The Effect of Exercise on Earnings: Evidence from the NLSY

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Abstract
This paper investigates whether engaging in regular exercise leads to higher earnings in the labor market. While there has been a recent surge of interest by economists on the issue of obesity, relatively little attention has been given to the economic effects of regular physical activity apart from its impact on body composition. I find that engaging in regular exercise yields a six to ten percent wage increase. The results also show that while even moderate exercise yields a positive earnings effect, frequent exercise generates an even larger impact. These findings are fairly robust to a variety of estimation techniques, including instrumental variables via two-stage least squares and propensity score matching.

Keywords: exercise, earnings, obesity, propensity score matching

JEL codes: I19, J21

1. Introduction

It is widely acknowledged that regular exercise has a beneficial impact on well-being. In addition to the positive impacts on heart health, weight and a variety of other medical issues, studies in the psychology and biology/medicine literatures show that exercise leads to improved mental function (Etnier et al 1997, Tomporowski 2007, Hillman et al 2008), psychological condition (Folkins and Sime 1981, Spence et al 2005) and higher energy levels (Puetz 2006). Exercise has also been found to have an indirect effect on job satisfaction by directly impacting enthusiasm at work (Thogersen 2005). All three of these traits can translate into higher earnings by raising productivity. As outlined in Lechner (2009), in addition to the direct effect, exercise can have an indirect positive impact on labor market outcomes by serving as a signal to potential employers that the individual is dedicated and disciplined or through social networking effects. These studies suggest that individuals who regularly engage in physical activity may have a lower probability of being unemployed and higher wages relative to non-exercisers.

Identification of potential links between exercise and labor market outcomes is an important part of understanding the full benefits of exercise and healthy lifestyle choices. Studies have investigated the labor market effects of drinking alcohol (Auld 2005, Hamilton and Hamilton 1997, Jones and Richmond 2006, MacDonald and Shields 2001, Renna 2008, van Ours 2004, Ziebarth and Grabka 2009), smoking (Auld 2005, van Ours 2004) and obesity (Morris 2006). While the studies on alcohol consumption yield mixed results, several show that moderate amounts of use are associated with higher earnings (Auld 2005, Hamilton and Hamilton 1997, MacDonald and Shields 2001), a result that may stem from social networking effects akin to those posited by Lechner (2009). These studies also point to the potential for nonlinear effects of leisure time behaviors on labor market outcomes

This paper investigates whether engaging in regular exercise leads to higher earnings in the labor market. While there has been a recent surge of interest by economists on the issue of obesity, relatively little attention has been given to the economic effects of regular physical activity apart from its impact on body composition. The only other published study (that the author is aware of) to investigate the direct labor market effects of regular physical activity finds a positive earnings effect when applying semi-parametric techniques to German data (Lechner 2009). Lechner finds that participating in sports at least monthly has a positive effect on both monthly earnings and hourly wages for men and women, but does not have any significant impact on employment.

What might cause the observed correlation between exercise and wage earnings? There are three categories of explanations: 1) exercise leads to higher wages; 2) wage changes affect individuals' level of physical activity; 3) other, unobserved factors cause differences in both exercise frequency and earnings. Explanations in the third category all point to an endogeneity problem when attempting to identify a causal relationship between exercise and labor market outcomes. Unobserved factors that may affect both commitment to exercise and earnings include, but are not limited to differences in discount rates and discipline. People with lower discount rates and greater discipline are less likely to put off exercising on a regular basis; they are also more likely to undertake investments in their human capital and work more diligently, leading to higher potential earnings. Exercise frequency during adulthood may also capture the labor market effects of being an athlete in high school and college (see Barron, Ewing and Waddell 2000 and Eide and Ronan 2001 for examples) since individuals who participated in organized sports are more likely to continue to exercise later in life.

Explanations in the second category suggest the causal link runs in the opposite direction. Wage changes can affect exercise frequency through the labor supply decision. As is well known, if the substitution effect dominates the income effect, a wage increase will induce individuals to work more hours, taking less leisure time and leaving less time for exercise. If the income effect dominates, the opposite will occur. Thus, higher wages can lead to either more or less exercise. Given the relatively small estimates for labor supply elasticity, I expect this mechanism to be secondary in magnitude, at best. Additionally, the empirical model controls for hours of work per week, which should capture most of this effect.

Finally, exercise can lead to higher wages by raising a worker's productivity. Regular physical activity has been linked to improved mental function, psychological wellbeing and energy levels, all of which can result in increased productivity and translate into higher earnings. The issue at hand is how to disentangle the third mechanism from the others. Doing so requires an estimation strategy that can deal with both the omitted variables bias and the potential reverse causality.

The present paper contributes to the literature by examining whether there is a causal effect of engaging in regular exercise on labor earnings using data for the United States. This requires an estimation routine that can deal with the potential bias due to omitted variables as well as reverse causality (income changes leading to changes in physical activity). To account for these issues, I employ both instrumental variables (IV) estimation and propensity score matching (PSM). In total, each model is estimated using seven different estimators (including three different matching routines for the PSM). I find that regular exercise results in a six to ten percent wage increase. The results also show that while even moderate exercise yields a positive earnings effect, frequent exercise generates an even larger impact.

2. Methodology

There are two significant data issues which must be addressed by the empirical methodology. The first is the potential bias which might arise either from the endogeneity of the exercise variable (as outlined above) and possible measurement error in the exercise variable. It is widely known that the latter creates what is known as an attenuation bias- coefficients are biased towards zero- when least squares estimation is applied to the data. Endogeneity can lead to either an upward or downward bias, depending on the source of the endogeneity. Thus, it is not clear from a theoretical standpoint whether using least squares estimation results in an over or under-estimate of the true effect of the true correlation between exercise and earnings.

Second, previous research indicates that earnings may affect behaviors that have a direct impact on health, including exercise. Thus, the conditional correlation between exercise and earnings estimated via least squares models may reflect reverse causality. Fixed effects estimation (at the individual level) can account for the bias due to unobserved time-invariant factors. However, it does not address changes in the individual's situation, including job prospects and free time, or even a change in motivation to exercise (such as a health scare) that may also lead to changes in other behaviors that also affect earnings. Nor can it deal with reverse causality. I employ two different estimation techniques in order to deal with both data issues. First, I employ instrumental variables estimation (via two-stage least squares). Second, I estimate the average treatment effect of engaging in regular (and frequent) exercise through propensity score matching. Estimates obtained via least squares, fixed effects, and the Heckman selection estimator are presented for the sake of comparison, in addition to the IV and PSM results.

The instrumental variables approach used in this paper assumes that individuals who exercise regularly are also likely to prefer active leisure over sedentary leisure. The two instruments are a variable capturing the frequency with which an individual participates in light physical activities such as walking or gardening (active leisure) and a variable which measures the number of passive activities in which an individual participates (passive leisure). These activities include going to the movies, listening to music and viewing art. Given that individuals are time constrained, they will have to choose how much time to allocate between these categories of leisure time activity and to exercise. The more time an individual spends exercising (which may in fact provide disutility for individuals) the less time she has for other activities. The validity of these instruments requires a correlation between the instruments and exercise frequency. Thus, the instrumental variables approach rests on the assumption that a person who exercises frequently may also more generally live an active lifestyle, spending more time pursuing active leisure and leaving less time for passive leisure. Sample statistics in addition to test statistics from the first stage IV estimation results are provided to support this assumption.

Valid instruments must also meet the exclusion restriction: they are not independently correlated with the dependent variable and thus do not belong in the second stage regression. Some might argue that light physical activity is still just another form of physical activity. However, results including the light activity variable as an explanatory variable in the wage equation support its exclusion (see table 5, column 2). The argument here is that only engaging in more rigorous physical activity, not light activities such as walking, generates labor market benefits. For example, Puetz et al (2006) find that chronic exercise has a positive impact on feelings of energy. The authors define chronic exercise as "cumulative, acute bouts of physical activity that are planned, structured, and repeated and result in improvement or maintenance of one or more components of physical fitness, including cardio respiratory capacity, muscle strength, body composition, and flexibility" as opposed to physical activity, which "refers to skeletal muscle activation resulting in energy expenditure beyond that of a resting level." The meta-analyses conducted by Etnier et all (1997) and Tomporowski (2003) – the former analyze 134 studies – focus on the effects of acute exercise on mental function. Investigating the link between exercise and "mental well-being," These studies indicate that there is a difference between physical activity broadly defined and exercise consisting of more rigorous exertion.

The biggest potential drawback when using IV estimation is the question of whether the instruments satisfy the exclusion restriction. While test statistics can provide support for the instruments, there is no definitive test. Furthermore, whether one wants to accept the validity of the instruments can be arbitrary, leading to both false acceptance of non-valid instruments and incorrect rejection of valid ones. The literature has many examples of instruments which were once deemed valid, only to have their validity disproven.[1] Thus, as an alternative strategy to determining whether there is a causal relationship between engaging in exercise and earnings, I employ propensity score matching routines to estimate the average treatment effect. Propensity score matching takes place in three stages. In the first stage, a probit (or logit) model is estimated for the probability of belonging to the treatment group and the propensity score estimated.[2] Next, observations from the treatment group are matched to those not in the treatment group based on their propensity scores and the sample is tested to see if the individuals in the treated group share the same characteristics (as measured by the covariates) as their

[1] One good example of this is the use of height as an instrumental variable in wage equations. Persico et al 2004 show that height in fact has an impact on earnings, invalidating its use as an instrumental variable.
[2] Thus, I can no longer employ the categorical exercise variable. Instead, the PSM estimation focuses on the effects of regular and frequent exercise.

matches from the untreated group. If the individuals in the two groups are sufficiently similar in their underlying characteristics, then the balancing requirement is met and we move on to step three. In the final step, the effect of treatment is obtained by comparing the means of the dependent variable across the two groups.

While PSM estimation provides an alternative to regression analysis, there are potential drawbacks to this approach. In order to produce unbiased estimates of the treatment effect, PSM requires large sample sizes (not a problem in the present study), substantial overlap between the treatment and comparison groups and a rich set of covariates to estimate the propensity score. PSM rests on the assumption that assignment to treatment and control groups is random after conditioning on observable characteristics. Omitting variables which affect both assignment to the treatment (engagement in regular exercise) and the outcome variable (weekly earnings) from the first stage can lead to biased estimates (Heckman et al 1997). Thus, estimates obtained via PSM may eliminate some, but not all of the bias present when estimating treatment effects via least squares estimation. This may lead some to take a 'kitchen sink' approach, including as many variables as possible in the first stage estimation to obtain the propensity score. However, this approach runs the risk of understating the treatment effect if some of the values of some of these variables are themselves affected by the treatment (Smith and Todd 2005). For example, exercise leads to greater fitness and lower BMI scores. Thus, we should not include the BMI score in the first stage probit model. Both IV and PSM have potential drawbacks and neither may fully eliminate bias due to non-random sorting. Therefore, I present estimates using both estimation techniques, in addition to other regression based estimates to show that there is a consistent, positive effect of regular exercise on earnings. As mentioned in the introduction, Lechner (2009) employs a matching estimator to show a positive causal effect of exercise on earning for German workers. Additionally, studies have used propensity score matching to evaluate whether there is a causal relationship between alcohol consumption and earnings (see for example Balsa and French 2009 and Jones and Richmond 2006).

It should also be noted that the results obtained by PSM estimation are not directly comparable to those obtained via IV estimation (or indeed any regression based analysis). The coefficients obtained from a regression model are interpreted as the average treatment effect (ATE), while those obtained via PSM are interpreted as the average treatment effect for the treated (ATT). If the treatment effect does not vary across the population, then the two effects are the same. Otherwise, they may differ and we should be careful to interpret the estimates appropriately.

In the first part of the empirical analysis, I estimate an augmented Mincerian wage equation where log weekly labor income is the dependent variable. The model uses standard controls including highest grade completed, age, log tenure in years, log tenure in years squared, the individual's armed forces qualifying test (AFQT) score as a measure of ability, indicator variables for whether the individual is female, black or Hispanic and an indicator variable for whether the individual is covered by a union contract/collective bargaining agreement.

Several studies have investigated the causes of rising obesity in the United States. A few of these findings are important for the present study, particularly those which emphasize a link between obesity and labor market outcomes. Consistent with widely held beliefs, Chou et al (2004) find that obesity and BMI are negatively correlated with income in the United States. Other studies have investigated the relationship between obesity and wages, treating income as the dependent variable. Using fixed effects estimation and sibling differences to control for unobserved fixed effects, Baum and Ford (2004) find a wage penalty associated with obesity.

Using both fixed effects and instrumental variables estimation, Cawley (2004) finds a negative correlation between obesity and wages for white women, but not for other demographic groups. Consistent with the life-cycle hypothesis, Ruhm (2005 and 2000) find that exercise increases and obesity decreases during economic downturns. In particular, the increase in activity appears to stem from a decline in work hours, not from the decline in incomes.[3] Each of these studies indicates a properly specified empirical model also needs to control for body composition. To account for this, I make use of data on individuals' height and weight to construct their body mass index (BMI). Additionally, Ettner (1996) finds increases in income lead to increases in both physical and mental health. This raises the question of causality and also indicates the need to control for health measures to make sure that we are not picking up the effects of changes in health in the coefficient for our exercise variable.

Ruhm's (2005) finding that a reduction in hours of work is a likely cause of the negative correlation between exercise and macroeconomic conditions indicates it is also critical to control for hours of work in order to account for the effect of labor market conditions on exercise. Including information on local unemployment rates might capture some of the change in labor market conditions but it will not account for differences across occupations. Therefore, each model also includes a set of occupation indicator variables. Lakdawalla and Philipson (2002) find that BMI is negatively related to job strenuousness. Occupation indicators should capture most of this effect, but will not capture differences in job strenuousness and other factors that vary within occupational group. In light of these findings, and in the absence of a variable that comprehensively measures physical strenuousness, I include body composition variables as

[3] While the life-cycle hypothesis predicts that individuals will substitute towards leisure when wages are low (as they are during an economic downturn) it is important to bear in mind that hours worked is not a decision taken unilaterally by the worker. A significant portion of the decline in average work hours during an economic downturn is likely dictated by employers.

additional controls. Thus, the estimated effect of exercise on earnings is independent of its effect on a person's weight and body composition. Finally, I also include indicator variables for whether the respondent reports his health limits either the type or amount of work she can perform. These controls are necessary to ensure that the estimated effect of exercise on earnings is not capturing effects of health (aside from exercise's impact on general health) on earnings.

The second part of the empirical analysis employs PSM routines to estimate a causal relationship between exercise and earnings. Two models are estimated, one for each exercise variable. The first model includes indicator variables for whether the individual participated in athletic clubs during high school and whether the individual currently watches sports or attends sporting events as a leisure activity. Individuals who played sports in high school or currently watch sports are more likely to also exercise compared to those who do not. Furthermore, we can safely conclude that current exercise levels do not affect high school activities. Additional controls are the frequency of religious attendance in 1979, indicator variables for whether anyone in the household had a magazine subscription or received newspapers regularly when the individual was fourteen years old. All three variables capture aspects of the household environment when the individual was a teenager, a period of time that strongly influences lifelong exercise habits. The indicator variable for whether health limits the kind of work the individual can perform is also included while the indicator for health limiting the amount of work has been excluded from the model since it did not show a significant correlation with exercise. Hours worked per week, highest grade completed, AFQT score, age, number of children in the household, marital status, gender and race indicators make up the remaining controls.

3. Data

This paper employs the 1998 and 2000 waves of the National Longitudinal Surveys of Youth 1979 dataset (NLSY79). The NLSY79, which conducted surveys every year starting in 1979 through 1994, then in even numbered years, began with an initial sample of 12,686 individuals. The initial sample contained oversamples of poor white individuals and members of the armed forces. The military and poor white oversamples were dropped in 1985 and 1991. The present study is restricted to the 1998 and 2000 waves because the exercise and light activity variables are only available in those years. During those years, survey participants ranged in age from thirty-three to forty-one, thus we are capturing workers during their prime working years and at a time in the life cycle when weight gain starts to set in. Observations were excluded from the final sample if the individual reported working fewer than 500 hours or more than 3500 per year or a weekly income less than one-hundred dollars. These restrictions are employed to remove observations where the individual has a weak labor market attachment or where there may be reporting error in the hours worked. All monetary values for 2008 have been deflated to 2006 dollars using the consumer price index.

The survey contains several questions about individuals' activities. Respondents were asked to answer the following question: "How often do you participate in vigorous physical exercise or sports - such as aerobics, running, swimming, or bicycling?" Responses were assigned the following values: 1 = 3 times or more each week, 2 = once or twice a week, 3 = one to three times each month, 4 = less than once a month, 5 = never. Survey participants were also asked about other physical activities: "We would like to know a little about your physical activity. How often do you participate in light physical activity - such as walking, dancing, gardening, bowling, etc?" The responses are coded using the same categories as the exercise variable. Both variables have been re-coded so that never takes a value of zero and 3 times or more each week takes a value of 4. Thus, a larger number indicates more frequent participation. The exercise variable is not a perfect measure of physical activity. There are two drawbacks with this variable. First, it is not a perfect measure of time spent exercising. An individual who goes for a two hour bicycle ride twice a week spends more time on physical activity than an individual who jogs three days a week for thirty minutes each time. Second, the data do not capture variations in exercise intensity, which may be an important factor determining the benefits of exercise. In spite of these limitations, the exercise variable does contain important information on exercise habits and provides a useful instrument for determining whether there is a link between physical activity and labor market outcomes.

A report by the US Department of Health and Human Services (1998) touting the psychological benefits of exercise in addition to the physical benefits also notes that benefits occur at moderate levels of activity and these benefits increase with activity level. To address these issues, I construct alternative measures for the exercise variable. The first is an indicator variable for regular exercise which takes a value of one if the individual exercises at least weekly and zero otherwise. I also construct indicator variables for frequent exercise (three or more times a week) and moderate exercise (one to two times per week). These variables are used to examine whether the earnings effects of exercise are non-linear and whether there is a threshold before these effects take place.

Regular exercise can affect wages directly through any of the channels discussed in the literature review or indirectly through its impact on physical health. Given the established link between income (and wages) and obesity and this study's focus on the direct effect of exercise on earnings, it is important to control for the individual's body composition. Each individual's body mass composition (BMI) is calculated using the standard formula: BMI = Weight in pounds*703/Height in inches squared. Individuals can be grouped into the following categories given their BMI: underweight if BMI = <18.5; normal weight if18.5<= BMI <25; overweight if 25 <=BMI <30; obese if BMI >30. I then construct indicator variables for whether an individual is overweight or obese (so that underweight and normal weight individuals serve as the reference group). In addition to the overweight and obese indicator variables, I also include indicator variables for whether the individual's health limits either the type or amount of work she can perform. Including these variables in the model provide greater security that the coefficient on the exercise variable is not capturing effects due to the individual's general health. Illnesses that limit the type or amount of work a person can perform are also likely to affect his ability to exercise or participate in physical activities more generally. Inclusion of these variables in the model results in the loss of an additional 232 observations.

The light physical activities variable described above serves as the primary instrument for the exercise frequency variable. The second instrument measures the number of passive leisure activities in which the individual engages. Respondents indicated whether they watched movies, listened to music or viewed art. Positive responses for each are coded with a one and negative with a zero. The passive activities variable sums these three indicator variables so that it takes values between zero and three. The instrumental variables approach relies on the prediction that people who exercise more frequently are more likely to also engage in light physical activity and less likely to participate in many passive activities. Table two shows a sizable correlation (ρ = .3806) between exercise and light activities frequency and a smaller correlation between exercise and passive activities (ρ = .0453).

Table one shows the frequency of responses for the exercise and light activity variables for the estimation sample. Over thirty-one percent of the respondents never exercise while less than twenty percent exercise three or more times per week. The former statistic is similar to that reported in Ruhm (2005), who analyzed the Behavioral Risk Factor Surveillance System (BRFSS) survey. However, in Ruhm's (2005) sample, forty-two percent of respondents exercise regularly.[4] In the NLSY79 sample, we see that less than thirty-nine percent exercise at least once a week. A big reason for the difference between the two samples may lie in the definition of exercise in the BRFSS. The BRFSS includes walking and gardening in their definition of exercise, where the present study keeps exercise and light physical activity in separate categories. One might postulate the difference in the two sets of summary statistics arises from the present paper's focus on employed individuals. However, re-creating the statistics in table one for the full sample (employed and non-employed individuals) shows little change. Additionally, the lack of any duration attached to the exercise frequency question may lead to a difference in how individuals report their exercise activity. For example, a respondent may not report a twenty minute jog in the NLSY sample believing it was too short to qualify, while this episode would be captured in the BRFSS. The table also shows that most people in the sample participate in light activity at least once or twice a week with nearly half of the sample participating three or more times per week.

Table three provides summary statistics for the key variables for the full sample and by gender. Given the discussion of exercise and light activity above, I will focus on some of the other key variables. In the full sample (column 1) we see that 36.7 percent of the sample is overweight while 28.2 percent is classified as obese (so that 64.9 percent of the sample is at least

[4] Ruhm defines regular exercise as exercising three or more times a week for at least twenty minutes. The NLSY79 did not collect information on the duration or intensity of exercise, only the frequency.

overweight). Nearly four percent report their health limits the kind of work they can perform and three percent report being limited in the amount of work. Average weekly income is $782.35 (in 2006 dollars). A comparison of the summary statistics by gender shows that men earn significantly more than women. Men are also more likely to be categorized as being overweight although the incidence of obesity is roughly comparable between the two groups. While men average 5.5 additional hours of work per week compared to women, they are also more likely to exercise regularly. This discrepancy may be due to a disparity in time devoted to home production, leaving women with less free time (and energy) for exercise. However, there is little difference in rates of light activity by gender and women report higher average participation in passive activities.

Table 4 provides summary statistics for some of the key variables by level of physical activity. Columns one and two report the results for individuals who report they exercise regularly (at least once a week) and those who do not, respectively. The table highlights the differences between exercisers and non-exercisers. Regular exercisers earn more than two hundred dollars more per week on average compared to their non-exercising counterparts. They are much less likely to be obese; however they have a higher incidence of overweight. This might be explained by the fact that individuals who exercise regularly have greater muscle mass, which raises the BMI. This is particularly true for men who train with weights on a regular basis. A closer look at the data shows that this observation only holds true for the men in the sample; women who exercise regularly have lower rates of both overweight (26.2 versus 28.9 percent) and obesity (18.6 versus 34.5 percent) relative to non-regular exercisers. Conversely, men who exercise regularly have a higher incidence of overweight (51.2 compared to 42.1 percent) and a lower rate of obesity (22.7 versus 31.7 percent). Regular exercisers also average nearly one additional year of schooling completed and have a higher average AFQT score percentile. These comparisons underscore the importance of dealing with the potential endogeneity of the exercise variable since body composition, educational attainment and exercise frequency may all be codetermined by unobservable factors such as self-control and ability to delay gratification.

4. Results

The results for the earnings equations are presented in table three. Robust standard errors are presented in parentheses and all models include year and occupation indicator variables. Column one provides the results when the model is fitted via least squares estimation. Exercise exhibits a positive correlation with earnings. An individual who exercises only one to three times per month earns on average 5.2 percent more than a sedentary individual. To put this result in context, it is equal to slightly less than one additional year of schooling (which raises earnings by six percent) or a roughly 13.2 point increase in the AFQT score percentile (a little under one-half of a standard deviation). This correlation is independent of exercise's impact on body composition, which itself shows a negative correlation with earnings, but only for individuals who are obese. Individuals whose health limits the type of work they can perform earn significantly less than healthy workers. The other variables generally have the expected signs. Column two provides the estimates for the model when the instruments are included as explanatory variables. This exercise has two functions: it provides additional evidence that the instruments satisfy the exclusion restriction and it shows the estimates are not affect by the reduction in sample size (which in this case is rather modest). Their inclusion does not have a significant impact on the parameter estimates and the results show that neither the light activity nor the passive activities variables are correlated with weekly earnings, providing greater confidence that they are valid instruments.

While the results in columns 1-2 show a positive correlation between exercise and earnings, we would like to know whether there is any causal relationship. To address this issue and deal with both omitted variables and measurement error biases, the models are estimated using a fixed effects (FE) estimator (column three) and instrumental variables (IV) estimation (column four) via two-stage least squares. The FE estimates continue to show a positive relationship between exercise and earnings; however the effect is less than half the size found in the OLS estimates. A sedentary individual who starts to exercise a few times per month will on average see a 2.2 percent increase in his weekly earnings. The FE model also shows some unusual results; becoming either overweight or obese is associated with a wage increase of seven and 7.6 percent, respectively. This may reflect reverse causality: individuals respond to a wage or salary increase by eating more or eating out more frequently, leading to an increase in bodyweight. Alternatively, the wage increase may be part of a promotion which results in greater stress at work, which can lead to changes in eating behavior and cause the body to store more fat. The remaining coefficients are qualitatively similar.

The FE model has three significant drawbacks. The very short time-series component of the panel (potentially two observations per individual) may result in a significant attenuation bias given the prospect of substantial measurement error in the exercise variable. Second, the model cannot account for time varying unobservable characteristics. Finally, the FE model does not eliminate the possibility of reverse causality, as discussed in the correlation between obesity and earnings. While the models control for hours of work, a wage/salary increase may lead the individual to substitute for home production with market goods (say by hiring a cleaning service or eating out more often) providing more time to devote to exercise.

The Heckman selection estimator is employed to account for the selection bias that may arise from the fact that we only observe wages for individuals who are employed. The bias arises if people who exercise regularly are also more likely to be employed (for reasons outside of a direct effect of exercise on employment status). The selection equation is identified by including the number of children in the household as additional variable.[5] The Heckman model yields a very similar estimate to the one obtained via OLS. Thus it appears that selection bias is not a significant factor. However, the Heckman estimator cannot account for reverse causality or other forms of endogeneity bias. While the FE and Heckman models can account for some of the estimation issues which may lead to biased estimates, neither can eliminate all sources of bias.

To address these issues, I employ instrumental variables estimation. The indicator variables for participation in light and passive activities serve as the instruments. The results (column four) yield highly similar results to those in columns one and two. Exercising at least a few times per month yields a five percent earnings increase compared to individuals who never exercise. The first stage partial R-squared (0.1134) and the Anderson statistic (745.9) both show the relevance of the instruments, while Hansen's J-statistic (0.24) fails to reject the hypothesis that the instruments have been properly excluded from the second stage regression. Thus, all of the appropriate tests support the validity of the instruments. The fact that the IV and OLS estimates are highly similar suggests that omitted variables bias is not a significant factor.

[5] Sample selection is more of a potential problem for the women in the sample. Women are less likely to work if there are many children still living at home.

Alternatively, it could be that the upward bias due to endogeneity and the attenuating bias due to measurement error roughly offset each other in the least squares estimates.

4.1 Alternative specifications for the exercise variable

Next, I ask whether the earnings effect of exercise depends on the frequency of participation. Specifically, I adopt two alternative measures of exercise frequency. First, I replace the exercise variable with an indicator variable for regular exercise, where the variable takes a value of one if the individual exercises at least once per week and zero otherwise. Then I include indicator variables for frequent (three or more times per week) and moderate (1-2 times per week) exercise. The results are presented in panels A and B of table five, respectively. The results in panel A consistently show a positive and statistically significant correlation between exercise and earnings. Excluding the FE estimates, regular exercise leads to a weekly earnings increase of between six and nine percent. Once again, the relevant test statistics support the validity of the instruments. Additionally, a Wald test for the Heckman estimation rejects the null hypothesis that the selection equation and the earnings equation are independent.

The results in panel B show that frequent exercise has a greater effect on earnings than moderate exercise frequency. This distinction is supported by the least squares, FE and Heckman selection models. The IV estimates do not support these findings; however the results are called into question since the instruments appear to be rather weak predictors of moderate exercise frequency. Focusing on the Heckman selection estimates, we see that frequent exercise results in a nearly ten percent wage boost while moderate exercise frequency does not show a statistically significant correlation with earnings. Even the FE estimates show a greater than five percent earnings boost for individuals who begin to exercise frequently. Overall, the results in both tables four and five support the hypothesis that engaging in regular exercise can result in greater earnings.

Finally, the results in panel C estimate the model using the indicator variable for frequent exercise, dropping the moderate exercise variable. This model is estimated to provide a basis for comparison with the estimates obtained via PSM estimation. The results continue to show a positive correlation between exercise and earnings. The IV estimate shows that engaging in frequent exercise raises earnings by over fifteen percent. While this estimate is larger than the one for regular exercise, the size of the standard errors does not allow us to conclude that this difference is statistically significant. Overall, the results in all three panels indicate that exercise does have a positive impact on earnings.

4.2 Propensity score matching estimates

As additional evidence of a causal relationship between exercise and earnings, PSM is employed to estimate the effects of regular and frequent exercise. Table 7 presents the results from the first stage for the propensity score matching estimates. All variables have statistically significant coefficients at the ten percent level or better, except for the following variables: the newspapers indicator, AFQT score, number of children, Hispanic. The results in column 1 show that, as expected, individuals who participated in athletics in high school and those who currently watch sports or attend sporting events are more likely to exercise on a regular basis. Individuals whose health limits the types of work they can perform are also less likely to exercise as are those who work more hours. The background variables show that individuals who attended religious services frequently as a child are less likely to exercise today, while those who lived in households where someone had a library card are more likely to do so. Consistent with the literature, we see that more educated individuals are more likely to exercise. Older individuals and those who are married are less likely to exercise; the latter correlation may be due either to the increase in alternative options for leisure time activity that often occurs after marriage or to a decline in the incentives for exercise. Women and blacks are less likely to exercise than men and non-blacks. Column 2 presents the results for the frequent exercise variable. In order to meet the requirement that the strata are balanced across observed characteristics, the AFQT score and race indicator variables have been removed. The results in column 2 (frequent exercise) are generally similar, except that age, marital status and race no longer show a significant correlation with exercise.

Table 8 presents the estimates for the average treatment effect of the treated for the PSM using three different matching estimators for each exercise variable: stratification, nearest neighbor and kernel matching. The estimates using the stratification matching method show that engaging in regular exercise results in a nearly eight percent increase in the weekly wage. Results using nearest neighbor and kernel matching show even an even stronger earnings effect form exercise (8.4 and 10.6 percent, respectively). These results are qualitatively similar to those presented in table 6 panel A, excluding the fixed effects estimates, which may understate the true effect due to attenuation bias. The results for frequent exercise also mirror those presented in table 6 (panel C). Again, stratification matching yields the smallest estimate while kernel matching gives the strongest estimated effect of exercise on earnings. Frequent exercise shows a stronger effect on earnings, however the differences are not very large compared to the standard errors. Overall, the results obtained via PSM corroborate the regression based estimates, indicating that there is indeed a causal effect of participation in regular exercise on earnings.

5. Conclusions

This paper finds a positive and significant labor earnings effect of engaging in exercise. Furthermore, results suggest that regular or frequent exercise may be required to derive this earnings benefit. The results are fairly robust to a variety of estimation techniques, including instrumental variables and propensity score matching, suggesting a causal link between exercise and earnings. As a next step, data with more detailed information on exercise duration, type and frequency should be used to examine whether the effects found in this study are robust to various types of exercise and whether they depend on exercise intensity or of an intensity threshold exists. Furthermore, more work is needed to investigate other potential labor market benefits of exercise such as lower unemployment rates or changes in the likelihood of promotion. Increasing public awareness of the labor market benefits of exercise may provide another tool in motivating people to adopt more active lifestyles.

From an employer's perspective, the present findings combined with earlier findings that exercise can positively affect job satisfaction (Thogersen et al 2005) and the connection between job satisfaction and multiple workplace factors such as absenteeism (Clegg 1983) and productivity (Mangione and Quinn 1975) suggest employer sponsored exercise programs and gym memberships may have a positive impact on firms' financial health beyond their impact on attracting workers and lowering health insurance premiums. More work is needed to assess the effectiveness of these programs in raising productivity and profitability.

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Exercise and Earnings

Table 1: Frequency of responses for exercise and light activity

	Exercise	Light Activity
Never	31.09	6.45
Less than once a month	15.93	7.46
One to three times each month	14.25	12.27
Once or twice a week	19.13	25.29
Three times or more each week	19.6	48.53

Percent of responses in each category are reported.

Table 2: Correlations between activity variables

	Exercise	Light Activity	Passive Activities
Exercise	1		
Light Activity	0.3806	1	
Passive Activities	0.0464	0.0453	1

Table 3: Summary statistics

	All	Men	Women
Weekly income	782.35	926.38	630.57
	(664.97)	(766.47)	(494.26)
Exercise	1.8	2.08	1.51
	(1.53)	(1.5)	(1.51)
Exercise frequent	0.196	0.236	0.154
	(.397)	(.425)	(.361)
Exercise moderate	0.191	0.224	0.156
	(.393)	(.417)	(.363)
Light activity	3.02	3.06	2.97
	(1.53)	(1.19)	(1.24)
Passive activities	1.5	1.38	1.62
	(.963)	(.983)	(.925)
Overweight	0.367	0.451	0.278
	(.482)	(.498)	(.448)
Obese	0.282	0.274	0.29
	(.45)	(.446)	(.454)
Health limit kind of work	0.038	0.031	0.047
	(.192)	(.173)	(.211)
Health limit amount of work	0.03	0.022	0.04
	(.172)	(.145)	(.196)
Hours worked per week	42.79	45.47	39.97
	(9.28)	(8.62)	(9.12)
Highest grade completed	13.17	13.04	13.3
	(2.36)	(2.45)	(2.25)
AFQT score percentile	0.404	0.406	0.401
	(.282)	(.296)	(.267)
Job tenure in years	5.81	5.89	5.72
	(5.53)	(5.63)	(5.42)
Covered by union contract	0.05	0.041	0.06
	(.218)	(.199)	(.237)
Female	0.487	0	1
	(.5)	(.0)	(.0)
Black	0.282	0.273	0.292
	(.45)	(.445)	(.455)
Hispanic	0.182	0.185	0.178
	(.386)	(.389)	(.383)

Table provides means with standard errors in parentheses.

Table 4: Key statistics by level of physical activity

	Exercises Regularly	Does Not Exercise Regularly
Weekly income	926.29	691.38
	(806.49)	(537.88)
Overweight	0.399	0.347
	(0.49)	(0.476)
Obese	0.208	0.329
	(0.406)	(0.47)
Highest grade completed	13.72	12.82
	(2.49)	(2.2)
AFQT score percentile	0.454	0.372
	(0.293)	(0.27)
Number of Observations	2,456	3,886

Table provides means with standard errors in parentheses.

Regular exercise is defined as exercise frequency equal to or greater than once per week.

Table 5: Exercise frequency and earnings

	OLS (1)	OLS (2)	FE	IV	Heckman
Exercise	0.026**	0.027**	0.011*	0.025**	0.025**
	(0.0042)	(0.0046)	(0.0055)	(0.013)	(0.0059)
Overweight	-0.0042	-0.0041	0.07**	-0.0042	-0.0017
	(0.015)	(0.015)	(0.027)	(0.015)	(0.02)
Obese	-0.039*	-0.038*	0.076†	-0.039*	-0.0019
	(.016)	(.016)	(0.04)	(0.017)	(0.022)
Health limit kind of work	-0.113**	-0.118**	0.083	-0.118**	-0.213**
	(0.044)	(0.044)	(0.058)	(0.044)	(0.058)
Health limit amount of work	-0.039	-0.032	-0.078	-0.032	0.044
	(0.049)	(0.05)	(0.058)	(0.05)	(0.072)
Hours worked per week	0.02**	0.02**	0.0077**	0.02**	0.015**
	(0.0009)	(0.0009)	(0.001)	(0.0009)	(0.001)
Highest grade completed	0.06**	0.061**	0.059*	0.061**	0.051**
	(0.0037)	(0.0038)	(0.029)	(0.0039)	(0.0055)
AFQT score percentile	0.391**	0.404**		0.404**	0.256**
	(0.032)	(0.032)		(0.032)	(0.05)
Age	-0.00018	-0.00016	0.033	-0.00024	-0.0067
	(0.0029)	(0.0029)	(0.023)	(0.0029)	(0.0043)
Log of tenure in years	0.063**	0.063**	0.023**	0.063**	0.055**
	(0.0056)	(0.0057)	(0.0073)	(0.0056)	(0.008)
Log of tenure in years squared	0.016**	0.015**	-0.00058	0.015**	0.02**
	(0.0024)	(0.0024)	(0.0039)	(0.0024)	(0.0036)
Covered by union contract	0.017	0.013	0.042	0.013	0.018
	(0.029)	(0.029)	(0.035)	(0.029)	(0.033)
Female	-0.246**	-0.243**		-0.244**	-0.202**
	(.015)	(.015)		(0.017)	(0.023)
Black	0.0006	0.0004		0.0041	0.053*
	(.016)	(.017)		(0.017)	(0.027)
Hispanic	0.084**	0.08**		0.081**	0.115**
	(0.018)	(0.018)		(0.018)	(0.028)
Light activity		-0.0011			
		(0.0057)			
Passive activities		0.0031			
		(0.0067)			
R-squared	0.4803	0.4795	0.1211	0.4794	--
Observations	6,342	6,199	6,342	6,199	10,373

Robust standard errors are reported in parentheses.

All models include year and occupation indicator variables.

Table 6: Exercise frequency and earnings by exercise intensity

Panel A:	OLS	FE	Heckman	IV	IV tests:	
Regular exercise	0.069**	0.029†	0.061**	0.09**	1st stage partial R-squared:	0.086
	(0.013)	(0.016)	(0.018)	(0.045)	Andersen statistic:	557.7 (.00)
R-squared	0.4795	0.1208	--	0.4785	Sargan statistic:	0.22 (.64)
Panel B:	OLS	FE	Heckman	IV	IV tests:	
Frequent exercise	0.097**	0.053**	0.098**	0.034	1st stage partial R-squared for	
	(0.017)	(0.022)	(0.024)	(0.06)	Frequent exercise equation:	0.0812
Moderate exercise	0.042**	0.015	0.025	0.141	Moderate exercise equation:	0.0301
	(0.016)	(0.018)	(0.021)	(0.095)	Andersen statistic:	126.8 (.00)
T-test	7.62 (.01)	2.75 (.10)	7.04 (.01)	0.68 (.41)	Sargan statistic:	0.26 (.61)
R-squared	0.4802	0.1221	--	0.4732		
Panel C:	OLS	FE	Heckman	IV	IV tests:	
Frequent exercise	0.085**	0.047**	0.091**	0.152*	1st stage partial R-squared:	0.0436
	(0.016)	(0.02)	(0.024)	(0.076)	Andersen statistic:	276.6 (.00)
R-squared	0.4796	0.1218	--	0.4775	Sargan statistic:	0.23 (.63)

Robust standard errors are reported in parentheses.

All models include year and occupation indicator variables.

Wald tests for Heckman equations: 318.08 (.00) and 324.64 (.00) in panels A and B, respectively.

Exercise and Earnings

Table 7: First stage results from propensity score matching

Variable	Regular Exercise	Frequent Exercise
Athletic clubs in high school	0.164**	0.164**
	(0.036)	(0.04)
Activities: sports	0.208**	0.158**
	(0.038)	(0.044)
Religious attendance in 1979	-0.022*	-0.035**
	(0.01)	(0.012)
Library card at age 14	0.086**	0.13**
	(0.036)	(0.042)
Newspapers at age 14	-0.032	0.066
	(0.039)	(0.045)
Health limit kind of work	-0.478**	-0.201†
	(0.095)	(0.106)
Hours worked per week	-0.0044*	-0.0039†
	(0.0019)	(0.0021)
Highest grade completed	0.097**	0.084**
	(0.0093)	(0.086)
AFQT score percentile	0.015	
	(0.087)	
Age	-0.018*	-0.0029
	(0.007)	(0.0077)
Number of children	-0.021	-0.044**
	(0.015)	(0.017)
Married	-0.065†	-0.03
	(0.038)	(0.042)
Female	-0.372**	-0.27**
	(0.037)	(0.015)
Black	-0.2**	
	(0.046)	
Hispanic	-0.063	
	(0.049)	
Observations	6,190	6,190
Regular/Frequent exercises	2,456	1,243
Non-regular exercisers	3,886	5,099
Log likelihood	-3,866.22	-2,910.83

Table presents the coefficient estimates from the probit regressions used to estimate the propensity score.

Table 8: Propensity score matching estimates

	Effect of Regular Exercise			Effect of Frequent Exercise		
	Stratification	Nearest Neighbor	Kernel	Stratification	Nearest Neighbor	Kernel
Average treatment effect	0.078**	0.084**	0.106**	0.089**	0.092**	0.143**
	(0.016)	(0.024)	(0.018)	(0.021)	(0.03)	(0.024)
Observations in treatment	2,403	2,456	2,456	1,214	1,243	1,243
Observations in control	3,787	1,570	3,886	4,976	1,117	5,099

Table presents the estimated average treatment effect using three separate matching estimators.