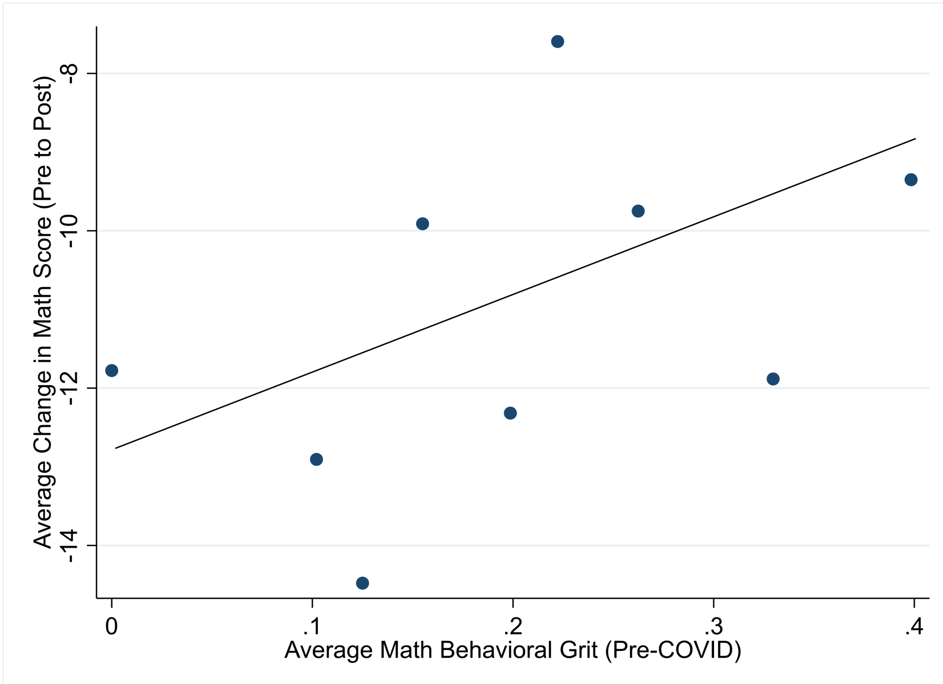
Notes: Binned scatterplots of correlation between behavioral grit and change in math scores

FIGURE 2: PRE-COVID BEHAVIORAL GRIT AND ACADEMIC RESILIENCE IN SCIENCE



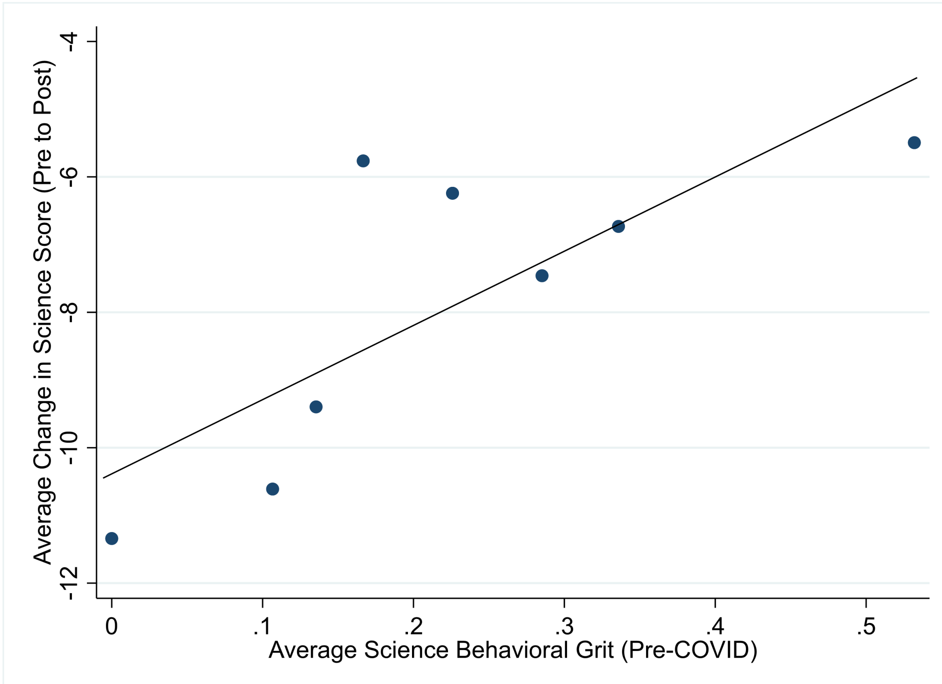
Notes: Binned scatterplots of correlation between behavioral grit and change in science scores

FIGURE 3: SURVEY GRIT AND ACADEMIC RESILIENCE IN MATH



Notes: Binned scatterplots of correlation between survey grit and change in math scores

FIGURE 4: SURVEY GRIT AND ACADEMIC RESILIENCE IN SCIENCE



Notes: Binned scatterplots of correlation between survey grit and change in science scores

Appendix

A Questions for the survey grit measure:

1. New ideas and projects sometimes distract me from previous ones.
2. Setbacks don't discourage me. I bounce back from disappointments faster than most people.
3. I have been obsessed with an idea or project for a short time but later lost interest.
4. I am a hard worker.
5. I often set a goal but later choose to follow a different one.
6. I have difficulty keeping my focus on projects that take more than a few months to complete.
7. I finish whatever I begin.
8. I am diligent.