Is Poor Fitness Contagious?
Evidence from Randomly Assigned Friends

Scott E. Carrell[†]
UC Davis and NBER

Mark L. Hoekstra[†]
University of Pittsburgh

James E. West[†]
USAF Academy

January 30, 2010

Abstract

The increase in obesity over the past thirty years has led researchers to investigate the role of social networks as a contributing factor. However, several challenges make it difficult to demonstrate a causal link between friends' physical fitness and own fitness using observational data. This study uses a randomized treatment design and shows that friends' fitness affects own fitness as well as the probability of being classified as unfit. In equilibrium, our estimates imply that each out-of-shape individual creates two additional out-of-shape individuals through their social interactions, thus supporting the provocative notion that obesity spreads on a person-to-person basis.

[†]Scott E. Carrell: University of California-Davis, Department of Economics, One Shields Ave., Davis, CA 95616 (email: secarrell@ucdavis.edu). Mark L. Hoekstra: University of Pittsburgh, Department of Economics, 4714 WW Posvar Hall, 230 S. Bouquet St., Pittsburgh, PA 15260 (email: markhoek@pitt.edu). James E. West: Department of Economics and Geosciences, United States Air Force Academy, CO 80840 (email: jim.west@usafa.edu).

One of the most striking health trends in recent years has been the decline in the physical fitness of the U.S. population. Nearly two-thirds of adults are currently overweight, while more than 30 percent are obese (Hedley, et al., 2004). In response, researchers have proposed several explanations. While some point to societal factors that have shifted people toward increased food consumption or decreased exercise (Hill & Peters 1998; Cutler, Glaeser, & Shapiro, 2003) a provocative recent explanation is that the effects of social and environmental factors may be amplified by the person-to-person spread of obesity (Christakis & Fowler, 2007). This explanation has profound implications, as it suggests that social networks can multiply the effects of otherwise smaller changes in the determinants of obesity. Conversely, if social networks are an important determinant of health, policies that increase individual health could conceivably combat the obesity epidemic through the social multiplier effect.

However, credibly estimating the causal effect of social networks ties on individual health outcomes has been difficult. There are three main empirical challenges to overcome: self-selection, common environmental factors, and reflection.[1] Self-selection implies that people tend to associate with those similar to them. For example, two individuals who prefer a sedentary lifestyle may both socialize together and gain weight over time, making it impossible to distinguish the effect of the lifestyle from that of the friend. In addition, people within a social network may be subject to common environmental factors, which confound the social network effects. For example, family members may both spend a lot of time together and share genetic predispositions toward weight gain, making it difficult to distinguish the effect of one factor from the other.

[1] The medical literature often refers to self-selection as "homophily" (love of the same). Common environmental factors are often referred to as "correlated effects" or "common shocks" (Manski, 1993).

Similarly, people within a neighborhood may share the same proximity to fast food restaurants and city parks. Finally, it is empirically difficult to overcome what social science researchers have referred to as the reflection problem (Manski, 1993). That is, between two friends, each friend affects the other simultaneously.

While understanding whether social network effects exist is an important question for public health policy, overcoming these identification problems using observational data is challenging. As such, the causality of estimates in the recent social network health literature has been drawn into question.[2] In this study, we overcome these identification challenges by utilizing data from the US Air Force Academy in which 3,323 college students were randomly assigned to (residential) social networks from 2001 to 2005 to examine the role of such networks in shaping physical fitness outcomes. To our knowledge, this study is the first to use a randomized treatment design to estimate peer effects in health outcomes, enabling us to overcome the problem of self-selection.[3] Additionally, our data contain an individual level pre-treatment measure of fitness, which enables us to overcome issues with common environmental factors and reflection.

We evaluate whether being assigned to peers who were less fit during high school affects college fitness scores as well as the probability of failing tests consisting of a 1.5-mile run and various calisthenics. We also examine whether the effects we find are

[2] These concerns have perhaps been best illustrated in Cohen-Cole and Fletcher's (2008a and 2008b) critiques of Christakis and Fowler (2007) who use data from the Framingham Heart Survey to show that obesity, smoking, and happiness appear to spread through social ties. Cohen-Cole and Fletcher report that the same methodology also yields social network effects in implausible outcomes such as height and headaches and that employing additional controls for self-selection and environmental confounders reduces the estimates and renders them statistically indistinguishable from zero. While we make no attempt to delve into the nuances of these critiques and their responses, we argue that this clearly highlights the general difficulty with making causal inferences using observational data.

[3] We note that a number of recent studies have used randomization at the college roommate and/or college peer group level to identify peer effects in *academic achievement*. See Sacerdote (2001), Zimmerman (2003), Stinebrickner & Stinebrickner (2005), Foster (2006), Lyle (2007), and Carrell, Fullerton & West (2009) for examples.

caused primarily by exposure to the least or most fit friends in one's own social network. Results indicate that poor fitness does spread on a person-to-person basis, with the largest effects caused by friends who were the least physically fit.

Data

The data utilized in our study consist of 11,321 observations on 3,323 freshmen and sophomore students from 2001 to 2005 at the United States Air Force Academy (USAFA). These data are utilized because of one extraordinary feature of the environment there: while most individuals have a significant amount of choice over the group of people with whom they associate, USAFA students are randomly assigned to groups of 30 students with whom they are required to spend the majority of their time. Prior to the start of the freshman and sophomore years, administrators implement a stratified random assignment process in which females are first randomly assigned, followed by male ethnic and racial minorities, then nonminority recruited athletes, then students who attended a military preparatory school, and then all remaining students. This critical feature of our data set enables us to overcome bias due to self-selection.

Statistical resampling tests provide evidence that the algorithm that assigns students to peer groups is consistent with randomization (Lehmann & Romano, 2005). To implement the test, for each peer group we randomly drew 10,000 groups of equal size from the relevant cohort of students without replacement. We then computed empirical p-values for each group, representing the proportion of the simulated peer groups with higher average pre-treatment fitness scores than that of the observed group. Under random assignment, any unique p-value is equally likely to be observed; hence the expected distribution of the empirical p-values is uniform. We tested the uniformity of the distributions of empirical p-values in each year using the Kolmogorov-Smirnov one-sample equality of distribution test. We failed to reject the null hypothesis of random placement for both the freshman and sophomore peer group assignments, with p-values of 0.934 and 0.578, respectively.[4]

Students are required to spend the majority of their time interacting with peers in their assigned group: they live in adjacent dorm rooms, dine together on meals served family-style, compete in intramural sports together, and study together. During the freshman year, students have limited ability to interact with students outside of their social network.[5] However, across peer groups, nearly all other aspects of life and work at USAFA are similar. Specifically, during both the freshmen and sophomore years, all students primarily take the same courses in which they are randomly assigned to professors, are served the same meals in the cafeteria, live on the same campus in the same dorm buildings, and are subject to the same physical conditioning requirements. Consequently, there is little scope for environmental confounders to bias estimates of social network effects.

A second advantage of this study relates to the outcomes examined. While most existing studies examining physical fitness/obesity use weight-to-height comparisons such as body mass index (BMI), there is consensus that such measures do not adequately

[4] For further evidence of the randomization of peer groups at the USAFA, see Carrell, Fullerton, and West (2009).

[5] In their sophomore year, students have more opportunity to interact with students from other groups, though students within groups still live in adjacent dorm rooms, dine together, compete in intramural sports together and in general interact together frequently. We note, however, that interaction with students outside the group would likely bias our estimates toward zero by introducing measurement error in the peer variable (Carrell, Fullerton, and West (2009).

measure whether an individual is actually physically fit and healthy (Smallley, et al, 1990; Gallagher, et al, 1996; Burkhauser & Cawley, 2008).[6] In contrast, our dataset from the USAFA provides for two, arguably superior, health outcome measures: the overall physical education score achieved during the semester and whether or not the individual failed the physical fitness requirements.[7] As shown in Table 1, roughly nine percent of the students failed to meet these requirements and were thus put on athletic probation by the USAFA. The average physical education score was 2.61, out of a maximum of 4.00.

Importantly, we also collected data on individuals' physical fitness prior to enrolling at the academy. This is critical for making causal inferences for two reasons. First, because we examine whether friends' fitness in *high school* affects an individual's own fitness in *college*, we can rule out the possibility that common environmental factors are causing the correlation between own health and friends' health. For example, it is difficult to conceive of a factor that would simultaneously affect own fitness in college as well as a friend's fitness in high school, since the two were not yet friends in high school.[8] Finally, we can rule out the possibility of reflection, since it is impossible for one's own current health to affect a friend's health (i.e. high school fitness score) before she or he entered the social network.

---

[6] In response to those same concerns, in 2005, the US Air Force came to its own conclusion that its' weight management program based on BMI was flawed and instead began using an annual fitness exam that included a timed 1.5 mile run, sit-ups, push-ups, and pull-ups.

[7] The physical education average (PEA) score consists of a weighted average of scores on the following tests: 1) a 1.5 mile timed run called the aerobic fitness test (15%), 2) a physical fitness test consisting of pull-ups, push-ups, sit-ups, standing long-jump and a 600 yard sprint (50%), and 3) grades in mandatory physical education courses (35%). Failing the fitness requirement occurs when an individual fails to meet the minimum standards on any of the subcomponents of the physical education score.

[8] Students at the USAFA come from every congressional district in the United States; therefore, it is highly implausible that common environmental factors could affect both the high school and college fitness exams.

The full set of summary statistics is shown in Table 1. The average combined SAT score of students at the academy is 1,298, which is similar to other undergraduate institutions such as UCLA, University of Michigan, University of Virginia, and UNC-Chapel Hill. Eighteen percent of the sample is female, 5 percent is Black, 6 percent is Hispanic, and 5 percent is Asian. The average high school health fitness score of peers randomly assigned to one's social network is 460, with a standard deviation of 18 points across groups and a standard deviation of 96 across individuals.

While the USAFA data offer distinct advantages with respect to both the randomization of peers and the availability of an absolute measure of fitness, there is an open question regarding whether the effects we find would be similar in other contexts. The USAFA is somewhat unique in that students tend to both eat and exercise with their (randomly assigned) friends, which suggests our estimates may overstate the effects found in other environments. However, other factors suggest the effects of peers may be larger elsewhere. Unlike most other settings, students at the USAFA are subject to mandatory physical fitness requirements and face serious repercussions—including possible expulsion—if they fail.[9] In addition, all students are offered the same family-style meals in the cafeteria, leaving little potential for friends to affect the *type* of foods eaten. These factors suggest that there may be less scope for friends at USAFA to impact individuals' physical fitness relative to other settings. Consequently, we remain agnostic

[9] If students fail to meet the minimum requirements in a given semester they are placed on athletic probation and put into a mandatory reconditioning program. Repeated failures lead to expulsion. The minimum time requirement for the 1.5-mile run is 11:15 for males and 13:20 for females. Students must score at least 250 points on the physical fitness test (PFT) and achieve the following minimums on each component: 1) pull-ups (7-males, 1-females), 2) long jump (7'00"-males, 5'09"-females, 3) sit-ups (58-males, 58-females), 4) push-ups (35-males, 18-females, and 5) 600 yard run (2:03-males, 2:23-females). However, minimums on every event result in a total score of 125 points and failure of the PFT.

regarding whether effects presented here would be larger or smaller for other populations in other environments.

Methods

To determine the effect of friends on physical fitness, we estimate standard logistic and ordinary least squares regressions in which the dependent variables are whether the individual was placed on athletic probation and the overall physical education average (PEA) score, respectively. The main explanatory variable of interest is the average high school fitness score of one's peers, and in all specifications we include a control for own high school fitness as well as graduation class fixed effects. To ease interpretation, own fitness scores are normalized to have mean zero and standard deviation one. Similarly, the peer high school fitness score variable is normalized by subtracting the mean and dividing by the *individual-level* standard deviation. We normalized the peer variable in this manner to ensure comparability between the coefficients on the own and peer high school fitness variables. We cluster our standard errors at the peer group level to allow for correlation across individuals within the same network.

Although the average high school fitness of peers in one's network is determined by random assignment within a graduation class cohort, in some specifications we also include additional controls to examine the robustness of our results. Specifically, we include graduation class by semester fixed effects, year by semester fixed effects, and state of residence fixed effects. This allows for changing factors over time that might affect the entire cohort of students in a given semester, such as differing academic requirements or changes in the dietary menus. We also include controls for individual-level characteristics that may affect fitness including math and verbal SAT scores, a high school academic composite (GPA and class rank) score, a leadership composite score, and indicators for student race, whether the student was recruited to the academy as an athlete, and whether the student attended a military preparatory school.

Results

Results are shown in Table 2, which reports marginal effects from a logistic regression in which failing the fitness requirement is the dependent variable. Column 1 adjusts estimates only for own fitness in high school and indicators for graduation year. The estimate indicates that peers' fitness (as measured in high school) has a large and statistically significant effect on the probability that one fails the fitness requirements in college. The marginal effect shows that a one standard deviation increase in the high school fitness score of *all* peers in the group results in a statistically significant -3.8 percentage point change in the probability of failing the fitness requirements. This effect size represents a 42 percent reduction relative to the baseline failure rate of 9 percent. By comparison, a similar sized improvement in own fitness is associated with a statistically significant 6.0 percentage point drop in the failure rate. This is striking, as it suggests that the effect of friends' high school fitness on current fitness is about half as strong as the effect of own high school fitness.

To account for individual-level factors that may affect own health, in columns (2) and (3) of Table 2 we sequentially add the individual controls and the fixed effects. The magnitude of the peer effect decreases slightly, but is statistically indistinguishable from the estimate in column (1). These results are expected given that peer groups were randomly assigned.

While the estimates in columns (1) through (3) imply that the underlying fitness of friends does have a significant impact on whether one is classified as being in poor fitness, it is also possible that the effect is caused by other peer factors correlated with fitness. For example, perhaps less fit peers are also less motivated to achieve success generally. Similarly, it may be that less fit peers are also less likely to take a leadership role among friends at the academy and this lack of leadership, rather than the lack of physically fit friends, causes students to fail the fitness requirements.

To address these possibilities, we include additional peer controls in column (4). Specifically, we control for the average SAT math and verbal scores, high school academic composite score, and high school leadership composite of peers in one's social network. Results show that the impact of friends' fitness on the likelihood of failing the fitness requirement remains strong and statistically significant, with a marginal effect of 2.2 percentage points. This result suggests that the effects we find are likely caused by friends' fitness and not by a lack of general motivation or leadership ability.

Next, we examine whether friends affect the overall fitness level, as measured by the physical education average (PEA) score. Results are shown in Table 3 and indicate that the average fitness of one's friends has a statistically significant effect on own fitness level. The effect remains large and statistically significant when including additional controls in columns 2 through 4. The estimated effect (0.129) in column (4) indicates that a one standard deviation decrease in the high school fitness score of all of one's peers causes a 0.129 standard deviation decrease in one's own college fitness level. This effect is roughly one-third as large as the predicted impact of own high school fitness score.

Given that friends' average high school fitness affects own college fitness, a natural question to ask is whether this effect is driven by the positive benefit from being around extremely fit friends, or by negative spillovers from physically inactive friends. To investigate this question, we examine how own fitness is affected by the proportion of randomly assigned friends who were in the bottom and top 20 percent of the high school fitness score distribution. These estimated effects are relative to having peers from the middle 60 percent of the fitness distribution.

Results are shown in Table 4. Column (1) shows that while we find little evidence that having friends who are extremely physically fit affect the likelihood of failing the fitness exam, we do find that it is the *least fit* friends who induce students to fail the fitness requirements (marginal effect = 5.7 percentage points, $p<0.05$). Similarly, results in column (2) indicate that it is the least fit friends who have the largest impact on average physical fitness (estimate = 0.36, $p<0.01$). The estimates imply that if half of your friends were to become out-of-shape for reasons unrelated to you, your own fitness level would drop by nearly 20 percent of a standard deviation and you would be 30 percent more likely to fail the fitness requirements.

Figure 1 shows this result graphically by plotting the predicted probability of failing the fitness exam against the proportion of randomly assigned friends who were among the 20 percent of entering freshmen who were least physically fit. We plot outcomes for three hypothetical individuals: one who is in the 10^{th} percentile of fitness upon entering the academy, one who is in the 50^{th} percentile of fitness, and one who is in the 90th percentile of fitness. Figure 1 shows a proportional increase in the probability of failing the fitness exam as one increases the proportion of unfit friends. The largest absolute changes, however, are borne by the least fit individuals. For example, for an individual who is in the 10th percentile of fitness, the probability of failing the fitness exam is only 7 percent when none of his friends are in similarly poor shape, but increases to 21 percent if half of his friends are among the least fit at the academy.

Our results thus yield two notable findings. First, they indicate that the fitness peer effect we find is driven by the least physically fit friends. Second, the individuals most at risk from exposure to unfit friends are those who themselves struggle with fitness. These results imply the social multiplier for physical fitness is 1.96, indicating that in equilibrium, each out-of-shape individual creates approximately two more individuals who are out-of-shape.[10] Thus, our results suggest that the goal of health policy ought likely to be focused primarily on reducing the prevalence of individuals in particularly poor fitness.[11]

Conclusion

Understanding the nature of social interactions is important for both diagnosing the causes of the decline in physical fitness and assessing policy strategies to combat the decline. However, because individuals can select their friends based in part on preferences for diet and exercise and because friends are likely to be subjected to the

[10] Following Glaeser, Sacerdote, & Sheinkman (2003) the social multiplier is calculated as the ratio of the group level and individual level coefficient. The endogenous social multiplier assumes a complete expansion of new unfit friends begetting other new unfit friends. As such, we consider this to be a long-run upper bound of the peer effects we measure.

[11] The multiplier suggests factors that negatively affect the health and fitness of one person such as a sedentary job or high-calorie diet can multiply quickly throughout the population.

same environmental factors, it is difficult to credibly estimate the effect of peers on fitness and obesity using observational data.

We estimate the impact of friends on own physical fitness by exploiting a unique data set in which college students are randomly assigned to a group of 30 students with whom they spend the majority of their time. To our knowledge, this is the first study to examine the effect of social networks on health outcomes using a randomized treatment design. We find strong evidence that friends' fitness affects own fitness as well as the probability of being classified as unfit. More specifically, we find that if half of one's friends become out-of-shape, the probability of failing the basic fitness requirements triples. In equilibrium, our estimates imply that each out-of-shape individual creates two additional out-of-shape individuals through their social interactions, thus supporting the provocative notion that obesity spreads on a person-to-person basis. Consequently, even relatively small health policy interventions may ultimately affect the health of many more individuals by harnessing the effect of the social multiplier.

Bibliography

Burkhauser, Richard V. and John Cawley. 2008. Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. *Journal of Health Econonomics*, 27: 519-529.

Carrell, Scott E., Richard L. Fullerton, and James E. West. 2009. Does Your Cohort Matter? Estimating Peer Effects in College Achievement, *Journal of Labor Economics*, 27, 439-464.

Christakis Nicholas and James Fowler. 2007. The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*; 357: 370-9.

Cohen-Cole, Ethan and Jason M. Fletcher. 2008a. Detecting Implausible Social Network Effects in Acne, Height, and Headaches: Longitudinal Analysis. *British Medical Journal*, 337: a2533.

Cohen-Cole, Ethan and Jason M. Fletcher. 2008b. Is Obesity Contagious? Social Networks vs. Environmental Factors in the Obesity Epidemic. *Journal of Health Economics*, 27 (5): 1382-1387.

Cutler, David O., Edward L. Glaeser, and Jesse M. Shapiro. 2003. Why Have Americans Become So Obese? *Journal of Economic Perspectives,* 17 (3): 93-118.

Foster, Gigi. 2006. It's not your peers, and it's not your friends: some progress towards understanding educational peer effects, *Journal of Public Economics*, 90 (8-9): 1455-1475.

Gallagher, Dympna, Marjolein Visser, Dennis Sepulveda, Richard N. Pierson, Tamara Harris, and Steven B. Heymsfield. 1996. How useful is body mass index for comparison of body fatness across age, sex, and ethnic groups? *American Journal of Epidemiology,* 143 (3): 228–239.

Glaeser, Edward L., Bruce L. Sacerdote, and Jose A. Scheinkman. 2003. The Social Multiplier. *Journal of the European Economic Association* 1 (2–3): 345–53.

Hedley, Allison. A., Cynthia L. Ogden, Clifford L. Johnson, Margaret D. Carroll, Lester R. Curtin, and Katherine M. Flegal. 2004. Prevalence of overweight and obesity among US children, adolescents, and adults, 1999-2002. *Journal of the American Medical Association*, 291: 2847-50

Hill, James O. and John C. Peters. 1998. Environmental contributions to the obesity epidemic. *Science*, 280: 1371-4.

Kremer, Michael and Dan Levy. 2008. Peer Effects and Alcohol Use Among College Students. *Journal of Economic Perspectives*, 23 (3): 189-206.

Lehmann, Erich L. and Joseph P. Romano. 2005. Testing Statistical Hypotheses. Secaucus, NJ: Springer Texts in Statistics, 3rd ed.

Lyle, David S. 2007. Estimating and Interpreting Peer and Role Model Effects from Randomly Assigned Social Groups at West Point. *Review of Economics and Statistics* 89 (2): 289–99.

Manski, Charles F. 1993. Identification and Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies*, 60: 531-542.

Sacerdote, Bruce. 2001. Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics*, 116, 681-704.

Smalley, Karl J., Anita N. Knerr, Zebulon V. Kendrick, Jerry A. Colliver, and Oliver E. Owen. 1990. Reassessment of body mass indices. *American Journal of Clinical Nutrition*, 52, 405–408.

Stinebrickner, Ralph, and Todd R. Stinebrickner. 2006. What Can Be Learned About Peer Effects Using College Roommates? Evidence From New Survey Data and Students From Disadvantaged Backgrounds. *Journal of Public Economics* 90 (8–9): 1435–54.

Zimmerman, David J. 2003. Peer Effects in Academic Outcomes: Evidence from a Natural Experiment. *The Review of Economics and Statistics*, 85 (1): 9–23.

Figure 1: Predicted Probability of Failing the Fitness Requirements

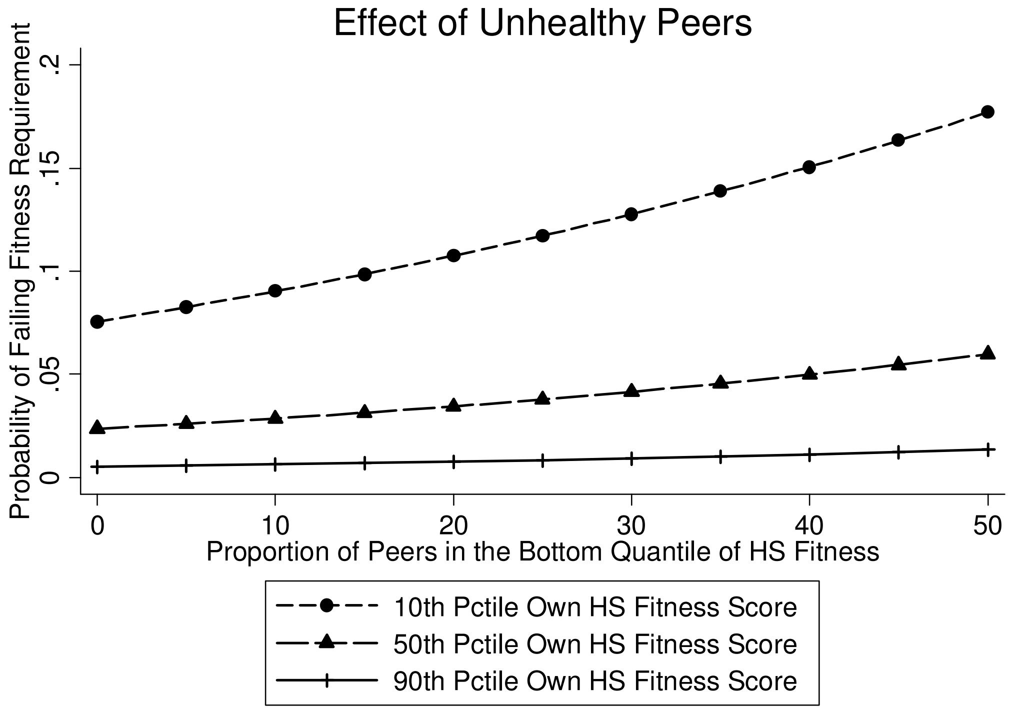

Table 1: Summary Statistics

Variable	Mean (std. dev)		Range
Panel A: College Student Performance and Demographics			
College Fitness Score	2.61	(0.51)	0.35-4.00
Fail Fitness Test	0.09	(0.29)	0-1
High School Fitness Score	461	(96)	215-745
High School Fitness Score (normalized)	0.00	(0.99)	-2.54-2.94
Black	0.05	(0.22)	0-1
Hispanic	0.06	(0.24)	0-1
Asian	0.05	(0.23)	0-1
Female	0.18	(0.38)	0-1
Panel B: Social Network Performance in High School			
Peer High School Fitness Score	460	(18)	405-513
Peer High School Fitness Score (normalized)	0.00	(0.18)	-0.57-0.55
Peer SAT Math	667	(13)	623-709
Peer SAT Verbal	632	(12)	587-671
Peer Academic Composite	1,287	(384)	1,187-1,438
Peer Leadership Composite Score	1,724	(333)	1,603-1,825

Figures come from data on 3,323 students and a total of 216 unique social networks.

Table 2: The Effect of Peer Fitness on Failing the Fitness Requirements

Dependent Variable: Fail Fitness Requirements	(1)	(2)	(3)	(4)
Peer High School Fitness Score	-0.038**	-0.028**	-0.023**	-0.022**
	(0.017)	(0.012)	(0.010)	(0.010)
Own High School Fitness Score	-0.060***	-0.052***	-0.041***	-0.041***
	(0.003)	(0.002)	(0.002)	(0.002)
Observations	11,321	11,321	11,317	11,317
Includes individual controls?	No	Yes	Yes	Yes
Includes year by semester & state of residence fixed effects?	No	No	Yes	Yes
Includes average peer SAT verbal, SAT math, academic composite and leadership composite scores?	No	No	No	Yes

The dependent variable in each specification is the probability of failing the semi-annual fitness test or 1.5 mile run. Standard errors clustered at the peer group level are in parentheses. Each specification controls for graduate class fixed effects. Individual-level controls include SAT verbal and math scores, academic and leadership composite scores, and indicators for Black, Hispanic, Asian, female, recruited athlete, and preparatory school attendance.

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table 3: The Effect of Peer Fitness on Own Fitness Score

Dependent Variable: Physical Fitness Score	(1)	(2)	(3)	(4)
Peer High School Fitness Score	0.165**	0.129**	0.131**	0.129**
	(0.072)	(0.057)	(0.056)	(0.057)
Own High School Fitness Score	0.434***	0.421***	0.418***	0.418***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,321	11,321	11,321	11,321
Includes individual controls?	No	Yes	Yes	Yes
Includes year by semester & state of residence fixed effects?	No	No	Yes	Yes
Includes average peer SAT verbal, SAT math, academic composite and leadership composite scores?	No	No	No	Yes

The dependent variable in each specification is the college fitness exam score. Standard errors clustered at the peer group level are in parentheses. Each specification controls for graduate class fixed effects. Individual-level controls include SAT verbal and math scores, academic and leadership composite scores, and indicators for Black, Hispanic, Asian, female, recruited athlete, and preparatory school attendance.

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table 4: The Effect of Very Physically Unfit and Fit Friends on Own Fitness Outcomes

	Fail Fitness Requirements	Physical Fitness Score
Variable	(1)	(2)
Proportion of Peers in Bottom Quintile of High School Fitness	0.057**	-0.360***
	(0.025)	(0.129)
Proportion of Peers in Top Quintile of High School Fitness	-0.026	0.062
	(0.021)	(0.131)
Own High School Fitness Score	-0.041***	0.418***
	(0.002)	(0.011)
Observations	11,313	11,321
Includes individual and peer controls?	Yes	Yes
Includes year by semester & state of residence fixed effects?	Yes	Yes

Marginal effects from logit estimations are reported in column (1), while coefficients from OLS regression are reported in column (2). Standard errors clustered at the peer group level are in parentheses. Each specification controls for graduate class fixed effects. Individual-level controls include SAT verbal and math scores, academic and leadership composite scores, and indicators for Black, Hispanic, Asian, female, recruited athlete, and preparatory school attendance. Peer controls include peer SAT scores, peer high school composite scores, and peer leadership

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level