Peers and Mental Health*

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Abstract

In this paper, we study the effects of students' ordinal ranks on their mental health. Guided by a theoretical framework, we find that having a better ordinal ranks in school improves students' immediate mental health. In particular, moving a student from the 25th to the 75th percentile improves her mental health by 10-11% of a standard deviation. These effects are more pronounced for low-ability student and persistent for over 14 years. Moreover, we document a strong asymmetry in our effects: Rank effects are driven by individuals that receive negative rather than positive shocks. Our results provide evidence how features of the school environment can have long-lasting consequences for individuals' well-being.

Keywords: Peer effects, Mental health, Rank Effects
JEL-Codes: I21, I14, J24

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1 Introduction

Mental health is a growing concern with substantial costs for the economy both in the United States and around the world. In particular, the total costs of mental health disorders are estimated to be as high as 2.5% of the GDP in the U.S. and 3.5% in Europe (OECD, 2015). Many of these mental health issues can be traced back to symptoms during youth as about 20% of all adolescents suffer from diagnosable mental health disorders (Kessler, Angermeyer, and Anthony, 2007), and this number increased by a third between 2005 and 2014 (Mojtabai, Olfson, and Han, 2016). It is therefore important to understand the causes and long-term consequences of mental health disorders during school-age.

In this paper, we study how features of the school environment – in our application students' ordinal ranks in their school cohort – affect students' mental health and how these effects evolve over time. We begin by formulating a theoretical framework in which students are uncertain about their ability and face two decisions: how much time to spend on studying and how much effort to exert while studying. While school performance increases in study time and is affected by some noise, the return to studying depends on effort choices. Students can either shirk and have a low return to effort or exert effort to have a return to effort equaling their ability. Only the latter allows them to learn about their ability. Due to noise in the educational production function, students learn only imperfectly from observed performance. Based on this setup, we derive three predictions: First, negative shocks to performance in school decrease a student's belief about her own ability, which we interpret as mental health (see, e.g., de Quidt and Haushofer, 2016, for a similar assumption). This interpretation is motivated by pessimism being one of the main symptoms of depressions (Beck, 1967). Second, the consequences of such shocks are more pronounced at the lower end of the ability distribution as students attribute shocks relatively more to their own ability. Third, since students refrain from exerting effort once their beliefs about their own ability are sufficiently low, they do not receive any new informative signals implying that negative shocks have persistent effects over time.

To test these predictions, we exploit idiosyncratic variation in the ability composition of cohorts within schools. More specifically, we argue that conditional on a student's school, the ability composition of peers is as good as random and conditional on a student's ability, her ordinal rank in her cohort is also as good as random, which we interpret as exogenous shocks affecting a student's mental health. We use data from the National Longitudinal Study of Adolescent to Adult Health (AddHealth), a survey of a representative sample of U.S. adolescents in grades 7-12, first interviewed during the 1994/1995 academic year. Importantly, AddHealth repeatedly assesses students' mental health using a well-established measure to diagnose depressions (Center of Epidemiological Studies Depression Scale, CES-D; Radloff, 1977).

We find that ordinal ranks significantly affect students' mental health. Increasing a student's rank from the 25th to the 75th percentile improves her mental health by 10-11% of a standard deviation on average. This effect is similar to a one standard deviation increase in a student's ability and comparable to rank effects estimated for standardized test scores of British students (Murphy and Weinhardt, forthcoming) and is in line with our first prediction. Our estimates do not change once we include additional controls such as peer effects in several dimensions and a sensitivity analysis based on Oster (2019) shows that unobservables are unlikely to drive our estimates. Moreover, using a different identification strategy with grade-by-school fixed effects, yields similar results.[1]

Moving to our second prediction, we find that this effect is larger at the lower end of the ability distribution: Students from the lowest decile of the ability distribution improve their mental health by 35% of a standard deviation when increasing the ordinal rank from the 25th to the 75th percentile, while this effect slowly fades out for higher deciles. When studying further heterogeneities, we find suggestive evidence that rank effects are more pronounced for females, non-white students, and for students with non-college educated parents, as well as for students from larger cohorts with high dispersion in ability, but unfortunately lack statistical power to provide concluding evidence.

These heterogeneous effects in own ability are persistent over at least 14 years and last from adolescence to adulthood. In fact, we observe that rank effects are at least as large in wave IV, when individuals in our dataset are 26-32 years old, as they are in wave I, when they were adolescents. These findings provide strong support for the third prediction of our theoretical framework and additionally lend support for models introducing mental health capital similar to general health (Grossman, 1972). Furthermore, we provide evidence that our effects are driven by negative shocks, i.e., having lower ranks in their school cohort than across students from all schools and cohorts.

Our study is closely related to the literature on rank effects.[2] This literature argues that ordinal ranks affect outcomes due to social comparisons and describe these effects as "big fish in a little pond" effects (Festinger, 1954; Marsh, 1987). In particular, there is evidence that such comparisons affect individuals' job satisfaction or general well-being (Card et al., 2012; Luttmer, 2005; Brown et al., 2008).[3] Recent papers have used these ideas in educational contexts to estimate the effect of ordinal ranks on educational outcomes (Murphy and Weinhardt, forthcoming; Elsner and Isphording, 2017; Elsner, Isphording, and Zölitz, 2019) and subsequent earnings (Denning, Murphy, and Weinhardt, 2018). Moreover, there is evidence on rank effects for risky behavior (Elsner and Isphording, 2018) and skill development (Pagani, Comi, and Origo, forthcoming). We use a similar empirical approach as these previous papers and guide our analysis using a theoretical framework based on learning about one's

[1]This strategy exploits variation of students' ranks within cohorts and compares these students to others from different cohorts and schools after all observed and unobserved characteristics on a school-cohort level are removed.

[2]These rank effects are a specific form of peer effects, in which the ordinal rank rather than the mean (for an overview, see, e.g., Sacerdote, 2011) or the variance (Tincani, 2017) affects outcomes. There exists a small literature on peer effects in mental health, but its evidence so far is mixed with strong spillover effects in some studies (e.g., Fowler and Christakis, 2008) and only modest (Eisenberg et al., 2013) or zero effects Zhang (2018) in others.

[3]Relative rankings may also affect behavior and outcomes such as consumption, well-being, performance, and effort provision as in Hopkins and Kornienko (2004), Luttmer (2005), Gill et al. (2019), and Kuziemko et al. (2014), respectively.

own ability in the presence of noisy signals. In line with predictions from our model, we document strong, heterogeneous, and persistent rank effects on mental health. Apart from studying a novel margin of rank effects, we move beyond the previous papers by introducing asymmetric effects based on positive or negative shocks. The idea behind these is that due to limited cohort sizes, the rank within a school cohort differs from the rank in the cohort across all schools and hence this yields either positive or negative shocks relative to a rank one might expect. In our application, we find that our rank effects on mental health are driven by negative shocks, in line with what we would expect based on our model.

We focus on mental health for several reasons. First, mental health and psychological well-being are important outcomes in their own right by directly entering an individual's utility function (Kahneman and Deaton, 2010). As a consequence, there exist many studies estimating, the causal relationship of, e.g., early life circumstances (Adhvaryu, Fenske, and Nyshadham, 2019), income shocks from cash transfers (Baird, de Hoop, and Özler, 2013), religion (Fruehwirth, Iyer, and Zhang, 2019), and psychotherapy interventions (Baranov et al., forthcoming) on mental health. Second, mental disorders can be a cause of important economic outcomes such as limited human capital accumulation (Currie and Stabile, 2006; Fletcher, 2010) or reductions in employment and earnings (Bartel and Taubman, 1986; Frank and Gertler, 1991; Ettner, Frank, and Kessler, 1997; Stewart et al., 2003; Fletcher, 2014). Third, it can also be a likely mechanism that potentially explains how other economic outcomes are affected by shocks in early life or adolescence (e.g., Persson and Rossin-Slater, 2018, on maternal stress and the consequences for children). Moreover, our focus on mental health relates to the growing evidence on the importance of non-cognitive skills in the development of children (Cunha and Heckman, 2008; Cunha, Heckman, and Schennach, 2010) and for subsequent education and labor market outcomes (Heckman, Stixrud, and Urzua, 2006).

Finally, this paper adds to the accumulating evidence on the long-lasting effects of features of the school environment. Although the long-term effects of smaller class sizes (Angrist and Lavy, 1999; Krueger and Whitmore, 2001; Chetty et al., 2011) or better teachers (e.g., Chetty, Friedman, and Rockoff, 2014) are well-established, only recent studies have shed light on the long-term effects of peers during school: Carrell, Hoekstra, and Kuka (2018) document that having disruptive peers during childhood decreases earnings, while Bietenbeck (2019) shows that low-achieving peers can increase non-cognitive skills. Our results highlight the long-term effects of ordinal ranks for psychological well-being that in turn may affect education attainment, labor market outcomes as well as general health.

The remainder of this paper is structured as follows. In Section 2 we lay out a theoretical model in which students are uncertain about their ability and based on noisy signals. We present the data we use to test our predictions in Section 3 and describe our empirical strategy in Section 4. Our main results are presented in Section 5. Finally, Section 6 concludes.

2 Theoretical Framework

Before we turn to our empirical analysis, we outline a simple belief updating model to formalize our predictions how different shocks – in our empirical application information quasi-exogenous variation in students' ordinal ranks – may affect the mental well-being of students. Our model follows de Quidt and Haushofer (2016) closely and conceptualizes the belief about the returns to one's own ability as a proxy for mental health. This interpretation is motivated by pessimism, i.e., downwards biased and incorrect beliefs about the returns to one's own ability, being one of the main symptoms of depression (Beck, 1967).

Our model builds on two features. First, students are uncertain about the return to effort and learn about their ability based on their performance in school (for evidence of students' imperfect knowledge about their ability and return to effort, see, e.g., Jensen, 2010; Zafar, 2011; Stinebrickner and Stinebrickner, 2012). Second, since school cohorts only have limited size, the ability composition of students varies across cohorts and schools. This implies that a student with a specific ability may be ranked highly in one cohort, but in would be only a mediocre student in another cohort. This variation in the ability distribution is unanticipated from a student's point of view and she therefore uses this signal to update her prior about her own ability. Thus, receiving a negative signal reduces her belief about her ability, while positive signals increases her belief. Following de Quidt and Haushofer (2016), we interpret a student's belief about ability or perceived returns to effort as a proxy for mental health.[4] Yet, updating only occurs if the student exerts effort to receive a good grade. If she shirks, she will not attribute her educational success to her ability. Thus, if the prior about one's ability is sufficiently low, a student may refrain from exerting any effort to avoid further negative signals. This implies that a negative mental health status or low belief about one's own ability may constitute an absorbing state, in which no further updating occurs.

To formalize this intuition and derive more precise predictions, we adopt a simple educational production function, in which "school success" depends on own ability, effort, and exogenous shocks. More specifically, let A_i denote a student's ability or return to effort which is drawn from some distribution F_A. For the ease of exposition, we keep the individual index i implicit and present the model for a single individual with ability A. Let y_t denote the "school success" in period t. The educational production function is specified as

$$y_t = [Ae_t + \underline{A}(1 - e_t)]s_t + \epsilon_t, \tag{1}$$

in which a student's school success depends on the amount she studies, s_t, and her decision to exert high ($e_t = 1$) or low effort ($e_t = 0$). High effort yields a return to studying of A, while shirking yields a low return of $\underline{A}$, assumed to be known to the student. Moreover, school success is subject to exogenous shocks $\epsilon_t \sim N\left(0, \sigma^2_{\epsilon,t}\right)$. In the empirical part of our paper, we

[4]Alternatively, we can assume that there exist a link between the beliefs about one's own ability and mental health given by some monotonic increasing function $g(\cdot)$.

will use shifts in the rank of a student due to having better classmates as a shock to the signal y_t.

The student is uncertain about her own ability and has a prior or belief about her ability denoted by μ_t. Hence, from a student's perspective, her ability is a random variable $A \sim N\big(\mu_t, \sigma^2_{A,t-1}\big)$. We assume that a student maximizes her expected utility by allocating time between studying and leisure. While studying increases her educational success, leisure also enters positively into her utility function. Her utility function is given by

$$EU(e_t, s_t, l_t|\mu_t) = \underbrace{\big[\mu_t e_t + \underline{A}\big(1 - e_t\big)\big] s_t}_{\text{exp. school success}} + \underbrace{\phi\big(l_t\big)}_{\text{utility from leisure}}, \tag{2}$$

where s_t and l_t denote study and leisure time, respectively, total time available is normalized to 1 such that $s_t + l_t = 1$, and $\phi'(\cdot) > 0$, $\phi'' \leq 0$. Expected school success depends on the prior about her ability, μ_t, and the decision to exert effort, e_t, as described above.

Given this setup, a students optimal effort decision is

$$e_t^* = \mathbb{1}\big\{\mu_t > \underline{A}\big\}, \tag{3}$$

and, hence, we can replace $[\mu_t e_t^* + \underline{A}(1 - e_t^*)] = \max\{\mu_t, \underline{A}\}$.[5] Optimal time spend studying equals

$$s^* = 1 - \phi'^{-1}\big[\max\big\{\mu, \underline{A}\big\}\big] \tag{4}$$

and is increasing in perceived own ability.

We now want to characterize how a student learns about her ability. Consider a student who wants to update her prior belief μ_{t-1} given she received a signal y_{t-1} about her own ability. If the student only exerts low study effort, $e_{t-1} = 0$, she does not learn new information about her ability A as studying yields the fixed return $\underline{A}$. If she exerts high effort ($e_{t-1} = 1$), she can learn about her ability. For this, rewrite y_{t-1} as follows:

$$y_{t-1} = As_{t-1} + \epsilon_{t-1} =: x_{t-1} + \epsilon_{t-1}, \tag{5}$$

where $x_{t-1} = As_{t-1} \sim N(\mu_{t-1}s_{t-1}, \sigma^2_{A,t-1}s^2_{t-1})$. Given the signal about school success, y_{t-1}, the student tries to learn about her ability, A. Using the new notation, she wants to infer the

[5]Assuming e_t to be continuous on $[0, 1]$ would not affect this results as linearity implies a corner solution.

expected value of x_{t-1} given y_{t-1}, i.e., the posterior $E[x_{t-1}|y_{t-1}]$:

$$E[x_{t-1}|y_{t-1}] = \frac{\sigma_\epsilon^2}{Var(x_{t-1}) + \sigma_\epsilon^2} E[x_{t-1}] + \frac{Var(x_{t-1})}{Var(x_{t-1}) + \sigma_\epsilon^2} y_{t-1} \tag{6}$$

$$= E[x_{t-1}] + \frac{Var(x_{t-1})}{Var(x_{t-1}) + \sigma_\epsilon^2}(y_{t-1} - E[x_{t-1}]) \tag{7}$$

$$= \mu_{t-1}s_{t-1} + \frac{\sigma_{A,t-1}^2}{\sigma_{A,t-1}^2 + \sigma_\epsilon^2/s_{t-1}^2}\left[(A - \mu_{t-1})s_{t-1} + \epsilon_{t-1}\right]. \tag{8}$$

Hence, the corresponding posterior belief μ_t is:

$$\mu_t = \mu_{t-1} + \frac{\sigma_{A,t-1}^2}{\sigma_{A,t-1}^2 + \sigma_\epsilon^2/s_{t-1}^2}\left[(A - \mu_{t-1}) + \frac{\epsilon_{t-1}}{s_{t-1}}\right]. \tag{9}$$

Several results emerge. First, a negative shock ($\epsilon_{t-1} < 0$) decreases a student's belief about her own ability (i.e., μ_t decreases) and thus has detrimental effects on her mental health, while a positive shock ($\epsilon_{t-1} > 0$) benefits mental health.

Prediction 1. *Negative shocks decrease mental health.*

Second, a student's study time, s_t, (weakly) decreases in the belief about her ability and low-ability students have lower priors μ_{t-1}. This implies that shocks have stronger effects for low-ability students as the term ϵ_{t-1}/s_{t-1} becomes larger.

Prediction 2. *The consequences of shocks are more pronounced for low-ability individuals.*

Third, once the student's belief μ_t decreases below $\underline{A}$, the student withdraws effort and thus stops updating her beliefs.[6] This implies that shocks have persistent effects over time and especially so for low-ability students with priors close to $\underline{A}$.

Prediction 3. *The effects of shocks are persistent over time. They are more pronounced for students with low ability.*

In summary, our theoretical framework predicts that if students have imperfect knowledge about their ability, they learn about it by receiving signals through their school success. Negative shocks to a student's school success decrease her belief about her own ability, these effects are more pronounced in the lower part of the ability distribution, and the consequences persist over time.

[6]Evidence in line with this mechanism has been found in the psychology literature. Kuppens, Allen, and Sheeber (2010) show that individuals with low self-esteem or depressions display high levels of emotional inertia in response to emotional fluctuations relative to individuals with normal levels of self-esteem and no depressions.

3 Data

In order to test the predictions from the previous section, we use restricted data from the National Longitudinal Study of Adolescent to Adult Health (AddHealth). AddHealth is a longitudinal study of a set of representative middle and high schools in the United States.

For our analysis, AddHealth has several key features. First, it covers multiple cohorts within schools, which we need for identification of ordinal rank effect. Second, a representative set of students from each cohort is sampled. Third, students were first interviewed in 1994/95, when students were between 13 and 18 years old. In our analysis, we lever data up to wave IV, the latest wave available, to track students until 2008/09, i.e., when they are 26-32 years old. Fourth, the dataset has repeated measures of an established mental health self-assessment and a standardized test of cognitive ability. In the following, we discuss these two key measures in more detail.

3.1 Data on Students' Mental Health

We assess the mental health status of students using the Center of Epidemiologic Studies Depression Scale (CES-D, Radloff, 1977), an established screening measure to test for depression and depressive disorder that is one of the most widely used instruments in psychiatric epidemiology. The CES-D consists of 19 symptoms (e.g., "You felt sad") and asks respondents how often each symptom applied to them over the course of the past week. Responses are then rated on a scale from 0 ("never or rarely") to 3 ("most of the time or all of the time") and aggregated to a final score ranging from 0 to 57, with higher scores indicating a higher propensity for depressive symptoms. In particular, a score of 16 or higher is commonly interpreted as an indicator for depressions (Radloff, 1977). Appendix Table A1 presents all items of the CES-D score.

The CES-D scale is a widely used instrument to study mental health: it has been adopted to study how far an individual's mental health status spreads through a social network (Fowler and Christakis, 2008; Rosenquist, Fowler, and Christakis, 2011), the effect of mental health for educational attainment (Fletcher, 2008, 2010), and the consequences of wealth shocks (Schwandt, 2018), cash transfers (Haushofer and Shapiro, 2016), or religion (Fruehwirth, Iyer, and Zhang, 2019) on mental health. Moreover, a rich literature in psychology and psychiatric epidemiology has examined the concurrent validity (i.e., the extent to which the CES-D and a subsequent diagnosis coincide; e.g., Lewinsohn et al., 1997), reliability, and internal consistency of the CES-D scale (e.g., Radloff, 1991; Roberts et al., 1990), and it is frequently used in clinical practice (Murphy, 2011).

We present the distribution of the CES-D in Appendix Figure A1: The distribution is highly skewed and about 25% of all respondents can be classified as depressive (i.e., have a CES-D score above 16). In the main part of our analysis, we focus on the 19-item CES-D scale as a measure of mental health. Yet, later waves only administered a short scale comprising of nine and ten items. Thus, when studying the persistence of our results, we scale the CES-D scores of later waves to compare them across waves.[7]

3.2 Constructing a Student's Ordinal Rank Measure

Our main variable of interest is a student's ordinal rank in her school cohort. This is constructed based on an ability assessment that is comparable across cohorts and schools. More specifically, we use the condensed version of the revised Peabody Picture Vocabulary Test (PPVT-R; Dunn and Dunn, 2007) that was administered as part of wave I and provides us with an objective, age-specific, and standardized ability measure.

To construct a student's ordinal rank, we follow Murphy and Weinhardt (forthcoming) as well as Elsner and Isphording (2017, 2018). We first rank students based on their ability within their cohort by assigning them an absolute rank based on their ability.[8] Due to differing school and cohort sizes, we subsequently normalize the absolute rank to an ordinal rank by dividing by the cohort size:

$$\text{ordinal rank} = \frac{\text{absolute rank} - 1}{\text{cohort size} - 1}. \tag{10}$$

This results in an ordinal rank which assigns the value 1 to the highest-ranked student and 0 to the lowest-ranked student. We illustrate how this ordinal rank varies with a student's ability in Figure 1. The average ordinal rank increases in a student's ability. Yet, as we are interested in estimating the effect of a student's ordinal rank on her mental health holding her ability constant, we need sufficient variation in ranks for a given ability level. Figure 1 provides some evidence that this is indeed the case: for each ability decile in the global ability distribution, we observe variation in a student's local rank. However, conditioning on various variables, most notably own ability, will likely capture some of the variation depicted in Figure 1. In Section 4, we address this issue and study whether there is sufficient variation in the rank variable after conditioning on a set of controls suggested by our empirical strategy. Here we find that variation in ranks across the ability distribution, although reduced, continues to hold.

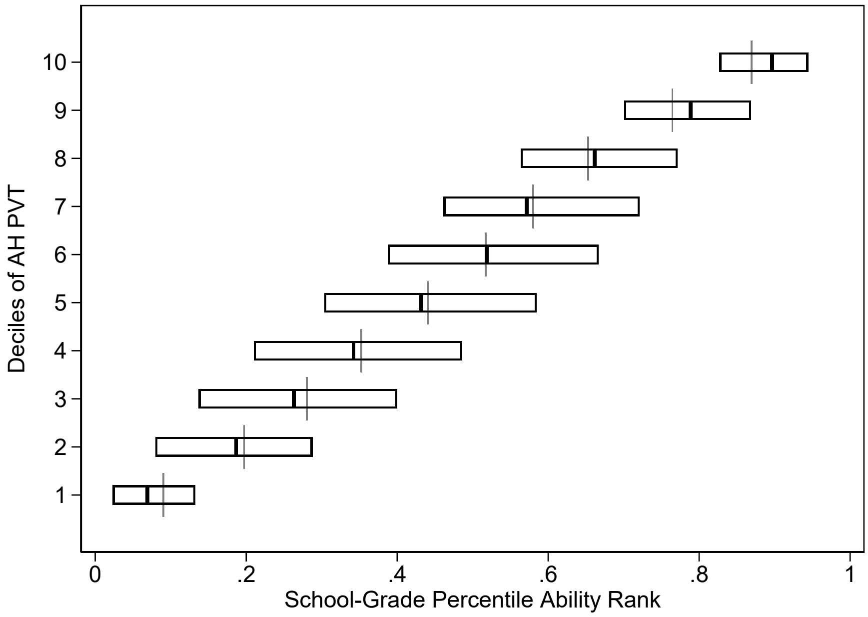
A potential confound of our rank measure based on AddHealth's Picture Vocabulary Test is that neither students nor teachers learn the results of this test.[9] The question remains how salient is our rank measure. We evaluate this potential confound and study the relationship of ordinal ranks based on our ability measure and students' self-assessment about their relative

[7]Using data from wave I, Appendix Figure A2 shows that the short and long versions of the CES-D scale indeed are highly correlated. To perform the rescaling, we scale the nine (ten) item scales by 19/9 (19/10) to match the 19 item scale.

[8]We assign the student with the lowest ability the rank 1 and then increase the absolute rank. Thus, the higher a student's absolute rank, the higher her ability. If two students have the same ability, they are assigned an equal rank.

[9]Alternatively, we could have used a student's GPA to calculate ranks. Yet, this measure would have major limitations. First, GPA may be comparable within a school cohort, but comparisons across cohorts and schools may be difficult. Moreover, teachers have discretion about the grades of students potentially capturing confounding effects, and students' GPA may be affected by classical peer effects.

Figure 1. Variation in Students' Ordinal Ranks by Ability Decile



Notes: This figure presents the variation in ranks for each ability decile. In particular, for each decile, black boxes illustrate the 25th, 50th, and 75 percentile of ordinal ranks, while gray lines indicate the mean ranks.

ability and also their desires and expectations for attending college. We report these results in Appendix Table A3. Reassuringly, we find a strong and positive association between ability rank and self-assessed relative ability, mitigating the concern that ranks are not salient to students. Moreover, we observe that those students with a higher rank also have significantly higher expectations regarding their educational attainment.

A second concern is that ability was measured as part of wave I and, hence, could be determined simultaneously with students' ranks. Yet, cognitive ability is only malleable early in life and is considered as stable from age 10 onward (Jensen, 1998). At the time of AddHealth's wave I, when students were on average 15.6 years old, cognitive ability can therefore be seen as predetermined and unaffected by features of the school environment and students' own, or their parents', investments.

Finally, we only observe a random sample of students in each school cohort introducing additional sampling variation in our data. Using a series of Monte Carlo simulations with the same data and a similar identification strategy, Elsner and Isphording (2017) show that sampling variation is only a minor concern. Taken together, defining ordinal ranks based on AddHealth's Picture Vocabulary Test yields a measure that is pre-determined, salient, and comparable across cohorts as well as schools. In the following, we therefore use this measure to investigate the causal effects of ranks on students' mental health.

3.3 Summary Statistics

We present summary statistics of our sample in Table 1. In total, we observe 18454 students in wave I. 51% of these students are female and they are on average 15.6 years old. The majority of students are white (53%) and 34% of all students come from college-educated households. Moreover, the mean CES-D score in our sample is 11.3.

Table 1. Summary Statistics

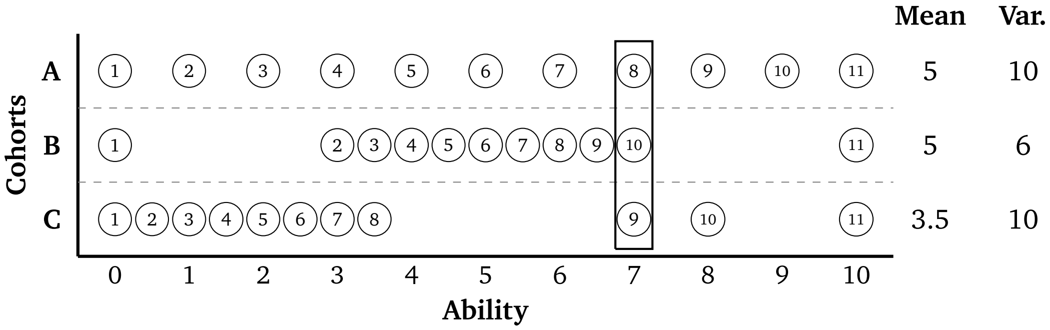
	Mean	SD	Min	Max
CES-D Wave I	11.33	7.60	0.00	56.00
Ordinal Rank	0.47	0.28	0.00	1.00
Ability (AH PVT scores)	100.17	14.66	13.00	139.00
Female	0.51	0.50	0.00	1.00
Age	15.63	1.70	11.00	19.00
Ethnicity				
White	0.53	0.50	0.00	1.00
Black	0.22	0.41	0.00	1.00
Hispanic	0.17	0.37	0.00	1.00
Asian	0.07	0.25	0.00	1.00
Other	0.02	0.14	0.00	1.00
Parental Background				
Less HS	0.18	0.38	0.00	1.00
HS or GED	0.28	0.45	0.00	1.00
Some College	0.20	0.40	0.00	1.00
College	0.22	0.42	0.00	1.00
Post-Graduate	0.12	0.32	0.00	1.00
Single Parent Household	0.32	0.47	0.00	1.00
Grade				
Grade 7	0.13	0.34	0.00	1.00
Grade 8	0.13	0.34	0.00	1.00
Grade 9	0.18	0.38	0.00	1.00
Grade 10	0.20	0.40	0.00	1.00
Grade 11	0.19	0.39	0.00	1.00
Grade 12	0.16	0.37	0.00	1.00
Observations	18454			

Notes: This table presents summary statistics for the sample used in the analysis.

4 Empirical Strategy

Our aim is to estimate the causal effect of a student's ordinal rank on her mental health holding both own and peer ability constant. Before we describe our identification strategy, we want to provide some intuition for the identifying variation that we are exploiting. Consider a single school, in which we observe at least two cohorts. To identify a rank effect, we compare two students having the same ability, but different ranks within their respective cohorts. Figure 2 presents an example of this identifying variation. In this example, either the mean or the variance of ability differs within cohorts. This gives rise to different ranks for students with the same ability of 7 (i.e., their rank varies between 8 and 10 in our example).

Figure 2. Illustrative Example of the Identifying Variation



Notes: This figure illustrates how variations in the ability distribution across cohorts allows to identify rank effects. In these examples, we fixed the minimum and maximum of the ability distribution and allow either the mean or the variance of the ability distribution to differ across cohorts. Students are ranked according to their ability. A comparison of cohort A and B shows that holding the mean ability constant can give rise to different ranks for individuals of the same ability. A comparison of cohorts A and C illustrates that a variation in mean ability, but constant variance in ability also can give rise to different ranks.

The identifying variation illustrated in Figure 2 describes our first identification strategy. We follow Hoxby (2000a,b) and exploit the idiosyncratic variation ability across cohorts within the same school. This motivates the following empirical specification:

$$y_{ics} = \alpha rank_{ics} + f\left(a_{ics}\right) + \mathbf{X}_i'\beta + \theta_{ics} + \epsilon_{ics}, \tag{11}$$

in which y_{ics} denotes the mental health of student i in cohort c and school s. $rank_{ics}$ is this student's ordinal rank within her cohort, as defined in equation (10), and $f\left(a_{ics}\right)$ denotes a flexible functional form of a student's own ability (in our application we use a fourth order polynomial). $\mathbf{X}_i$ corresponds to a vector of student characteristics which includes gender, age and age squared, indicators for race or ethnicity (Asian, Black, Hispanic, Other), indicators for their parents' highest degree (less than high school, high school/GED, some college, college degree, post-graduate degree), and an indicator for being raised in a single parent household. The term θ_{isc} consists of school, δ_s, and cohort fixed effects, γ_c, to capture unobserved heterogeneity by school and cohort.

One concern with equation (11) is that a student's ordinal rank is related to the average ability within the cohort. As we are interested in the causal effect of ordinal ranks, we do not want our rank measure to be confounded by typical peer effects. We therefore add two further variables capturing peer effects: the mean, $\overline{a}_{-ics}$, and standard deviation, $\sigma\left(a_{-ics}\right)$, of the other students' ability.[10] In our first empirical specification, we control for $\theta_{ics} = \lambda\overline{a}_{-ics} + \gamma_c + \delta_s$. In

[10]To calculate the mean and standard deviation of peer ability, we exclude student i.

refinements to this specification, we add further peer variables and the peer ability standard deviation.

In a second specification, we go a step further and control for any heterogeneity of a cohort in a given school. We do this by introducing school-specific cohort fixed effects, i.e., $\theta_{ics} = \zeta_{cs} = \gamma_c \times \delta_s$. Using these cohort-by-school fixed effects, we absorb any potential peer effects in terms of means, variances or any higher moment. In this case, to identify rank effects, we rely on the variation of students' ranks within their cohort and compare it to other cohorts and schools after all observed and unobserved differences between school-specific cohorts are removed.

In order to identify the causal effect of ranks, α, the ordinal rank has to be as good as randomly assigned. More specifically, this means that we need to assume exogeneity of ranks conditional on a rich set of controls and fixed effects, that is,

$$E\left[\epsilon_{ics}|rank_{ics}, f\left(a_{ics}\right), \mathbf{X}_i, \theta_{ics}\right] = 0. \tag{12}$$

In essence, this assumption implies that ϵ_{ics} is uncorrelated with a student's ordinal rank conditional on her own ability, individual characteristics and a set of cohort-level controls. In our first specification, we assume that that these cohort-level controls are given by separate school and cohort fixed effects, as well as peer effects in students ability. Using these and individual controls, we compare students in the same school and cohort, with similar peers, and with the same observable characteristics and own-ability but who have different ranks.

Nonetheless, there might be other factors potentially affecting a student's mental health and her rank that are unobservable to us. If such factors are present, this violates our exogeneity assumption and, hence, prevents us from estimating unbiased rank effects. Therefore, we adopt a second specification with school-specific cohort fixed effects, which absorb all observable and unobservable differences between cohorts and schools. As mentioned above, we then identify rank effects from variations in ranks within school cohorts or, more specifically, from combinations of different shapes of the ability distribution across school cohorts and own ability that define ordinal ranks.

A natural question is how much variation is left in our rank variable after conditioning on our set of controls and different fixed effects. The standard variation in ranks without controls is 0.28 as shown in Table 1. However, since a student's rank and ability are positively correlated, some part of the variation may just be due to ability. Moreover, as our analysis will be focused on heterogeneous effects by ability decile, we need to ensure that there is sufficient variation in our variable of interest in each of the deciles. To assess this condition, we calculate the residual variation in ranks after controlling for potential confounds and compare this to the raw standard deviation in ranks. Appendix Table A2 shows that the raw standard deviation in ranks by decile varies between 0.09 and 0.18 (see also Figure 1 for a graphical representation of the raw variation in ranks by ability decile). Conditioning on school and grade fixed effects and our set of baseline controls, reduces this variation to 0.07-0.12. Using school-specific grade fixed effects, reduces the variation slightly further to 0.07-0.11. Hence, our rich set of controls and fixed effects, leaves at least 40% of the raw variation. We therefore think that the residual variation in ordinal ranks is sufficient to study their causal effect on mental health.

5 Results

How does a student's ordinal rank causally affects her mental health? Our theoretical framework in Section 2 generates three predictions: First, we should observe that positive (negative) shocks, in our application a higher rank, benefit (worsen) a student's mental health. Second, these effects are predicted to be stronger at the lower end of the ability distribution, where students are more likely to withdraw their study effort in response to negative shocks. Third, the framework suggests that these effects are persistent at the lower end of the distribution.

5.1 Average Effect of Students' Ranks on Mental Health

We begin by studying the average effect of a student's rank on her mental health. More specifically, we relate a student's mental health measured by CES-D scores to her ordinal rank based on our main specification in equation (11) with standard errors clustered on the school-grade level. We present our results in Table 2. Based on our first empirical specification controlling for separate school and cohort fixed effects and ability peer effects, column (1) shows that higher ranks reduce CES-D scores, i.e., improve student's mental health. Moving a student at the 25th percentile to the 75th percentile, improves her mental health by 0.8 CES-D points or 0.11SD. We interpret this as a large effect since we compare students with the same observable characteristics, in particular the same ability, and the same average cohort ability that only happen to be in a cohort where they have different ranks.

Allowing for peer effects in ability only is potentially restrictive. In particular, the literature on linear-in-means peer effects has identified a range of different peer characteristics that causally affect a student's performance and thereby may also affect their mental health. Examples include the share of females, minorities, or students with high socioeconomic status (Lavy and Schlosser, 2011; Hoxby, 2000b; Cools, Fernández, and Patacchini, 2019). In column (2) we add these additional peer effect terms. Furthermore, in column (3), we also add controls for the standard deviation in peer ability and other peer characteristics, as they have been shown to also affect school performance (e.g., Tincani, 2017). Our estimates show that the the rank effect is robust to the inclusion of these additional peer effects and vary only slightly.

In column (4), we adopt our second empirical specification using grade-by-school fixed effects. This set of fixed effects accounts for all potential peer effects and uses the individual-level variation within school-cohorts to identify the effect of ordinal ranks on the mental health status of students. The coefficient of interest slightly increases in magnitude.

Our identification strategy assumes that a student's rank is exogenous conditional on own ability and school and cohort fixed effects. It is reassuring that our findings remain nearly

Table 2. Average Effect of Ordinal Ranks on Mental Health

	Mental Health (CES-D score)			
	(1)	(2)	(3)	(4)
Panel A: Baseline effects				
Rank	-1.58	-1.58	-1.60	-1.68
	(0.71)**	(0.71)**	(0.71)**	(0.72)**
	[0.75]**	[0.75]**	[0.76]**	[0.76]**
Individual Controls	Yes	Yes	Yes	Yes
Ability Peer Effects (mean)	Yes	Yes	Yes	No
Further Peer Effects (mean)	No	Yes	Yes	No
Ability Peer Effects (SD)	No	No	Yes	No
Further Peer Effects (SD)	No	No	Yes	No
School and Grade FE	Yes	Yes	Yes	No
School × Grade FE	No	No	No	Yes
N	18454	18454	18454	18454
R^2	0.108	0.108	0.109	0.127
Panel B: Standardized Effects				
Standardized effect	-0.21	-0.21	-0.21	-0.22
	(0.09)**	(0.09)**	(0.09)**	(0.09)**
	[0.10]**	[0.10]**	[0.10]**	[0.10]**
Panel C: Role of Unobservables				
Oster's δ ($R^2_{max} = 1.3R^2$)	-1.02	-1.2	-1.9	-1.58

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses are clustered at the school-grade level, standard errors in brackets are clustered at the school level. Each coefficient presents a regression of CES-D scores (lower scores corresponding to better mental health) on an individual's percentile rank at the school-grade level based on equation (11). We include a fourth-order polynomial in own ability, gender, ethnicity, age and age-squared, parental education and being raised by a single parent as control variables. Peer ability includes the leave-one-out mean and standard deviation of peer ability, peer controls comprises additional peer effect terms in gender, ethnicity, and parental education. We present standardized effects of our main effect below each specification. Oster's δ quantifies how severe selection based on unobservables would need to be for zero rank effects (Oster, 2019). To calculate δ, we follow Oster (2019) and assume a maximum R^2_{max} of 1.3 times the actual R^2.

unaffected once we control for additional potential confounds and if we adopt a second identification strategy using school-specific cohort fixed effects. A more formal approach to test for the role of unobservables is to ask how severe selection based on unobservables would need to be to drive down the estimated rank effects to zero. In order to quantify this, we follow Oster (2019) and calculate δ, a measure for the degree of selection based on unobservable relative to observable characteristics. If δ is larger than one, this indicates that selection on unobservables would need to be at least as important as selection based on observables to explain our effects. As shown in the bottom of Table 2, δ is larger than one in all specifications. Since we controlled for arguably the most important factors that could bias students' ordinal ranks and that may affect mental health through differences in the cohort composition, we conclude that unobservables are unlikely to drive our estimated rank effects.

As our treatment – a student's rank in her cohort – is assigned on the school-grade level, we cluster standard errors on the school-grade level as suggested by Abadie et al. (2017). However, one might think that there are common shocks affecting all students at a given school. For robustness, Table 2 also reports standard errors clustered on the school-level in brackets. Our conclusions are unaffected by this.

Taken together, the results from Table 2 document that the ordinal rank of students causally affect their mental health measured by CES-D scores. The estimated effects are comparable to increasing a student's ability by approximately one standard deviation (see Appendix Figure A3) or half of the effect of losing one's job (Marcus, 2013). Taking a one standard deviation increase in ranks, the effects correspond to a 0.06 standard deviation increase in CES-D scores and are there about the same size as the effect of ordinal ranks on standardized test scores of British students (0.08SD; Murphy and Weinhardt, forthcoming).

5.2 Heterogeneous Rank Effects

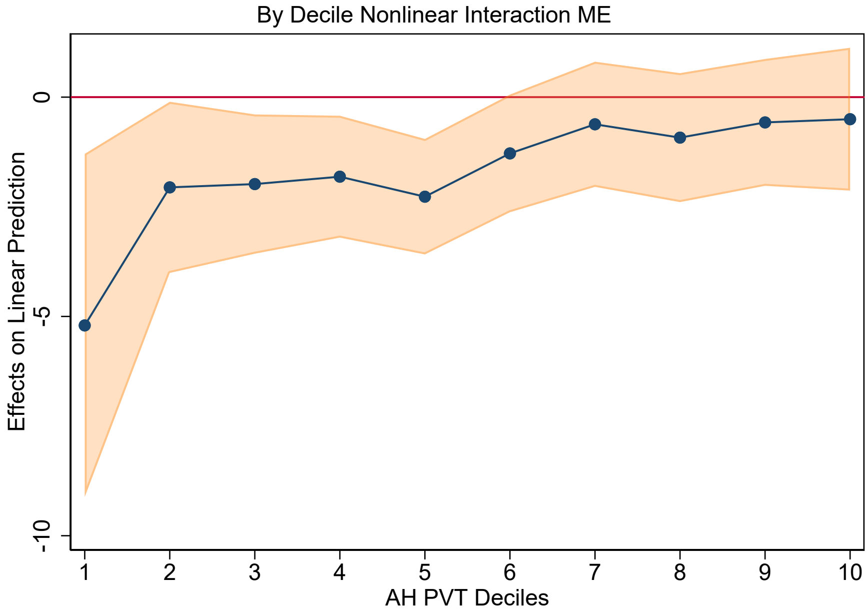
Our theoretical framework suggests that shocks have more pronounced effects on students at the lower end of the distribution (cf. Prediction 2). To test this prediction, we study whether effects of ordinal ranks differ by ability decile. In a second step, we want to provide a more comprehensive picture by considering heterogeneities in other observable characteristics that may be of interest when designing policies exploiting positive or alleviating negative effects of ranks.

5.2.1 Heterogeneity by Ability

Prediction 2 suggests that the shocks to students at the lower end of the distribution are larger than for higher-ability students as a lower perceived ability decreases study time which subsequently amplifies the effect of exogenous shocks. If the prediction is correct, we should observe stronger (weaker) rank effects for lower (higher) ability quantiles. We therefore enrich our main specification given in equation (11) by interacting the rank with indicators for each ability decile.

Figure 3 displays the results of this analysis graphically, while Table 3 presents the corresponding regression estimates. We indeed find that rank effects are more pronounced at the lower end of the distribution. In particular, the ordinal rank reduces the CES-D score by 5.2 points when moving a student from the bottom to the top rank, corresponds to 0.70SD. This effect amounts to three times the average effect and would suffice to move a student diagnosed with a moderate depression according to a threshold of 16 (Radloff, 1977) to the average CES-D score of 11.3 in our sample. While the point estimates are negative for all deciles, the estimated effects slowly fade out, and are rather small and not significant at the top end of the distribution (coefficient of -0.50 with a p-value of 0.51 for the tenth decile). These results are therefore consistent with Prediction 2 of our theoretical framework, which suggests that effects should be more pronounced for low-ability students.

Figure 3. Effects of Ordinal Ranks by Ability Decile



Notes: This figure presents the effect of ordinal ranks by ability decile. We estimate the effects using enriching specification (11) and interact a student's rank with indicators for ability deciles. Shaded area indicates 90% confidence intervals clustered on the school-grade level.

Table 3. Effects of Ordinal Ranks by Ability Decile

	Effect on Mental Health by Decile									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rank	-5.20**	-2.06*	-1.98**	-1.81**	-2.27***	-1.28*	-0.62	-0.92	-0.58	-0.50
	(2.23)	(1.17)	(0.89)	(0.81)	(0.83)	(0.76)	(0.78)	(0.82)	(0.83)	(0.94)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the school-grade level. We include all base controls, peer ability, school and grade fixed effects as in our preferred baseline specification presented in column (1) of Table 2.

5.2.2 Further Heterogeneities by Other Individual and Cohort Characteristics

Although our theoretical framework is not aimed at providing predictions for specific subsamples, they are nevertheless important for policy-makers interested in targeting policies and contribute to a better understanding of rank effects on mental health. We focus on three observable characteristics of students – their gender, ethnicity, and socioeconomic status – to identify whether certain groups react more to ranks than others. A priori it is not clear for which subsamples we should observe stronger effects. While previous research has shown that females may be more responsive to features of the environment (Croson and Gneezy, 2009), males are more likely to enter competitions which have rankings as inherent characteristics (Niederle and Vesterlund, 2007). Similarly, individuals from low socio-economic status may be more stressed by social rank concerns (Hackman, Farah, and Meaney, 2010), but students from college-educated parents could also be more receptive to ranks as part of the competition for colleges.

In two further checks, we focus on margins that are subject to frequent debates in the design of schools and classrooms and evaluate their potential consequences for students' mental health. More specifically, we ask whether tracking regimes, or restricting the size of cohorts, impacts rank effects on mental health. There is an active debate about the consequences of tracking regimes (e.g., Duflo, Dupas, and Kremer, 2011; Garlick, 2018), and although we do not observe formal tracking, we exploit one feature of tracking: it creates more homogeneous groups in terms of students' ability. In principle, this increase in homogeneity within cohorts could introduce some more pressure and amplify the consequences of signals about one's own ability. Relatedly, reducing cohort or classroom sizes might have beneficial effects on educational outcomes (Angrist and Lavy, 1999; Krueger, 1999; Hoxby, 2000a; Krueger and Whitmore, 2001), but smaller cohorts and classes also increase the salience of students' ranks as students can easily compare their own performance to that of their peers. In the last two analyses, we therefore consider whether differences in the variance in ability and the cohort size give rise to potential heterogeneous rank effects.

Table 4 presents effects of the ordinal rank by gender (Panel A), minority status (Panel B), as well as socioeconomic status proxied by whether parents attended college or not.[11] Rank effects on mental health seem to be more pronounced among females, non-white students, and students from households without college educated parents, but we lack statistical power to provide concluding evidence (p-values of the differences in coefficients between groups are 0.28, 0.45, and 0.11 for splits by gender, race, and socioeconomic status, respectively).

In the remaining panels of Table 4, we study heterogeneities based on cohort characteristics. More specifically, we perform a median split based on the variance in ability for each cohort (Panel D) and analyze differences by cohort size (Panel E, where we adopt the classification in small, medium, and large as used by Elsner and Isphording, 2017). Consistent with the idea that ranks become more salient in cohorts with higher dispersion in ability, we find suggestive evidence that rank effects are larger in cohorts with high variance, but cannot reject that these coefficients equal each other (p-value = 0.64). When looking at the size of the cohort, we observe that effects are more pronounced for larger cohorts and this difference is significant when comparing small and large cohorts (p-value = 0.10).

Based on these heterogeneous effects, rank effects seem to be more pronounced for females, minorities, and students from low socioeconomic backgrounds. This suggests that policies that try to alleviate rank effects should be targeted at these groups. Perhaps surprisingly, we do not observe that rank effects are more pronounced in small cohorts. To the contrary, we find stronger effects for larger cohorts, maybe because facing more higher or lower ranked students increases the salience of one's own rank.

[11] We focus on heterogeneities of the average rank effect. While it would be interesting to study differential patterns in the heterogeneities by ability documented in the previous subsection, we lack power to do this.

Table 4. Heterogeneities by Gender, Race, Socioeconomic Status, and School Characteristics

	Effect on Mental Health					
	A. By Gender			*B. By Race*		
	Females	Males	p-value (F=M)	White	Non-white	p-value (W=NW)
Rank	-2.22**	-0.68	0.277	-1.03	-2.11*	0.450
	(1.11)	(0.85)		(0.95)	(1.10)	
	C. By Socioeconomic Status			*D. By Ability Variance*		
	College	No College	p-value (C=NC)	Low Var.	High Var.	p-value (L=H)
Rank	0.05	-2.15**	0.109	-1.12	-1.92	0.635
	(1.15)	(0.84)		(1.04)	(1.32)	
	E. By Cohort Size					
	Small (<150)	Medium (150-299)	Large (≥ 300)	p-value (S=M)	p-value (S=L)	p-value (M=L)
Rank	-0.16	-0.67	-2.93***	0.774	0.096	0.153
	(1.25)	(1.24)	(1.10)			

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the school-grade level. We include all base controls, peer ability, school and grade fixed effects as in our preferred baseline specification in column (1) of Table 2.

5.3 Persistence of Rank Effects

We have established that the ordinal rank exerts a causal effect on students' mental health and this effect is more pronounced for low-ability students. We now want to explore the dynamic effects of ordinal ranks. As there is a strong association between ability and mental health (see Appendix Figure A3), and students at the lower end of the distribution experience stronger effects, they also have a higher risk of becoming depressed as a result of negative shocks. Following our theoretical framework and evidence from the psychological and neuroscience literature (e.g., Holtzheimer and Mayberg, 2011), we think of depressions as absorbing states. If this is the case, we should observe that our effects are persistent for those at-risk students.

To explore this persistence, we use CES-D scores elicited in each of the following waves. In particular, we can study the short-term persistence using wave II, which was conducted one year after wave I, medium-term effects approximately seven years after wave I using data from wave III, and long-term persistence using wave IV data 14 years after the baseline, when respondents were between 24 and 32 years old. Similar to Section 5.2.1, we estimate our main specification (11) but study the heterogeneous effects of the ordinal rank in wave I by ability decile on measures of mental health in later waves. Unfortunately, not all waves conducted the 19-item version of the CES-D but adopted a short-version comprising ten and nine of the original items in waves III and IV, respectively. To compare our estimates from all waves to the baseline, we scale the mental health measures from the short scales by $^{20}/_{9}$ and $^{20}/_{10}$ to correspond to the same range from 0 to 57 as the baseline scale.[12]

Table 5. Effects of Ordinal Ranks by Ability Decile

	Effect on Mental Health by Decile										Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Panel A. Immediate Effects (Wave I, 1994/1995)											
Rank	-5.20**	-2.05*	-1.98**	-1.81**	-2.27***	-1.28*	-0.62	-0.92	-0.57	-0.50	18454
	(2.23)	(1.17)	(0.89)	(0.81)	(0.83)	(0.76)	(0.78)	(0.82)	(0.83)	(0.94)	
Panel B. Short-term Effects (Wave II, 1996)											
Rank	-6.02**	-1.73	-1.76*	-1.66*	-2.35***	-1.31	-0.97	-0.89	-1.02	-1.97*	12892
	(2.70)	(1.44)	(1.06)	(0.92)	(0.86)	(0.89)	(0.94)	(0.95)	(0.94)	(1.07)	
Panel C. Medium-term Effects (Wave III, 2001/2002)											
Rank	-5.07**	-0.58	-0.78	0.19	0.15	-0.23	-0.23	-0.00	0.48	0.48	13541
	(2.54)	(1.49)	(1.17)	(1.01)	(0.98)	(0.91)	(0.96)	(1.00)	(1.02)	(1.18)	
Panel D. Long-term Effects (Wave IV, 2008)											
Rank	-9.40***	-2.30*	-1.19	-1.40	-0.28	0.90	0.17	0.25	0.05	-0.56	14016
	(2.27)	(1.36)	(1.18)	(1.05)	(0.98)	(0.96)	(1.02)	(1.05)	(1.06)	(1.20)	

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the school-grade level. We include all base controls, peer ability, school and grade fixed effects as in our preferred baseline specification of column (1) in Table 2.

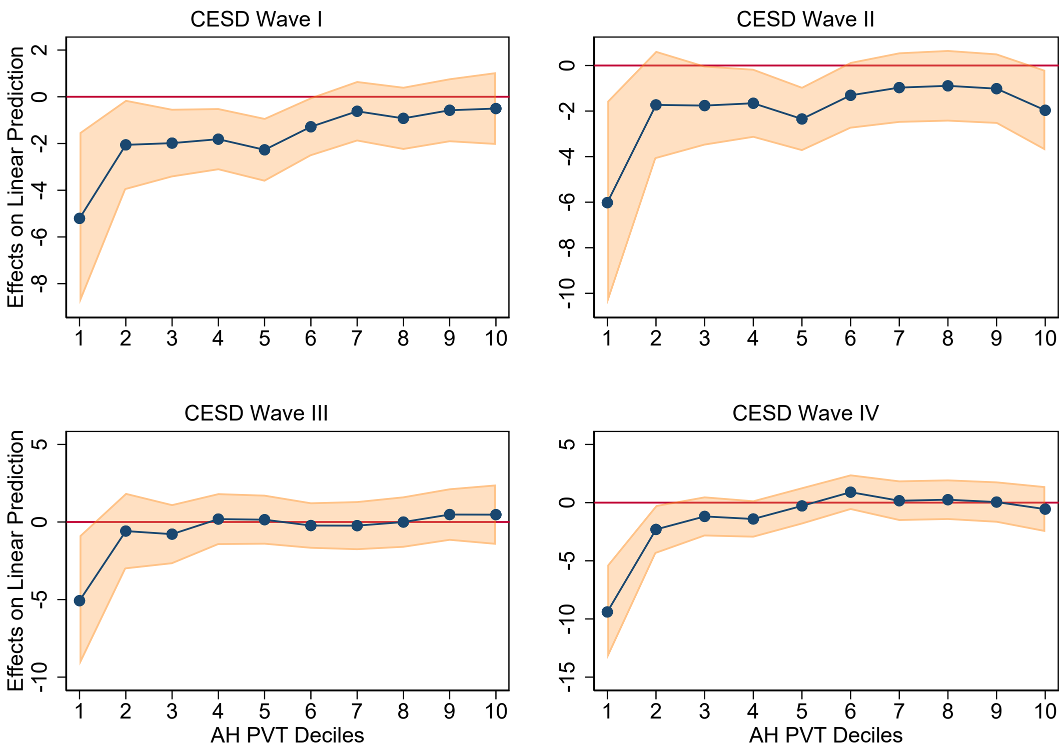
Figure 4 shows that the general pattern persists across all four waves: the effect of ordinal ranks in wave I is significant and pronounced at the bottom of the ability distribution and insignificant as well as smaller in magnitude for higher ability deciles. Table 5 quantifies these effects. Panel A replicates the estimates of Section 5.2.1, while Panels B through D consider the short-, medium-, and long-term effects of ordinal ranks in wave I. We find that the the significant effects for the lowest ability decile persist across waves and amount to -5.07 to -9.40 CES-D points, and fade out for higher ability deciles. This pattern is strikingly similar from wave I, when students are 12-18 years old, to wave IV, when those students are adults of 26-32 years.

These results are in line with the Prediction 3 suggesting that once a negative shock reduces a student's belief in a her ability sufficiently, she withdraws study effort and therefore avoids new signals. As a consequence, her belief about the returns to ability remains low, positive updating is less likely, and depressions are some form of absorbing states. In other words, her mental health remains in a poor state.

Taken at face value, the estimates further suggest that the effects even become more pronounced over time. This points towards an interpretation of depressions as absorbing states, and negative shocks as triggers for potential vicious cycles. In the following section, we therefore explore whether there is indeed an asymmetry in positive and negative shocks.

[12] As shown in Appendix Figure A2 the short- and long-versions of the CES-D are highly correlated in wave 1. We therefore use scaled version to compare our results to the baseline effects documented in Section 5.2.1.

Figure 4. Persistent Effects of Ordinal Ranks by Ability Decile



Notes: This figure presents the effect of ordinal ranks by ability decile for each of the waves as shown in Table 5. Shaded area indicates 90% confidence intervals clustered on the school-grade level.

5.4 Exploring asymmetries in shocks

We documented large and persistent effects of ordinal ranks on mental health. Yet, not all shocks are similar. In particular, our results suggest that once students, especially low-ability students, experience a negative shock, their mental health deteriorates and remains in a poor condition. We now want to provide more evidence on the asymmetry of these effects. If our conjecture is right, we should observe more pronounced rank effects for negative than for positive shocks.

In order to differentiate between positive and negative shocks, we calculate the expected rank of students, independent of the ability composition of their school cohort. To do this, we calculate rank measures similar to equation (10), but consider students in a given cohort across all schools. In other words, we calculate individual i's rank, $rank_{ic}$, among all students in a given cohort c, i.e., independent of their school s rather than within a school as in the case of $rank_{ics}$. We then define student i receiving a negative shock if her rank in her school cohort, $rank_{ics}$ is lower than the rank among all students in a given cohort, $rank_{ic}$:

$$\text{negative shock} = \mathbb{1}\{rank_{ics} < rank_{ic}\}. \tag{13}$$

In the literature, there is some evidence on asymmetric updating and information avoidance after negative signals based on experiments. While some papers find support for the so-called "good news-bad news" effect (e.g., Eil and Rao, 2011; Möbius et al., 2014), in which people react to good news about themselves but neglect negative signals, others find evidence of asymmetric updating in self-relevant domains along the lines of our conjecture (Ertac, 2011). Focusing on interactions of belief updating and mental health, Gotlib et al. (2004) provide evidence that depressed individuals have attentional biases for negative, but not positive information. We thus expect that negative signals, i.e., having a rank that is lower than one might expect, leads to stronger responses in mental health as positive shocks.

In Table 6, we study asymmetric responses using our definition of negative shocks from equation (13). Column (1) replicates our baseline result of the first column of Table 2 that ranks significantly reduce CES-D scores. We then study the causal effect of receiving a negative shock on mental health, while abstracting from rank effects. Column (2) shows that negative shocks increase CES-D scores by 0.36 points corresponding to 0.05 SD. In other words, negative shocks are detrimental to mental health.

Table 6. Asymmetric Effects of Ordinal Ranks

	Effect on Mental Health		
	(1)	(2)	(3)
Rank	-1.58**		-0.73
	(0.71)		(0.84)
Neg. shock		0.36**	0.61**
		(0.17)	(0.28)
Rank × Neg. shock			-0.76*
			(0.43)

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses and are clustered at the school-grade level. We include all base controls, peer ability, school and grade fixed effects as in our preferred baseline specification of column (1) in Table 2.

Column (3) explores the interaction of ranks and negative shocks by regressing CES-D scores on ranks, an indicator for negative shocks, as well as their interaction. We find that once we account for ranks, negative shocks have even more pronounced effects increasing CES-D scores by 0.61 (0.08 SD). Moreover, rank effects seem to be driven by those who receive negative shocks.

These results provide evidence that the effects of ordinal ranks on mental health we observe are due to negative shocks, i.e., they stem from effects of ranks on those who rank lower in their school cohort than expected. In line with Ertac (2011) and evidence from the psychological literature, but contrasting Eil and Rao (2011) and Möbius et al. (2014), we find that students update stronger in case of negative shocks.[13]

[13] Eil and Rao (2011) also show that subjects in their experiment have an aversion to new information after receiving a negative signal, which is in line with what we expect despite opposite results on asymmetric information processing.

6 Conclusion

What are the lasting effects of peers on students' mental health? We present a theoretical framework in which students face uncertainty over their own ability and need to allocate their time between studying and leisure. Conditional on studying, they can exert effort to learn about it from noisy signals. Based on this framework, we derive several predictions. Negative signals should worsen a student's mental health, these effects are more pronounced at the lower end of the ability distribution, and persist over time. In order to test these predictions we use data from AddHealth, a longitudinal study of a representative set of students in the United States, and lever quasi-exogenous variation in the ability distribution across cohorts. This creates quasi-random variation in a student's ordinal rank, which we interpret as a signal about her ability, and allows us to identify the causal effect of ranks on students' mental health.

We find that ranks causally affect students' mental health measured by CES-D scores, an established self-assessment of mental health. Increasing a student's rank from the 25th to the 75th percentile, improves her mental health by 10-11% of a standard deviation and is comparable to rank effects estimated for test scores (Murphy and Weinhardt, forthcoming) and are about half of the effect of losing one's job on mental health (Marcus, 2013). Moreover, these effects are more pronounced at the lower end of the ability distribution and this pattern persists over time. Even 14 years after the first wave of the survey, when individuals in our data are approximately 26-32 years old, we find the same pattern as in wave I and show that these initial effect persists over time. In addition, when differentiating between positive and negative shocks, we find pronounced asymmetries in those effects. In particular, only negative shocks seem to affect mental health.

Our study provides evidence on the long-lasting effects of features of the school environment and raises several avenues for further research. The persistence of our effects helps to understand why mental health affects educational attainment (Currie and Stabile, 2006; Fletcher, 2010), and therefore may be an additional skill valued on the labor market (Heckman, Stixrud, and Urzua, 2006; Fletcher, 2014). Our results therefore point towards a mental health formation process similar to the accumulation of general health (Grossman, 1972) or the formation of other cognitive and non-cognitive skills (Cunha and Heckman, 2008; Cunha, Heckman, and Schennach, 2010). Extending these models would shed light on the relationship between these skills and mental health more generally. Moreover, such a model could be used to quantify the role of mental health to explain rank effects on educational outcomes.

The asymmetry of rank effects also allows to consider potential consequences for policymakers and school administrators. If effect of ranks on other outcomes apart from mental health are also asymmetric, this could provide a rationale to think about optimal classroom assignment as in Carrell, Sacerdote, and West (2013). Note, however, that the consequences of different assignments may be ambiguous if peer effects are present in multiple dimensions (Kiessling, Radbruch, and Schaube, 2019).

We think that studying different causes of mental health and their long-term effects are a fruitful area for future research. Given the rise of mental health issues in the developed world and the wide-spread prevalence in developing countries, policy-makers have high interest in understanding the causes of these issues to design policies alleviating these effects.

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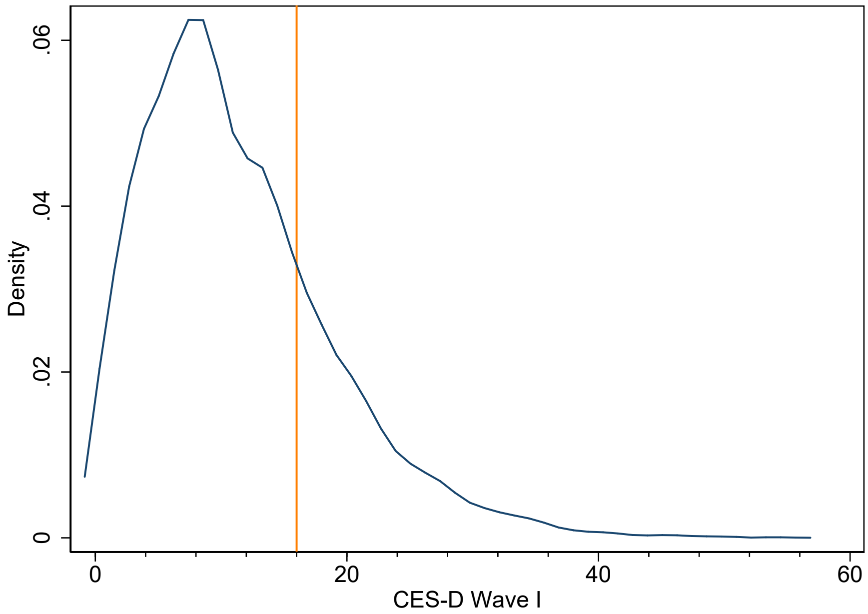
A Appendix

Table A1. Items of the CES-D Scale

How often was the following true during the past week?	Wave I	Wave II	Wave III	Wave IV
1. You felt depressed.	X	X	X	X
2. It was hard to get started doing things.	X	X		
3. People were unfriendly to you.	X	X		
4. You didn't feel like eating, your appetite was poor.	X	X		
5. You enjoyed life.	X	X	X	X
6. You felt fearful.	X	X		
7. You felt hopeful about the future.	X	X		
8. You felt life was not worth living.	X	X		
9. You felt lonely.	X	X		
10. You felt sad.	X	X	X	X
11. You felt that people disliked you.	X	X	X	X
12. You felt that you could not shake off the blues, even with help from your family and your friends.	X	X	X	X
13. You felt that you were too tired to do things.	X	X	X	X
14. You felt you were just as good as other people.	X	X	X	X
15. You had trouble keeping your mind on what you were doing.	X	X	X	X
16. You talked less than usual.	X	X		
17. You thought your life had been a failure.	X	X		
18. You were bothered by things that don't usually bother you.	X	X	X	X
19. You were happy.	X	X		X
Number of items	19	19	9	10

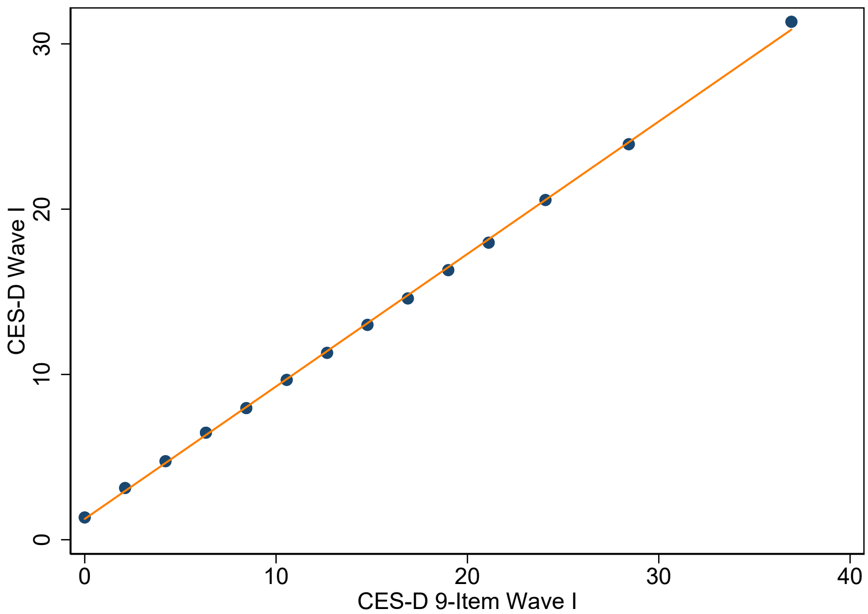
Notes: This table presents all items of the CES-D scale and in which wave they were elicited. Responses are rated on a scale from 0 ("never or rarely") to 3 ("most of the time or all of the time") and aggregated to a final score ranging from 0 to 57, with higher scores indicating a higher propensity for depressive symptoms. CES-D scores in wave II and IV are scaled by 19/9 and 19/10, respectively.

Figure A1. Distribution of CES-D Scores at Wave I



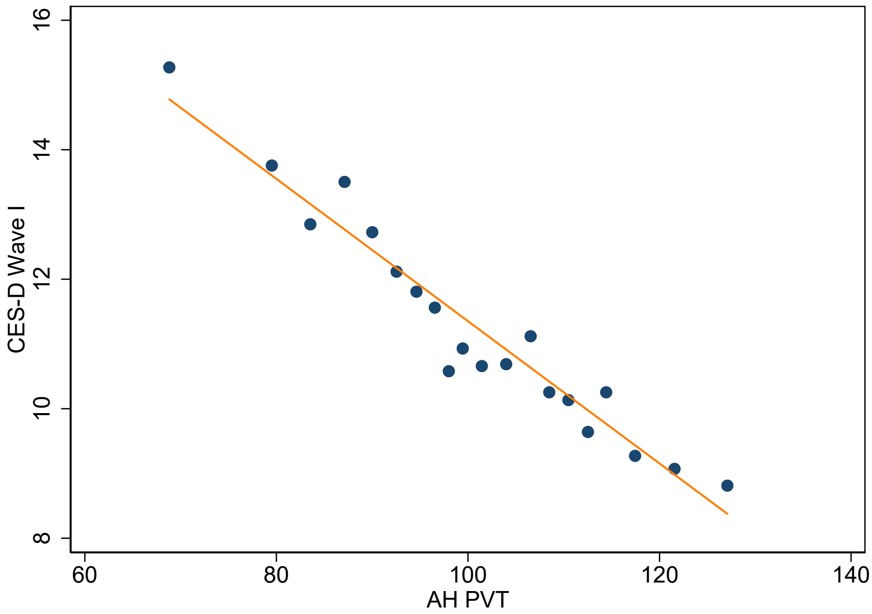
Notes: This figure presents the distribution of the our mental health measure (CES-D score) in wave I. The vertical line indicates a threshold of 16 often used as an indicator of depressions (Radloff, 1977).

Figure A2. Relationship of Long- and Short-Scale of the CES-D Score



Notes: This figure presents the relationship of the CES-D using 20 items as used in wave I and the short version adopted in later waves.

Figure A3. Relationship of CES-D Score and Ability



Notes: This figure presents a linear fit of the CES-D score in wave I on our ability measure.

Table A2. Variation in Ranks

	Standard Deviation in Rank Variable										
	Full	By Decile									
	Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No Controls	0.28	0.09	0.14	0.17	0.18	0.18	0.18	0.17	0.16	0.14	0.11
Controls, School and Grade FE	0.08	0.09	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.09	0.12
Controls, School-by-Grade FE	0.08	0.09	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.11
N	18454	1870	1983	2006	2141	1340	2004	1630	1904	2003	1573

Notes: This table presents the variation in our variable of interest for the full sample and by ability decile. The first row presents the raw variation. The second row takes out all variation from individual controls, school and grade fixed effects as in our baseline specification and presents the standard deviation in the rank residuals. The third row additionally controls for school-by-grade fixed effects similar to our alternative identification strategy.

Table A3. Ability Rank Salience Check

	Intelligence	College Expectations
Rank	0.28***	0.44***
	(0.10)	(0.16)
R^2	0.159	0.163

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses are clustered at the school-grade level. Each specification includes all controls as in our preferred baseline specification. Column headers denote the dependent variable. Intelligence is how intelligent the adolescent feels compared to other people their age (1-6 with 1 moderately below average and 6 extremely above average). College expectations is a scale based on the sum of the adolescent's report on how much they want to go to college and how likely it is they will go to college (each is 1-5 with 1 low and 5 high).