Mental Health and Academic Success in College

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Abstract

Mental health problems represent a potentially important but relatively unexplored factor in explaining human capital accumulation during college. We conduct the first study, to our knowledge, of how mental health predicts academic success during college in a random longitudinal sample of students. We find that depression is a significant predictor of lower GPA and higher probability of dropping out, controlling for prior academic performance and other variables. The association between depression and academic outcomes is strongest among students with a positive anxiety disorder screen. In within-person estimates using our longitudinal sample, we find again that co-occurring depression and anxiety are associated with lower GPA, and we find that symptoms of eating disorders are also associated with lower GPA. This descriptive study highlights the policy relevance of generating more definitive causal estimates of the effect of mental health on college success, which will likely require a randomized trial.

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Americans are inundated with messages about success—in school, in a profession, in parenting, in relationships—without appreciating that successful performance rests on a foundation of mental health.

United States Surgeon General's Report on Mental Health, 1999

1. Introduction

Among children and adolescents in the United States, mental disorders are estimated to account for a larger burden of disease, as measured in disability-adjusted life years (DALYs), than any other class of health conditions (Michaud et al., 2006). One of the primary concerns in younger populations is that mental health problems may affect human capital accumulation—in particular, the amount and productivity of schooling—which may in turn have lifelong consequences for employment, income, and other outcomes. Understanding the link between mental health and academic success is therefore a crucial step towards assessing the returns to preventing, detecting, and treating mental health issues among young people.

In this paper we analyze the connection between mental health and detailed measures of academic success *during college*. In the modern economy, college education has become an increasingly important component of human capital, and is associated with substantially higher earnings (Jaeger & Page, 1996; Kane & Rouse, 1995) and better health outcomes (Cutler & Lleras-Muney, 2006; Ross & Mirowsky, 1999). Approximately two thirds of high school graduates attend college (U.S. Department of Education, 2006), but fewer than 50 percent of college enrollees graduate (Knapp, 2007), and this proportion is 12-18 percent lower among students who are black, Hispanic, American-Indian, or lower socioeconomic status (Horn & Berger, 2004). Previous studies have considered a range of factors—such as financial aid (Dynarski, 1999) and academic and social involvement (Tinto, 1998)—that affect remaining in and completing college. Another important factor may be mental health.

Mental disorders frequently have first onset shortly before or during the typical college age range (18-24) (Kessler et al., 2005), yet relatively little is known about the link between mental health and academic success in college. Understanding this connection could be valuable due to the many ways in which college settings can reach young people; college represents the only time in many people's lives when a single setting encompasses their main activities, social networks, and a range of supportive services and organizations.

We examine how symptoms of mental disorders predict academic outcomes during college using unique data collected at a large, academically competitive, public university. We surveyed a random sample of approximately 2,800 undergraduate and graduate students about a range of mental health issues in fall 2005, and we conducted a follow-up survey with a subset of the sample in fall 2007. In this paper we focus on three of the most common types of mental disorders among adolescents and young adults: depression, anxiety disorders, and eating disorders. We link the survey data on mental health to academic measures collected from the university's administrative records.

This is the first study, to our knowledge, that examines how mental health predicts GPA and dropping out in a random sample of college students. We find that depression is a significant predictor of lower GPA and higher probability of dropping out, even after controlling for symptoms of anxiety and eating disorders, prior academic performance, and other covariates. Depression also appears to interact with anxiety; the association between depression and academic outcomes is particularly strong among students who also have a positive screen for an anxiety disorder. Among the symptoms of depression, the strongest negative predictor of academic performance is anhedonia (lack of pleasure and interest in usual activities). By contrast, negative affect per se (feeling depressed or hopeless) is not independently associated with a lower GPA. Finally, in fixed effects (within-person) regressions of GPA on mental health variables using the longitudinal sample, we find again that co-occurring depression and anxiety are associated with lower GPA, and we also find that symptoms of eating disorders are associated with lower GPA.

This study is best characterized as a detailed descriptive analysis of the association between mental health and academic outcomes in college, rather than a causal analysis. In the final section of the paper we illustrate that, if the estimates were assumed to be reasonable approximations of causal relationships, then they would imply sizeable economic returns, relative to the likely costs, from programs to increase the detection and treatment of depression among college students. This exercise underscores the policy relevance of acquiring more definitive knowledge about the causal effect of mental health on college success, which will likely require a randomized trial of mental health treatment that collects detailed academic outcomes.

2. Conceptual Framework and Related Literature

Conceptual Framework

Mental health may affect college students' academic outcomes along two margins: 1) the decision to remain in school; 2) productivity, or performance, given that one is in school.[1] Regarding the first margin, in a simple economic model of schooling attainment the individual chooses the amount of schooling, *s*, to maximize the present discounted value of future income, *V(s)*, where *y* denotes earnings, *r* denotes the discount rate, *A* denotes abilities, and *R* denotes the time of retirement or death (Becker, 1993).

$$V(s) = \int_s^R y(s;A)e^{-rt}\,dt$$

Poor mental health could reduce the marginal return to continuing schooling ($\partial V / \partial s$) for any of the following reasons: a) decreasing one's performance while in school, which may reduce the accrual of both real skills and outward signals (e.g., graduating with a high GPA) that increase expected job opportunities and productivity; b) decreasing one's expected future mental health, which in turns decreases one's expected productivity in future employment (e.g., by decreasing one's expected reliability); and, c) shortening the time horizon over which one expects to be in the labor force (reducing *R*). Although in theory these factors could imply that poor mental health causes an *increase* in schooling (due to the income effect—the higher marginal value of income at lower levels, in this case), we hypothesize that these factors on balance would cause a decrease in schooling (due to the predominance of the substitution effect—the lower marginal return to schooling) and therefore an increase in the likelihood of dropping out. This hypothesis is also based on the additional possibility that poor mental health may decrease one's interest in the future (one's discount rate), which would reduce one's willingness to make long-term investments like schooling.

As a simplified model of the second margin of interest—academic performance while in school—Todd and Wolpin (2003) propose that achievement *T* (e.g., test scores or grades) at age *a* is a function of family inputs, $F_i(a)$, and schooling inputs up until age *a*, $S_i(a)$, and a fixed natural ability, A_{i0}:

$$T_{ia} = T_a[F_i(a), S_i(a), A_{i0}]$$

Cunha and Heckman (2006) supplement this type of model by emphasizing that ability consists of cognitive and noncognitive skills that evolve over time. They mention several examples of noncognitive skills that may affect the acquisition of cognitive skills: persistence, motivation, consistency, patience, self-control, self-discipline, self-esteem, and interpersonal behavior. Each of the mental health

[1] We acknowledge that the discussion here does not reflect a number of factors that are likely to affect academic outcomes in college, such as financial aid (Dynarski, 1999) and learning about one's ability (Stinebrickner & Stinebrickner, 2008). We omit these factors from our brief conceptual discussion because it is difficult to predict how mental health would affect, interact with, or be affected by them.

problems that we consider—depression, anxiety, and eating disorders—could plausibly affect these noncognitive factors, in addition to having direct effects on cognitive ability.

Specifically, a number of depressive symptoms may affect the productivity of time in academic activities and/or the amount of time dedicated to academic activities.[2] These symptoms include reduced interest or pleasure in usual activities (anhedonia), sleep disturbances (less or more than normal), reduced energy, difficulty concentrating or making decisions, restlessness or slowing of movement, and suicidal thoughts (which may impair concentration or decrease interest in investing in the future) (Sadock & Sadock, 2000). In addition, negative affect (feeling sad or hopeless) may decrease interest in the future.

A common anxiety disorder, generalized anxiety, is marked by excessive worrying and difficulty controlling this worrying. At lower levels anxiety can actually be productive, but at higher levels it often impairs concentration and the ability to remain on task (Sadock & Sadock, 2000). Generalized anxiety shares many symptoms of depression (e.g., reduced energy, sleep disturbance, and reduced concentration) and therefore could affect academic outcomes for many of the same reasons that depression would. Another anxiety disorder that we measure, panic disorder, consists of recurrent and unexpected panic attacks, which include at least four of the following symptoms: palpitations, sweating, shaking, shortness of breath, feeling of choking, chest pain, nausea, feeling dizzy, derealization/depersonalization, fear of "going crazy," fear of dying, numbness or tingling sensations, and chills or hot flashes (Sadock & Sadock, 2000). The attacks do not typically last long enough to impair productivity by themselves, but they can lead to significant worrying and attempts to avoid attacks (e.g. avoiding class or studying if those activities are associated with the anxiety).

The two main types of eating disorders are anorexia nervosa and bulimia nervosa. People suffering from anorexia nervosa are often debilitated by physical symptoms such as fatigue, cardiac problems, and electrolyte disturbances (Sadock & Sadock, 2000). These symptoms, as well as any associated hospitalizations, could negatively affect academic productivity and time available. In addition, obsessions with weight and food could limit the time or concentration students have for studies. For people suffering from bulimia nervosa, frequent binging and purging can also consume time and energy. Eating disorders may also impair the

[2] It is also important to acknowledge that depression and other disorders may affect the marginal product and utility of time spent in non-school activities (i.e., leisure and employment). Therefore, the premise of our conceptual framework, more precisely, is that mental health problems have a substantially larger effect on the marginal product and utility of time in school activities than they do on other common uses of time. This seems plausible due to all of the possible channels described, but is a fundamental assumption that merits further study.

productivity of studying to the extent that they cause cognitive deficits, such as poor attention and working memory (Tchanturia, 2004).

Finally, depression, anxiety, and eating disorders can be especially impairing when they co-occur. For example, co-occurring depressive and anxiety disorders is associated with high severity of illness (Joffe, 1993), functional impairment (Joffe, 1993; Kessler, 1999), recurrence (Van Valkenburg, 1984), and poorer treatment outcomes (Brown & Madonia, 1996).

EMPIRICAL LITERATURE

While many studies assess the effect of physical health on human capital outcomes (see Currie (2008) for a review), we focus here on the studies that investigate how mental health affects human capital. Several studies describe the association between mental health early in life and subsequent educational attainment. Among studies that assess early-life mental health retrospectively, one study finds that early-onset (before adulthood) depression, is associated with less schooling (Berndt et al., 2000), whereas another study finds that a number of early-onset psychiatric disorders (although not major depression) are associated with early termination of schooling (Breslau et al., 2008). Studies that use longitudinal data also find mixed evidence on the relationship between early-life emotional and mental health and subsequent educational attainment. For example, two studies find that early-life externalizing behavioral problems (e.g., conduct disorders or ADHD), but not early-life internalizing behavioral problems (e.g., depression or anxiety), are associated with lower subsequent education (McLeod & Owens, 2004; Miech et al., 1999). Two other studies focus specifically on the long-term consequences of adolescent depression: a study of New Zealand adolescents finds no association between early-adolescent depression and subsequent educational attainment after controlling for socio-demographic characteristics (Fergusson & Woodward, 2002), while a study using U.S. data finds that adolescent depression is positively correlated with high school drop-out and negatively correlated with college enrollment (Fletcher, 2008). An additional two studies investigate a variety of psychiatric disorders, and find negative associations between mental illness during adolescence and graduating from high school (Marcotte et al., 2004; Vander Stoep et al., 2003).

In addition to these descriptive studies, a small number of recent studies have attempted to address explicitly the endogeneity of mental health with respect to academic outcomes (e.g., mental health may be correlated with unobserved variables related to the ability vector *A* noted earlier). First, two complementary studies use sibling fixed-effects models to control for family-level unobservable factors that might be correlated with both ADHD and academic outcomes (Currie & Stabile, 2006; Fletcher & Wolfe, 2007). Both studies suggest that ADHD has a strong effect on academic outcomes in secondary school, including standardized test scores, grade repetition, and special education use. One of these two studies also examines longer-term effects of ADHD, and finds no evidence of an effect on total years of education and college attendance (Fletcher & Wolfe, 2007). Second, researchers have used specific genotypes as instruments for mental health, positing that variation in genotypes affects mental health but does not directly affect educational attainment (Ding et al., 2007; Fletcher & Lehrer, 2008). The two studies are suggestive of effects of mental health on academic outcomes, but come to somewhat different conclusions. Ding and colleagues find that depression leads to significantly lower GPA among high school students, and some evidence that attention deficits (without hyperactivity) reduce GPA, although the latter results are sensitive to the model specification. Fletcher and Lehrer's findings suggest an effect of ADHD and depression on verbal test scores, although the IV estimates are not significant at conventional levels. This latter study also estimates instrumental variable models with sibling fixed effects and finds marginally significant effects of attention deficits (but not hyperactivity) on verbal test scores.

The aforementioned studies are important in advancing the understanding of how mental health may affect academic outcomes among children and adolescents, but they generally do not address the relationship between mental health and human capital accumulation in higher education. The roles of depression, anxiety, and eating disorders in college are particularly important to examine, as the incidence of these conditions during late adolescence and young adulthood greatly exceeds that of most other mental disorders including ADHD (Kessler et al., 2005). In addition, although severe mental illness such as bipolar disorder is somewhat less prevalent among college students as compared to same-aged non-college students, depression and anxiety disorders are equally prevalent across the two groups (Blanco et al., 2008).

Only two studies, to our knowledge, specifically examine the relationship between mental health and academic outcomes during college. One recent study compares the GPA of 121 students during six months following a diagnosis of depression at the university's student health center to the GPA of a control group selected from the overall student population (Hysenbegasi et al., 2005). This study finds a significant, negative association between GPA and untreated depression (whereas treated depression is not associated with a significant difference in GPA). An important limitation is that the study only includes students who presented to the student health center, and it is unclear how this group might differ from the overall population of students with significant depressive symptoms. Another study uses data on 351 students at a British university and finds that depression (but not anxiety) measured midway through the second year is negatively related to exam scores at the end of the second year (Andrews & Wilding, 2004).

Our study contributes to the literature on mental health and academic outcomes due to a number of features. First, as noted above, we focus on the important but relatively understudied setting of postsecondary education. Second, our analyses utilize clinically-validated measures of self-reported mental health status, detailed measures of academic outcomes, and a rich set of control variables including multiple measures of prior academic performance. Third, this is the first study to our knowledge to estimate the relationship between mental health and GPA during college using mental health data at two time points, which enable us to control for time-invariant individual characteristics that may otherwise bias the estimated relationship between mental health and human capital accumulation. Fourth, we consider independent associations between academic outcomes and three of the most common types of mental disorders among young adults: depression, anxiety, and eating disorders.

3. Data and Empirical Framework

Sample

Our data are from a randomly selected sample of undergraduate and graduate students enrolled in fall 2005 at a large, public, academically competitive university. Mental health measures and a range of other variables were collected via web-based surveys as part of the Healthy Minds Study, a survey study examining mental health and help-seeking behavior among college students (Eisenberg et al., 2007a, 2007b). All participants gave informed consent and the study was approved by the university's Health Sciences IRB. In fall 2005, a random sample of 5,021 students was recruited for the survey using an introductory note via regular mail followed by email invitations, and 2,798 students (56%) completed the survey. Students completed the survey during a three week period around the middle of the semester, during late October and early November (the fall semester runs from early September to mid-December). We fielded the survey during the middle of the semester because we wanted to minimize the influence of transitions (e.g., moving into a new residence) and high-stress periods (e.g., final exams) on self-reports of recent symptoms of mental health problems.

Of the 2,798 students who completed the baseline survey, 1,272 were still enrolled in fall 2007 and were invited for a two-year follow-up survey with a nearly identical set of questions. Among those who were no longer enrolled as of fall 2007, approximately 90% had graduated and 10% had left the university without graduating. This indicates the predominant reason for attrition from our study was normal academic progress; the other reason, dropping out, is one of the outcome variables in our analysis, as explained below. Of the 1,272 students remaining at the university as of fall 2007, 747 (59%) completed the follow-up survey. As described in more detail later, we construct survey nonresponse weights in order to adjust for differences between responders and nonresponders.

ACADEMIC MEASURES

Our dependent variables come from students' academic records while at the university. First, we examine GPAs during specific terms (semesters), as a measure of human capital accumulation conditional on being in school. We compute GPAs as weighted averages of course grades in those terms, where the weights are equal to the number of credit-hours for each course. GPAs are measured on a 0-4.3 scale, where A+ equals 4.3, A equals 4.0, A- equals 3.7, and so on. Students with missing GPA values are excluded from these analyses.[3] As shown in Table 1, the average GPA in our sample is 3.38.

Our second main outcome variable is whether a student dropped out of the university before graduating. For each term following the baseline (fall 2005), we define a variable equal to 1 if the student dropped out by that term and 0 otherwise. We define a student as having dropped out as of term X if she or he meets each of the following conditions: a) not enrolled in term X; b) not enrolled in any subsequent term that we observe (through winter 2008); and, c) not graduated from a degree program since the baseline semester (fall 2005).[4] As shown in Table 1, among our baseline sample 2% of students dropped out by winter 2006, 4% by winter 2007, and 8% by winter 2008. These proportions are significantly lower than national averages, reflecting the academically competitive profile of students who attend this institution.[5]

[3] Some students do not have GPAs for some or all terms (e.g., 21% of the sample during the fall 2005 term), because they chose to take courses as pass/fail or because their courses were only offered as pass/fail (we cannot distinguish between these two possibilities). The vast majority (96%) of students with missing GPA values are graduate students, of which 80% are in their 2nd year or higher. Therefore having a missing GPA appears to be primarily a function of one's academic program as opposed to one's decision to take classes pass/fail.

[4] All students in our sample were enrolled in degree programs (i.e., there were none taking a few classes for non-degree purposes), so it is reasonable to think of people who leave as dropping out.

[5] For example, nationally 34% of students beginning college leave their first school within three years without having graduated (Berkner & Choy, 2008), as compared to 12% in our data. We cannot determine whether someone who is no longer enrolled has left college entirely or has transferred. We would ideally distinguish between transfers and people who leave college, but both are significant outcomes in that they often involve difficult transitions, in terms of academic progress, social networks, and other factors (Laanan, 2007; Skahill, 2002).

Table 1: Sample characteristics (weighted means)

	Baseline sample, fall 2005 (N=2,798)		Longitudinal sample, in fall 2005(N=747)		Longitudinal sample, in fall 2007 (N=747)	
Dependent variables	Mean	SD	Mean	SD	Mean	SD
GPA in…						
Fall 2005	3.38	0.56	3.43	0.54		
Fall 2007	3.38	0.58			3.47	0.54
Credit hours in…						
Fall 2005	13.2	3.6	13.4	3.6		
Fall 2007	12.4	4.3			12.4	4.1
Dropped out* by:						
Winter 2006	0.02					
Winter 2007	0.04					
Winter 2008	0.08					
Mental health variables						
PHQ depression score (0-27)	5.16		5.13	4.22	5.61	4.68
PHQ score: 0-4	0.56		0.55		0.49	
PHQ score: 5-9	0.30		0.30		0.34	
PHQ score: 10-14	0.11		0.11		0.13	
PHQ score: 15-19	0.02		0.03		0.02	
PHQ score: 20-27	0.01		0.01		0.02	
Change PHQ of 5+ ('05 vs '07)					0.08	
Panic disorder (positive screen)	0.02				0.03	
Change in status ('05 vs '07)					0.03	
Generalized anxiety (positive screen)	0.03				0.04	
Change in status ('05 vs '07)					0.06	
Eating disorder (positive screen)	0.08		0.09		0.08	
Number of ED symptoms (0-5)	0.62		0.64		0.66	
Change in ED screen ('05 vs '07)					0.1	
Dep. (PHQ>=10) & anxiety	0.03		0.02		0.05	
Dep. & ED (positive SCOFF)	0.03		0.03		0.03	
Anxiety & ED	0.01		0.01		0.02	

Table 1 (cont'd)

Other independent variables	Baseline sample, fall 2005 (N=2,798)		Longitudinal sample, in fall 2005(N=747)	
	Mean	SD	Mean	SD
Female	0.48		0.48	
Age				
18-22	0.65		0.71	
23-25	0.14		0.12	
26-30	0.14		0.11	
31+	0.08		0.06	
Race/ethnicity				
Asian	0.20		0.18	
Black	0.06		0.04	
Hispanic	0.04		0.04	
White	0.62		0.65	
Multi	0.05		0.07	
Other	0.03		0.02	
Degree program				
Bachelors	0.63		0.66	
Masters	0.20		0.14	
JD	0.04		0.02	
MD	0.04		0.04	
PhD	0.14		0.21	
Finances while growing up:				
Very poor	0.02		0.02	
Enough to get by	0.26		0.25	
Comfortable	0.56		0.58	
Well-to-do	0.16		0.15	
Undergrad admissions variables				
SAT score (max=1600)	1292	143	1309	143
ACT score (max=36)	28.2	3.7	28.6	3.2
HS GPA (undergrads)	3.93	0.18	3.94	0.17
Grad student admissions variables				
GRE (verb. + quant.)	1260	167	1287	154
LSAT (max=180)	163	7.6	165	7.4
GMAT (max=800)	663	67	671	60
MCAT (max=13)	11.3	1.1	11.6	0.85
Undergrad GPA (grad studs.)	3.47	0.41	3.55	0.38
Cumulative GPA (pre fall '05)	3.35	0.47	3.43	0.47

As a third dependent variable we examine the number of credit hours taken by students during specific terms. The average number of credit hours is just over 13 in our fall 2005 sample. In our data we only observe the number of credit hours completed in a semester, and not the number of credit hours that the student signed up for at the beginning of the semester. Therefore we cannot examine dropping classes during the semester as an outcome. Nevertheless, to the extent that mental health problems cause students to drop courses during the semester, we expect to observe a negative relationship between these problems and completed course hours. Of course, this negative relationship may also stem in part from students who anticipate that they will have mental health problems during the semester and sign up for fewer courses from the beginning.

In addition to the dependent variables, a few key covariates are taken from the university's administrative records. The purpose of these covariates is to control for academic performance prior to when we measure mental health in fall 2005. First, we include cumulative GPA at the university, prior to fall 2005, as a covariate. To allow for a nonlinear relationship between this measure and the dependent variables (academic outcomes during and after fall 2005), we construct categorical dummy variables: none/missing (for first year students), 0.00-3.30, 3.30-3.69, 3.70-3.99, and 4.00-4.30.[6] Second, we use admissions records as additional covariates. For undergraduates, the admissions data include high school GPA as well as SAT or ACT score (most students took one or the other). We code high school GPA using categorical dummies as described above, and we code admission test scores as quintile dummies (based on the distribution within our sample). Similarly, for graduate students the admissions data include college GPA and test scores (GRE, GMAT, LSAT, or MCAT), which we code as categorical dummies in analogous fashion. The means of these and other variables are shown in Table 1.

MENTAL HEALTH MEASURES

We measure symptoms of depression, anxiety, and eating disorders, which are three of the most common types of mental disorders among adolescents and young adults (Kessler et al., 2005). These disorders may affect academic outcomes for reasons discussed earlier. In the surveys we measure these

[6] These numerical intervals split the sample with nonmissing cumulative GPAs roughly into quartiles; in sensitivity analyses we also use smaller intervals (dividing the sample roughly into deciles) and find that the main results do not change. In additional sensitivity analyses, we control for both cumulative GPA and GPA during the semester prior to baseline (i.e., winter 2005), to account for the possibility that students with mental health problems in fall 2005 were already experiencing declines in performance in the prior semester. Again, our main results remain the same under this specification.

symptoms with widely used brief screens that have been validated in a range of populations including young adults. To measure depression, we use the Patient Health Questionnaire-9 (PHQ-9), a nine-item screening instrument based on the nine DSM-IV criteria for a major depressive episode. This instrument asks the respondent to indicate the frequency of various symptoms over the past two weeks. Following previous studies (Huang, 2006; Weiss, 2006) as well as common clinical use of this screen,[7] we convert the responses to these nine items to a continuous score on a 0-27 scale, with higher scores indicating higher severity of depressive symptoms. This screening tool has been validated as highly correlated with diagnosis by mental health professionals and more detailed assessment tools in a variety of populations and settings (Diez-Quevedo et al., 2001; Henkel et al., 2004; Kroenke et al., 2001; Martin et al., 2006; Spitzer et al., 1999). To measure anxiety, we use the PHQ screens for panic disorder and generalized anxiety disorder. These screens ask about symptoms over the past four weeks, and have been validated as being highly correlated with clinical diagnoses of these conditions (Spitzer et al., 1999). These anxiety screens do not translate to continuous measures, so we simply use indicators for whether a student has a positive screen for each anxiety disorder or not. To measure eating disorders, we use the SCOFF screening instrument, a 5-item questionnaire designed to identify subjects likely to have an eating disorder (Cotton et al., 2003; Morgan et al., 1999; Parker et al., 2005). Each item is a yes/no question about a current symptom, and we convert each student's answers to a 0-5 score based on the number of yes's.[8]

Table 1 shows the mean values of the mental health measures in our analytic samples (both baseline and longitudinal). Based on these measures, depression is the most prevalent mental health condition, with 14% of students at baseline scoring 10 or higher on the PHQ-9 (10 is often used as the threshold for a positive screen). Eight percent of students have a positive screen for eating disorders, 3% for generalized anxiety, and 2% for panic disorder. The prevalence of these conditions in this student population is similar to that at other colleges and universities we have studied.[9] The prevalence of co-occurring conditions is

[7] For example, in the National College Depression Partnership, a recently developed initiative to improve depression care on college campuses, participating campuses are screening students and monitoring their depressive symptoms using the continuous PHQ scores.

[8] Some studies have used 2 yes's as the cutoff for a positive screen (Parker et al., 2005) whereas others have used 3 (Cotton et al., 2003). We focus instead on a continuous measure in order to approximate severity.

[9] In fall 2007, in addition to the follow-up survey used in the present study, a new data collection was conducted with random samples at 13 colleges and universities nationwide, including the large public university that is the setting for the present study. This set of schools represents a relatively diverse mix in terms of geographic location and enrollment size: California State-Chico, Emory, Miami of Ohio, New Mexico State, Penn State, Tufts, University of Michigan, UNC-

3% for depression and anxiety, 3% for depression and eating disorders, and 1% for anxiety and eating disorders. As shown in Table 1, the longitudinal sample is similar at baseline to the overall sample in terms of mental health, and the longitudinal sample's symptoms of depression and anxiety increase slightly between 2005 and 2007.

OTHER COVARIATES

Our analysis includes several additional covariates measured in the survey, as shown in Table 1: gender, age, race/ethnicity, degree program, and financial situation while growing up. In previous work we have found each of these variables to be independently associated with at least one of the mental health conditions examined in the present study (Eisenberg et al., 2007b). In addition to these variables, in our regressions we control for a vector of dummy variables corresponding to the student's year in degree program, as well as a vector of dummies corresponding to the student's field of study (divided into 22 different categories, such as humanities, social science, natural science and math, business, medicine, engineering, etc.).

EMPIRICAL FRAMEWORK

Our analysis of the baseline sample uses variants of the following regression equation, which is analogous to the commonly used "value-added" empirical model of academic achievement described by Todd and Wolpin (2003):

$$Academics_{(i,t+n)} = \beta_0 + \beta_1 MH_{(i,t)} + \beta_2 Academics_{(i,t-1,t-2,...)} + \beta_3 X_{(i)} + \varepsilon_{(i)}$$

$Academics_{(i,\ t+n)}$ refers to an academic outcome (GPA, credit hours, or dropping out) for individual *i* as of semester $t+n$, where n>=0. $MH_{(i,\ t)}$ refers to mental health during semester t (the baseline semester, fall 2005, in most regressions). $Academics_{(i,\ t-1,\ t-2,\ ...)}$ refers to academic outcomes prior to semester t (i.e., pre-university GPA and test scores, and GPA at the university prior to semester t). $X_{(i)}$ refers to other covariates measured in the survey (gender, age, race/ethnicity, degree program, and financial situation while growing up). In our analyses of GPA and credit hours we use ordinary least squares regressions. For the binary outcome of dropping out, we find that the results remain similar across linear, probit, and logistic specifications, and for ease of interpretation we present the marginal effects for the probit specification.

Chapel Hill, UNC-Greensboro, UI-Springfield, UI-Chicago, UI-Urbana Champaign, and Yeshiva. In preliminary analysis of these data, we have found that the estimated prevalence rates of depression, anxiety, and eating disorders at the large public university in the present study are not statistically different from the means for the overall sample of 13 schools.

In this framework, three factors could bias our estimates from the true causal effect of mental health on academic outcomes. First, the causal path may be bidirectional—the dependent variable (academic outcome) may affect our key independent variables (mental health). This seems particularly plausible for regressions in which the dependent variable is GPA or credit hours in the same semester that we measure mental health. Even though course grades are determined at the end of the semester (one to two months after we measure mental health), these grades partly reflect midterms and assignments that may have taken place prior to our measure of mental health. If poor grades on these earlier assignments and midterms influence mental health, then this would bias our estimates (presumably in a negative direction). On the other hand, this source of bias would not apply to our estimates of how mental health in the baseline semester relates to GPA in *subsequent* semesters. It is worth noting that our results are not sensitive to whether we control for not only cumulative GPA prior to baseline but also GPA during the semester prior to baseline (winter 2005), which would at least account for the possibility that academic performance is already declining prior to the baseline semester. Also, we find that GPA in the previous semester (winter 2005) is not a significant predictor of mental health in the baseline semester (fall 2005), conditional on the other covariates.

Second, there may be omitted variables bias. Mental health is of course not randomly distributed (as we discuss in more detail in the next section), and students with mental health problems may be different in ways that are correlated with unobserved factors (e.g., the ability vector A noted earlier) that affect academic performance. We control for several individual characteristics, including multiple measures of prior academic performance, but we cannot rule out this source of bias.

Third, the "value-added" framework may misspecify the true relationship between inputs (mental health in our context) and academic achievement, if past inputs affect current achievement even after conditioning on current inputs and achievement as of the previous period. As a specification check for this issue, Todd and Wolpin (2003) suggest adding past inputs as a covariate and examining whether they have significant coefficients. We perform this check by including previous diagnoses of any mental disorders and of depression specifically as proxies for past mental health, and we find that these variables are not significant and their inclusion does not change the coefficients on the current mental health.

To control for time-invariant individual characteristics, we turn to our longitudinal data, with baseline and follow-up survey data from fall 2005 and fall 2007 respectively. We estimate the following linear regression of GPA on mental health and individual and time (semester) fixed effects, which is analogous to the within-person empirical approach discussed by Todd and Wolpin (2003):

$$GPA_{(i,t)} = \beta_0 + \beta_1 MH_{(i,t)} + \beta_2 Individual_{(i)} + \beta_3 Semester_{(t)} + \varepsilon_{(i,t)}$$

In this framework, identification of the effect of mental health on GPA (or credit hours) depends on assumptions that bidirectional causality (as described above) is not present and there are no time-variant omitted variables that are correlated with mental health and significantly affect grades. These assumptions cannot be definitively tested, of course, but are important to keep in mind in interpreting the results of this study.

Another empirical issue is how to account for treatment of mental health problems. In this study we omit treatment from our primary analyses, because it is likely to be highly endogenous with respect to mental health and academic outcomes (e.g., correlated with unmeasured or imperfectly measured factors such as severity of symptoms and motivation to succeed in college). Including treatment in the analysis would therefore add another layer of uncertain assumptions for interpreting the results for mental health variables. In the final section of this paper, however, we briefly mention results from analyses that include treatment variables.

NON-RESPONSE ADJUSTMENTS

To account for survey non-response in our analyses, we include sample probability weights in all regressions, although it is important to note at the outset that none of our main results are sensitive to whether we include these weights. The weights are equal to one divided by the predicted probability of survey response, which is estimated using logistic regressions of survey response (yes/no) on variables that are available for both responders and non-responders. For the baseline sample, these variables come from administrative data on all students randomly selected to be invited to the study, which include gender, degree program, race/ethnicity, international/domestic citizenship, and GPA. The weights are further adjusted using mental health data from an abbreviated survey of a random sample of non-responders to the main survey, which indicates that people with mental health problems were somewhat more likely to respond to the main survey, as detailed in the appendix to Eisenberg et al (2007a). Other significant positive correlates of responding to the survey are female gender and graduate student status, and significant negative correlates are African-American race and age (controlling for academic level). Responding at baseline is also positively correlated with measures of prior academic performance, although this relationship is not entirely consistent (response is lower among students in the lowest admission test and admissions GPA categories, but not significantly different across the other groups; also, response is highest among students in the highest category of cumulative GPA at the university, but not otherwise different across groups). Importantly, however, responding at baseline is *not* significantly associated with the key outcome variables (GPA during fall 2005, and dropping out subsequent to fall 2005), conditional on other covariates.

For the longitudinal sample, the weights are constructed based only on information about students who were eligible for the follow-up survey (those who completed the baseline survey in fall 2005 and were still enrolled in fall 2007). The predicted probability of response at follow-up is estimated using demographic and mental health variables from the survey at baseline. Thus, the panel weights are intended to account only for non-response at follow-up.[10] The significant baseline predictors of nonresponse at follow-up are being female and being a PhD student (both of which are positive predictors), and none of the baseline mental health variables significantly predict response at follow-up.

4. RESULTS

In Table 2 we compare the means of covariates, including demographic characteristics and prior academic measures, across mental health status. The purpose of these comparisons is to acknowledge that mental health is not randomly distributed across students; given this fact, examining differences in observable characteristics by mental health status is useful for thinking about how unobservable differences might bias our estimates from true causal effects.

Female students are more likely to experience symptoms of each mental health problem of interest (depression, anxiety, and eating disorders). Younger students are more likely to experience symptoms of depression and eating disorders, but not anxiety. For the most part, the racial/ethnic composition of students across mental health categories is consistent; the only exception is that Asian students are less likely to report elevated anxiety.[11] Table 2 also shows that depressed or anxious students are more likely to report having grown up in a poor

[10] We construct weights in this way because we are mainly concerned about accounting to the extent possible for attrition from the baseline sample, rather than weighting the sample to be representative of all students who were enrolled in both fall 2005 and fall 2007 (which does not correspond to a population of any particular policy relevance).

[11] It is important to note that while some of these differences may be related to how people report their symptoms, as opposed to “true” differences in symptoms, the screening tools were designed to minimize such biases and have been validated in settings and populations with a wide range of demographic characteristics (Huang et al., 2006).

Table 2: Sample characteristics, by MH status (Baseline sample, N=2,798)

	Depression (PHQ-9)				Anxiety (PHQ)			ED (SCOFF)		
	Low (0-9)	Med. (10-14)	High (15-27)		Neg.	Pos.		Neg.	Pos.	
N	2,343	311	144		2,642	146		2,550	224	
Female	0.47	0.49	0.60	*	0.47	0.68	*	0.46	0.76	*
Age										
18-22	0.64	0.67	0.71	*	0.65	0.66		0.64	0.75	*
23-25	0.14	0.15	0.15		0.14	0.14		0.14	0.13	
26-30	0.14	0.12	0.10	*	0.14	0.15		0.14	0.09	*
31+	0.08	0.07	0.04	*	0.08	0.05		0.08	0.04	*
Race/ethnicity										
Asian	0.20	0.21	0.18		0.21	0.13	*	0.20	0.20	
Black	0.06	0.07	0.05		0.06	0.06		0.07	0.04	
Hispanic	0.04	0.04	0.02		0.03	0.06		0.03	0.04	
White	0.62	0.59	0.66		0.62	0.64		0.62	0.63	
Multi	0.05	0.06	0.06		0.05	0.08		0.05	0.07	
Other	0.03	0.03	0.03		0.03	0.03		0.03	0.03	
Finances growing up:										
Very poor	0.02	0.03	0.06	*	0.02	0.06	*	0.02	0.03	
Enough to get by	0.25	0.30	0.29		0.26	0.28		0.26	0.22	
Comfortable	0.57	0.47	0.57		0.56	0.54		0.56	0.56	
Well-to-do	0.16	0.20	0.08	*	0.16	0.12		0.16	0.19	
Admissions test percentile	0.52	0.51	0.51		0.52	0.45	*	0.52	0.49	
HS GPA (undergrads)	3.94	3.93	3.89		3.94	3.92		3.93	3.95	
Undergrad GPA (grad studs.)	3.47	3.42	3.49		3.47	3.46		3.47	3.43	
GPA at univ. (pre fall '05)	3.36	3.29	3.29		3.36	3.22	*	3.35	3.35	
PHQ depress. score >= 10	0.00	1.00	1.00		0.12	0.71	*	0.13	0.35	*
Anxiety (positive screen)	0.01	0.12	0.46	*	0.00	1.00		0.04	0.08	*
ED (positive screen)	0.06	0.18	0.21	*	0.08	0.15	*	0.00	1.00	

"*" denotes that the variable means are significantly different by MH categories to the left at $p<0.05$

family, whereas symptoms of eating disorders are not correlated with one's financial situation while growing up.

Measures of academic performance prior to the baseline survey differ significantly by mental health status only in the case of anxiety disorders. Students with positive screens for anxiety disorders have slightly lower admissions test scores and cumulative GPAs at the university. Finally, the bottom rows in Table 2 show that the three mental health conditions are significantly correlated with each other, which is consistent with an extensive mental health literature documenting the co-occurrence of disorders (Kessler, 2008). This co-occurrence highlights the value of examining depression, anxiety, and eating disorders simultaneously in our analyses, in order to disentangle their independent associations with academic outcomes.

Overall, the comparisons of covariates by mental health status indicate that, while mental health problems are far from randomly distributed in the student population, they are relatively prevalent among nearly all types of students that we examine. Therefore, the central comparisons in this study—academic outcomes across mental health status—are based on comparisons of students who differ somewhat but not drastically in terms of observable characteristics.[12] At the same time, the fact that students with mental health problems are more likely to come from poor families and students with symptoms of anxiety disorders in particular have lower prior academic performance raises the question of how other, unmeasured differences across mental health status might affect academic outcomes.

Our first set of main results are shown in Table 3, which reports the association between mental health measured in fall 2005 and the GPA that students obtained in that semester.[13] Perhaps the most notable findings are that depression has a significant negative association with GPA and that the co-occurrence of depression and anxiety is associated with a significant additional drop in GPA. The magnitude of the coefficients in column 7 indicates, for

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[12] To complement the simple comparisons in Table 2, we also examine the independent associations between these covariates and mental health status using regressions. The results of this analysis are largely consistent with the comparisons in Table 2. Female, age, and past financial situation are independently associated with mental health (significant at $p<0.05$), whereas previous academic performance generally is not (the exceptions are that admission test scores are negatively associated with anxiety and eating disorders, and previous GPA at the university is negatively associated with anxiety).

[13] Among the estimated coefficients for covariates other than mental health (not shown in Table 3), the following were positive and significant at $p<0.05$: female, growing up in a "well-to-do" family, admissions test score, and cumulative GPA at the university prior to the baseline survey. The following covariates were negative and significant at $p<0.05$: being black or Hispanic, and being a bachelor's or JD student. Also, many of the 22 fields of study differed significantly from each other in terms of mean GPA conditional on other covariates. These additional results are available on request.

Table 3: Association between mental health and GPA in same semester

Linear regressions of GPA in fall 2005 on MH in fall 2005, with SEs in parentheses.

	1	2	3	4	5	6	7
PHQ depression (0-27)	-0.019			-0.022	-0.019	-0.013	-0.011
	(0.003)			(0.004)	(0.005)	(0.003)	(0.004)
Panic disorder (0/1)		-0.083		0.015	0.154	0.101	0.201
		(0.097)		(0.095)	(0.124)	(0.083)	(0.106)
Gen. anxiety (0/1)		-0.213		-0.023	0.212	-0.073	0.092
		(0.078)		(0.081)	(0.149)	(0.068)	(0.133)
ED symptoms (0-5)			0.008	0.035	0.044	0.017	0.022
			(0.013)	(0.013)	(0.023)	(0.013)	(0.022)
Dep. (0-27) * anx. (0/1)					-0.021		-0.015
					(0.010)		(0.009)
Dep. (0-27) * ED (0-5)					-0.002		-0.001
					(0.003)		(0.003)
Anx. (0/1) * ED (0-5)					0.045		0.026
					(0.051)		(0.049)
N	2209	2200	2189	2184	2184	1935	1935
Covariates	NO	NO	NO	NO	NO	YES	YES

Covariates: Female, race dummies, degree program dummies (bachelors, masters, JD, MD, PhD, financial situation growing up (categories listed in Table 2), admission test quintile dummies, admissions GPA dummies (0-3.29, 3.3-3.69, 3.7-3.99, 4-4.3, or none/missing), cumulative GPA at university prior to fall 2005 (0-3.29, 3.3-3.69, 3.7-3.99, 4-4.3, or none/missing).

example, that a 15 point increase on the PHQ-9 scale (which would be the difference between what are considered low levels and severe levels of depressive symptoms) corresponds to a 0.17 drop in GPA in the absence of anxiety ($p<0.01$), and a 0.40 drop in the presence of anxiety ($p=0.10$). These differences in GPA are modest in absolute terms but represent, respectively, 0.3 and 0.7 standard deviations in the GPA distribution, and would lower a student with the 50th percentile GPA (3.61) down to the 37th and 23rd percentiles, respectively. Without controlling for other variables, a positive screen for generalized anxiety is significantly and negatively associated with GPA, whereas a positive screen for panic disorder or eating disorders is not significantly associated with GPA. After controlling for other mental health variables and covariates, however, generalized anxiety is no longer significant and symptoms of eating disorders become *positively* and significantly associated with GPA in some specifications. The sensitivity of these results to the inclusion of other mental health measures highlights again the importance of examining multiple conditions simultaneously, given the prevalence of co-occurrence.

We also find that credit hours completed in fall 2005 are negatively related to mental health problems during that semester (results available on request), but these results are not significant at $p<0.10$. Even at the upper bound of the 95% confidence interval, the estimated association between depressive symptoms and credit hours is small, implying less than a one credit reduction for a 15 point increase on the depression scale. This suggests that, although depression is associated with lower GPA, it is not a significant contributor to people's dropping courses during the semester.[14]

Depression is a significant predictor of not only GPA but also the likelihood of dropping out from the university (Table 4). Controlling for covariates, each additional point on the depression scale is associated with a 0.31% increase in the probability of dropping out ($p<0.01$) (column 5 of the table), which would imply that a 15 point increase on the depression scale corresponds to a 4.7% increase in the probability of dropping out, or a 60% increase relative to the mean probability of dropping out (8%). The coefficients for the other mental health variables (panic disorder, generalized anxiety, and eating disorders) are not significant at $p<0.10$, although the imprecise coefficient for panic disorder implies a more than doubling of the probability of dropping out. We also do not find any significant interactions between mental health variables (results not shown).[15] As mentioned earlier, the main pattern of results for dropping out remain similar in linear and logistic specifications.

Given the signification association at baseline between depression and GPA, we examine the persistence over time in this relationship in two ways. First, we consider GPA during each semester following fall 2005 as a separate outcome, and we estimate separate regressions of these GPAs on baseline mental health and covariates. In Appendix Figure 1, each point in the figure represents the estimated coefficient on depression from a regression where the dependent

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[14] This is likely to be related to the fact that at this university the deadline for dropping a course is only three weeks after the beginning of the semester.

[15] Among covariates other than mental health (not shown in Table 4), the only one that is significantly associated with dropping out at $p<0.05$ is cumulative GPA at the university prior to the baseline survey (as expected, lower GPAs are associated with significantly higher odds of dropping out).

Table 4: Association between MH and dropping out (by winter 2008)

Probit models with "marginal effects" and SEs reported	1	2	3	4	5	6	7
Dep. score (0-27)	0.0024			0.0021	0.0005	0.0031	0.0022
	(0.0011)			(0.0013)	(0.0016)	(0.0011)	(0.0014)
Panic disorder (0/1)		0.0552		0.0414	0.0387	0.0607	0.1120
		(0.0508)		(0.0479)	(0.0643)	(0.505)	(0.0900)
Gen. anxiety (0/1)		0.0293		-0.0038	-0.0139	-0.0216	0.0109
		(0.0312)		(0.0275)	(0.0504)	(0.0186)	(0.0572)
ED symptoms (0-5)			0.0053	0.0025	-0.0075	0.0009	-0.0067
			(0.0052)	(0.0052)	(0.0086)	(0.0048)	(0.0076)
Dep. (0-27) * anx. (0/1)					0.0028		-0.0010
					(0.0037)		(0.0032)
Dep. (0-27) * ED (0-5)					0.0016		0.0012
					(0.0010)		(0.0008)
Anx. (0/1) * ED (0-5)					-0.0336		-0.0297
					(0.0205)		(0.0168)
N	2798	2788	2774	2769	2769	2472	2472
Covariates	NO	NO	NO	NO	NO	YES	YES

Covariates: Same as listed in note to Table 3.

variable is GPA measured for a different semester.[16] The negative association between baseline (fall 2005) mental health and semester GPA at subsequent time points remains significant, and diminishes only slightly, over the course of 1.5 years (through winter 2006, fall 2006, and winter 2007). It is also important to note that if depression at baseline makes students more likely to drop out, as suggested by the results in Table 4, then this would probably bias the estimates shown in Figure 1 towards zero (assuming that students who dropped out would

[16] We also estimate analogous regressions for dropping out, in which the dependent variables are defined as whether the student has dropped out as of each semester following the baseline semester (fall 2005). The results indicate that depression in fall 2005 maintains a relatively consistent relationship with the likelihood of dropping out by subsequent time points (results available on request).

have obtained low grades if they had remained in school). Second, we explore this pattern over time from a somewhat different angle. As in Appendix Figure 1, we regress GPA during each semester on depression variables and covariates. The difference here is that the key independent variable is a set of dummies referring to the 2x2 combinations of depression status that one could have at baseline (fall 2005) and follow-up (fall 2007) (yes/yes, yes/no, no/yes, no/no). Therefore the sample is restricted to students who completed both surveys. The idea is to compare people with persistent or recurrent depression (yes/yes) to the nondepressed (no/no) and the depressed at only one time point (yes/no and no/yes). Although the coefficients are not all significant at $p<0.05$, the results generally suggest that those with persistent or recurrent depression do significantly worse than all three other groups.

In order to control for the effect of time-invariant individual characteristics on GPA, we next analyze the longitudinal data using regressions with individual and time fixed effects (Table 5). This analysis only applies to people surveyed in both fall 2005 and fall 2007. When each mental health variable is included separately, each has a negative association with GPA, with depression and panic disorder significant at $p<0.01$ and generalized anxiety and eating disorders significant at $p<0.10$. When the mental health variables are included together (column 4), the results remain similar, except the depression coefficient declines in absolute value and is not significant at conventional levels and generalized anxiety is no longer significant. When we look at interactions between mental health conditions (column 5), we see that co-occurring depression and anxiety has a negative and significant association with lower GPA.[17]

Next, because our results described earlier reveal a significant relationship between depression at baseline and subsequent GPA, we look inside the “black box” of depression by examining the nine specific symptoms measured in the survey (corresponding to the nine DSM-IV symptoms of major depression, as noted earlier). In the columns of Appendix Table 2, the "separate" header indicates that each cell in that column represents a separate regression for each symptom, and the "together" header indicates that all nine symptoms (from the PHQ-9) are in the same regression (i.e., the column refers to a single regression). Following the general scoring system for the PHQ-9, each symptom is coded as 0-3, depending on the frequency with which the symptom is reported for the previous two weeks (0 = “not at all”, 1 = “several days”, 2 = “more than half the days”, 3 = “nearly every day”). When entered into separate regressions, each symptom is significantly associated with a lower GPA, which is not surprising

[17] Fixed effects results for credit hours (available on request) are generally similar to the baseline results for this dependent variable (Table 4). A positive screen for panic disorder is associated with 1.56 fewer credit hours ($p=0.03$), whereas symptoms of eating disorders and depression are negatively but not significantly associated with credit hours.

given that the overall depression index is significantly associated with a lower GPA and the symptoms are correlated with each other. More importantly, when all nine symptoms are entered into the same regression, the only symptom that remains significant at $p<0.05$ is the first, anhedonia ("Little interest or pleasure in doing things"). Also, one other symptom, psychomotor retardation or agitation, is marginally significant ($p=0.09$) ("moving or speaking slowly? Or the opposite -- being fidgety or restless").

Table 5: Fixed effects (within-person) regression of GPA on mental health

Linear regression with individual and time fixed effects, with coefficients and SE reported.

	1	2	3	4	5
Depression score (0-27)	-0.014			-0.009	0.002
	(0.006)			(0.006)	(0.007)
Panic disorder (0/1)		-0.470		-0.467	-0.115
		(0.177)		(0.167)	(0.221)
Generalized anxiety (0/1)		-0.148		-0.072	0.456
		(0.096)		(0.105)	(0.244)
ED symptoms (0-5)			-0.044	-0.046	-0.033
			(0.026)	(0.027)	(0.043)
Depression (0-27) * anxiety (0/1)					-0.045
					(0.017)
Depression (0-27) * ED (0-5)					-0.002
					(0.004)
Anxiety (0/1) * ED (0-5)					0.078
					(0.062)
N	1126	1139	1136	1117	1117

Note: The reported N's include two observations per student (there are 563 unique students in these regressions). Note that the sample size is smaller than the full longitudinal sample because some students have missing GPA values, for reasons discussed in the text.

POTENTIAL MECHANISM: TIME SPENT ON SCHOOL WORK

Although our data have little information about potential *mechanisms* by which mental health could affect academic outcomes, we do have information on the amount of time spent on school work in the fall 2005 survey. Participants were asked, "During a typical week, about how many hours a week do you spend doing work for school (includes time in class, doing homework or assignments, studying, research)?" We find that the mean hours per week are 28 (25 for undergraduates, 32 for graduate students). In a regression of hours of school work per week on the mental health variables and all other covariates, we find that panic disorder is the only mental health variable significantly related to hours of school work (-6.0 hours, p=0.06). This suggests that the significant negative association between depression and GPA is not due to less time spent on school work, but rather the productivity of that time. Also, when we add time studying as a covariate in our main GPA regression, the coefficient for depression hardly changes (and in fact becomes slightly more negative), again suggesting that time use is not the major mechanism.

STRATIFIED ANALYSES: GENDER AND ACADEMIC LEVEL

We run all of our main analyses separately by gender, motivated by the fact that females report a higher prevalence of mental health problems and some of the previous studies noted earlier find different relationships between mental health and academic outcomes by gender. For the most part, however, we find that the results are similar by gender. For example, the relationship between depression score and GPA (as in Table 3, column 8) is -0.011 (p=0.01) for females and -0.013 (p=0.01) for males, and the relationship between depression score and dropping out (as in Table 4, column 5) is 0.0032 (p=0.03) for females and 0.0028 (p=0.05). On the other hand, a few differences by gender are notable. First, the negative relationship between anxiety disorders and credit hours appears to be driven by females, for whom the coefficient on panic disorder is -0.91 (p=0.01) and the coefficient on generalized anxiety is -0.96 (p=0.04), whereas the coefficients for males are small and insignificant. Second, among the nine symptoms of depression, for females the most significant are anhedonia (-0.038, p=0.13), sleep impairment (-0.029, p=0.14), and appetite problems (-0.037, p=0.09), whereas for males the most significant are anhedonia (-0.067, p=0.06) and psychomotor retardation or agitation (-0.088, p=0.04). This suggests that the ways in which depression impairs people may differ significantly by gender. Finally, in the fixed effects analysis of GPA, we find that the results are stronger for depression, panic disorder, and co-occurring depression and anxiety among females, whereas the results are stronger for generalized anxiety among males.

We also run our analyses separately for undergraduates and graduate students, because these two groups are different in age and academic demands, among other potentially important factors. Two of our key results—the significant associations between depression at baseline and both GPA and dropping out—remain nearly identical for both undergraduates and graduate students. On the other hand, a few results are stronger for undergraduates than graduate students. First, co-occurring depression and anxiety are significantly associated with lower GPA for undergraduates but not graduate students. Second, panic disorder is significantly associated with higher drop-out among undergraduates but not graduate students. Third, in the fixed effects results, depression and panic disorder are negatively and significantly associated with GPA for undergraduates, but not for graduate students. Collectively, these results suggest that the general negative relationship between mental health and academic outcomes is more robust for undergraduates than graduate students at the institution in our study.

SENSITIVITY CHECKS

We examine the sensitivity of our results to including three additional control variables relevant to college life: current financial situation (whether one's situation is a "struggle", "tight," or "not a problem"), frequent binge drinking (defined as consuming at least four drinks if female, or five drinks if male, on at least three occasions in the previous two weeks), and exercise (hours per week on average in the previous month). We find that including these variables does not alter any of our main findings for the mental health variables, but it is interesting to note that binge drinking is negatively and significantly related to GPA in both the baseline (-0.06, p=0.05) and fixed effects (-0.154, p=0.02) regressions. Binge drinking (and other substance use) is not a focus of this paper, but appears to warrant attention in future research on health and behavioral determinants of college academic outcomes.

5. DISCUSSION

While our general finding that mental health problems are associated with lower academic success is consistent with our prediction, a number of specific findings raise additional questions.

First, the results for eating disorders are notably different between our analysis using only baseline measures of mental health and our within-person analysis using measures at two time points. The latter analysis indicates a negative association with GPA, whereas the cross-sectional results indicate a positive (though not significant) association. The cross-sectional estimates may be confounded by the fact that people prone to eating disorders also tend to have personality characteristics that can enhance their academic performance, such as perfectionism and obsessive attention to detail (Halmi, 2000; Kaye et al., 2004). In the longitudinal analysis, where we look at within-person differences, we may be seeing that these people actually have better academic performance when they are not actively experiencing the symptoms of eating disorders. This is just one possibility, and further research that adjusts for these types of personality characteristics would be useful to understand these discrepancies.

Another contrast between the baseline and longitudinal analysis is that the negative association between depression and GPA is weaker in the latter analysis. This may reflect a combination of factors, including: a) in contrast to the explanation offered for the eating disorders results, in the case of depression time-invariant personal characteristics might not bias the estimates towards zero; b) if depression causes people to be more likely to drop out, as suggested by our results in Table 4, this may bias the fixed effects estimates towards zero (as students who would have both increased depression and lower grades at follow-up are not in the sample); c) as suggested by the results in Appendix Table 1, the persistence of depression may be a pivotal factor in the extent to which it causes impairment, and our within-person fixed effects analysis cannot identify the effects of depression for people with similarly elevated depressive symptoms at both time points.

The apparent importance of persistent depression may be related to the fact that these people tend to have greater impairment to verbal memory than people with first episodes of depression (Fossati, 2004). It is also possible that some students with persistent depression are in a self-perpetuating cycle, in which depression impairs performance, which in turns lowers one's self-assessment of abilities, which in turn contributes to continued depression and lower investment in school work. These possibilities are concerning in light of the fact that depression is often lasting and recurring (Eaton, 2008).[18]

Another interesting aspect of the results for depression is that anhedonia is significantly associated with GPA, independent of other depressive symptoms, whereas negative affect (the second symptom, "feeling down, depressed, or hopeless") is not. This appears to highlight the fact that many students can feel severely depressed but still remain highly functional. Serious impairment in academic functioning appears to arrive only once someone loses interest or enjoyment in usual activities.

Our finding that co-occurring depression and anxiety appear to be especially impairing is consistent with clinical and epidemiological research. Compared to either depression or anxiety alone, co-occurring depression and anxiety (often referred to as anxious depression) is associated with substantially higher severity of illness (Joffe, 1993), functional impairment (Joffe, 1993; Kessler, 1999), and chronicity (Van Valkenburg, 1984). The co-occurrence of these two disorders also frequently predicts poor treatment outcomes (Brown & Madonia, 1996). Given the high prevalence of both depression and anxiety disorders among college students (Blanco et al., 2008), improving knowledge

[18] We have also found in other analyses of the data sets in the present study that depression in fall 2005 is highly correlated with depression in fall 2007 (Zivin et al., 2009)).

about their co-occurrence and how this affects academic outcomes would be valuable.

Although this study represents a first step, future studies are needed to characterize the course of mental health over time within individuals in college. In our study we do not necessarily know whether students are experiencing mental health problems for the first time or if their symptoms are a continuation of earlier problems. To some extent our fixed effects analysis controls for this issue, by focusing on within-person changes, but the effects of mental health on academic performance may vary substantially over time for a given individual, particularly if they find treatments or other strategies to cope effectively with these problems. In analyses not shown, we explore these possibilities in two simple ways. First, we include variables indicating treatment (medication or therapy/counseling in the previous year) in the regressions.[19] These results, however, indicate no significant relationship between treatment and academic outcomes, which may be because the benefits of treatment are confounded by negative selection (more severe cases) into treatment. Second, we conduct our analysis with the sample restricted to students who reported being diagnosed with a mental disorder (by fall 2005), which includes 19% of the sample (and depression is the most common diagnosis, at 13%). Most of these students presumably have been aware of mental health problems for some time. We find that these results, though imprecise due to the smaller sample, are largely the same as for the full sample.

POTENTIAL POLICY IMPLICATIONS

As noted earlier, the data in this study have unique advantages but do not permit definitive causal estimates. Regardless of causality, however, the estimates pertain to the question of whether including mental health criteria would be worthwhile in efforts to screen for risk of poor academic outcomes such as dropping out (with the aim of intervening to reduce drop-out rates among those identified as higher risk). As a simplified example, consider the question of whether to use a risk screen based on the previous semester's GPA ("high risk" if GPA<3.0, "low risk" if not) versus a screen based on both GPA and mental health criteria ("high risk" if GPA<3.0 *or* positive screen for depressive or anxiety disorder). Applying these criteria to our sample, we find that adding the mental health criteria would substantially increase the proportion of eventual drop-outs who are identified (from 11% to 30% of all drop-outs). However, at the university in our study drop-out rates are low enough (less than 10% over more

[19] In other work we document that about 30% of students with a positive screen for depression or an anxiety disorder received treatment (medication or therapy) in the previous year (Eisenberg et al., 2007).

than a two-year period for our baseline sample) that screening solely for the purpose of reducing the drop-out rate may not be cost-effective. Even in the highest risk category in the example above (those with low GPA *and* a positive screen for a mental disorder), only 25% of students go on to drop out. This implies a low specificity of screening efforts (i.e., a high "false positive" rate). On campuses with higher drop-out rates, screening would be more likely to be cost-effective, and our estimates suggest that mental health criteria may substantially increase the identification of those at risk. Alternatively, mental health criteria could be used to restrict the screening criteria and increase the efficiency of screening: note that in the example above, we find that the drop-out rate is 25% among students who meet both GPA and mental health criteria, as compared to 9% among students who only meet the GPA criterion.

As a second policy consideration, we examine what our estimates would imply about the economic returns to increasing treatment for mental disorders among college students, if the estimates were assumed to be reasonable proxies for the causal effect of mental health on remaining in school. This informal exercise in cost-benefit analysis can illustrate the relevance of establishing this relationship more definitively with a randomized trial of depression treatment among college students. To begin, we assume that treating depression with medication has an average effect of reducing depressive symptoms by approximately one standard deviation.[20] This translates to a reduction of -4.6 points on the PHQ depression score in our sample, which, when combined with our estimate of the association between PHQ score and dropping out within one year (0.003), translates to a reduction of -0.0138 in the probability of dropping out due to treatment. We next assume that the marginal present discounted value of earnings due to a year of college is approximately $50,000, using 2008 Current Population Survey (CPS) earnings data with an assumption of a 7% return to a year of schooling (Card, 1999) and a 3% discount rate. On the other hand, the opportunity costs of a year in college would include foregone earnings (a difference of approximately $9,000 in earnings per year for 19-22 year-olds with a high school but no college degree, as compared to 19-22 year old college students, according to the 2008 CPS) and tuition costs (about $10,000 per year on average at four-year institutions) (National Center for Education Statistics, 2008). If we assume that dropping out implies a loss of two years of college, on average

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[20] For simplicity we focus on medication, for which a recent meta-analysis indicates that the average effect size, relative to placebo, is a 0.8 standard deviation reduction in the level of depressive symptoms (Rief et al., 2009). Given that the placebo has therapeutic value in itself, the true clinical benefit of medication is likely to be significantly more than 0.8 standard deviations, so one standard deviation can be considered a conservative estimate. Certain forms of psychotherapy such as cognitive behavioral therapy have been shown to have similar clinical benefits as medication (U.S. Department of Health and Human Services, 1999), and would therefore imply similar returns in this exercise (though at a somewhat higher cost of treatment).

(note that most drop-outs tend to occur early in a degree program, but some people will return to college at a different school, which we cannot observe), then the numbers would imply that the net income return from treatment in college is about $860. This benefit is larger than the average cost of outpatient treatment (including medication costs and physician time) (Valenstein et al., 2001), even though it does not account for potential returns via improved learning and GPA, nor does it account for arguably the main benefit of treatment, improved quality of life.

Colleges and universities may be interested in how these estimates would apply to a screening program that aims to reduce the prevalence of untreated depression. If a school conducted a universal screening program, then it might expect to identify 7% of its students with untreated depression (out of a total of 10% with untreated depression, based on our data), given that the PHQ-9 screen has a sensitivity in the range of 70% (Kroenke et al., 2001). If the screening program increased the probability of receiving treatment by 20% among this 7%, then the screening program could yield about $12 per student in the overall population in economic returns ($860 * 20% * 7%). If we account for outpatient treatment costs (which the school would incur for the majority of students, based on our data on service use), and assume these costs to be in the range of $400 on average (Valenstein et al., 2001), then the net economic benefit would be about $7 per student in the overall population. This amount compares favorably to the costs per person of administering a brief depression screen, which are estimated to be $5 (Valenstein et al., 2001). Of course, these estimates are imprecise and subject to many assumptions, but they suggest that the economic returns to depression treatment in college may be significant and would be worth quantifying more accurately. This will probably require a relatively large randomized trial of mental health treatment that collects academic outcomes, because it is difficult to imagine a naturally occurring instrumental variable that significantly affects mental health in college without affecting other factors that contribute to academic success.[21]

CONCLUSIONS

This descriptive analysis shows that depression, anxiety, and eating disorders are significantly associated with academic outcomes among college students. To the extent that these represent causal relationships, college campuses may be able to further their central educational missions, and generate significant economic

[21] One possibility, however, would be to exploit the substantial variation in the supply of mental health services across campuses and over time as a quasi-experiment. It remains to be seen whether this quasi-experiment is exogenous or strong enough (particularly because the effectiveness of treatment depends on a number of consumer and provider factors).

returns for society, by investing in mental health resources. Randomized studies of mental health treatment in college populations would be valuable for further clarifying the potential for these benefits. In addition, the association between mental health and GPA may be relevant to improving understanding of the broader issue of how mental health affects productivity more generally.[22] Because workplace productivity is typically difficult to measure, GPA may represent a useful proxy for studying issues that could plausibly generalize from academic to employment settings. To the extent that productivity fluctuates as a function of mental health, whether in an academic or workplace setting, this suggests a wrinkle in the concept of human capital that is relevant for a sizeable proportion of the population.

[22] A number of studies suggest that mental health affects work productivity (Ettner et al., 1997; Marcotte & Wilcox-Gök, 2001), and a recent randomized study indicated that improved treatment of depression can increase productivity (Wang et al., 2007).

Appendix Table 1: Semester GPA as a fx of depression at baseline/follow-up

Linear regressions with coefficients and standard errors reported.

	N	NO/NO	NO/YES	YES/NO	YES/YES
Fall 2005	575	(ref)	0.072	-0.081	-0.098
			(0.067)	(0.076)	(0.083)
Winter 2005	550	(ref)	0.020	-0.039	-0.105
			(0.072)	(0.096)	(0.088)
Fall 2006	499	(ref)	-0.048	0.060	-0.189
			(0.087)	(0.106)	(0.104)
Winter 2007	462	(ref)	0.057	-0.089	-0.175
			(0.089)	(-0.129)	(0.087)
Fall 2007	453	(ref)	-0.001	0.073	-0.109
			(0.071)	(0.107)	(0.090)
Winter 2008	392	(ref)	0.024	-0.035	-0.160
			(0.083)	(0.089)	(0.080)

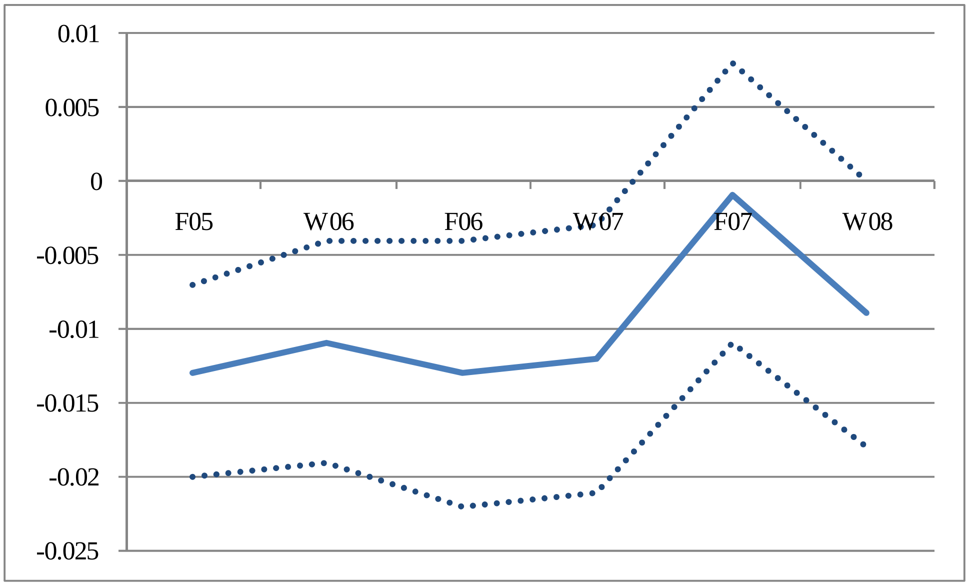
Notes: Each row corresponds to a separate regression. 'NO/YES' means, for example, that the student did not have a positive screen for depression baseline, but did at follow-up two years later.

Appendix Table 2: Association between GPA and depressive symptoms

	1	2	3	4
	SEPAR	TOGETH	SEPAR	TOGETH
1: Little interest or pleasure in doing things	-0.112	-0.091	-0.067	-0.054
	(0.023)	(0.032)	(0.019)	(0.024)
2: Feeling down, depressed or hopeless	-0.057	0.039	-0.04	0.005
	(0.019)	(0.028)	(0.017)	(0.023)
3: Trouble falling or staying asleep,	-0.068	-0.036	-0.024	-0.005
or sleeping too much	(0.017)	(0.020)	(0.015)	(0.017)
4: Feeling tired or having little energy	-0.051	0.007	-0.014	0.022
	(0.019)	(0.024)	(0.015)	(0.019)
5: Poor appetite or overeating	-0.052	-0.002	-0.043	-0.023
	(0.016)	(0.019)	(0.017)	(0.018)
6: Feeling bad about yourself -- or that you are	-0.068	-0.012	-0.042	-0.012
a failure or have yourself or your family down	(0.018)	(0.024)	(0.016)	(0.021)
7: Trouble concentrating on things, such as reading the	-0.083	-0.027	-0.053	-0.024
newspaper or watching television	(0.019)	(0.023)	(0.018)	(0.019)
8: Moving or speaking slowly? Or the opposite --	-0.11	-0.049	-0.077	-0.047
being fidgety or restless	(0.029)	(0.030)	(0.027)	(0.028)
9: Thoughts that you would better off dead				
or hurting yourself	-0.1	-0.019	-0.042	0.012
	(0.032)	(0.041)	(0.032)	(0.035)
Covariates			X	X

Notes: Baseline sample is used (Ns are same as in Table 3); and covariates are same as listed below Table 3. 'SEPAR' denotes that the symptoms are entered into separate regressions (each row in the column is from a separate regression), whereas 'TOGETH' denotes that all symptoms are entered into the same regression (the column refers to a single regression).

Appendix Figure 1: Association between GPA and baseline depression



Notes: "F05" refers to the Fall 2005 semester, "W06" the Winter 2006 semester, etc. Each point in the solid line refers to the estimated coefficient for PHQ depression score (0-27), controlling for anxiety, ED symptoms, and all covariates noted below Table 3, in a regression with the GPA in that semester as the dependent variable. The dotted lines refer to the upper and lower bounds of the 95% confidence intervals.

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