THE IMPACT OF PERSONALITY ON ECONOMIC DECISIONS

BY
ROBERT GIRTZ

A DISSERTATION SUBMITTED TO THE GRADUATE SCHOOL AT MIDDLE TENNESSEE STATE UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE

DOCTOR OF PHILOSOPHY/ECONOMICS

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DEDICATED TO MY PARENTS

BOB AND MARILYN GIRTZ

IN SHORT, THANKS FOR EVERYTHING.

DEDICATED TO MY WIFE

RENEE GIRTZ

FOR YOUR LOVE. TO OUR FUTURE.

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ABSTRACT

This dissertation contains three chapters focusing on the impact of several personality traits – locus of control, self-esteem and self-monitoring - on economic outcomes including wages, educational attainment, and decisions in game-theoretical experiments. In the first chapter, entitled "The Effects of Personality Traits on Wages: A Matching Approach," I utilize the National Longitudinal Survey of Youth 1979 to estimate the effects of adolescent measurements of self-esteem and locus of control on adult wages using propensity score matching. An adolescent possessing high self-esteem will experience between 8.5 to 9.2 percent higher wages as an adult. When cognitive skill and family background characteristics are controlled for, locus of control as an adolescent is insignificant in explaining adult wages.

In the second chapter entitled "Self-esteem, Educational Attainment and Wages: A Question of Selection," I use the National Longitudinal Survey of Youth 1979 again to explore the relationship between self-esteem and wages found in the first chapter more closely. I find that self-esteem partially estimates selection into higher levels of education. Conditional on this selection, the remaining direct effects of self-esteem on wages are negligible. This evidence suggests that self-esteem affects wages indirectly through educational attainment.

In the third chapter, co-authored with Mark Owens and Josh Hill, entitled "Self-monitoring and Risk Preferences: Responsibility in the Stag Hunt," we analyze how self-monitoring and risk preferences affect decision-making strategies in Rousseau's classic Stag Hunt game. Past research indicates that people tend to change their decision in this game when being faced with responsibility over another individual's outcomes. We further this literature by analyzing how these traits affect their decisions. We find that high self-monitors tend to generally switch their decisions when being faced with responsibility over another's outcomes and that risk averse individuals tend to make a cautious shift in decisions given the same circumstances. In addition, those with more risk-loving preferences tend to play Stag more often than their risk-averse counterparts regardless of the way the game is set up.

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CHAPTER 1

THE EFFECTS OF PERSONALITY TRAITS ON WAGES: A MATCHING APPROACH

1.1 INTRODUCTION

Economists have a long-running interest in the impact of individual characteristics on outcomes in the labor market. Standard components of human capital models include educational attainment, work experience, tenure and cognitive ability.[1] In addition to these canonical components of human capital investment, economists have recently begun to examine the effects of factors characterizing an individual's personality on labor market outcomes.[2] This strand of literature is growing and focuses on noncognitive skills, broadly defined as an individual's set of personality traits. Several personality traits have

1. See Becker (1967) and Mincer (1970) for standard examinations of the human capital model.
2. See Borghans, Duckworth, Heckman and ter Weel (2008) for a survey on the expansion of personality based research in economics.

been studied and found to be significant explanatory variables in models involving wages and other economic outcomes, such as educational attainment. The broad scale of traits examined include, but are not limited to, locus of control, self-esteem, sociability, withdrawal, aggression, level of caring, the importance of money in one's life and the Big Five (see Andrisani 1977; Coleman and DeLeire 2003; Osborne Groves 2005; Cebi 2007; Borghans, ter Weel and Weinberg 2008; Borghans, Duckworth, Heckman and ter Weel 2008; Krueger and Schkade 2008b; Fortin 2008 for examples).

The personality traits I examine are self-esteem and locus of control. Self-esteem is an assessment of one's self worth. Persons who have a high self-esteem consider themselves to be considerably worthwhile as an individual, whereas a person with a low self-esteem believes the converse (Rosenberg 1965). Locus of control is defined as "a generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences," (Rotter 1966). Persons with an internal locus of control believe that their actions have a direct effect on their outcomes, whereas persons with an external locus of control believe that fate controls their lives and the outcomes they experience are simply out of their control.

Self-esteem has been shown to positively affect worker productivity (Brockner 1988) and is among the set of traits attributed by Goldsmith, Veum and Darity (1997a) as "psychological capital". These traits have the ability to alter a person's productivity, and therefore their wages. Waddell (2006) showed that self-esteem is a necessary ingredient in human capital models, but is generally left out of conventional models. The fact that employer surveys show that attitude is highly valued at work gives reason for further consideration of its effects on labor market outcomes (Waddell 2006).

Locus of control affects wages due to the perceived relationship between initiative and success. If a person believes there is a causal link between his actions and his outcomes then it is much more likely that a person will demonstrate initiative. Internal persons believe that success results from hard work and determination. They feel that failure is their responsibility. This perception of their hard work being important increases the chance that they will work hard and experience higher wages (Andrisani 1977). The theory of motivation by Atkinson (1964) can be applied to labor market outcomes. Simply valuing a successful life means nothing unless one has the belief that their actions will aid in attaining it (Duncan and Dunifon 1998).

In this article I use propensity score matching (PSM) to examine whether including these personality traits in standard human capital models is recommended. The two main questions I address are whether persons with high self-esteem as adolescents experience significantly different wages as adults than their peers who have relatively lower self-esteem and whether persons with an internal locus of control as adolescents experience significantly different wages as adults than their peers who have an external locus of control. These questions have been analyzed before to some extent, but a more careful estimation is needed to fully characterize the importance of these traits for usage in human capital models. If, by using a more detailed approach, I find these personality traits to be significant in estimating wages then leaving them out of future studies of a similar nature can lead to omitted variable bias and other estimation issues. The potential for bias arises if these important traits are left out of a model this will create overestimation or underestimation of other correlated variables. If I find that the variation in wages ascribed to personality traits can be effectively picked up by standard human capital covariates or by personality altering variables such as family background characteristics (Cunha and Heckman 2008; Segal 2008), then their inclusion in future studies is not recommended.

I follow the logic of Caliendo, Cobb-Clark and Uhlendorff (2010) in implementing PSM as a means of extracting more precise and efficient estimates of the effects of self-esteem and locus of control on wages than that of previous studies.[3] Other studies examining this topic have utilized ordinary least squares methods (Andrisani 1977; Duncan and Morgan 1981; Duncan and Dunifon 1998; Cebi 2007) and instrumental variable approaches (Goldsmith, Veum and Darity 1997a; Osborne Groves 2005) to estimate the effects of locus of control and self-esteem on wages. I use a novel approach, PSM, as a more precise method of estimating the effects because it only compares persons who are very similar in all respects except for the explanatory variable of interest.[4]

I find that persons who have a high self-esteem enjoy higher wages in the future, ranging from 8.5 to 9.2 percent when controlling for all covariates. Adolescent locus of

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3. Caliendo, Cobb-Clark and Uhlendorff (2010) estimate the effect of locus of control on reservation wages and job search intensity.
4. PSM is a more efficient method assuming that the first stage includes enough explanatory variables to achieve unconfoundedness (see section 4.2.2 for a detailed explanation). I have added all relevant variables that affect both outcome and treatment insofar as is available in the dataset. The NLSY79 provides a very rich set of covariates to explain both the treatment and outcome.

control has a significant effect on adult wages until cognitive and family background characteristics are included as covariates. Locus of control is then found to be insignificant. This result differs from much of the literature on locus of control and its effects in the labor market. The explanatory power that locus of control has on wages can be captured by cognitive and family background measurements. Therefore it is likely that the inclusion of locus of control is not needed in future human capital studies.

1.2 Literature Review

Latent noncognitive factors have been shown to be significant predictors of schooling, wages and behavioral outcomes. Heckman, Stixrud and Urzua (2006) argue that there are a certain number of true noncognitive and cognitive skills that have explanatory power across the entire spectrum of economic outcomes. Survey instruments only capture portions of each true skill. Cognitive and noncognitive skill formation has been explored by Cunha and Heckman (2008). They show that there are several sensitive periods for parental investment to foster positive growth in both cognitive and noncognitive skills with the sensitive period for noncognitive skill formation occurring later than cognitive skill formation. Research by Segal (2008) coincides with Cunha and Heckman (2008) by showing that classroom behavior is related to family background characteristics. Specifically, they find that more educated parents, parents with higher income and children who live in a traditionally structured family are all associated with better behaved eighth graders.

Studies involving locus of control and self-esteem generally find that persons with internal loci of control and higher self-esteem end up having higher wages, either contemporaneously or in the future. There are, however, some studies which show that locus of control does not directly affect labor market outcomes (Duncan and Morgan 1981; Goldsmith, Veum and Darity 1997a).[5]

Andrisani (1977) uses the National Longitudinal Survey (NLS) to study how locus of control is related to subsequent labor market outcomes measured shortly thereafter. He uses several OLS models with the explanatory variable of interest, locus of control, measured two years prior to the labor market outcomes of interest. He finds that locus of control is strongly related to average hourly earnings, occupational attainment, total earnings and the growth of these variables. He also finds that locus of control could not explain the differences between black and white persons in various labor market outcomes.

Duncan and Morgan (1981) replicate Andrisani's (1977) analysis with Panel Study of Income Dynamics (PSID) data. They question the causal interpretation of Andrisani (1977) due to only being a two year time horizon between locus of control and the labor market outcomes in his study. They also examine the problem of endogeneity between achievement and locus of control. Regardless, they replicate Andrisani's (1977)

5. A brief summary of the main papers estimating the effects of locus of control and/or self-esteem can be found in Table A2.

analysis with two and four year time horizons and find that locus of control has a small and generally insignificant effect on labor market outcomes.

Goldsmith, Veum and Darity (1997a) use the National Longitudinal Survey of Youth (NLSY) to test whether "psychological capital" affects wages. They allow for wages and self-esteem to be determined simultaneously, obtaining identification through strong exclusion restrictions. They implement a two stage least squares approach with an ordered probit to estimate locus of control and an OLS model to estimate wages. The authors assume that locus of control does not directly affect wages, but does so via affecting self-esteem. They show that psychological capital has both a direct effect, through self-esteem, and an indirect effect, through locus of control, on an individual's wage. A person's wage is more sensitive to changes in self-esteem than to comparable alterations in human capital.

Duncan and Dunifon (1998) use the PSID and find that locus of control does eventually affect labor market outcomes 15 to 20 years later. Their argument is that the longer time frame helps mitigate the problem of endogeneity found in the Duncan and Morgan (1981) paper. Changing the outcome variable to one that is further away in years from the main explanatory variable than the outcome variable in research by Andrisani (1977) and Duncan and Morgan (1981), however, does not completely rid the analysis of endogeneity.

Coleman and DeLeire (2003) use the NELS (National Education Longitudinal Studies 1988) dataset to show that locus of control affects a teenager's decision to invest in education and their occupational expectations. They conclude that locus of control affects human capital investment decisions and is consistent with both the human capital investment model and the perception of locus of control shared by psychologists.

Osborne Groves (2005) uses both U.S. and U.K. data to explain the effects of personality on wages for women. She uses both an instrumental variable approach and a Heckman Selection model to try to alleviate the issues of endogeneity and selection. She finds that locus of control, aggression and withdrawal are all statistically significant factors in wage determination models of white women. Her finding that persons with internal loci of control enjoy higher wages in the future coincides with past research.

Waddell (2006) analyzes the effects of self-esteem on economic outcomes. He finds that youth who have low self-esteem obtain fewer years of education, are less likely to be employed in the future and when employed have lower earnings than persons with higher self-esteem.

Using the NLSY79 dataset, Cebi (2007) contradicts Coleman and DeLeire (2003) by showing that locus of control does not affect either educational attainment or occupational expectations. Being an internal person, however, rewards a person later in life with higher wages. This result is found using a similar analysis to Andrisani's (1977), namely a multi-year cross-sectional OLS model.

In addition to studies on the effects of these personality traits on wages, several studies have gone a step further and investigated the effects of locus of control and self-esteem on the gender pay gap (Fortin 2008; Manning and Swaffield 2008) as well as racial labor market gaps (Urzua 2008).

1.3 DATA, METHODS AND SURVEY INFORMATION

The data I use are from the National Longitudinal Survey of Youth 1979 (NLSY79) which is a longitudinal survey administered by the Bureau of Labor Statistics. It is a nationally representative sample of 12,686 young men and women between the ages of 14 and 22 at the time of the first interview in 1979. Since their first interview, they have been interviewed annually until 1994, and biennially thereafter. The NLSY79 is a rich data set that includes annual measures of education, occupational status, marital status, wages, health data and many other variables that are person-specific. For my research the key explanatory variables of interest are locus of control and self-esteem. The main outcome variable is logged hourly wages in the year 2000.

To measure locus of control I use the Rotter Internal-External Locus of Control Scale. In the NLSY79 it is a four-item abbreviated version of a 23-item forced choice questionnaire, adapted from the 60-item Rotter Adult I-E scale developed by Rotter (1966). The scale measures the extent to which someone feels they are in control of their lives. Persons exhibiting an internal locus of control will feel that through their own self-motivation or self-determination they can have control over the outcomes they experience in their lives. People exhibiting an external locus of control will feel that the environment or, similarly, random chance controls their lives. Respondents are asked to select one of each of four paired statements and then decide whether the selected statement is much closer or slightly closer to the view they hold of themselves.[6] The scale is created so that the higher the score, the more external a person is. I invert the scale, so that an increase in the locus of control variable can be interpreted as the change in wage resulting from a person becoming more internal.

To measure self-esteem I use the Rosenberg Self-esteem scale. In the NLSY79 it was administered during the 1980, 1987 and 2006 surveys. It is a 10-item scale that measures self-evaluation, that is, how people feel about themselves. The Rosenberg scale is meant to describe a degree of approval or disapproval toward oneself (Rosenberg, 1965). Each question is extracting self-approval or disapproval from the respondent, where in answering, they specify whether they strongly agree, agree, disagree, or strongly disagree.[7] I use only the 1980 wave of self-esteem data, as the effect of an adolescent self-esteem on adult wages is what I need to test my hypothesis. The 1980 self-esteem measurement would also be the most likely to be affected by parental investment

6. The Rotter questionnaire in the NLSY79 is as follows:
1.(a) What happens to me is my own doing; or (b) Sometimes I feel that I do not have enough control over the direction my life is taking.
2. (a) When I make plans, I am almost certain that I can make them work; or (b) It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow.
3. (a) In my case, getting what I want has little or nothing to do with luck; or (b) Many times, we might just as well decide what to do by flipping a coin.
4. (a) Many times, I feel that I have little influence over the things that happen to me; or (b) It is impossible for me to believe that chance or luck plays an important role in my life.

7. The Rosenberg questionnaire in the NLSY79 is as follows:
1. I am a person of worth. 2. I have a number of good qualities. 3. I am inclined to feel that I am a failure. 4. I am as capable as others. 5. I feel I do not have much to be proud of. 6. I have a positive attitude. 7. I am satisfied with myself. 8. I wish I had more self respect. 9. I feel useless at times. 10. I sometimes think I am "no good" at all.

variables, assuming that self-esteem and other personality traits are malleable up to adolescence and then become relatively stable, which is a viable behavioral assumption given past research.[8]

Debate arises whether these relatively subjective measurements of personality have reliability, meaning that what a person responds will be consistent from period to period, given other control variables collected between the periods. Krueger and Schkade (2008a) show using Day Reconstruction Methods (DRM) that exhibited test-retest correlations for subjective well-being measurements generally fall in the range of 0.50 – 0.70. They note while these figures are lower than the reliability ratios found for variables such as education, income and other microeconomic variables, they argue they are sufficiently high to yield informative estimates for much of the research that uses subjective well-being measurements.

The rest of the data collected are from the 1979, 1980, 2000 and 2004 interviews. These years are chosen because in the PSM estimations using locus of control as the treatment I employ controls from 1979 and in the PSM estimations using self-esteem as the treatment I employ controls from 1980. Control variables for my OLS models are extracted from the 2000 survey. I chose the main outcome variable to be in the year 2000

8. Goldsmith, Veum Darity (1996;1997b), Cunha and Heckman (2008), Segal (2008) all include reasoning and analysis behind the stability of personality traits from childhood/adolescent to adulthood.

because by then most respondents have settled into their occupations and it coincides with the outcome year chosen for wages in past literature by Cebi (2007).[9]

The cognitive measurement is constructed similar to Cebi (2007). I construct it as the sum of the standard scores for the word knowledge, arithmetic reasoning and mathematical knowledge sections of the Armed Forces Vocational Aptitude Battery (ASVAB). The use of the usual percentile scores found in the NLSY79 for the Armed Forces Qualifications Test (AFQT) shown as AFQT80 and AFQT89 in the dataset are not used due to the finding that ability follows a normal distribution while a percentile follows a uniform distribution (Blackburn 2004). I denote my constructed cognitive measurement as the AFQT score during my analysis.

In order to use PSM I must split each empirical personality distribution into two groups. One group is the treatment group, and the other group is the synthetic control group, or untreated group. I follow Caliendo, Cobb-Clark and Uhlendorff (2010) and split the empirical distribution at the mean. The individuals above this given threshold are the treated individuals, and persons below the threshold are the untreated, or control group. Persons who score a 23 or above on the Rosenberg scale are deemed to have high self-esteem, and persons who score a 12 or above on the Rotter scale are deemed to have an internal locus of control. In addition, as a robustness check, I also use cognition as a

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9. I also include logged hourly wages in 2004 as a robustness check for every model I employ. Results for these models available from the author upon request.

treatment in a separate PSM estimation.[10] The cutoff for persons with high cognition is a score of 142 on the three subsets of the ASVAB I named above. Persons who are below that threshold are in the untreated group.

Table 1 shows the wage disparity in the year 2000 between the treated and untreated individuals. For every case the treated group has a higher log wage and the difference is statistically significant at the 1 percent level. These results give initial evidence for a relationship between each of these personality traits and wages, and helps make a stronger case for further investigation into this issue. Persons with an internal locus of control experience higher wages in 2000 than those with an external locus of control by 0.167 log points. Those with high self-esteem experience higher wages in 2000 than those with a low self-esteem by 0.237 log points. The qualitative nature of these figures coincide with much of the past economics literature on these personality traits.

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10. The cognitive treatment is estimate to examine whether cognition becomes insignificant in explaining wages after controlling for locus of control and self-esteem. If it remains significant this lends strength to the insignificance of locus of control that I find when adding in cognition and family background.

1.4 Estimation Methods and Results

1.4.1 OLS Regression Models and Results

I estimate for each personality trait a basic OLS multiple regression model of the following nature:

$$\ln y_i = \beta_0 + \beta_1 \text{trait}_{i,j,u} + \boldsymbol{\beta_2 X'_i} + \boldsymbol{\varepsilon_i} \tag{1}$$

The variable y_i is the hourly wage rate of the person i in the year 2000; $\text{trait}_{i,j,u}$ corresponds to the explanatory variable of interest which is one of the three personality traits in the study. j corresponds to the specific trait, i refers to the individual respondent and u corresponds to how the personality trait enters the equation. Two methods of how the personality trait enters are used: first, the standardized score and second, a dummy variable for whether the person is treated or not, using the same threshold value used for the PSM models. $\mathbf{X'}_i$ is a vector that includes the remaining set of person specific controls, which are specified in Table 2. First I use the baseline set. Second, I use the baseline set and include cognition. Third, I use the baseline set with cognition and then include the other personality trait.[11] The baseline controls are the same as the controls that are used in OLS regressions in Cebi (2007); the β are parameters to be estimated and ε_i is the idiosyncratic error term, assumed to be distributed $N \sim (0, \sigma^2)$. The results for all of these OLS regressions specified in equation (1) are presented in Table 2.[12]

When the standardized scores are used as the main explanatory variables, both are statistically significant in their respective regressions using the baseline results. Self-esteem is significant and robust across all specifications. When all controls are included a one standard deviation increase in a person's Rosenberg score results in a 4.5 percent increase in adult wages. Using the treatment dummy, having high self-esteem amounts to a 6.7 percent increase in wages later in life. Locus of control becomes insignificant, however, when the cognitive trait and self-esteem are controlled for.[13]

The finding that the treatment dummy and standardized score for locus of control is insignificant when cognition and other facets of personality are controlled for in a standard OLS model gives additional reason to pursue the PSM approach. Past findings have shown that locus of control is significant in OLS models even when controlling for cognition. The point estimate on the explanatory variable of interest in an OLS regression represents a mean effect. Using PSM I will match and compare persons who are very

11. The progression of control variables is shown in the bottom three rows of Table 2.
12. The parameter estimates for the controls and the constant are suppressed, but are available from the author upon request.
13. The second column in Table 2 for the effect of a one standard deviation increase in a person's Rotter score leading to a 1.9 percent increase in wages is a replication of the human capital model in Table 4, column 4 of Cebi (2007). It matches the result insofar as statistical significance, and is only a 0.2 percent difference in the magnitude (her analysis showed a 2.1 percent increase in wages for the same increase in their Rotter score).

similar in all relevant aspects, except for the specific personality trait. This should provide a more precise estimate and could uncover a significant effect whereas the significance is buried within the context of OLS, by only showing the mean effect and assuming strict functional form.

1.4.2 Propensity Score Matching Models and Results

1.4.2.1 Description

Propensity score matching is a non-experimental approach to estimating treatment effects. A problem with observational studies is that the data do not come from randomized trials. The PSM method attempts to sort persons into treatment and control groups. They are then matched with someone who has a similar propensity to be treated (propensity score), who is in the opposite group. The relevant outcomes are then compared among the people with the most similar pre-treatment characteristics. Intuitively, my main explanatory variables, personality traits, are not selectable traits, therefore by using PSM I am not correcting for selection bias, but attempting to obtain more precise estimates using the PSM approach.

Rosenbaum and Rubin (1983) were the first to propose PSM as a method to reduce bias in the estimation of treatment effects. Generally, this method is used when the treatment is specified as a labor market policy of interest (see Sianesi 2004; Larsson 2003; Dehejia and Wahba 2002 for examples), where the outcome variable is the target variable the given labor market policy intends to alter. However, PSM has been extended to non labor policy studies as well (see Levine and Painter 2003; Brand and Halaby 2006 for examples). The PSM method can be used for virtually any type of study where there is a definable treatment group, a definable control group, and a method to estimate the propensity to be in one of the two groups, given an economically sound model of the treatment.[14] The key is to choose economically relevant pre-treatment variables that will estimate the propensity to be in one of the two groups. The propensity score can be described as the propensity to be treated. In essence it is a predicted probability to be treated given specified pre-treatment, or at the very least, non-endogenous covariates.

PSM is a two stage procedure. In the first stage I estimate the predicted probability of being treated. Treatment in this context is having a specific facet of a personality trait, be it an internal locus of control or having a high self-esteem. In the second stage I match persons who have similar probabilities of being treated, where one is untreated and one is treated.[15] I then compare their wages later in life. The fact that the wages are measured over twenty years after the measurement of the personality trait

14. See Caliendo and Kopeinig (2008) and Imbens and Wooldridge (2009) for technical details regarding the PSM method.
15. I use a synthetic control group (akin to Abadie, Diamond and Hainmueller 2010; Abadie and Gardeazabal 2003). The synthetic control group methodology is used when one is unsure of which individuals the actual control group is comprised. In the case of a labor market policy, it is clearer, but for treatment such as a personality trait it is less so. Using this approach I aggregate a pool of untreated individuals (those below the mean value levels of the survey instrument score). Then, based off of the first stage specification of predicted probability of treatment, coupled with the second stage matching methods, I determine who the actual control individuals are for each specific treated individual.

helps mitigate some of the problems of overt endogeneity among the main explanatory variables and the main outcome variables. In addition, the personality traits are all measured before the person enters the labor market, and personality traits tend to form during childhood and stabilize during adolescence (Sherman 1984; Borghans, Duckworth, Heckman and ter Weel 2008). These facets of the time frame chosen for analysis and important explanatory variables allow for a more precise identification of the true effects.

1.4.2.2 First Stage: Estimation of the Propensity Score

In the first stage of the propensity score model I estimate treatment using probit models.[16] I estimate four different probit models for each treatment, using the four different sets of controls for each PSM model. These covariate sets are described in Table A1. I initially use the covariates listed as (A), which is the baseline set of covariates. Second, I estimate a propensity score model with covariates (B), which is the baseline set of covariates plus a vector of family background characteristics. I then estimate a third propensity score estimation with covariates (C), which is the baseline set of covariates plus the cognitive measurement. Finally, I estimate a fourth propensity score estimation

16. The first stage probit model results are not presented in a formal table. They are available upon request.

with covariates (D), which is the baseline set of covariates, plus both the vector of family background characteristics and cognitive measurement.

For PSM to be valid, certain model attributes must be satisfied. Unconfoundedness must hold, which means that a person's actual assignment to treatment must be independent of the outcomes. In other words, one must include all variables that will affect both outcome and treatment.[17] In most cases given the density of varying attributes of a person, some variables tend to be unobservable (Caliendo and Kopeinig 2008). I include all covariates that are available in the NLSY79 and are relevant in affecting a person's personality both as they grow up and as they are at the current time of personality trait measurement. This includes their family background information, other personality trait information, a measure of their cognition, as well as various contemporaneous measurements comprised of general characteristics of the individual. These variables coincide with the literature (Cunha and Heckman 2008; Segal 2008; Caliendo, Cobb-Clark and Uhlendorff 2010). In adding all relevant variables available in the NLSY79 I make the assumption that I have reached unconfoundedness as there is no formal test to check whether or not it exists in your model. In addition to unconfoundedness, the model must exhibit overlap. If there is a positive probability of being treated and untreated, given the first stage covariate specification, then the model

17. Treatment should not have a causal effect on the covariates in the first stage. Correlation is allowed among the treatment and the covariates, but the treatment having a causal effect on the covariates is not warranted. To help ensure that this is not taking place, I use adolescent measurements that are relatively out of the child's control at the age of measurement to estimate treatment. These first stage covariates help estimate the personality trait treatment, however through correlation. Information on what these variables are can be found in Appendix Table A1.

exhibits overlap. When the properties of unconfoundedness and overlap are satisfied, the model exhibits ignorability (Rosenbaum and Rubin 1983).

Balancing of the propensity score model in the first stage is of utmost importance. This means that the distribution of all specified covariates in the first stage model must be equally balanced across all propensity score values. If for a given specification there is an unbalanced block (sub-division of the propensity score that people are sorted into) in the propensity score estimation algorithm, then one must re-specify the model. Adding in squared, cubed and interaction terms to the original specification is the recommended method of getting the covariates in each block to balance (Caliendo and Kopeinig 2008). The effect on the ATT for the outcome variable of adding these higher ordered terms is negligible. Using this method I was able to satisfy the necessary balancing property in all PSM models I specified.[18] I also achieved significant overlap in my propensity score in every case. The treatment and control groups have balanced covariates in all blocks of propensity scores and the overlap is significant.

1.4.2.3 Second Stage: Matching Types and ATT Results

The expected value of the ATT is defined as the difference between expected outcome values with and without treatment, given that the person has been treated. The

18. STATA log files are available from the author, showing that the balancing property is satisfied.

case of someone receiving treatment, and then collecting their untreated outcome values is not observable to the researcher. Only one of these two cases exists in the data. Therefore, constructing a closely related comparison group of controlled individuals who have a similar propensity to be treated (citing intention to treat), but do not receive treatment, is a close approximation. The value of the outcome variable for the untreated individual, compared to the treated individual's outcome when they both have similar propensity to be treated, is the closest approximation of ATT one can obtain. Put another way one must compare persons who were both intended to be treated by the treatment program.[19] The difference in outcomes between these two groups is what is reported as the average treatment on the treated.

I use three different matching methods in the second stage of each propensity score model. Each method has positive and negative aspects attributed to it, related to a bias and variance tradeoff (see Caliendo and Kopeinig 2008; Becker and Ichino 2002 for details). In the next paragraph I will discuss each method, opting for a more descriptive and intuitive explanation of these methods.[20]

The first matching method shown in the first row of Tables 3, 4 and 5 is the Stratification method. The algorithm divides members into a certain number of strata, with similar propensity scores.[21] The average mean differences in outcomes between treated and control observations are calculated for each stratum and these results enter a

19. Treatment program generally refers to a public policy or optimally a random treatment assignment.
20. Please refer to Smith and Todd (2005) or Imbens (2004) for technical details.
21. I use the initial number of strata calculated in the balancing of the propensity score.

weighted average. This is the average treatment on the treated (Caliendo and Kopeinig 2008). This method makes use of the common support only.[22]

The second method I use is the Nearest Neighbor matching method with replacement. The method is featured in the second row of Tables 3, 4 and 5. This is the most straightforward of all matching methods (Caliendo and Kopeinig 2008). Nearest Neighbor matching takes the closest 'neighbors' for the treatment and control observations based off of propensity score, and compares their outcomes. The method I use involves matching with replacement, meaning an untreated person can be used more than once as a counterfactual for treated individuals. In choosing to use replacement there is a tradeoff. The bias is reduced, but the variance is increased (Smith and Todd 2005). This method also makes use of the common support only.

The third and final matching method I use is the Kernel matching method. It is shown in the third row of Tables 3, 4 and 5. This is a nonparametric matching estimator that uses weighted averages of nearly all individuals in the control group to construct the comparison group for the treatment group (Caliendo and Kopeinig 2008). This differs from most matching methods, which make use of the common support. A major advantage of the kernel method is that it uses substantially more information because of the use of many observations, thus achieving a lower variance. For the same reason, however, there is the possibility of using bad matches, causing attenuation bias. Smith and Todd (2005) show that kernel matching can be viewed as a weighted regression of

22. The common support is the area of the propensity score where there is significant overlap.

counterfactual outcomes on an intercept with weights given by the kernel weights. Weights depend on the distance between each individual from the control and treatment groups. The value of the intercept (estimated) provides the counterfactual mean (Caliendo and Kopeinig 2008). Bootstrapping of the standard errors is necessary due to the nonparametric nature of the matching method. In addition a kernel function and bandwidth size must be chosen when implementing the kernel matching method.[23]

The results of the second stage matching methods for the personality trait treatments are shown in Tables 3, 4 and 5. Table 3 displays the ATT results for the treatment of having high self-esteem and its effects on logged wages in 2000. The first column uses covariates in the first stage of the PSM model denoted as (A) from Table A1. Every result is statistically significant and robust across matching types, at the 1 percent level. An adolescent who exhibits high self-esteem can expect to have an 11.5 to 13.5 percent higher wage as an adult. When controlling for all covariates in the first stage, denoted by column (D) in Table 3, the ATT result is still significant at the 1 percent level across all three matching methods. Persons who have a high self-esteem relative to their peers as an adolescent can expect to enjoy an 8.5 to 9.2 percent higher wage as adults. These results show that self-esteem is an important economic factor in explaining wages and should be included in future research employing human capital models.

23. I use 100 repetitions of the model for bootstrapping the standard errors. I choose the Gaussian kernel, and I use bandwidth of 0.06 in all cases.

Table 4 presents ATT results for the internal locus of control treatment on logged wages in 2000. The first column of Table 4 uses the standard covariates denoted as (A) from Table A1 in the first stage. The results are statistically significant and are robust across all matching methods. This shows that people who have an internal locus of control, relative to their peers with loci of control below the mean level, experience anywhere from 6.1 to 8 percent higher wages in the future. When the vector of family background characteristics are added, denoted by column (B) in Table 4, all matching methods still show significance, but the magnitude of the effect falls to a range of 4.9 to 6 percent.

When the AFQT score is added to (A), denoted by column (C) of Table 4, the significance begins to disappear for both the Stratification and Nearest Neighbor matching methods, but is still significant for the Kernel method. When all covariates are included, denoted by column (D) in Table 4 the effects falls to a range of 2 to 3.1 percent higher wages experienced by internal persons, but are insignificant. Intuitively this means that once treated persons are paired with good matches from the synthetic control group including persons who have similar cognitive skills and family background characteristics, the effect of locus of control as an adolescent on wages as an adult becomes insignificant – therefore it is not recommended to include locus of control in future studies of human capital, as it does not explain a significant amount of variation in wages once cognition and family background characteristics are accounted for.

Table 5 displays the ATT results for the treatment of having high cognition and its effects on logged wages in 2000. This is a robustness check to see whether adding locus of control in the first stage specification of the treatment of being highly cognitive eliminates the treatment effects of cognition as an adolescent on wages in the future. This result would show that it is uncertain whether it is cognition or locus of control which is the important variable in explaining wages. My results, however, show that cognition remains highly significant regardless of the specification in the first stage of the PSM. The covariates listed in each column are slightly different in this table than the covariates found in Table A1. The first column uses covariates still denoted as (A) from Table A1 and the second column uses covariates still denoted as (B) from Table A1. However, the third column lists a new set of covariates listed as (P). This is the standard set of covariates (A) plus the locus of control and self-esteem variables. Persons who have higher levels of cognition as adolescents experience higher wages as adults. The cognition premium ranges from 26.4 to 33.1 percent depending upon specification. This result gives further evidence to the lack of importance of locus of control as an explanatory variable on wages.

1.5 Conclusion and Discussion

I examine the effects of locus of control and self-esteem on wages using PSM, which I implement to extract more precise estimates. I find that persons who exhibit high self-esteem as adolescents enjoy higher wages in the future. This result is robust across the matching type used. This finding coincides with previous literature such as Goldsmith, Veum and Darity (1997a) and Waddell (2006). I find that persons who exhibit an internal locus of control enjoy higher wages in the future, but when I control for cognition and family background characteristics, locus of control becomes insignificant in explaining wages. This result does not coincide with the conclusions found by Cebi (2007), Andrisani (1977), Duncan and Dunifon (1998) and Osborne Groves (2005) among others who all show that having an internal locus of control does in fact lead to higher wages. The reasoning behind the difference in how locus of control affects wages is due to the more efficient results garnered from the PSM approach.

The fact that the high self-esteem treatment was robustly significant across all match types maintains an argument that certain noncognitive skills play a rather large role in economic outcomes. Other noncognitive skills, however, may not play a role in explaining economic outcomes. I conclude that locus of control is relatively unimportant as a viable economic variable to explain wages. It picks up much of the same variation in wages as the cognitive measurement and family background characteristics do. A fruitful future research agenda in this field can attempt to identify which of the myriad personality traits have significant effects on economic outcomes.

Public policy could be implemented to support stable families for children and cultivation of both self-esteem and cognitive skills as children make the life-cycle adjustment into becoming adolescents. By designing successful public policy to help alter these traits in individuals, the people affected by such a policy are likely to experience higher wages in the future and also enjoy a higher standard of living.

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TABLES

TABLE 1. LOG WAGE MEANS AND DIFFERENCES BETWEEN TREATMENT AND CONTROL GROUPS

Trait	Treatment Mean	Control Mean	Difference
Self-esteem	2.753 (0.569)	2.516 (0.525)	0.237**
N	2939	3429	
Locus of Control	2.713 (0.576)	2.546 (0.529)	0.167**
N	3018	3350	
Cognition	2.861 (0.551)	2.417 (0.476)	0.444**
N	2991	3377	

Notes: Log Wage Means shown for the year 2000. Standard Errors presented in parentheses.

* = significant at the 5% level. ** = significant at the 1% level.

The significance shown is found using a Mann-Whitney U Test (Wilcoxon).

TABLE 2. EFFECTS OF EACH PERSONALITY TRAIT ON WAGES USING OLS

	Standardized Score			Treated/Untreated Dummy		
Self-esteem	0.059** (0.007)	0.047** (0.007)	0.045** (0.008)	0.089** (0.015)	0.067** (0.015)	0.065** (0.015)
N	6462	6308	6256	6462	6308	6256
Locus of Control	0.031** (0.007)	0.019** (0.007)	0.011 (0.008)	0.047** (0.014)	0.026 (0.014)	0.02 (0.015)
N	6660	6411	6256	6660	6411	6256
Baseline	X	X	X	X	X	X
Cognition		X	X		X	X
Other Trait			X			X

Notes: The dependent variable is the log(hourly wage) in 2000. The Baseline set of Covariates are as follows: years of education, age, a quadratic in age, a set of occupational dummies and dummies for: residence in an SMSA, residence in an urban area, gender, race/ethnicity and marital status. Cognition is the AFQT score and Other Trait is the other personality trait.

To get an economic interpretation of the effect of each personality trait on log wages, a transformation of the original estimate must be made. (exp(estimate) – 1) will garner the true percentage effects. These are the values I mention in the text

The Standardize Score the Rotter and/or Rosenberg scale normalized to a mean 0 standard deviation 1 variable. The Treat/Untreat dummy is a dummy variable indicating the person is in the treatment group for a given personality trait. This is based on the mean score of the Rotter or Rosenberg scale.

* = significant at the 5% level. ** = significant at the 1% level.

TABLE 3. SECOND STAGE ATT ESTIMATES OF SELF-ESTEEM ON WAGES USING PSM

	Covariates^			
Matching Type	(A)	(B)	(C)	(D)
Stratification	0.109** (0.017)	0.106** (0.020)	0.073** (0.017)	0.082** (0.021)
N (Treat/Cont)	2363/2769	1830/2003	2317/2705	1792/1944
NearestNeighbor	0.127** (0.023)	0.097** (0.027)	0.075** (0.024)	0.082** (0.027)
N (Treat/Cont)	2363/1215	1830/928	2317/1171	1792/883
Kernel^^	0.125** (0.015)	0.116** (0.019)	0.087** (0.016)	0.088** (0.020)
N (Treat/Cont)	2363/2787	1830/2022	2317/2721	1792/1975

Notes: Shown are the second stage ATT results of the PSM models. The dependent variable in all cases is log(hourly wage) in 2000.

To get an economic interpretation of the effect of each personality trait on log wages, a transformation of the original estimate must be made. (exp(ATT) – 1) will garner the true percentage effects. These are the values I mention in the text.

* = significant at the 5% level. ** = significant at the 1% level.

^ = Covariates refer to those used in the first stage and are as specified in Table A1.

^^ = Kernel method standard errors are bootstrapped. All other matching methods use the variance calculation method proposed by Lechner (2001)

TABLE 4. SECOND STAGE ATT ESTIMATES OF LOCUS OF CONTROL ON WAGES USING PSM

	Covariates^			
Matching Type	(A)	(B)	(C)	(D)
Stratification	0.062** (0.017)	0.048* (0.019)	0.023 (0.017)	0.020 (0.020)
N (Treat/Cont)	2401/2660	1832/1957	2345/2611	1784/1925
NearestNeighbor	0.060** (0.022)	0.054* (0.026)	0.022 (0.023)	0.021 (0.028)
N (Treat/Cont)	2401/1267	1832/952	2345/1237	1784/897
Kernel^^	0.077** (0.015)	0.062** (0.020)	0.041** (0.016)	0.031 (0.018)
N (Treat/Cont)	2401/2667	1832/1972	2345/2620	1784/1940

Notes: Shown are the second stage ATT results of the PSM models. The dependent variable in all cases is log(hourly wage) in 2000.

To get an economic interpretation of the effect of each personality trait on log wages, a transformation of the original estimate must be made. (exp(ATT) – 1) will garner the true percentage effects. These are the values I mention in the text.

* = significant at the 5% level. ** = significant at the 1% level.

^ = Covariates refer to those used in the first stage and are as specified in Table A1.

^^ = Kernel method standard errors are bootstrapped. All other matching methods use the variance calculation method proposed by Lechner (2001)

TABLE 5. SECOND STAGE ATT ESTIMATES OF COGNITION ON WAGES USING PSM

	Covariates^		
Matching Type	(A)	(B)	(P)
Stratification	0.303** (0.023)	0.268** (0.048)	0.286** (0.049)
N (Treat/Cont)	2469/2407	2006/1602	2415/2379
NearestNeighbor	0.313** (0.041)	0.260** (0.056)	0.253** (0.055)
N (Treat/Cont)	2469/841	2006/637	2415/808
Kernel^^	0.262** (0.025)	0.262** (0.027)	0.234** (0.026)
N (Treat/Cont)	2469/2553	2006/1753	2451/2462

Notes: Shown are the second stage ATT results of the PSM models. The dependent variable in all cases is log(hourly wage) in 2000.

To get an economic interpretation of the effect of each personality trait on log wages, a transformation of the original estimate must be made. (exp(ATT) – 1) will garner the true percentage effects. These are the values I mention in the text.

* = significant at the 5% level. ** = significant at the 1% level.

^ = (A) and (B) Covariates refer to those used in the first stage and are as specified in Table A1. The (P) Covariates are (A) plus Locus of Control and Self-esteem.

^^ = Kernel method standard errors are bootstrapped. All other matching methods use the variance calculation method proposed by Lechner (2001)

APPENDIX

TABLE A1. COVARIATES INCLUDED IN FIRST STAGE PSM SPECIFICATIONS

Control Indicator	Covariates Included
(A) Baseline	Dummies for: gender, race/ethnicity, living in an urban area*, living in an SMSA*, region of country*, marital status*, unemployment status*, high school dropout*, poverty status*. Measurements of: years of education*, age*, family size*, family income* and the other personality trait^.
(B) Baseline + Family Background	Everything included in (A). Also included are Dummies for: Mother working when respondent was 14, Father working when respondent was 14, Father born in the US, Mother born in the US, Respondent born in the US, Foreign Language spoken in home when respondent grew up, Mother being dead, Father being dead, Being born in the South (U.S.), Residing in the South at age 14, Whether respondent had access to a library card, newspapers and/or magazines at age 14, residing in an urban area at age 14, being raised without a religion. Also included are: measurements of Years of Education of Father, Years of Education of Mother, Number of Siblings and Number of Siblings older than the respondent.
(C) Baseline + Cognitive	Everything included in (A) and the respondent's AFQT score, comprised of the sum of the Arithmetic, Word and Mathematical section scores of the ASVAB battery of tests.
(D) All	Everything included in (A) + Cognitive Covariate + Family Background Covariates.

Notes: *= This indicates that the measurement is for the year the specific treatment being studied is measured. In other words, for Locus of Control these will be 1979 measurements and for self-esteem these will be 1980 measurements.

^ = The other personality trait is the trait not currently being focused on as the treatment.

TABLE A2. BRIEF SUMMARY OF LITERATURE CONTAINING EXAMINATIONS OF THE EFFECTS OF LOCUS OF CONTROL AND/OR SELF-ESTEEM ON WAGES

Author and Year	Trait(s)	Data	Methods	Results
Andrisani (1979)	Locus of Control	National Longitudinal Survey (NLS)	Ordinary Least Squares (OLS)	Internal locus of control leads to higher average hourly earnings, occupational attainment and total earnings
Duncan and Morgan (1981)	Locus of Control	Panel Study of Income Dynamics (PSID)	Ordinary Least Squares (OLS)	Replication of Andrisani (1979) but with conflicting results
Goldsmith, Veum and Darity (1997)	Self-esteem and Locus of Control	National Longitudinal Survey of Youth 1979 (NLSY79)	Two-stage Least Squares (2SLS)	Self-esteem affects wages directly, while locus of control affects wages indirectly through self-esteem.
Duncan and Dunifon (1998)	Locus of Control	Panel Study of Income Dynamics (PSID)	Ordinary Least Squares (OLS)	Internal locus of control as an adolescent leads to higher wages as an adult. This refutes Duncan and Morgan (1981)
Osborne Groves (2005)	Locus of Control	National Longitudinal Survey of Young Women and National Child Development Study	Instrumental Variable (IV) and Heckman Selection Models	Locus of control affects wages for white women.
Waddell (2006)	Self-esteem	National Longitudinal Study of the High School Class of 1972 (NLS-72)	Ordinary Least Squares (OLS), Logit and Probit Models	Youth with low self-esteem obtain fewer years of education, are less likely to be employed and earn lower wages
Cebi (2007)	Locus of Control	National Longitudinal Survey of Youth 1979 (NLSY79)	Ordinary Least Squares (OLS) and Probit Models	Adolescent locus of control does not affect educational attainment or occupational expectations. It does, however affect adult wages.

CHAPTER 2

SELF-ESTEEM, EDUCATIONAL ATTAINMENT AND WAGES: A QUESTION OF SELECTION

2.1 INTRODUCTION

Soft skills, such as self-esteem, locus of control, emotional intelligence and social skills have recently become a point of interest in economic research. These characteristics, otherwise labeled as noncognitive skills or personality traits, can help explain economic phenomena such as wages, length of unemployment, and educational attainment. Self-esteem (SE) is an assessment of one's self worth. Persons who have a high SE view themselves as having considerable self worth, whereas persons with low SE believe the converse (Rosenberg 1965).

Research has shown that adolescents with higher SE experience higher wages as adults. (Goldsmith, Veum and Darity 1997; Waddell 2006; Drago 2011; Murnane, Willett, Braatz and Duhaldeborde 2001; Graham, Eggers and Sukhtankar 2004). The established reasoning in the literature explaining why this relationship occurs is that those with higher SE are more productive and persistent when faced with difficult tasks. (Brockner 1988; Wylie 1979; Dweck and Leggett 1988; Goleman 1995). Research has also shown that it is sometimes beneficial for people to have incorrect beliefs about their ability. High SE can lead to inflated beliefs about ability. This belief gives some people extra initiative, at the margin, to achieve their goals. (Benabou and Tirole 2002; Santos-Pinto and Sobel 2005).

In this article I estimate the effects of SE on two variables: educational attainment and wages, using data from the National Longitudinal Survey of Youth 1979 cohort (NLSY79). As stated above, past research has shown that higher SE creates more productivity and tenacity in the workplace. If this is so, then productivity and tenacity produced by higher SE should have a similar role in completing education. This basic relationship between SE and educational attainment has not, to my knowledge, been analyzed yet in the economics literature.

First, I estimate educational attainment using both linear regression and probit models. I find that higher SE positively and significantly affects educational attainment for those people who attain education beyond high school.[1] Second, I replicate the general results found in past articles showing that higher SE leads to higher wages. Third, I ask whether SE affects wages directly or indirectly. Does SE affect educational

[1] As high school completion is largely mandatory in the US, a noncognitive variable such as self-esteem may not create a significant difference for this outcome.

attainment, wages, or both? To analyze this question I employ Heckman selection models. (Heckman 1979). I find that family background characteristics and individual traits – including self-esteem play a role in selection of education. Conditional on this selection, the remaining direct effect of higher SE on wages is negligible.

The result is somewhat contrary to past literature of SE on wages. The selection model results appear to negate the previous findings in the literature that SE affects wages. However, I argue that my findings assist past research by estimating the relationship between SE and wages more precisely. Specifically, my empirical findings support past results that SE does affect wages, but it does so through its effect on educational attainment. If higher SE does lead to higher levels of educational attainment then public policies meant to steer people towards higher valuations of their self-worth could help people more fully internalize the external benefit to society from having an educated populace. Theoretically, this will help solve inefficient outcomes in educational markets due to positive externalities.

2.2 LITERATURE REVIEW

General studies of noncognitive skills and their importance are becoming prominent in economics. Heckman, Stixrud and Urzua (2006) argue that there are a certain number of true noncognitive and cognitive skills that have explanatory power across the entire spectrum of economic outcomes. Survey instruments only capture portions of each true skill. Lindqvist and Vestman (2011) use Swedish military data to show that noncognitive ability is a substantially stronger predictor of labor market outcomes than cognitive ability. They find that people who do not fare well in the labor market tend to lack noncognitive skills rather than cognitive skills.

Cognitive and noncognitive skill formation has been explored by Cunha and Heckman (2008). They show that there are several sensitive periods for parental investment to foster positive growth in both cognitive and noncognitive skills and that the formative period for cognitive skills precedes that of noncognitive skills. Research by Segal (2008) coincides with Cunha and Heckman (2008) by showing that classroom behavior is related to family background characteristics.

Moving from general noncognitive studies to the specific, SE has been found to be a significant variable in predicting labor market success. Goldsmith, Veum and Darity (1997) use the National Longitudinal Survey of Youth to test whether "psychological capital" affects wages. They allow wages and SE to be determined simultaneously, obtaining identification through strong exclusion restrictions. They implement a two stage least squares approach with an ordered probit to estimate locus of control and an OLS model to estimate wages. The authors assume that locus of control does not directly affect wages, but does so via affecting SE. They show that psychological capital has both a direct effect, through SE, and an indirect effect, through locus of control, on an individual's wage. A person's wage is more sensitive to changes in SE than to comparable alterations in human capital.

Murnane, Willett, Braatz and Duhaldeborde (2001) use NLSY data to examine how skills of male teenagers predict wages at age 27 and 28. They examine academic skills, speed of mental task completion and SE. They find that all three types of skills play roles in predicting subsequent wages. They find that people who have one standard deviation above average SE tend to see 3.8 percent higher wages in their adult lives, even when controlling for measurements of cognition. They give two reasons for high SE to have effect on wages, that people with high SE are more productive and more persistent at the margin.

Waddell (2006) uses the National Longitudinal Study of the High School Class of 1972 and analyzes the effects of SE on economic outcomes. He finds that youth who have low SE obtain fewer years of education, are less likely to be employed in the future and when employed have lower earnings than persons with higher SE. Graham, Eggers and Sukhtankar (2004) find that income is partially determined by happiness – which is a combination of optimism and SE. Happiness leads to higher income. It is especially effective for those at lower levels of income.

The latest research investigating SE's effect on wages is by Drago (2011). He uses the NLSY79 dataset and estimates standard human capital models with SE in 1980 as the variable of interest and finds statistically significant and positive effects of higher SE on wages in 1988. Drago then utilizes a later measurement of SE taken in 1987 and uses the 1980 SE as an instrumental variable (IV) for 1987 SE. He states that the 1980 SE is exogenous to wages seen later in life, whereas the 1987 SE measurement may face problems of endogeneity. Exploiting the exogenous variation in 1987 SE using the IV, Drago finds that SE actually has more of an effect on wages than previously thought (about two times more).

The 1987 SE measurement, however, can still be affected by numerous life outcomes. This causes a feedback relationship and confounds what the 1987 measurement of SE is truly measuring. Drago states that the 1980 SE is a person's core measurement of SE, since it occurs before significant life events. It is untarnished. The 1987 SE measurement is a mixture of core SE and another portion of SE caused by life events. Therefore, using this measurement muddles the effects of SE on wages that he finds.

Research by Cunha and Heckman (2008) have shown that SE[2] is mainly affected by family background characteristics, and then remains relatively stable.[3] Backed with this information, coupled with endogeneity problems inherent in the 1987 measurement of SE, I use only the 1980 core measurement of SE that occurs before major occupational life outcomes are experienced. This is the internal, relatively nonmalleable,[4] portion of SE that I ascertain as the important factor.

[2] The research investigates noncognitive traits in general – which includes SE.

[3] This is when the core, and as I am interpreting, most important SE is determined. This core SE has the longest-ranging effects on a person's economic outcomes.

[4] This measurement is nonmalleable by post-adolescent and post-childhood variables . These post-adolescent variables will confuse the true meaning of a later measurement of SE's effects on economic outcomes.

2.3 DATA AND SURVEY INFORMATION

The data I use are from the National Longitudinal Survey of Youth 1979 (NLSY79) which is a longitudinal survey administered by the Bureau of Labor Statistics. It is a nationally representative sample of 12,686 young men and women between the ages of 14 and 22 at the time of the first interview in 1979. Since their first interview, they have been interviewed annually until 1994, and biennially thereafter. The NLSY79 is a rich data set that includes annual measures of education, occupational status, marital status, wages, health data and many other variables that are individual-specific. For my research the key explanatory variable of interest is SE that is measured in 1980, via the Rosenberg Scale.

The main outcome variables in the models I employ are logged wages in 2004, a continuous measurement of education as highest educational attainment (in years) in 2004, and binary educational outcome variables.[5] To create the binary educational outcome variables I take data ranging from 1988 to 2004 where respondents indicate their highest degree attained at that year. I then create a variable of highest degree attained by the year 2004.[6] These binary variables are the outcome variables for my educational attainment probit models. For some models the dependent variable is for people who have a certain degree, for example, those who finished a bachelor's degree and did not go

[5] Wages are top and bottom coded, to remove hourly wage outcomes that appear miscoded.

[6] I choose 2004 as the cutoff year as the question is not asked afterwards in the survey.

further. For other models the dependent variable is for those obtaining at least a certain degree, for example those who finished at least a bachelor's degree.[7]

To measure SE I use the Rosenberg SE scale. In the NLSY79 it was administered during the 1980, 1987 and 2006 surveys. It is a 10-item scale that measures self-evaluation, that is, how people feel about themselves. The Rosenberg scale is meant to describe a degree of approval or disapproval toward oneself (Rosenberg 1965). Each question is extracting self-approval or disapproval from the respondent, where in answering, they specify whether they strongly agree, agree, disagree, or strongly disagree.[8]

I use only the 1980 wave of SE data, as the effect of an adolescent SE on adult economic outcomes is what I need to test my hypothesis. I am interested in finding the effect of a person's core SE on their outcomes, therefore I do not utilize later SE measurements which face feedback relationships with the outcome variables.[9] After carefully cleaning the data, I standardize the Rosenberg SE scale, so that the variable is expressed with a mean of zero and standard deviation of 1.[10] This makes for easier interpretation of the effects of SE on wages and educational attainment. The coefficient

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[7] I indicate which outcome variable I am using in each table.
[8] The Rosenberg questionnaire in the NLSY79 is as follows:
1. I am a person of worth. 2. I have a number of good qualities. 3. I am inclined to feel that I am a failure. 4. I am as capable as others. 5. I feel I do not have much to be proud of. 6. I have a positive attitude. 7. I am satisfied with myself. 8. I wish I had more self respect. 9. I feel useless at times. 10. I sometimes think I am "no good" at all.
[9] See Drago (2011) or see the literature review in this article for information on core SE.
[10] As is standard practice with noncognitive variables (see Drago 2011, Cebi 2007, Goldsmith, Veum and Darity 1997)

or marginal effect, depending upon model specification, is interpreted as the effect of increasing SE by one standard deviation.

Debate often arises as to whether these relatively subjective measurements of personality are reliable, how a person responds will be consistent from period to period, given other control variables collected between the periods. Krueger and Schkade (2008) show using Day Reconstruction Methods (DRM) that exhibited test-retest correlations for subjective well-being measurements generally fall in the range of 0.50 – 0.70. They note while these figures are lower than the reliability ratios found for variables such as education, income and other microeconomic variables, they argue they are sufficiently high to yield informative estimates for much of the research that uses subjective well-being measurements.

The cognitive measurement is constructed similar to Cebi (2007). I construct it as the sum of the standard scores for the word knowledge, arithmetic reasoning and mathematical knowledge sections of the Armed Forces Vocational Aptitude Battery (ASVAB). The use of the usual percentile scores found in the NLSY79 for the Armed Forces Qualifications Test (AFQT) shown as AFQT80 and AFQT89 in the dataset are not used due to the finding that ability follows a normal distribution while a percentile follows a uniform distribution (Blackburn 2004). I denote my constructed cognitive measurement as the AFQT score during my analysis. As with the Rosenberg SE scale, I also standardize the AFQT score, so that the variable is expressed with a mean of zero and standard deviation of 1. This makes for easier interpretation of the effects of AFQT on wages and educational attainment. The coefficient or marginal effect is interpreted as the effect of increasing AFQT by one standard deviation.[11]

Other control variables in my models include standard human capital covariates. These have been extracted from the 2004 survey wave of the NLSY79 if they are measurements that are taken yearly, such as occupational code, living in an urban/rural area, marital status, etc.[12] If the variable is time-invariant, I extract that data from the first survey wave, 1979. Variables that are time-invariant include race, gender, numerous family background characteristics, etc.[13] After the data are cleaned I finish with a sample size of 4,128 individuals.

Table 1 shows how SE varies by educational attainment level. The subsamples are sorted by educational attainment levels of at least a certain degree. For example, in row 1, the HS Diploma group would indicate those people who have attained at least a high school diploma.[14] Interestingly, adolescent SE rises as I subsample through the ranks of educational attainment. For example, those with a Bachelor's degree or higher have a standardized Rosenberg SE scale of 0.362 on average, whereas those who have less than a Bachelor's degree have an average standardized Rosenberg SE scale score of -0.107. The result is different and statistically significant at the 1 percent level using a Wilcoxon Mann-Whitney U Test.

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[11] The results of cognition on educational attainment and wages are that AFQT is generally highly significant and positive. The specific magnitudes are suppressed in the majority of the tables, but the results are available from the author.

[12] Full explanation of which covariates are included in the human capital, educational attainment and selection models are included in the notes of each corresponding table.

[13] Again, the full explanation of what is included in each model will be fully explained in the notes of each corresponding table.

[14] This means the sample includes those with Associate, Bachelor, Master's, Doctoral and Specialist degrees, as well as those with only a high school diploma.

This table indicates that each subsample of higher level of educational attainment shows statistically significant higher adolescent SE. Since 1980 SE could not be affected by highest educational attainments obtained thereafter, this analysis shows a very promising relationship that has not yet been examined in the economics literature. The results seen in Table 1 also help me generate and solidify the main hypothesis of this paper. Does high SE cause selection of educational attainment that leads to higher wages?

2.4 METHODS AND RESULTS

2.4.1 EDUCATIONAL ATTAINMENT MODELS: LINEAR REGRESSION AND PROBIT

The results in Table 1 show educational attainment varies greatly by adolescent SE. This leads me to estimate inferential educational attainment models. First, I estimate an ordinary least squares regression in the following manner:

$$educ_i = \propto_0 + \propto_1 SE_i + \propto_k \mathbf{X}'_{i,k} + \varepsilon_i \tag{1}$$

The outcome variable $educ_i$ is a continuous measurement of years of education for individual i attained by the year 2004; SE_i corresponds to the explanatory variable of interest, SE of the individual measured in 1980, standardized with a mean 0 and standard deviation of 1. $\mathbf{X'}_{i,k}$ is a vector of covariates of degree k, including race, gender, age, height, a large vector of family background characteristics and cognition. The $\propto_k$ are parameters to be estimated and ε_i is the idiosyncratic error term, assumed to be distributed $N \sim (0, \sigma^2)$. The result for $\propto_1$ in this OLS regression specified in equation (1) is presented in column 1 of Table 2.[15] The result shows that for a one standard deviation increase in a person's SE, they can expect to complete, on average, an additional 0.189 years of education, or approximately an additional one-fifth of a year.

Second, and to more precisely examine the effects of SE on educational attainment I estimate probit models where the outcome variable is a binary variable indicating degree completion. For example, in column 2 of Table 2, the outcome variable is for people whose highest degree attainment is less than a high school diploma. A one standard deviation increase in SE pertains to a 1.5 percent decrease in the probability that they do not finish high school. This makes intuitive sense, as people who view themselves as having less self-worth would be more likely to drop out of high school.

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[15] The parameter estimates for the covariates and constant are suppressed, but are available from the author upon request.

To highlight the difference in interpretation between dependent variables showing single degree completion and those showing degree completion of at least a certain level I will explain columns 3 and 4 in Table 2. Column 3 indicates that the effect of a one standard deviation increase in SE on the chance of completing high school - and high school only - is -0.6 percent, and is insignificant. This means that SE is not related to finishing high school and not continuing. This makes intuitive sense as well, since in the U.S. high school completion is generally mandatory.[16] It follows that SE would not have much of an effect on something that is not viewed as a choice for many.

In column 4 the effect of a one standard deviation increase in SE on the probability of getting at least a high school diploma is 1.5 percent and is statistically significant at the 1 percent level. This means that SE does significantly affect the probability that people pursue education beyond high school. In examining the entire table of results, it is evident that except for those only getting a high school diploma, having higher SE positively affects the probability that persons will pursue further education and negatively affects the probability that persons will drop out of high school.

[16] Although not everyone graduates high school, the general mandatory nature of it is assumed make it not a true autonomous choice.

2.4.2 LOG-WAGE MODELS

The next step in my econometric analysis is to replicate general results in the literature by estimating human capital models using log-wage equations. (see Mincer 1970). Using ordinary least squares (OLS) regression I specify several log-wage equations in the following manner:

$$\ln y_i = \beta_0 + \boldsymbol{\beta}_1 SE_i + \boldsymbol{\beta}_k \mathbf{X}'_{i,k} + \boldsymbol{\varepsilon}_i \tag{2}$$

The variable y_i is the hourly wage rate of the person i in the year 2004; SE_i corresponds to the explanatory variable of interest, SE of the individual, measured in 1980, standardized with a mean 0 and standard deviation of 1. $\mathbf{X}'_{i,k}$ is a vector of covariates of degree k, including race, gender, age, marital status, height, weight, tenure at primary job, region of residence, urban/rural residence, union membership, education, cognition and a large vector of occupational dummies. The $\boldsymbol{\beta}_k$ are parameters to be estimated and $\boldsymbol{\varepsilon}_i$ is the idiosyncratic error term, assumed to be distributed $N \sim (0, \sigma^2)$. The results for $\boldsymbol{\beta_1}$ in all of these OLS regressions specified in equation (2) are presented in Table 3.[17]

The results of these log-wage equations are shown in Table 3. The first column shows results for a regression using the full sample of 4,128 individuals. Matching the literature, higher SE as an adolescent positively and statistically significantly affects wages. Having a one standard deviation higher SE as an adolescent equates to 2.4 percent higher wages as an adult.

To more precisely examine the effects of SE on wages the rest of the columns in Table 3 show results for log-wage equations subsampled by educational attainment level. The majority of these models split by educational attainment show that SE does not significantly affect wages. For example, in column 7 of Table 3, those who have obtained a exactly a bachelor's degree achieve a 0.1 percent increase in log wages given a one standard deviation increase in SE. This result, however, is statistically insignificant. As shown in column 8, those people have obtained a bachelor's degree and higher, when all aggregated together, do not experience higher wages by having higher SE.

From these subsample results, it appears that the positive and statistically significant gains from higher SE when looking at an entire sample of individuals may be upwardly biased by those who have obtained a master's degree or higher. Those people receiving a master's degree see a 7.8 percent increase in their wages from a one standard

[17] The parameter estimates for the covariates and constant are suppressed, but are available from the author upon request.

deviation increase in their SE and the result is statistically significant. From these results it is clear that high SE does not stimulate wages similarly for all individuals. The effect differs depending upon educational level. The combined results from Tables 1, 2 and 3 warrant further investigation into this matter.

2.4.3 SELECTION MODELS

My final and culminating modeling approach in this paper is to use Heckman selection models (Heckman 1979) to evaluate whether selection plays a role in this analysis. Based on the educational attainment models I estimated, people appear to obtain more education later in life based on having a higher SE as an adolescent. The subsample log-wage equation results presented in Table 3 show that SE affects people differently based on their varying levels of educational attainment.

These results, along with economic intuition, hint that selection of education, partially based on SE, may be playing a role in steering the true effect of SE on wages. Individuals with higher levels of SE as adolescents will end up choosing to consume more education, which will in turn supply them with higher wages as adults. The sample of working individuals appearing to experience higher wages due to higher SE may also be comprised of more highly-educated individuals. Based on my current empirical evidence shown in Table 2, more highly educated individuals have become more highly educated partially due to higher SE. Therefore, attributing higher wages to higher SE may be misleading without investigation into how SE affects educational attainment. To address this potential problem of selection bias I estimate Heckman selection models, where the probit models of educational attainment discussed in section 2.4.1 are the selection equations, and the human capital model subsamples as specified in (2) are the outcome equations. The rationale behind the timing of this modeling approach is that people in their lives generally choose to consume education first and then begin their occupation and experience wages second.

To obtain identification in these selection models, I need at least one variable that is driving selection of education and not the wage outcome (Heckman 1979). My modeling approach is to allow a person's family background characteristics, such as education of parents, place of birth, access to educational materials when young, etc.[18] to influence educational selection, but not to affect wages later in life. Belzil and Hansen (2003) use structural modeling and find that family background characteristics such as these have a large effect on educational attainment, but have very little, if any, effect on wages. In addition, the sociological literature states that educational attainment is said to be largely based on parents setting up the resources needed to succeed. (Teachman 1987). Generally, educational attainment for an individual is affected by family background characteristics directly while wages are affected indirectly or not at all. (Belzil and

[18] Full list of family background characteristics included in the selection equations can be found in the notes section of Table 4.

Hansen 2003). Using the literature as a guide, I achieve identification (see Heckman 1979) in my Heckman selection models when I include the vector of family background characteristics in the selection equations and leave it out of the outcome equations.

The results of the second stage of the selection models I estimate are presented in Table 4. I present only the results for SE and the inverse mills ratio (IMR).[19] The first stage selection results of these selection models can be found in Table 2, as they are identical to the educational attainment probit models specified in section 2.4.1. As a reminder, higher SE had a positive effect on all educational attainment levels except for those people who only obtained a high school diploma.

The results in Table 4 show that when factoring in selection of education, the direct effects of SE on wages disappear. Compared to results in Table 3, the majority of these coefficients on SE have been dampened through selection, and all of them are now insignificant. For example, In Table 3 the effect of having a one standard deviation higher SE on wages for those attaining a high school diploma or higher was a 1.9 percent increase in wages and was significant at the five percent level. In Table 4, when factoring in educational selection based on SE, the effect of having a one standard deviation higher SE on wages for those attaining a high school diploma or more is dampened to 1.3 percent and becomes statistically insignificant.

[19] The remaining covariate coefficients are available from the author by request.

The IMR has been found statistically significant in two of the selection models I employ. It is significant for the subsamples of at least having a high school diploma, and at least having a Bachelor's degree. Since these are two relatively large groups of individuals who are mostly attaining higher than mandatory U.S. educational levels, I conclude that, in general, there is a significant amount of selection on education occurring based partially on SE.[20] Pursuant on educational selection the remaining direct effects of higher SE on wages becomes negligible.

2.5 CONCLUSION, DISCUSSION AND POLICY BRIEF

Economic, psychological and sociological research has shown that those with high SE are likely to be more productive and more persistent when faced with difficult tasks (Brockner 1988; Wylie 1979; Dweck and Leggett 1988; Goleman 1995). Heightened productivity and persistence due to higher SE has been used as a main line of reasoning in past economic studies to provide evidence for the reason why adolescents who have higher SE experience higher wages as adults. (Goldsmith, Veum and Darity 1997; Waddell 2006; Drago 2011; Murnane, Willett, Braatz and Duhaldeborde 2001; Graham, Eggers and Sukhtankar 2004).

[20] An insignificant IMR in certain subsamples does not necessarily mean selection is not occurring. I conclude that having IMR being significant in various subsamples that cover a large portion of the entire sample is enough to conclude selection in general.

In this study I use similar intuition of persistence and productivity to examine the relationship between SE and educational attainment. Significant persistence when faced with difficult tasks and high levels of productivity are needed when consuming higher education. This basic relationship between SE and educational attainment has not been studied in the economic literature up to this point. I find that higher SE affects post-secondary educational attainment positively and significantly. This result holds true for models with a continuous variable of education (by years) in an ordinary least squares context as well as for probit models with educational variables that are binary and indicative of specific degree attainment. The only educational level not affected by higher SE is those who finish high school and do not pursue further education. SE would not create a significant difference in high school completion as this is generally mandatory in the U.S.

I then estimate human capital models in an attempt to replicate past studies on this topic. I find that when using the entire sample of individuals in the NLSY79 that higher SE leads to higher wages. When I examine the data further and subsample by educational attainment level, I notice that for many subsample regressions, higher SE does not significantly affect wages. This result provides further reasoning to analyze this topic more closely.

Lastly, I estimate how SE affects wages more precisely than articles addressing this topic in the past. I factor in potential selection of educational attainment as the true driving force behind why people with higher SE experience higher wages. When factoring in that people with higher SE are more likely to complete post-secondary education, the direct effect of SE on wages becomes negligible. This analysis is a more thorough examination of the educational selection mechanism occurring that creates the seemingly direct effect of higher SE on wages as found in past literature. It is the selection of education via SE that leads to higher wages. SE itself does not have a direct effect on wages after selection is factored in.

I have shown that higher SE has a positive effect on the probability that someone completes post-secondary education. In my final model in this analysis I estimate a rather rudimentary model of SE attainment by regressing adolescent SE[21] on individual-specific variables such as cognition, age, gender, race and height. I also regress on a relatively large vector of family background characteristics. The purpose is to see whether there are certain characteristics that can be augmented that could alter a person's SE formation in their formative years. If there are some characteristics that could be altered and would lead to higher SE, then perhaps public policy could play a role in steering SE achievement.

In Table A1, I present the results for this model. There are several significant variables that have an effect on SE. According to this preliminary model, having access to library cards, magazines and/or newspapers boosts a person's SE. Public policy could supply educational materials at free or low cost to parents of young persons. Using the results in this model, the same could also be said for subsidization of education in

[21] As measured by the standardized Rosenberg SE scale.

general. If parental education is subsidized, then the children of the subsidized parents would have higher SE which would have a positive effect on their educational attainment, and so on throughout generations. If policy can be utilized in such a way as to alter SE in children and adolescents, it may play a role in helping individuals internalize the positive externalities associated with educational consumption.

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TABLES

TABLE 1. MEAN ROSENBERG SELF-ESTEEM SCORES AND DIFFERENCES GROUPED BY EDUCATIONAL ATTAINMENT

Educ Level (at least)	Yes (Educ Level = 1)	No (Educ Level = 0)	Difference
HS Diploma	0.067 (0.990)	-0.507 (0.930)	0.574***
N	3648	480	
Associate Degree	0.316 (0.978)	-0.147 (0.976)	0.463***
N	1314	2814	
Bachelor's Degree	0.362 (0.971)	-0.107 (0.983)	0.469***
N	939	3189	
Master's Degree	0.505 (0.974)	-0.033 (0.993)	0.538***
N	256	3872	

Notes: Means of Standardized Rosenberg Self-Esteem Scale shown. Standard Errors presented in parentheses.

* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

The significance shown is found using a Mann-Whitney U Test (Wilcoxon).

TABLE 2. THE EFFECTS OF SELF-ESTEEM ON EDUCATIONAL ATTAINMENT

	All	No HS	HS	HS at least	Assoc	Assoc at least	Bach	Bach at least	Master	Mast at lea
Self-Esteem	0.189*** (0.03)	-0.015*** (0.004)	-0.006 (0.008)	0.015*** (0.004)	0.013*** (0.005)	0.039*** (0.008)	0.009* (0.005)	0.023*** (0.006)	0.006*** (0.002)	0.006* (0.00:
N	4128	4128	4128	4128	4128	4128	4128	4128	4128	412ŧ
R^2	0.427	0.262	0.052	0.262	0.033	0.259	0.207	0.317	0.213	0.26:

Notes: The dependent variable for each educational attainment model is denoted in each column. The first column is a continuous measuremen education, thus OLS is used. For the remaining models, a probit specification is used. The key variable of interest is the Rosenberg Scale for Se Esteem. The covariates/controls used are as follows: AFQT score (for cognition), age, a quadratic in age, height, race/ethnicity dummies, gende dummies. In addition a vector of family background characteristics, extracted from the 1979 NLSY survey are included. They are as follows: highest educational level of mother, highest educational level of father, mother worked at age 14, lived in a urban area at age 14, had access to library cards / newspapers / magazines at age 14, mother living at age 14, father living at age 14, both in the U.S., born in the southern region o the U.S., lived with naturally born mother and father at age 14, raised with a religion, foreign language spoken in home, number of siblings, li\ in same residence from birth until age 14.

Presented in the first column is the coefficient on the self-esteem variable in the OLS model. Presented in the remaining columns are the margi effects on the self-esteem variable in each respective probit model. In parentheses are the standard errors.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

TABLE 3. THE EFFECTS OF SELF-ESTEEM ON WAGES USING OLS – SAMPLES SPLIT BY EDUCATIONAL LEVEL

	All	No HS	HS	HS at least	Assoc	Assoc at least	Bach	Bach at least	Master	Master at least
Self-Esteem	0.024*** (0.008)	0.026 (0.022)	0.012 (0.010)	0.019** (0.008)	0.037 (0.027)	0.026* (0.015)	0.001 (0.022)	0.020 (0.019)	0.078* (0.042)	0.078** (0.039)
N	4128	480	2334	3648	375	1314	683	939	207	256
R^2	0.455	0.468	0.348	0.436	0.385	0.398	0.330	0.370	0.499	0.508

Notes: The dependent variable is the log(hourly wage) in 2004. The covariates/controls used are as follows: AFQT score (for cognition), years of education, a set of degree attainment dummies, age, a quadratic in age, height, weight, tenure, regional dummies, occupation code dummies and dummies for: residence in an SMSA, residence in an urban area, gender, race/ethnicity, union membership, and marital status. All Covariates except for the race/ethnicity, height and gender are measurements from the year 2004.

To get an economic interpretation of the effect of self-esteem on log wages, a transformation of the original estimate must be made. (exp(estimate) – 1) will garner the true percentage effects. These are the economic interpretations I mention in the essay.

* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

TABLE 4. SELECTION MODELS SECOND-STAGE RESULTS. THE EFFECTS OF SELF-ESTEEM ON WAGES FACTORING IN SELECTION OF EDUCATIONAL ATTAINMENT

	No HS	HS	HS at least	Assoc	Assoc at least	Bach	Bach at least	Master	Master at least
Self-Esteem	0.017 (0.022)	0.01 (0.01)	0.013 (0.009)	0.038 (0.029)	0.02 (0.017)	-0.005 (0.022)	0.012 (0.019)	0.069 (0.043)	0.063 (0.042)
N^	480	2334	3648	375	1314	683	939	207	256
Inverse Mills Ratio	0.093 (0.083)	0.085 (0.115)	-0.214*** (0.072)	0.001 (0.244)	-0.111 (0.088)	-0.189 (0.122)	-0.155** (0.08)	-0.066 (0.177)	-0.154 (0.148)

Notes: The dependent variable in the second stage outcome equation is the log(hourly wage) in 2004. The covariates/controls used are as follows: AFQT score (for cognition), years of education, a set of degree attainment dummies, age, a quadratic in age, height, weight, tenure, regional dummies, occupation code dummies and dummies for: residence in an SMSA, residence in an urban area, gender, race/ethnicity, union membership, and marital status. All Covariates except for the race/ethnicity, height and gender are measurements from the year 2004.

To get an economic interpretation of the effect of self-esteem on log wages, a transformation of the original estimate must be made. (exp(estimate) – 1) will garner the true percentage effects. These are the economic interpretations I mention in the essay.

* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

The dependent variable for each educational attainment selection equation is denoted in the second row of the table. For all models, a probit specification is used for the first stage equation. The key variable of interest is the Rosenberg Scale for Self-Esteem. The covariates/controls used are as follows: AFQT score (for cognition), age, a quadratic in age, height, race/ethnicity dummies, gender dummies. In addition a vector of family background characteristics, extracted from the 1979 NLSY survey are included. They are as follows: highest educational level of mother, highest educational level of father, mother worked at age 14, lived in a urban area at age 14, had access to library cards / newspapers / magazines at age 14, mother living at age 14, father living at age 14, both in the U.S., born in the southern region of the U.S., lived with naturally born mother and father at age 14, raised with a religion, foreign language spoken in home, number of siblings, lived in same residence from birth until age 14.

The results of the first stage probit models can be found in Table 3.

^ number of people who 'selected' into this education level

APPENDIX

TABLE A1. EFFECTS OF INDIVIDUAL AND FAMILY BACKGROUND CHARACTERISTICS ON SELF-ESTEEM

Independent Variable	Coefficient / Standard Error
Cognition	0.309*** (0.018)
Age	0.276 (0.26)
Age-squared	-0.003 (0.003)
Female	-0.075* (0.043)
Black	0.433*** (0.042)
Hispanic	0.179*** (0.064)
Height	0 (0.005)
Highest Education Level of Dad	0.003 (0.005)
Highest Education Level of Mom	0.019*** (0.007)
Library / Magazines / Newspapers available in home at Age 14	0.18*** (0.06)
Mother is Deceased in 1979	-0.056 (0.113)
Father is Deceased in 1979	-0.005 (0.063)
Mother born in the US	0.136 (0.075)
Father born in the US	-0.197** (0.077)
Lived with natural Mother and Father at age 14	-0.027 (0.037)
Born in the US	0.063 (0.086)
Born in the South	0.014 (0.034)
Lived in an Urban area at age 14	0.093** (0.037)
Number of Siblings	-0.018*** (0.006)
Lived in the Same Residence All of your Life	0.004 (0.03)

Notes: Dependent variable is the Standardized Rosenberg Scale. Standard Errors presented in parentheses. * = significant at 10% level. ** = significant at 5% level. *** = significant at 1% level.

CHAPTER 3

SELF-MONITORING AND RISK PREFERENCES: RESPONSIBILITY IN THE STAG HUNT

3.1 INTRODUCTION

Recently, economists in various fields have begun to examine and clarify the importance of noncognitive skills and other individual factors, such as risk preferences, that lead to decision making. It is becoming evident that internal traits of an individual are important in driving many economic outcomes such as wages, educational attainment and decisions in experimental games. In this article we expand this burgeoning literature from an experimental economics angle. We analyze Rousseau's classic Stag Hunt game and examine decision making in this game where the participant is playing only for their own outcome, and also when they hold responsibility over another inactive player's outcome. We supplement Charness and Jackson (2009) by examining the underlying reasons why the participants behave as they do, focusing on risk preferences and on the personality trait of self-monitoring.

Charness and Jackson (2009) showed that some people switch their behavior when moving from playing the Stag Hunt game in a 'play for self' (PFS) manner - where the choice they make is tied to their outcome alone – to a 'play for pair' (PFP) manner – where the choice they make is tied to their outcome and another benign player's outcome. In their study they do not attempt to explain what may make a player choose to switch their behavior when playing the game in a one-shot situation. Our main agenda in this paper is to assess the effects of self-monitoring and risk preferences on people switching their behavior when faced with this responsibility allocation for the first time. In addition, we wish to examine how self-monitoring and risk preferences affect an individual's decisions in the Stag Hunt in general by analyzing what role two individual traits play in decisions for both the PFS and PFP treatments separately.

Self-monitoring (SM) is a measurement of how an individual acts in various situations, especially around other people. Persons who are high self-monitors tend to continuously adapt their behavior to make a positive impression upon others, while low self-monitors tend to be their true self, and make similar choices no matter the social situation (Snyder 1987). SM, then, lends itself to be a trait inherent in an individual that may likely create differing behavior in a Stag Hunt game when presented with responsibility over another. Switching may occur more often for a high self-monitor than for their low self-monitor counterparts.

Risk preferences are a sense of how likely an individual is to assume risk. A risk averse individual is less likely to take on risk than someone who is risk loving. In the Stag Hunt game, there is a riskier choice (Stag) and a less risky choice (Hare). The payoff for the participant can be larger, however, when more risk is assumed. Risk, in addition to being a component of how the game is played individually, may enter when dealing with responsibility over another's outcomes. The more risk averse person may wish to 'shelter' the other player from risk, even more than they do with themselves, just as the more risk loving individual may wish to maximize the payoff by assuming even more risk for the player for whom they are responsible.

Our findings, to be explained in detail in the remaining sections of our article, show that a high SM individual is more likely to switch their behavior across PFS to PFP treatments. However, there is no consistent direction to their switching i.e. they do not tend to switch to more risky decisions (Stag), or less risky decisions (Hare) – they just generally tend to switch. This coincides with what a high SM individual is – someone who behaves differently in social situations based on they feel society will perceive them. We find that risk averse individuals choose Hare more often in both the PFS and PFP treatments than their more risk loving counterparts. We also find evidence that risk averse individuals tend to choose to *cautious shift*[1] (switch to Hare) when given responsibility over another. This indicates that risk averse players tend to behave even more risk aversely when in control over another's outcomes – perhaps to shelter their benign

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[1] Cautious shift is a term we are borrowing that is used in Stoner (1961) to describe when people shift their risk preferences towards being less risky when in a group.

partner from potential losses from riskier decisions. Both findings for SM and risk preferences shed light on as to why Charness and Jackson (2009) witnessed switching phenomenon in their experiments.

In the following section we present a review of the experimental literature on the impact of personality[2] and risk preferences on decision making. In section 3.3 we discuss our experimental design, explain the Stag Hunt games played by the participants in our experiment and describe our methods in extracting risk preference and SM information. In Section 3.4 we present summary statistics, examine potential spurious relationships among variables, discuss our econometric methods and discuss the results of our study. We conclude in Section 3.5.

3.2 LITERATURE REVIEW

This study builds on the work of two separate strands in the experimental economics literature: the literature on personality's impact on decision making and the literature on risk preferences.

[2] The literature focuses on several personality traits, including self-monitoring behavior.

3.2.1 Personality and Behavior in Laboratory Experiments

A large and growing literature investigates the impact of noncognitive traits, especially personality, on decision making behavior in experimental games. There are a large number of available personality trait instruments developed by social and personality psychologists. Because of this, a large number of studies find evidence that several different personality measures significantly impact decision making in the context of experimental games. Boone et al. (1999), one of the first studies in the literature, find that individuals with certain personality traits are more likely to exhibit cooperative behavior in prisoners' dilemma games. Of these, self-monitoring plays an important role in determining decisions and outcomes. Gunnthorsdotter, McCabe, and Smith (2002) find that an instrument for Machiavellian tendencies is able to predict behavior in trust games. They also find that there is no difference in behavior between males and females once personality traits are included in their analysis. Schmitt et al. (2008) use the Myers-Briggs Type Indicator (MBTI) to investigate determinants of play in ultimatum games. They find that an individual's type, as indicated by the MBTI, has a significant impact on behavior in the ultimatum game. Several studies utilize the popular five-factor model of personality. Ben-Ner et al. (2004) find that several of the personality traits measured using the five-factor model significantly affect play in dictator games. They also argue that personality traits may explain a significant portion of the variation in behavior economics laboratory experiments that typically remain unexplained by economists. Biais et al. (2005) utilize the Snyder self-monitoring scale to determine trading behavior in an asset market experiment. They find that self-monitoring improves performance in the market and that its effect is significant for men but not for women. The current study builds upon the foundations laid by these researchers. Personality traits may play an important role in how individuals shift their decisions when responsible for others.

3.2.2 Risk Preferences in Laboratory Experiments

Individuals' decision making under uncertainty has received much attention in experimental economics. Holt and Laury (2002) find that, when faced with a choice of risky gambles, individuals tend to be more risk averse than previous theories would predict. Several studies observe similar risk preferences under a number of different experimental designs (Harrison et al., 2005; Chakravarty et al., 2005). Individual risk preferences have received much attention in the literature. A growing literature also investigates the influence of responsibility on risk preferences. Economic agents often make decisions that not only affect their outcomes, but directly affect the outcomes of people for whom they are responsible. Several studies hypothesize that an individual will shift their risk preferences when in a group. Stoner (1961) proposes the terms *risky shift* and *cautious shift* to describe this phenomenon. An individual either becomes less risk averse when in a group or more risk averse. While several theories explain differences between individual behavior in isolation and in a group, no theories have been proposed to explain differences in behavior when an individual is responsible for others.

Several experimental studies provide evidence that individuals tend to exhibit a cautious shift in risk preferences when responsible for other people's outcomes (Charness, 2000; Kerr and MacCoun, 1985). Reynolds et al. (2009) investigate whether individuals tend to become more or less cautious when making decisions for others. In their experiment, a player decides whether to accept a guaranteed amount or enter into a gamble where there is a chance that they earn more or less than the guaranteed amount. The game is played under two different treatments. First, participants make a decision in isolation that only affect their own outcomes. Second, participants make the same decision but are told that their decision directly affects the outcome of a second team member. The team member has no say in the decision and acts as a silent third party. They find that individuals are more risk averse when they are responsible for other and experience a cautious shift when responsible for other players. Pahlke, Strasser, and Veider (2010) find evidence disputing the cautious shift hypothesis. Using a similar experimental design, they introduce risky decisions with gains and losses. They find that people behave differently when facing decisions that could result in gains versus decisions that could result in a loss. They conclude that traditional loss aversion holds under responsibility. Charness and Jackson (2009) investigate a similar question using

Rousseau's classic stag hunt. Participants play a simultaneous move game against another player where they choose to hunt either a stag or a hare. Hunting hare results in a smaller, but more certain payoff than hunting stag. Hunting stag may result in a larger payoff if both players choose to hunt stag. The first round of play is simply the traditional stag hunt. The second round, as in Reynolds et al. (2009), introduces a silent second party that is affected by each player's decisions. The silent second party receives the same payoff as his/her active partner. They find that players are 18 percentage points more likely to choose Stag when choosing solely for their own payoffs as opposed to being responsible for another silent player. They also find that about one-third of their sample is sensitive to the introduction of responsibility in the game. They suggest three possible forces that may affect behavior: (1) concern over how the other group member might react, similar to guilt aversion in Charness and Dufwenberg (2006), (2) players genuinely care about the other group member, but believe that he or she likes risk more than the average person, and (3) players are "socialized" to believe that they should be more cautious when in a position of responsibility. If a combination of these forces applies, then people will be less risky when responsible for another's outcome. Even though they suggest several reasons that individuals behave differently under responsibility, they are unable to create testable hypotheses with their data to uncover the determinants of play. The current paper utilizes noncognitive traits, such as self-monitoring, to begin to uncover why some individuals behave differently when making decisions for others.

3.3 Experimental Design and Survey Information

3.3.1 Stag Hunt Game

Subjects were recruited via email to participate in five different experimental sessions. Over the five experimental sessions there were 120 participants in total. Participants earned a $7.00 show up fee and had the chance to earn more based on their decisions in the experiment. Once all participants arrived for a session and their identities were verified, they were randomly divided into two groups. One group was then moved to another room. All games were played against anonymous partners and at no point did any participant know the identity of their partner or opponent. Each group, led by one of the experimenters, then played two rounds of the stag hunt, shown in Figure 1.[3] In the first round, individuals were told that they must choose between two options, A or B, and their payoff depended on their choice and the choice of a randomly assigned opponent.

[3] Complete experimental instructions are available from the authors.

Payoffs were determined using the following matrix:

		Player 2	
		A	B
Player 1	A	5 , 5	1 , 4
	B	4 , 1	4 , 4

FIGURE 1 THE STAG HUNT GAME

Half of the participants played the "play for self" (PFS) treatment first and the other half played the "play for pair" (PFP) treatment first.[4] The PFS treatment is when the player is playing for their outcomes only, and is a one shot game without repetition. The difference in the PFP round is that participants are told that they would play the same game with a minor variation; their decision would affect an anonymous team member's payoff as well. The team member had no decision making abilities and would earn the exact same payoff as the decision making player. The participants were randomly assigned an inactive team member. Since the game was played anonymously, this random assignment of partners

[4] Because this ordering of PFS and PFP treatments differs based on room assignment, a room assignment dummy is added into all logit models and is also explored fully in the spurious results diagnoses section.

should not affect behavior or outcomes. As with the PFS treatment, the PFP treatment was played as a one shot game without repetition. After each round, experimenters collected answer sheets that contained the decisions, A or B, for each participant, and all participants were matched with their opponents answers to determine their payoffs. We also had individuals play a series of other games including the dictator, ultimatum, trust, and public goods games. We collected data from several rounds of experiments, also collecting demographic data on the 120 participants.

3.3.2 SNYDER SELF-MONITORING

We use the SM Scale created by Snyder (1987) to gather SM information about the participants. Originally, this was a 25-item scale (Snyder 1974), but it has been abridged to a more psychologically reliable 18-item version, which is the version we use. For each of the 18 questions, which can be found in Appendix Table A1, the participant was asked to choose true or false. We added one point for each question answered in a SM manner, as is standard.[5] Snyder (1987) reports an internal consistency, or coefficient alpha of 0.70 for his scale, and using our sample we estimate a Cronbach's alpha value of 0.7092, which matches Snyder's results. This Cronbach's alpha value we obtain also approximately matches results found in experimental studies by Jenkins (1993) and Biais et. al. (2005). Using standard benchmarks for Cronbach's alpha values, this result is

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[5] 10 of the 18 questions needed to be backwards coded, so that a choice of 'false' added one point to the Snyder scale. Please refer to the notes in Table A1 for specific backwards coded questions.

acceptable insofar as its internal consistency of the measurement – the 18 items are largely measuring the same underlying trait.

The sample mean for the Snyder scale, shown in Table 1, is 9.516. We denote high self-monitors as those above the sample average on the Snyder SM scale, whereas low self-monitors are those below the sample average.[6] This converts nicely to having those at 9 or below (equal to the bottom half of the scale) be low self-monitors, and those with a 10 and above (equal to the top half of the scale) to be high self-monitors. Given this method of denotation we obtain 59 high self-monitors and 61 low self-monitors. High self-monitors have an average Snyder scale of 12.325 and low self-monitors have an average Snyder scale of 6.773.

3.3.3 Risk Preferences

In order to measure individual's risk preferences, we conducted a Holt-Laury risk game (Holt and Laury, 2002). Individuals made ten decisions between paired lotteries, option A and option B. The lotteries are identical to Holt and Laury (2002), and this table of lottery choices is shown in Table A2. For the first decision, option A would result in a gamble where the player earned \$2.00 or \$1.60 and option B would results in a gamble where the player earned \$3.85 or \$0.10. For both gambles, the probability of the higher payoff is 1/10. At each sequential decision,

[6] Since the sample average is 9.516, there were zero individuals exactly at the sample average since the Snyder score is a discrete number ranging from 0 to 18.

the probability of the higher payoff increased by 1/10. So, for the last decision the gambles would pay either $2.00 or $3.85 with one hundred percent certainty. This design allowed us to easily measure risk preferences for each participant. Risk neutral players would choose option A four times before switching to option B for the remainder of their decision. The most risk-averse person should only switch to option B at the tenth decision and the most risk-loving person should choose option B every time. One possible criticism of this game is the low real payoffs that each participant faces. Holt and Laury (2002) conducted experimental sessions with payoffs as high as ninety times the payoffs we used. They found that individual risk preferences are very similar regardless of payoff size. An individual's risk preferences probably play an important role in determining their risk preferences when responsible for another person's outcomes.

For the purposes of our study we split the sample by the level of risk aversion, denoting the above average risk aversion scorers as 'risk averse' and the below average scorers as 'risk lovers'. Shown in Table 2 the average risk preference score is 5.525. Since the score is a discrete scale this translates to those who choose 6 or more risk averse choices to be deemed risk averse, and those who chose 5 or less risk averse choices are deemed to be risk loving. This is, of course, a relative scale taken within the sample – which will indicate effects of relative risk aversion among a group on Stag Hunt decisions. Given this method of splitting the sample, this garners 51 risk averse individuals and 69 risk loving individuals. The average risk preference score for people who are risk averse is 7.235, whereas the average score for people who are more risk loving is 4.26. The correlation between risk preferences and self-monitoring is - 0.063, which gives us evidence that these two measurements of individual traits are not related.[7]

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[7] In section 4.1 we also show that in Table 1 we see that risk preferences do not differ significantly by SM level, and also in Table 2 SM level does not differ significantly by risk preference level. This gives us further indication that these two scales are not measuring similar traits of the individual.

3.4 METHODS AND RESULTS

3.4.1 SUMMARY STATISTICS AND TWO-SAMPLE T-TESTS

To explore our data further and to motivate our research agenda, we calculate summary statistics – simple means and standard errors - for our sample. In Table 1 we present these summary statistics for the entire sample, and then for subsamples grouped by SM level. In Table 1 we also present results for tests comparing differences in means for high self-monitors and low self-monitors using two-sample t-tests.

In the PFS treatment 41.7 percent of individuals choose the riskier Stag choice, whereas in the PFP treatment 45 percent of individuals choose Stag.[8] There is no statistically significant difference between how high self-monitors and low self-monitors play the Stag Hunt game – whether in a PFS or a PFP framework. Statistically significant differences do take hold, however, when analyzing the switching behavior across SM level. Switching in this context is when an individual changes their behavior in the Stag Hunt game when faced with responsibility over another (the PFP method). This switching mechanism has been analyzed by Charness and Jackson (2009), as mentioned in the

[8] These results alone differ from the general results found in Charness and Jackson (2009). They witnessed Stag being played 18 percentage points less in the PFP treatment, whereas we see a 3 percent increase in Stag play.

introduction and literature review, but until now there have not been studies that attempt to ascertain why this switching may occur.

On average, switching is done by 26.7 percent of the sample when moving from PFS to PFP[9], where 11.7 percent *cautious shift* (switch from Stag to Hare) and 15 percent *risky shift*[10] (switch from Hare to Stag). 33.9 percent of high self-monitors switch, whereas 13.6 percent cautious shift and 20.3 percent risky shift. Low self-monitors switch 19.7 percent of the time, where 9.8 percent cautious shift and 9.8 percent risky shift. Nearly twice as many high self-monitors switch generally when compared to low self-monitors.

Using these sample means and a two sample Student's t-test we find that high self-monitors are more likely to switch than low self-monitors. High self-monitors are 14.2 percentage points more likely to switch their behavior when given responsibility over another player's outcomes than a low self-monitor and this result is statistically significant at the 5 percent level. Additionally, we find that high self-monitors are 10.5 percentage points more likely to risky shift than a low-self monitor. This is statistically significant at the 10 percent level. This result gives us an idea of what a high SM individual may be trying to attain for their benign partners when given responsibility over their outcomes. If they are switching their behavior to Stag, then they are attempting to get as much payoff as possible for their partner, by taking on more risk.

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[9] The switching result is in accordance more-so with Charness and Jackson (2009). They found about one-third of their sample to be sensitive to the introduction of responsibility, whereas we witness 26.7 percent – approximately one-third.

[10] Risky shift is again, a term mentioned in Stoner (1961) to describe those who switch their decisions to being more risky when in a group.

Other notable results from Table 1 include findings that females are more likely to be low self-monitors, white individuals are more likely to be high self-monitors and that there were more low-self monitors present in room X of our study. Since we are attempting to ascertain if SM affects switching behavior, and gender, race and room assignment are also significantly different across levels of SM – these other variables may be driving the difference in apparent switching behavior. Due to these potentially confounding factors, the relationships among gender, race, room assignment and the other covariates and how they pertain to decisions in PFS and PFP treatments, as well as switching, will be explored more in Section 3.4.2. Lastly, it bears noting that risk preferences are not statistically different across levels of SM, which further indicates their lack of relation.

Table 2 is presented exactly as Table 1 is, except the subsamples are grouped by risk preference level. The means and standard errors of the entire sample match the values presented in Table 1. Those who are more risk averse tend to play Stag in the PFS treatment 33.3 percent of the time, whereas more risk loving individuals tend to play Stag 47.8 percent of the time. Risk loving players are more likely to play Stag by 14.5 percentage points and this result is statistically significant at the 10 percent level.

The difference between how risk averse and risk loving individuals play Stag in the PFP treatment is even larger. Risk averse players pick Stag 29.4 percent of the time, whereas 56.5 percent of risk loving players pick Stag in the PFP treatment. This is a 27.1 percentage point difference and is statistically significant at the 1 percent level. The results indicate that risk preferences may play a large role in how the Stag Hunt is played, regardless of if there is responsibility over another's outcomes or not.

Switching behavior is nearly equal across risk preference levels. Risk averse players switch 27.5 percent of the time, whereas 26.1 percent of risk loving individual switch. The analysis, however, becomes more interesting when the type of switching is taken into account. Although the t-tests do not show statistical significance, it bears noting that there are relatively large differences in types of switching based on risk preferences. 15.7 percent of risk averse individuals cautious shift whereas only 8.7 percent of risk lovers cautious shift – resulting in a difference of 11.7 percentage points.[11] There is also a relatively large difference among how often risk averse and risk loving players risky shift: 5.6 percentage points. This result, however, is also not statistically significant. There are no other statistically significant differences by risk preferences in any other collected variables, therefore spurious relationships between risk and Stag Hunt decisions are less likely than with SM and switching behavior.

In the next section, we explore these other variables that differ significantly across SM levels more closely to try and rule them out as being the true driving forces behind this switching behavior we see in high self-monitors. To be thorough we closely assess all relationships among the remaining variables and Stag Hunt decisions, both in the PFS and PFP treatments, as well as switching behavior. Later on in section 3.4.3, we use logit models as our culminating econometric approach to assess the relationships among Stag Hunt decisions, SM and risk preferences.

[11] This result is nearly significant at the 10 percent level. The p-value on this relationship is 0.17

3.4.2 SPURIOUS RESULTS DIAGNOSES

Given the relationships found among gender, race, room assignment and SM, we estimate more two-sample t-tests that focus on the demographics of switching behavior as well as standard decisions in PFS and PFP treatments. If we are to confirm or deny our findings linking SM to decisions in the Stag Hunt game, we need to try and rule out the chance that these other variables are not truly driving this switching behavior. To be thorough, we present all collected variables and their relationships to decisions in the PFS and PFP treatments, as well as their relationships to switching, cautious shifting and risky shifting.

In Table 3A we present sample means and two-sample t-test results for participants split into subsamples based on their decisions in the PFS and PFP treatments of the Stag Hunt game. Columns 1-3 show results for persons who choose Stag in the PFS treatment and columns 4-6 show results for persons who choose Stag in the PFP treatment. We find that white individuals are less likely to choose Stag in both the PFS and PFP treatments. Both of these differences are statistically significant at the 5 percent level.

Another notable result in Table 3A is that age appears to play a significant role in how Stag is played in the PFS treatment. The average age of a person who played Stag in the PFS treatment is 21.18, while the average age of a person who played Hare is 20.071, for a difference of 1.109 years of age. Taking properties of the participants into account, however, can help explain this result. 113 of the 120 participants were 25 years of age or older. There were only a few individuals who were 35 years of age and older, and this could easily significantly skew these results into appearing that age plays a large role in Stag Hunt decisions in the PFS treatment, when it is merely the decision of a few older participants.

In Table 3B we present sample means and two-sample t-test results for participants split into subsamples based on their switching behavior. Columns 1-3 show results for persons who switch behavior in any fashion. Columns 4-6 show results for persons who cautious shift when moving from PFS to PFP, and columns 7-9 show results for persons who risky shift when moving from PFS to PFP.

White individuals are one group that showed statistically significant differences in how they are distributed by degree of SM. The results in Table 1 show that white individuals are more likely to be high self-monitors. Given the results in Table 3B, white individuals do not show any statistically significant results insofar as how frequently they switch their behavior when faced with responsibility over another. This result helps mitigate the problem of obtaining spurious conclusions – due to race- about SM leading to switching.

Female gender is another variable that showed significant differences across SM levels in Table 1. The results shown in Table 3B indicate that female is only statistically significantly different for the persons who risky shift when given responsibility over another. This potentially confounds the validity of the finding from Table 1 that high self-monitors tend to risky shift when given responsibility over another. This result could, in fact, be driven by the gender. There is, however, no statistically significant difference in generic switching behavior with regards to gender. 56.3 percent of switchers are female, whereas 47.7 percent of non-switchers are females. The difference is 8.5 percentage points and is not statistically significant. This result helps somewhat to mitigate the problem of obtaining spurious conclusions – due to gender – about SM leading to switching.

In Table 1 we showed that there were significantly less high self-monitors in room X. We now find that persons in room X tend to switch less: 21.3 percentage points less. This separation into rooms is random. This switching result could be because of the distribution of self-monitors in the two rooms (there are greater majority of high self-monitors in room Y), or it could be a function of the differing order of the Stag Hunt game played in each room. Room X players and Room Y players engaged in the Stag Hunt games in opposite order. This result warrants more investigation, and is precisely why we include a room assignment dummy in our logit models in section 3.4.3

Another notable result presented in Table 3B is the finding that age significantly impacts switching behavior. Younger individuals tend to switch at a higher rate. The average age of a switcher is 19.406, while the average age of a non-switcher is 20.943. This difference of 1.537 years is statistically significant at the 1 percent level. Again, the properties of the data, having only several individuals above age 25, can likely explain this result. Although the results in Table 3A and 3B help mitigate and understand the chances of obtaining spurious conclusions in regards to SM and switching behavior, there are still a few variables that are possibly the driving force behind switching behavior and general Stag Hunt decisions: age, race, room assignment and gender.

To analyze the relationships among SM, risk preferences and Stag Hunt decisions more effectively, in the next section we estimate several logistic regressions with one of five binary outcomes: general switching, cautious shifting, risky shifting, picking Stag in the PFS treatment or picking Stag in the PFP treatment. The two independent variables of interest are SM (with various modes of entry into the model) and risk (with various modes of entry in the model) with all other variables used as controls.

3.4.3 Logistic Regressions

To explore in more detail our t-test results, and to lower the probability of obtaining spurious conclusions about the relationships among SM, risk preferences and decisions in the Stag Hunt game, we estimate logit models with a full set of control variables. We specify each of the models, twenty in total, with the dependent variable being a binary variable. In each model the binary dependent variable is one of: PFS Stag

Hunt strategy, PFP Stag Hunt strategy, switching behavior, cautious shift or risky shift. The independent variables of interest are the degree of the SM personality trait – as extracted by the Snyder scale and risk preferences – as extracted by the Holt-Laury risk preference lottery. For each of the five different dependent variables, we specify four different methods of entry of the two independent variables of interest. The specifications include (1) using a raw score of the Snyder scale with a raw score of risk preference, (2) a high SM dummy with a raw score of risk preference, (3) a raw score of the Snyder scale with a risk averse dummy, and finally (4) a high SM dummy with a risk averse dummy. This amounts to twenty logit models in total. The control variables in every logit model are: age, dummies for gender, dummies for race, dummies for room assignment and ACT score (a measure of cognition).

We present the results for all of these models concisely in Tables 4 and 5. We show marginal effects[12] of the SM and risk preference variables of interest, and choose to suppress all control variable marginal effects and statistical significances.[13] Table 4 shows the results for the two types of models that include the dependent variables of Stag played in the PFS treatment and Stag played in the PFP treatment. There are no cases where SM is statistically significant. Risk preferences, however, are statistically significant in almost every case. A risk averse individual is 16.4 to 18.5 percent less likely to pick Stag in the PFS treatment, depending upon specification of the SM variable. These results are statistically significant at the 1 percent level.

[12] These marginal effects are estimated using robust standard errors.

[13] Results for the control variables are available from the authors upon request.

In the PFP treatment risk preferences play even a much larger role than in the PFS treatment. Using a risk averse dummy, risk averse individuals are 33.3 to 33.9 percent less likely to play Stag in the PFP treatment depending upon specification of the SM variable. These results are statistically significant at the 1 percent level. The risk preference raw score is also statistically significant in the logit models where we include risk in this manner. Using the raw score, an additional risk averse decision in the Holt-Laury lottery leads to a 9.3 percent less chance that the individual chooses Stag in the PFP treatment. Taken as a whole, Table 4 helps solidify the result that risk plays a large role in how the Stag Hunt game is played, regardless of PFS or PFP treatments, even when factoring in all potentially confounding covariates.

In Table 5 we present the results for the three types of logit models that include dependent variable involved with switching behavior. General switching behavior is affected by the SM personality trait. A high self-monitor tends to switch 16.8 to 17.2 percent more depending upon the specification of the risk preference variable. These results are significant at the 10 percent level. These logit results indicate that the spurious relationships among SM and other covariates explored before did not completely eliminate the effect of SM on switching. This result can be interpreted as self-monitors react differently when there is social pressure. Given this, the behavior of a high self-monitor translates to the Stag Hunt game when responsibility is present, although, there is no established direction of this switch. High self-monitors do not tend to cautious shift or risky shift more than others, instead the high self-monitors appear to merely take note of the new social surroundings when given responsibility and react by changing their decision and this adheres to SM behavior. As a reminder, the t-test results from Table 1 indicate that high self-monitors risky shift more than low self-monitors, but when using inferential techniques via the logit model these effects are not present.

We find that risk preferences affect cautious shifting. The raw score for risk preference indicate that one additional risk averse choice in the Holt-Laury risk lottery amounts to a 3.2 percent higher likelihood of cautious shifting These results are significant at the 5 percent level, and potentially indicate that risk averse individuals attempt to shelter those from risk who they have responsibility over even more-so than when playing for themselves.

Taken together, the results from Tables 4 and 5 indicate that there are traits about individuals that lead to differences in Stag Hunt game decisions. Switching phenomenon witnessed in Charness and Jackson (2009) can be explained by both SM and risk preferences. High self-monitors tend to switch their choices in the Stag Hunt game when given responsibility over another's outcomes, however not in any proposed direction. More risk averse individuals have a tendency to cautious shift in a possible attempt to guard the people who they are responsible over from loss in payoffs due to risky decisions. In addition to switching behavior, general Stag Hunt choices are affected by risk preferences. Risk averse individuals tend to choose Stag at a much lower rate than their risk loving counterparts.

3.5 CONCLUSION

This article extends two separate strands of the experimental economics literature, the effects of personality traits, namely SM, on economic decisions, and the myriad effects of risk preferences on economic outcomes. We collect data from several rounds of experiments sampling 120 participants in total and examine decisions made in Rousseau's classic Stag Hunt game. The Stag Hunt game is played in two different ways, akin to Charness and Jackson (2009) – playing the game only for your own outcomes, and also playing the game when you have responsibility over another passive player's outcomes, and we extend Charness and Jackson (2009) by factoring in SM and risk preferences.

Charness and Jackson (2009) witnessed sensitivity to the addition of responsibility – some participants switched their Stag Hunt decisions when being in control of another's outcome. We witness similar switching behavior, at about the same rate as in their article. We augment their analysis by asking why this switching phenomenon occurs and find that SM and risk preferences both play an active role. High self-monitors are 14.2 percentage points more likely to switch their behavior when given responsibility over another player's outcomes than a low self-monitor and this result is statistically significant at the 5 percent level. This result makes intuitive sense, as it coincides with what a self-monitor generally does, alters their behavior when in the presence of others. The direction of the shift is not clear, as the switching does take place for high self-monitors, but not in any definable fashion.

Risk preferences play a role in both switching behavior and standard choices in both the PFS and PFP treatments. The raw score for risk preference indicate that one additional risk averse choice in the Holt-Laury risk lottery amounts to a 3.2 percent higher likelihood of cautious shifting. This can be interpreted as risk aversion leading to even more risk averse choices than normal when given responsibility over another passive player. The risk aversion is increased in magnitude. This general cautious shift result coincides with papers by Charness (2000), Kerr and MacCoun (1985) and Reynolds et al. (2009). We also find using a risk averse dummy that risk averse individuals are 16.4 to 18.5 percent less likely to pick Stag in the PFS treatment and are 33.3 to 33.9 percent less likely to play Stag in the PFP treatment. It is apparent that riskier individuals tend to stick with riskier choices no matter the treatment.

Our findings extend results found in Charness and Jackson (2009) by describing reasons why switching phenomenon occurs when adding responsibility into the Stag Hunt – SM and risk preferences. This helps in understanding the internal mechanisms of this switching behavior. This article not only helps clarify the switching mechanism, but also helps in discussing why certain decision are made in the Stag Hunt game in general. Riskier individuals tend to make riskier decisions, and more risk averse individuals tend to make even safer choices when dealing with the outcomes of another. Internal traits of the individual do play important roles in how individuals behave. Additional research could be utilized in understanding welfare outcomes of these Stag Hunt decisions based on personality and risk preferences. This switching behavior and tendency for riskier players to decide on risky choices may lead to a pronounced social benefit or cost and warrants further investigation.

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TABLES

TABLE 1. SUMMARY STATISTICS GROUPED BY SELF-MONITORING LEVEL. DIFFERENCES IN SUMMARY STATISTICS BY SELF-MONITORING LEVEL USING TWO-SAMPLE T-TESTS

Variable	Entire Sample	High SM	Low SM	Difference (High SM – Low SM)
Snyder Score	9.516 (3.41)	12.325 (0.286)	6.773 (0.25)	5.551***
Risk	5.525 (0.172)	5.39 (0.214)	5.656 (0.268)	-0.266
Stag played in PFS	0.417 (0.045)	0.390 (0.064)	0.443 (0.064)	-0.052
Stag played in PFP	0.45 (0.046)	0.458 (0.065)	0.443 (0.064)	0.015
Switch behavior at all from PFS to PFP	0.267 (0.405)	0.339 (0.062)	0.197 (0.051)	0.142**
Cautious shift	0.117 (0.029)	0.136 (0.045)	0.098 (0.038)	0.037
Risky shift	0.15 (0.033)	0.203 (0.053)	0.098 (0.038)	0.105*
Female	0.5 (0.045)	0.373 (0.063)	0.623 (0.062)	-0.250***
White	0.61 (0.045)	0.702 (0.061)	0.525 (0.064)	0.177**
Age	20.530 (3.919)	20.593 (0.501)	20.475 (0.504)	0.118
ACT Score	23.112 (0.355)	23.462 (0.521)	22.754 (0.486)	0.708
Room X	0.5 (0.045)	0.407 (0.065)	0.59 (0.064)	-0.183**
N	120	59	61	--

Notes: Means presented. Standard Errors presented in parentheses. High SM means above average Snyder Scale score in the sample – low SM means below average Snyder Scale score in the sample. Overall average is for all individuals.

PFS = "play for self" treatment. PFP = "play for pair" treatment.

Cautious shift indicates those who switched from Stag to Hare when adding responsibility over another. Risky shift indicates those who switched from Hare to Stag when adding responsibility over another.

* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

The significance shown is found using a Student's T-Test.

TABLE 2. SUMMARY STATISTICS GROUPED BY RISK PREFERENCES. DIFFERENCES IN SUMMARY STATISTICS BY RISK PREFERENCES USING TWO-SAMPLE T-TESTS

Variable	Entire Sample	Risk Averse	Risk Loving	Difference (Risk Averse – Risk Loving)
Snyder Score	9.516 (3.41)	9.925 (0.495)	9.191 (0.411)	0.734
Risk Score	5.525 (0.172)	7.235 (0.185)	4.26 (0.127)	2.974***
Stag played in PFS	0.417 (0.045)	0.333 (0.067)	0.478 (0.061)	-0.145*
Stag played in PFP	0.45 (0.046)	0.294 (0.064)	0.565 (0.06)	-0.271***
Switch behavior at all from PFS to PFP	0.267 (0.405)	0.275 (0.063)	0.261 (0.053)	0.013
Cautious shift	0.117 (0.029)	0.157 (0.052)	0.087 (0.034)	0.117
Risky shift	0.15 (0.033)	0.118 (0.046)	0.174 (0.046)	0.056
Female	0.5 (0.045)	0.51 (0.071)	0.493 (0.061)	0.017
White	0.61 (0.045)	0.64 (0.069)	0.588 (0.06)	0.051
Age	20.530 (3.919)	20.059 (0.351)	20.884 (0.557)	-0.825
ACT Score	23.112 (0.355)	23.044 (0.542)	23.161 (0.477)	-0.117
Room X	0.5 (0.045)	0.509 (0.071)	0.493 (0.061)	0.017
N	120	51	69	--

Notes: Means presented. Standard Errors presented in parentheses. Risk Averse means above average risk preference score in the sample using the Holt and Laury (2002) risk lottery. Risk Loving means below average risk preference score in the sample. Overall average is for all individuals.
PFS = "play for self" treatment. PFP = "play for pair" treatment.
Cautious shift indicates those who switched from Stag to Hare when adding responsibility over another. Risky shift indicates those who switched from Hare to Stag when adding responsibility over another.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

TABLE 3A. TWO SAMPLE T-TESTS TO CHECK FOR INDICATION OF SPURIOUS RESULTS – PFS AND PFP STAG HUNT DECISIONS

	Stag played in PFS			Stag played in PFP		
Variable	Yes	No	Diff	Yes	No	Diff
Female	0.44 (0.071)	0.543 (0.06)	-0.102	0.518 (0.069)	0.485 (0.062)	0.034
White	0.5 (0.071)	0.691 (0.056)	-0.191**	0.519 (0.069)	0.688 (0.058)	-0.168**
ACT Score	22.64 (0.52)	23.44 (0.483)	-0.808	22.617 (0.48)	23.5 (0.511)	-0.883
Age	21.18 (0.583)	20.071 (0.437)	1.109**	20.778 (0.549)	20.333 (0.463)	0.444
Room X	0.52 (0.071)	0.486 (0.060)	0.034	0.426 (0.068)	0.561 (0.062)	-0.134*
N	50	70	--	54	66	--

Notes: Means presented. Standard Errors presented in parentheses. PFS = "play for self" treatment. PFP = "play for pair" treatment.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.
The significance shown is found using a Student's T-Test.

TABLE 3B. TWO SAMPLE T-TESTS TO CHECK FOR INDICATION OF SPURIOUS RESULTS – SWITCHING BEHAVIOR

	Switch Behavior			Cautious shift			Risky shift		
Variable	Yes	No	Diff	Yes	No	Diff	Yes	No	Diff
Female	0.563 (0.089)	0.477 (0.054)	0.085	0.429 (0.137)	0.509 (0.049)	-0.08	0.667 (0.114)	0.471 (0.050)	0.196*
White	0.594 (0.088)	0.616 (0.053)	-0.022	0.571 (0.137)	0.615 (0.048)	-0.043	0.611 (0.118)	0.61 (0.049)	-0.001
ACT Score	22.67 (0.511)	23.28 (0.457)	-0.612	22.714 (0.841)	23.17 (0.391)	-0.458	22.647 (0.667)	23.181 (0.407)	-0.553
Age	19.406 (0.232)	20.943 (0.469)	-1.537**	19.929 (0.438)	20.613 (0.396)	-0.685	19 (0.198)	20.803 (0.410)	-1.804**
Room X	0.344 (0.085)	0.557 (0.053)	-0.213**	0.5 (0.138)	0.5 (0.049)	0	0.222 (0.100)	0.549 (0.049)	-0.327***
N	32	88	--	14	106	--	18	102	--

Notes: Means presented. Standard Errors in parentheses. Switch behavior indicates whether the player switched their choice in the Stag Hunt when adding responsibility over another. Cautious shift indicates those who switched from Stag to Hare when adding responsibility over another. Risky shift indicates those who switched from Hare to Stag when adding responsibility over another.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.
The significance shown is found using a Student's T-Test.

TABLE 4. LOGIT REGRESSION RESULTS FOR PFS AND PFP STAG HUNT DECISIONS WITH SELF-MONITORING AND RISK PREFERENCES AS VARIABLES OF INTEREST – FOUR DIFFERENT MODEL SPECIFICATIONS

Dependent Variable	Raw Score SM	High SM Dummy	Raw Score Risk	Risk Averse Dummy
Stag played in PFS	0.016 (0.016)	--	-0.028 (0.031)	--
	--	-0.031 (0.111)	-0.027 (0.030)	--
	0.021 (0.016)	--	--	-0.185* (0.100)
	--	-0.006 (0.113)	--	-0.164* (0.099)
Stag played in PFP	0.018 (0.017)	--	-0.093*** (0.036)	--
	--	0.089 (0.125)	-0.093*** (0.036)	--
	0.026 (0.016)	--	--	-0.339*** (0.095)
	--	0.134 (0.121)	--	-0.333*** (0.096)

Notes: Marginal Effects (MFX) of SM and risk variables of interest presented. Robust Standard Errors in parentheses. Controls in all models include age, gender, race, room, ACT score.
PFS = "play for self" treatment. PFP = "play for pair" treatment.
All Raw score MFX are interpreted as the effect on the dependent variable given a 1 unit increase in the independent variable of interest.
All Dummy variable MFX are interpreted as the effect on the dependent variable given a change from "0" to "1" in the independent variable of interest.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

TABLE 5. LOGIT REGRESSION RESULTS FOR SWITCHING BEHAVIOR WITH SELF-MONITORING AND RISK PREFERENCES AS VARIABLES OF INTEREST – FOUR DIFFERENT MODEL SPECIFICATIONS

Dependent Variable	Raw Score SM	High SM Dummy	Raw Score Risk	Risk Averse Dummy
Switch Behavior	0.010 (0.012)	--	0.024 (0.023)	--
	--	0.172* (0.098)	0.024 (0.023)	--
	0.008 (0.013)	--	--	0.04 (0.092)
	--	0.168* (0.101)	--	0.025 (0.092)
Cautious shift	0.004 (0.008)	--	0.032** (0.015)	--
	--	0.036 (0.068)	0.032** (0.015)	--
	0.002 (0.008)	--	--	0.082 (0.072)
	--	0.020 (0.068)	--	0.082 (0.071)
Risky shift	0.003 (0.007)	--	-0.003 (0.010)	--
	--	0.080 (0.054)	-0.003 (0.009)	--
	0.004 (0.007)	--	--	-0.018 (0.04)
	--	0.083 (0.056)	--	-0.023 (0.038)

Notes: Marginal Effects (MFX) of SM and risk variables of interest presented. Robust Standard Errors in parentheses. Controls in all models include age, gender, race, room, ACT score.
Switch behavior indicates whether the player switched their choice in the Stag Hunt when adding responsibility over another. Cautious shift indicates those who switched from Stag to Hare when adding responsibility over another. Risky shift indicates those who switched from Hare to Stag when adding responsibility over another.
All Raw score MFX are interpreted as the effect on the dependent variable given a 1 unit increase in the independent variable of interest.
All Dummy variable MFX are interpreted as the effect on the dependent variable given a change from "0" to "1" in the independent variable of interest.
* = significant at the 10% level. ** = significant at the 5% level. *** = significant at the 1% level.

APPENDIX

TABLE A1. SNYDER SELF-MONITORING SCALE QUESTIONS

1. I find it hard to imitate the behavior of other people.	10. I'm not always the person I appear to be.
2. At parties and social gatherings, I do not attempt to do or say things that others will like.	11. I would not change my opinions (or the way I do things) in order to please someone or win his or her favor.
3. I can argue only for ideas that I already believe.	12. I have considered being an entertainer.
4. I can make impromptu speeches even on topics about which I have almost no information.	13. I have never been good at games such as charade and improvisational acting.
5. I guess I put on a show to impress or entertain others.	14. I have trouble changing my behavior to suit different people and different situations.
6. I would probably make a good actor.	15. At a party I let others keep the jokes and stories going.
7. In a group of people, I am rarely the center of attention	16. I feel a bit awkward in company and do not come across quite as well as I should.
8. In different situations and with different people, I often act like very different persons.	17. I can look anyone in the eye and tell a lie with a straight face (if for the right end).
9. I am not particularly good at making other people like me.	18. I may deceive people by being friendly when I really dislike them.

Notes: Questions 1, 2, 3, 7, 9, 11, 13, 14, 15, 16 were all backwards coded when compiling the complete scale.

TABLE A2. TEN PAIRED LOTTERY CHOICES FROM HOLT-LAURY (2002)

	Option A		Option B		Mark Selection A or B Here
1.	1/10 of $2.00	9/10 of $1.60	1/10 of $3.85	9/10 of $0.10	_____
2.	2/10 of $2.00	8/10 of $1.60	2/10 of $3.85	8/10 of $0.10	_____
3.	3/10 of $2.00	7/10 of $1.60	3/10 of $3.85	7/10 of $0.10	_____
4.	4/10 of $2.00	6/10 of $1.60	4/10 of $3.85	6/10 of $0.10	_____
5.	5/10 of $2.00	5/10 of $1.60	5/10 of $3.85	5/10 of $0.10	_____
6.	6/10 of $2.00	4/10 of $1.60	6/10 of $3.85	4/10 of $0.10	_____
7.	7/10 of $2.00	3/10 of $1.60	7/10 of $3.85	3/10 of $0.10	_____
8.	8/10 of $2.00	2/10 of $1.60	8/10 of $3.85	2/10 of $0.10	_____
9.	9/10 of $2.00	1/10 of $1.60	9/10 of $3.85	1/10 of $0.10	_____
10.	10/10 of $2.00	0/10 of $1.60	10/10 of $3.85	0/10 of $0.10	_____

Notes: This risk lottery matches that from Holt and Laury (2002). This is denoted as the risk lottery with low payoffs from that paper.

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