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Is poor fitness contagious?[☆] Evidence from randomly assigned friends

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ABSTRACT

The increase in obesity over the past 30 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. To overcome these problems, we exploit data from a unique setting in which individuals are randomly assigned to peer groups. We find statistically significant positive peer effects that are roughly half as large as the own effect of prior fitness on current fitness. Evidence suggests that the effects are caused primarily by friends who were the least fit, thus supporting the provocative notion that poor physical fitness spreads on a person-to-person basis.

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% 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 and Peters, 1998; Cutler et al., 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 and 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 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 (common) 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. 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.[2] In this study, we address these identification challenges by utilizing data

☆ The views expressed in this paper reflect those of the authors and do not necessarily reflect the official policy or position of the U.S. Air Force, Department of Defense, or the U.S. Government.

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[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).

[2] As such, the causality of estimates in the recent social network health literature has been drawn into question. These concerns have perhaps been best illustrated in Cohen-Cole and Fletcher's (2008a,b) 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 controlling for confounders reduces the estimates on BMI. Christakis and Fowler (2008) respond by questioning whether effects on height and headaches are implausible when the outcomes are self-reported, and report evidence that health peer effects estimates are robust across several specifications. While we leave the reader to judge the merits of these critiques and their responses, we do argue that the debate highlights the general difficulty with making causal inferences using observational data.

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from the US Air Force Academy in which 3487 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. While this population is unique in that the students are both younger and considerably more physically fit than the general population, these data offer us two extraordinary advantages with respect to estimating fitness peer effects. First, because students were randomly assigned to peer groups with whom they are required to spend the majority of their time interacting, we can estimate peer effects free of bias caused by self-selection into the group.[3,4] In addition, our data contain an individual level pre-treatment measure of fitness, which enables us to estimate peer effects free of biases due to 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 the academy's fitness requirements. We also examine whether the effects we find are 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.

1. Data

The data utilized in our study consist of 13,016 observations on 3487 freshmen and sophomore students from 2001 to 2005 at the United States Air Force Academy (USAFA).[5] 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 squadrons of approximately 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. Thus, while by design there is relatively little intergroup variation in attributes such as race or gender, the assignment of other attributes such as peer fitness is effectively random. 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 random assignment (Lehmann and 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.[6]

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.[7] 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. Importantly, students do *not* take academic or physical fitness courses[8] together with peers from their squadron, but rather are randomly assigned to professors and instructors along with the other students from their entire cohort. 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 measure whether an individual is actually physically fit and healthy (Smalley et al., 1990; Gallagher et al., 1996; Burkhauser and Cawley, 2008).[9] In contrast, our dataset from the USAFA provides for two, arguably superior, health outcome measures[10]: the overall physical education score achieved during the semester and whether or not the individual failed the physical fitness requirements.

The physical education average (PEA) score is measured on a 0.0–4.0 scale, where the average score is 2.61. It 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%).[11] Grades in the physical fitness courses are based primarily

[3] The only other study we know of that uses a randomized treatment design to study the impact of peer effects on fitness or obesity is Yakusheva et al. (2010), who examine whether a randomly assigned roommate's initial weight affects weight gain during the freshman year of college. They report no effect for men, and find that women assigned to heavier roommates *lose* weight. However, the lack of evidence of positive peer effects among roommates is roughly consistent with the findings of Carrell et al. (2009), who report only moderate evidence of peer effects in education among roommates, though they estimate much larger peer effects when the peer group is defined as the group with which the students spend the majority of their time (i.e., squadron).

[4] 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 and Stinebrickner (2006), Foster (2006), Lyle (2007), and Carrell et al. (2009) for examples. While most of these papers focus on whether peer academic ability affects achievement, Kremer and Levy (2008) examine the effect of roommate drinking on college GPA, and Carrell et al. (2008) examine peer effects in college cheating.

[5] In total there are three cohorts of students from the graduating classes of 2005–2007, with two years of semester-by-student level outcome data.

[6] We also regressed own peer high school fitness on peer pre-treatment characteristics such as peer high school fitness score, peer SAT verbal and math scores, peer academic composite score, and peer leadership score. None of the coefficients are statistically significant at the 10% level, and the p-value from the F-test of joint significance is 0.652. For further evidence of the randomization of peer groups at the USAFA, see Carrell et al. (2009).

[7] 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 et al., 2009).

[8] All students at USAFA are required to take mandatory physical education courses, which are non-academic in nature. For instance, all freshman students are required to take swimming and boxing (males) or unarmed combat (females). Scores in these courses are based on the student's athletic performance in the course such as a timed swimming test and two three-round boxing matches.

[9] 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.

[10] Unfortunately, BMI data are not available for the students in our sample, so we are unable to assess whether peer effects on BMI are different from peer effects on fitness.

[11] Approximately 13% of our observations having missing data for the PEA variable (1695 of 13,016). The PEA variable is not available for students who are unable to complete all components of the score. To test whether these missing observations could bias our estimates, we regressed an indicator for missing PEA on peer pre-treatment characteristics such as peer high school fitness score, peer SAT verbal and math scores, peer academic composite score, and peer leadership score. None of the coefficients are statistically significant at the 10% level, and the p-value from the F-test of joint significance is 0.985.

Table 1
Summary statistics for classes of 2005–2007.

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 (0.28)	0–1
High school fitness score	460 (97)	215–745
High school fitness score (normalized)	0.00 (1.00)	−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	1287 (384)	1187–1438
Peer leadership composite score	1724 (333)	1603–1825

Figures come from the data on 3487 students and a total of 216 unique social networks.

on performance, rather than knowledge or effort. For example, grades in the boxing class are based on one's performance against classmates during three-round fights and grades in swimming are based on distance swimming times and proficiency performing various swimming strokes.

Failing the fitness requirement occurs when an individual receives a PEA score lower than 2.0, or when he or she fails to meet certain specified minimum standards on any of the subcomponents of the PEA score. As shown in Table 1, on average, roughly 9% of the students fail to meet these requirements and were thus put on athletic probation by the USAFA.[12]

Importantly, we also collected data on individuals' physical fitness prior to enrolling at the academy. This score is based on applicants' performance on pull-ups, sit-ups, push-ups, a 600-yard shuttle run, the standing long jump and a basketball throw. The test is typically administered and certified by an official from the individual's high school, such as a physical education teacher.[13] Observing fitness prior to enrolling 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.[14] In addition, 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.

The full set of summary statistics is shown in Table 1. The average combined SAT score of students at the academy is 1298, 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% is Black, 6%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 97 across individuals.

2. External validity

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 generalize to the broader population. The most significant difference between USAFA students and their peers at other selective public universities is that USAFA students spend considerably more time exercising and playing sports. Only 12.5% of USAFA students reported spending 5 or fewer hours on sports and exercise per week in their last year of high school, compared to 48.2% of students at other selective public universities (Cooperative Institutional Research Program (CIRP), 2007). Similarly, 24.6% of USAFA students reported spending more than 20 hours on exercise and sports per week in their last year of high school, compared to 8% of students enrolled at selective public universities (Cooperative Institutional Research Program, 2007).

In addition to differences in incoming fitness levels, students at USAFA are held to rigorous physical fitness standards throughout their college experience. For example, one way in which students can fail the fitness requirement is by not meeting the minimum standards on any of the subcomponents of the physical education score. For the 1.5-mile timed run, minimum passing times are 11:15 for men and 13:20 for women. For the physical fitness test, students must score at least 250 points 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 test. Although our data do not contain each individual component of the PEA, anecdotal evidence suggests that failing the physical fitness test is the most common reason students fail the fitness requirement. However, we note that these are stringent requirements, and that even students who fail this requirement are likely more fit than the typical college student.

As a result of these fitness requirements, students at USAFA likely have lower body fat than typical college students. According to the USAFA Athletics Department, only about 7% of students during their freshman and sophomore years fail to meet body fat standards of 20% for males and 28% for females.

Since we are not aware of any other studies on fitness peer effects, we are unable to make direct comparisons of our estimates to those covering other populations. However, Carrell et al. (2009) report that *academic* peer effects at the academy are similar to those at other academic institutions when the peer group is defined as either roommates, as in Sacerdote (2001) and Zimmerman (2003), or as dorm halls, as in Foster (2006).[15]

There are several factors unique to USAFA that could cause the magnitude of fitness peer effects to be different than in other contexts. Students at USAFA both eat and exercise with their (randomly assigned) friends, suggesting our estimates may overstate the effects found in other environments. On the other hand, certain factors may cause our estimates to understate the effects in other contexts. For example, students at the USAFA face strict upper and lower bounds on the time devoted the physical activity that are not present for the general population. Similarly, the presence of mandatory, well-

[12] The 9-percent failure rate represents the average across all observations. In total, 12.2 percent of students in our sample (406 of 3323) failed the fitness requirement at least once.

[13] The high school fitness data were available for 99.5% of all students in the sample. We dropped from our sample the 19 of 3506 students who were missing the high school fitness score.

[14] 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.

[15] However, Carrell et al. (2009) estimate much larger academic peer effects when the peer group is defined as the squadron rather than as roommates or dormitory residents.

defined physical fitness requirements may reduce the need for peer comparisons, thus reducing the size of the peer effect estimates at USAFA relative to elsewhere.[16] In addition, all students at USAFA are offered the same family-style meals in the dining facility, which reduces the extent to which friends can affect the *type* of foods eaten. Finally, we note that the effect of other factors, such as living in an environment in which peers are randomly assigned, is more ambiguous.

For these reasons, we remain agnostic regarding whether effects would be larger or smaller for other populations in other environments. However, it clear is that regardless of the population in question, peer effects on outcomes such as fitness or obesity must occur by affecting own diet, own exercise, or both. Thus, our view is that at a minimum, the presence of such peer effects in one population increases the likelihood that peer effects in fitness exist more broadly.

3. Methods

To determine the effect of friends on own physical fitness, we estimate standard ordinary least squares regressions[17] in which the dependent variables are the overall physical education average (PEA) score and whether the individual was placed on athletic probation, 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 both the peer group level and individual level using multi-way clustering to allow for correlation across individuals within the same network (Cameron et al., 2011).

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 cohort by 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.

For aid in interpreting the reduced form parameters on our peer effects coefficient, consider the following linear in means peer effects model:

$$y_{ig} = \beta_1 x_{ig} + \beta_2 \bar{y}_g + \beta_3 \bar{x}_g + \theta_g + \varepsilon_{ig} \tag{1}$$

where x_{ig} is the pre-USAFA fitness score and y_{ig} is the contemporaneous fitness score. $\bar{x}_g$ and $\bar{y}_g$ are the average scores of the peer group excluding individual *i*. In Manski's (1993) framework, β_2 represents the *endogenous* peer effect, β_3 is the *exogenous* peer effect, θ_g represents common environmental factors, and ε_{ig} are other individual unobservables.

Taking averages within group *g*, one obtains a reduced form equation:

$$y_{ig} = \beta_1 x_{ig} + \frac{\beta_2(\beta_1 + \beta_3)}{1-\beta_2}\bar{x}_g + \tilde{\theta}_g + \tilde{\varepsilon}_{ig} \tag{2}$$

Hence, the coefficient in a regression of own college fitness on peer high school fitness is a function of both the endogenous and exogenous structural peer effects. Thus, while our reduced form estimates cannot distinguish between whether the peer effects we find are driven by the background characteristics or behavior of the group, we can say that our estimates are a causal effect of one's peers. That is, we can be confident that $\tilde{\varepsilon}_{ig}$ is uncorrelated with $\bar{x}_g$ because of the random assignment students to peer groups. Random assignment also ensures that there is no correlation between $\bar{x}_g$ and fixed components of θ_g (e.g. dorm proximity to the gym or cafeteria). However, it is theoretically possible that some common environmental factors endogenously adjust to the average high school fitness level of the group. For example, physical education teachers could adjust curriculum depending on the fitness level of the class. Fortunately, students of all squadrons are randomly assigned across courses at USAFA (including PE courses), ensuring there are no classroom level common shocks biasing our estimates. Additionally, given the rigidity of the academic, athletic, and military curriculum and standards at USAFA, we expect any such endogenous adjustments to be quite minimal.[18]

4. Results

Results are shown in Table 2, which reports the effect of peer high school fitness on the Physical Education Average (PEA) score. Column 1 controls 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 own fitness 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 0.165 standard deviation increase in college fitness.[19] By comparison, a similar sized improvement in own fitness is associated with a statistically significant 0.434 standard deviation increase in college fitness. This is striking, as it suggests that the effect of friends' high school fitness on own current fitness is nearly 40% as strong as the effect of own high school fitness.

To account for individual-level factors that may affect own fitness, 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 fitness in college, it is also possible that the effect is caused by other peer factors correlated with fitness. For example, perhaps more fit peers

[16] 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.

[17] We use a linear probability model rather than logistic regression when using the binary dependent variable to allow us to compute two-way clustered standard errors, which computational limitations prevent us from doing when using a logistic regression model. However, results are qualitatively similar when using logistic regression rather than OLS.

[18] The academic, athletic and military standards are constant across all squadrons at USAFA, with guidelines set forth in formal Air Force Instructions and Manuals.

[19] For ease in interpretation we present all of our results in terms of standard deviations. To get a sense of how fitness levels translate into standard deviation changes in the PEA score we provide the following examples for males: 1) A four minute change in the 1.5 mile (12 to 8 min), holding PE grades and the physical fitness test score constant would result in a one-half standard deviation change in the PEA score. 2) From the mean score, adding five pull-ups, 9 inches on the long jump, 14 sit-ups, 15 push-ups, and a 12 second decrease on the 600 meter run would result in roughly a one-standard deviation change in the PEA, holding the 1.5 mile run time and PE grades constant.

Table 2
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[a]	0.129[a]	0.131[a]	0.129[a]
	(0.073)	(0.058)	(0.057)	(0.057)
Own high school fitness score	0.434[b]	0.421[b]	0.418[b]	0.418[b]
	(0.014)	(0.013)	(0.013)	(0.013)
Observations	11,321	11,321	11,321	11,321
Includes individual controls?	No	Yes	Yes	Yes
Includes year by semester and 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 multi-way clustered at the peer group and individual 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.
[a] Significant at the 5% level.
[b] Significant at the 1% level.

Table 3
The effect of peer fitness on the probability of failing the fitness requirements.

Dependent variable: fail fitness requirements	(1)	(2)	(3)	(4)
Peer high school fitness score	−0.047[a]	−0.043[a]	−0.046[a]	−0.044[a]
	(0.021)	(0.017)	(0.017)	(0.018)
Own high school fitness Score	−0.064[b]	−0.061[b]	−0.062[b]	−0.062[b]
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	13,016	13,016	13,016	13,016
Includes individual controls?	No	Yes	Yes	Yes
Includes year by semester and 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 multi-way clustered at the peer group and individual 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.
[a] Significant at the 5% level.
[b] Significant at the 1% level.

are also more motivated to achieve success generally. Similarly, it may be that more fit peers are also more likely to take a leadership role among friends at the academy and this leadership, rather than the physically fit friends, causes students to become more fit in college.

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 remains statistically significant and similar in magnitude. This suggests that the effects we find are likely caused by friends' fitness and not by general motivation or leadership ability.

Next, we examine whether friends' fitness affects whether or not an individual fails the fitness requirement at the academy. Results are shown in Table 3 and indicate that there is a large and statistically significant effect that is unchanged when adding controls in columns 2 through 4. For example, the estimates in column 4 indicate that the effect of peer high school fitness on own college fitness (−0.044) is approximately 70% as large as the association between own high school fitness and own college fitness.

5. Mechanisms and heterogeneity

Given that friends' average high school fitness affects own college fitness, it is natural to wonder *how* peers matter. While any effect on the outcomes used in this analysis presumably works through either diet or exercise, we can identify several potential mechanisms. Peer effects may arise through increased positive knowledge about how to exercise or train. If so, we would primarily expect the effects to be driven by peers who are the most fit. In contrast, if the effects operate through the adoption of poor diet or negative exercise habits, we would expect the effect to be driven by the least fit members of the group.

Thus, to help assess these potential mechanisms, we examine more closely *which* peers appear to be causing the peer effect, and which groups of students are most affected. We begin by examining how own fitness is affected by the proportion of randomly assigned friends who were in the bottom and top 20% of the high school fitness score distribution.[20] These estimated effects are relative to having peers from the middle 60% of the fitness distribution.

Results are shown in Table 4. Columns (1) and (2) show that it is primarily the *least fit* friends who reduce average physical fitness (estimate = 0.360, $p<0.01$) and induce students to fail the fitness requirements (estimate = 0.105, $p<0.05$). The estimates imply that if half of your friends were to become among the least fit for reasons unrelated to you,[21] your own fitness level would drop by nearly 20% of a standard deviation and you would be nearly 60% more likely to fail the fitness requirements. Put differently, the effect of the least fit peers on college fitness is 85% of the effect of one's own high school fitness. Even more strikingly, the effect of the least fit peers on the probability of failing the fitness exam is *larger* than the effect of own high school fitness.[22]

Next, we examine which students are most affected by their peers. To do so, we interact average peer high school fitness with indicators for whether the individual's high school fitness score is above- or below-average. Results are shown in Columns (3) and (4) of Table 4. The estimates indicate that it is the college students on the lower end of the fitness distribution who are most affected by their peers.

Finally, we estimate the effects after allowing for interactions between whether own high school fitness was above- or below-average and exposure to peers from the top and bottom 20% of the high school fitness distribution. Results are shown in Columns (5) and (6) of Table 4. These results are consistent with results from Columns (1) through (4): exposure to the least fit peers is what matters, and college students with the lowest propensity to be fit are the ones who are most affected.

Our results thus yield two notable findings. First, they indicate that the peer effects in physical fitness we find are primarily 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. Collectively, this suggests that peer effects in fitness do not

[20] We also examined whether females respond differently to peers than males. We find that while the coefficients are larger for women, they are not statistically distinguishable from those for men.

[21] This is approximately the variation observed across peer groups in the data; the proportion of peers in one's squadron ranking below the 20th percentile prior to attending the academy ranges from 0 to 42%.

[22] We also investigated whether variance in peer fitness affects own fitness in college by regressing own college fitness on the standard deviation of peer high school fitness. We find that increased variance in peer fitness causes a reduction in own fitness, though the effect goes away once we control for the proportion of least fit peers, as in Table 4. This suggests that at least in this context, variance matters primarily because it means you are exposed to more of the least fit peers.

Table 4
The effect of the least and most fit peers on own fitness outcomes.

Variable	Physical fitness score (1)	Fail fitness requirements (2)	Physical fitness score (3)	Fail fitness requirements (4)	Physical fitness score (5)	Fail fitness requirements (6)
Proportion of peers in bottom quintile of high school fitness	−0.360[a]	0.105[b]				
	(0.130)	(0.041)				
Proportion of peers in top quintile of high school fitness	0.06	−0.05				
	(0.131)	(0.038)				
Peer high school fitness score * below average high school Fitness score			0.266[a]	−0.087[a]		
			(0.078)	(0.028)		
Peer high school fitness score * above average high school Fitness score			−0.022	0.005		
			(0.080)	(0.018)		
Proportion of peers in bottom quintile of high school fitness * Below Average high school fitness score					−0.535[a]	0.176[b]
					(0.180)	(0.069)
Proportion of peers in top quintile of high school fitness * Below average high school fitness score					0.26	−0.088
					(0.172)	(0.061)
Proportion of peers in bottom quintile of high school fitness * Above average high school fitness score					−0.190	0.03
					(0.193)	(0.041)
Proportion of peers in top quintile of high school fitness * Above average high school fitness score					−0.16	0.01
					(0.192)	(0.043)
Own high school fitness score	0.418[a]	−0.062[a]	0.445[a]	−0.068[a]	0.445[a]	−0.068[a]
	(0.013)	(0.004)	(0.022)	(0.006)	(0.022)	(0.006)
Observations	11,321	13,016	11,321	13,016	11,321	13,016
Includes individual and peer controls?	Yes	Yes	Yes	Yes	Yes	Yes
Includes year by semester and state of residence fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors multi-way clustered at the peer group and individual 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 scores.

[a] Significant at the 1% level.

[b] Significant at the 5% level.

appear to arise due to the spread of knowledge from highly fit to less fit individuals. Rather the results are more consistent with the notion that people imitate the diet or exercise habits of their least fit friends, or use those friends' fitness as a benchmark for their own.

6. 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 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' fitness 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. We find strong evidence that friends' fitness affects own fitness as well as the probability of failing the fitness requirements. The magnitude of the effect is large, as the effect of peer high school fitness is approximately 40 to 70% as large as the effect of own high school fitness. Thus, our findings are broadly consistent with the provocative notion that poor physical fitness spreads on a person-to-person basis.

Our results also indicate that the peer effects work largely through exposure to the least fit peers, and the students most affected are those at the lower end of the fitness distribution. This asymmetry in the nature of the peer effects suggests that individuals appear to either compare their own fitness to the least fit among them, or adopt the diet and exercise of the least fit. Thus, our results suggest that there is an efficiency motivation for improving the health habits of the least physically fit individuals, as doing so may ultimately affect the health of many more individuals by harnessing the effect of the social multiplier.

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