What's in a Relationship?
An Examination of Social Capital, Race, and Class in Mentoring Relationships

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Abstract

After twenty-five years of intense scrutiny, social capital remains an important yet highly debated concept in social science research. This research examines data from youths and mentors in several chapters of Big Brothers/Big Sisters to assess the importance of different mentoring relationship characteristics in creating positive outcomes among youths. The literature on social capital suggests that key characteristics are: (1) the amount of time spent between individuals, (2) racial similarity, (3) level of trust, (4) social class difference, and (5) intergenerational closure. I examine the effects of these social capital measures on both academic and deviant behavioral outcomes and run estimations using propensity score weighting to address selection bias. The results indicate that both the amount of time spent in a relationship and the level of trust consistently have positive effects for youths. Counter to what some theory suggests, race-matching has limited effects and social class difference between individuals has no significant effects on any of the examined outcomes. Finally, closure between parent and mentor increases the amount of time spent on homework and reduces drug use. These findings have important implications for future work on social capital and adolescent relationships in general.

INTRODUCTION

Although researchers from a variety of disciplines continue to examine the concept of social capital, research that incorporates multiple theories and operationalizations of social capital is lacking. Social capital conjures up confusion as researchers debate its basic definition and operationalize it in very different ways (Brunie 2009). One commonly accepted definition states that social capital is "the ability of actors to secure benefits by virtue of membership in social networks or other social structures" (Portes 1998:6). But what contributes to an individual's ability to extract benefits? Although the literature finds that social capital leads to a number of positive outcomes, the literature also lacks clear explanations of what is important in the creation of social capital. Prior research suggests that it may be the amount of time individuals spend together (Coleman 1988), their social class difference (Granovetter 1973; Lin, Enseli and Vaughn 1981), the level of trust between individuals (Coleman 1988; Lewicki and Brinsfield 2009; Uslaner 2008), their racial similarity (Kahne and Bailey 1999; Thomas 1989, 1990), or intergenerational closure (Coleman 1988).

Thus, social capital is an important but not well understood concept. Existing research provides different answers for why some relationships and networks lead to benefits for individuals whereas others do not. Mouw (2006) proposed that part of the disagreement within the literature is the result of endogeneity. Individuals exert choice when selecting relationships and this nonrandom sorting could represent a selection effect, not a peer effect. Those individuals most likely to benefit from social capital may seek other individuals who are most likely to provide such benefits, thus overestimating the effect of social capital. This inherent selection bias thus contributes to research that cannot accurately estimate causal effects, absent experimental data or advanced experimental approximation methods.

The present research strives to determine what factors contribute to the activation of social capital within relationships and thus create positive outcomes for youths in these relationships. I review the relevant literature regarding social capital and relate it to mentoring studies that support the various theories of social capital. These social capital theories suggest five characteristics of mentoring relationships that may have effects on youths: (1) the amount of time spent together in a relationship, (2) a youth's reported level of trust for their mentor, (3) racial similarity in a match, (4) social class difference in a match, and (5) closure between parent and mentor. To examine these dimensions of social capital, I analyze a dataset on youth mentoring in the Big Brothers/Big Sisters program to determine how these relationship characteristics influence two key areas of outcomes for youths: academic success and deviant behavior. To provide some insight into the relationship selection problem I use propensity score weighted models. The results uncover a nuanced view of social capital and suggest that multiple dimensions simultaneously affect academic and behavioral outcomes.

BACKGROUND AND SIGNIFICANCE

Contact Frequency and Time as Social Capital

James Coleman (1988) conceptualized social capital as the strength of a relationship between two individuals and explored it in the context of relationships between adults and youths. An adult can offer connections to other adults, experience, general knowledge, and specific information to a youth, but a youth must first have access to an adult to be able to benefit from her human capital. Thus, stronger relationships and more access to adult human capital come from adults spending greater amounts of time with youths. The human capital of an adult is important, but a high-quality relationship between two individuals must come first. Thus, certain resources (such as human capital) may be embedded in a relationship but an individual's ability to access them depends on the strength of their relationship with another individual (a measure of social capital).

For youths with a single parent, Coleman (Coleman 1988; Coleman and Hoffer 1987) found that both additional siblings and a mother with no expectation of college for her child increased the child's likelihood of dropping out of high school, independent of financial and human capital. These factors reduce the amount of time an individual child spends with his parent(s), and therefore, the relationship's amount of social capital. Thus, time spent together and strength of the bond (generally described as relationship quality) are a measure of social capital.

Some research is critical of Coleman's measure of social capital and calls for more refinement in measuring the concept. Researchers typically use a proxy for social capital, similar to Coleman's, that measures the lack or dilution of time a parent could potentially spend with a child. Sandefur, Meier, and Campbell (2006) used family structure and number of siblings and found negative effects of social capital dilution on college enrollment. Similarly, Parcel and Dufur (2001) used number of siblings and parental work hours and found negative effects of social capital dilution on test scores. Teachman, Paasch, and Carver (1996) attempted to better measure one dimension of social capital: interaction time spent between parent and child. Using data from the National Education Longitudinal Study (NELS), they found that parent-child connectivity had a negative effect on dropping out of high school.[1] Although at least one study fails to find support for Coleman's conceptualization of social capital (Wellman and Wortley 1990), much of the debate focuses on how best to measure time spent in a relationship.

Mentoring relationships represent an association between youths and adults that can test Coleman's conceptualization of social capital. Mentors provide youths with a one-on-one relationship that intends to create positive interaction, foster general growth, and perhaps, yield access to human capital. If Coleman is correct, the key to acquiring greater benefits from mentoring should be more time spent together and more frequent contact. Some research on youth mentoring finds that more frequent meetings (Slicker and Palmer 1993) and longer overall matches (Grossman and Rhodes 2002) lead to better academic and behavioral outcomes. However, these studies fail to address the problem of selection and do not account for additional theories of social capital.

The literature stemming from Coleman's conceptualization of social capital leads to the first hypothesis of this paper (H1): Greater amounts of time spent between youths and mentors lead to positive academic and behavioral outcomes for youths.

Trust, Strong Ties, and Racial Similarity in Relationships as Social Capital

Coleman (1988) also suggested that trust is another form of social capital within a relationship. If individuals are to form relationships that lead to a variety of benefits, they must be able to trust each other, particularly in the form of obligations and expectations. Although Coleman did not explicitly examine trust using the High School and Beyond data, a number of other scholars have explored the idea of trust as social capital and suggest that expectations, confidence, and assurance form the basis of trust (Lewicki and Brinsfield 2009; Lewicki et al. 1998).

Additionally, some literature suggests that certain forms of social homogeneity are a crucial element in the creation of social capital. The idea that similarity results in more intimate and longer-lasting relationships has been discussed at length by numerous scholars (Homans 1950; Laumann 1966; Lazarsfeld and Merton 1954). Merton (Lazarsfeld and Merton 1954) posited that an individual's network consists of more relationships based on similarity than difference. He found that individuals had more associations based on status homophily (including race) and value homophily (including racial attitudes) than heterophily. Moreover, similarity based on race and ethnicity is present in a wide range of relationships, from strong bonds such as marriages and friendships, to weak bonds such as short term contacts (Blau, Beeker, and Fitzpatrick 1984; Blau, Blum, and Schwartz 1982; McPherson, Smith-Lovin and Cook 2001).

Relationships based on racial similarity may be so prevalent throughout society because racial similarity, and similarity in general, inspires trust. The findings of at least two studies suggest that higher levels of trust stem from racial similarities and result in better use of social resources in networks (Light 1984; Light and Bonacich 1988). Additional research finds that minorities and low-SES individuals typically have lower levels of cross-racial trust (Alesina and La Ferrara 2002; Costa and Kahn 2003; Eckel and Wilson 2004; Smith 2010). If dissimilar individuals cannot form a trusting bond, it is unlikely that these relationships will result in positive outcomes.

Studies on workplace mentoring reveal that racial similarity leads to more positive outcomes. Thomas (1989) found that both blacks and whites formed a stronger bond in same-race rather than cross-race pairs. Tsui, Egan, and O'Reilly (1992) found that white workers were more satisfied in homogeneous, rather than heterogeneous, groups. Additionally, Thomas found (1990) cross-race relationships in the work environment were less supportive than same-race relationships. In a workplace environment experiment, Ensher and Murphy (1997) examined interns randomly assigned to mentors in either same-race or cross-race pairings and found that same-race protégés were more likely to report a higher relationship quality. The authors also found that same-race mentors were more likely to go above and beyond the goals of the program to support their protégés.

In a program analysis study, Kahne and Bailey (1999) examined the effects of Chicago area "I Have a Dream" (IHAD) programs on low-SES, mostly minority youths. Sponsored by wealthy families, these programs targeted entire sixth grade classes at various schools and promised college scholarships for those who graduated from high school. Project coordinators and other individuals were hired to oversee the students and provided tutoring, service connections, and other assistance. Kahne and Bailey found that students used these network connections when applying for jobs, scholarships, and school admissions, but "*[these] youth needed strong ties to benefit from weak ties*" (emphasis in original) (1999:331) – youths required strong trusting relationships with adults to capitalize on these connections. This finding highlights the idea that realizing the benefits of social capital may require social homogeneity within a dyad.

If, as the research indicates, individuals are more open with and trusting of other individuals who share their race, then same-race mentoring dyads should lead to positive outcomes. Youths involved in mentoring programs may not trust someone dissimilar to themselves entering their world and having close proximity to them on a regular basis. Lack of trust may create distance within a dyad and reduce the impact of a mentor. However, in a same-race relationship a youth may see a mentor as sympathetic and knowledgeable about her particular circumstances. Some youth mentoring studies find that racial matches create more positive behavioral and academic outcomes. Zirkel (2002) found that students in same-race relationships received better grades, reported more goals and more positive extracurricular activities, and were more likely to consider future plans. In another study that used the Big Brothers/Big Sisters of America dataset and examined the impact of same-race versus cross-race pairings for a variety of outcomes, Rhodes et al. (2002) found some positive effects for same-race relationships that varied by gender. Minority boys' self-assessments of scholastic competence improved when matched with a same-race mentor versus a cross-race mentor, while minority girls placed more importance on the value of school when matched with a same-race mentor versus a cross-race mentor.

Coleman's idea of trust as social capital leads to the second hypothesis of this paper (H2): Higher levels of trust for mentors lead to positive academic and behavioral outcomes for youths. Additionally, research on trust and the effect of racial similarity within relationships leads to the third hypothesis of this paper (H3): Racial similarity moderates the effect of trust on academic and behavioral outcomes.

Weak Ties and Social Class Heterogeneity in Relationships as Social Capital

Mark Granovetter (1973) suggested that two basic types of social relationships exist: those based on strong ties and those based on weak ties. Strong ties occur between close family members and friends, whereas weak ties occur through relationships with acquaintances or friends of friends. Weak ties form a network of heterogeneous members that creates valuable social connections and makes upward mobility possible.[2] Granovetter defined tie strength as a composite of several correlated factors, including time, emotional intensity, and intimacy involved in a relationship. Although there are some similarities between Granovetter's network tie definitions and Coleman's definition of social capital, Granovetter's theory suggests that more matters than the amount of time spent between two individuals.

Expanding on Granovetter's work, Lin, Ensel and Vaughn (1981:395) explained that social resources (capital) are "embedded in the positions of contacts an individual reaches through his social network." In their research, the authors found that males in the labor force obtained higher status jobs indirectly through weak ties. Weak ties lead to higher status individuals that lead to higher status jobs, because weak ties represent contacts who are different than the individual, in terms of social class (also see Lin, Vaughn and Ensel 1981).

Additionally, Marsden and Campbell (1984) suggested consideration of two aspects of tie strength measurement: predictors and indicators. They defined *predictors* of tie strength as measures of social homogeneity or heterogeneity, and *indicators* as the components that Granovetter suggested, including time and emotional intensity. They found that social class difference predicted weak ties whereas the duration and closeness (or emotional intensity) of a relationship and the frequency of contact had positive effects on tie strength; that is, they indicated strong ties. This suggests that duration and time in a relationship has a different effect than difference in social class in creating social capital.

Much of the literature supports the idea that social capital increases when the contact is higher in status or social class. Studies similar to Lin, Ensel and Vaughn (1981), show that higher-status contacts increase occupational prestige (Lai, Lin and Leung 1998; Marsden and Hurlbert 1988). Still, scholars debate both the importance of a social tie being weak and the definition and measurement of tie strength (see Lin 1999, for a detailed explanation of this literature).

One additional wrinkle in the discussion of weak ties and social capital is the possibility that the value of connections differs based on an individual's race. Thus, it may not simply be a tie of higher status that matters, but a tie who is white may matter for minorities. Studies examining this idea find that there are more positive effects of weak ties for non-whites (Smith 2000, Day and McDonald 2010)

Data on mentoring relationships can also test the notion that relationships based on social class difference lead to better outcomes. The weak tie hypothesis suggests that the best mentor for a disadvantaged youth may be a person who is higher in social status or class. A college-educated mentor, who is likely to have a network of college-educated friends and acquaintances, may prove very beneficial to a youth with few or no college-educated relatives. A mentor may serve as an example of how exhibiting more productive behavior and succeeding academically leads to upward social mobility, an example that may not be widely available for at-risk youths in their own communities. Research indicates that mentors do provide such benefits, including tutoring, information on continuing education and careers, and valuable connections to other influential people (Dreher and Cox 1996; Fagenson-Eland, Marks and Amendola 1997). Additionally, Erickson, McDonald and Elder (2009) found that, in informal mentoring relationships, youths of the lowest SES levels gained the most from mentors in terms of educational attainment.

Although the mentoring literature offers little other research on the impact of social class difference between mentors and youths, social capital theory indicates that a mentor of higher social class may be beneficial for a youth. Thus, the fourth hypothesis (H4) of this research is: Contact with a mentor of higher social class than the youth leads to positive academic and behavioral outcomes for youths. The fifth hypothesis (H5) of this research is: Contact with a mentor who is a weak tie (either higher social class or cross-race) has a differential effect for non-white youths.

Intergenerational Closure as Social Capital

A final important characteristic in the creation of positive outcomes for youths is intergenerational closure. Coleman (1988) suggested that closure between two individuals may help to enforce expectations and sanctions on a third individual in a network where all three individuals know each other. For example, a child may refrain from deviant behavior when he knows that other adults who talk to his parents may see him.

Research that examines Coleman's hypothesis regarding intergenerational closure is mixed. In an examination of the NELS data, Carbonaro (1998) found that intergenerational closure reduced a student's likelihood of dropping out of high school and positively affected math test scores but had no significant effect on cumulative GPA. Using data from the National Longitudinal Study of Adolescent Health, scholars reinforce the claim of intergenerational closure's effect on dropping out and also find a positive effect on GPA (Glanville, Sikkink and Hernandez 2008). However, both Morgan and Sorensen's (1999) findings using NELS and Morgan and Todd's (2009) findings using the Educational Longitudinal Study suggest that intergenerational closure may only have positive effects on test scores in Catholic schools. Finally, at least one study suggests that intergenerational closure may also reduce a youth's participation in other deviant behavior such as alcohol use (Bjarnason et al. 2005).

This theory lends itself to examination in the context of a mentoring relationship as well. The reinforcement of norms may occur through adult network connections, even if only one youth is involved.

Communication between parent and mentor may discourage a youth from participating in deviant behavior and may encourage a youth to increase their academic achievement. Thus, the final hypothesis (H6) of this research is: Contact between a mentor and a parent leads to positive academic and behavioral outcomes for youths.

The Effects of Social Capital

Finally, just as the literature suggests a number of different ways to measure and examine individual aspects of social capital, there are a number of different outcomes affected by social capital. Scholars typically examine the effects of social capital on two particular types of outcomes: academic and behavioral. Parcel, Dufur, and Zito (2010) present a thorough review of the literature on social capital, explain the focus on these types of outcomes, and suggest that adults make investments in children that facilitate socialization. In brief, social capital provides access to the human capital and support that helps youths succeed academically, while also providing regulation, structure, and support that help youths avoid behavioral problems. At minimum, an adult figure (parent, mentor, etc.) must be present to have the *opportunity* to provide such support and assistance.

In summary, theory on social capital indicates that five potential characteristics of mentoring relationships may be influential in promoting positive academic and behavioral outcomes: (1) the amount of time spent together, (2) the level of trust for the mentor, (3) racial similarity, (4) social class difference, and (5) intergenerational closure. The prior research on mentoring relationships is somewhat limited in scope and no research examines all of these relationship measures simultaneously. Additionally, research comes up short in accounting for the endogeneity problem discussed by Mouw (2006). The present study uses variables that closely match the concepts of the aforementioned social capital theories. I also contribute to the debate on important determinants of social capital by comparing OLS regression estimates to those of propensity score weighted estimates to account for some of the bias from selection into these relationships (although not the bias from selection into the network).

METHODS

Data and Sample[3]

I analyze data on mentoring relationships between youths and mentors in the Big Brothers/Big Sisters of America program (BBBSA) originally collected by Public/Private Ventures. For this research, BBBSA program staff arranged relationships between youths and adults with no previous connection. Although matches between youths and adults were not completely random, staff members recorded why each match was made. The information on length of match, meeting frequency and hours, survey questions on trust and closure, and race and socioeconomic status data on both youths and mentors allow me to conduct critical tests of my hypotheses.

Using a quasi-experimental design, researchers took a random sample from existing BBBSA applicants waiting for assignment to a mentor in eight selected cities (Philadelphia, Pennsylvania; Rochester, New York; Minneapolis, Minnesota; Columbus, Ohio; Wichita, Kansas; Houston, Texas; San Antonio, Texas; and Phoenix, Arizona). In total, 959 youth applicants to the program completed a baseline interview (before random assignment) and follow-up interview (eighteen months later). Roughly half (487) of the applicants were randomly assigned to receive a mentor (treatment group) and the remaining applicants (472) were randomly assigned to a waiting list (control group).[4] From the initial treatment group pool, 376 youth were successfully matched with a mentor.

In this research, I examine only white, black, and Hispanic youths, dropping the 21 youths of other races, all of whom were placed in cross-race matches. Thus, 355 of the 376 total youths who spent time with mentors are examined from this dataset. Mentors were self-selected adult volunteers, predominantly white and most with education levels beyond high school. However, a variety of social class and racial matches were possible within this pool of volunteers. Table 1 includes descriptive statistics on both youths and mentors.

(Table 1 about here)

Independent Variables

To capture the amount of interaction between mentors and youths and closely represent the relationship quality described by Coleman (1988) as social capital, I create a composite variable of relationship time (hereafter referred to as relationship time) by multiplying the monthly meeting frequency of the dyad by the average number of hours of each meeting by the number of months of the match. I then use a log transformation of this variable. To capture the amount of trust youths have for their mentors, I use three questions asked of each youth at time 2: (1) if the mentor consistently showed up when they said they would (labeled "Trust - reliable"), (2) if the mentor made and kept promises to the youth (labeled "Trust - promises"), and (3) if the mentor accepted the youth for who they really are (labeled "Trust - acceptance"). I dichotomize each of these variables to indicate if the statement accurately describes the youth's mentor. To test the importance of racial similarity in the relationship, I create a dichotomous variable that expresses either a same-race or a cross-race match. Next, I create a dichotomous variable to correspond to the social capital theories of Granovetter (1973) and Lin, Ensel and Vaughn (1981) that denotes the match is with a mentor of higher social class than the youth. This variable is based on household income categories (<$10,000, $10,00-$24,999, and >=$25,000 per year) but the results are similar when parental versus mentor education is used instead. Finally, to represent closure I use a question that asked parents if their child's mentor talked with them.

The additional control variables I use for each youth in all of the models are: age, sex, race, location (BBBSA chapter city), number of siblings, if the youth has a learning disability, and if the youth's household income is less than $25,000 per year. Descriptive statistics for all independent variables are shown in Table 1.

Dependent Variables

I examine four dependent variables, including two academic outcomes: self-reported GPA and self-reported time spent per week on homework; and two deviant behavioral outcomes: self-reported frequency of alcohol use in the last year and self-reported frequency of drug use in the last year. Youths in this sample have decreases in GPA, increases in hours spent on homework, increases in alcohol usage, and increases in drug usage over the time period (see Table 1). For the regression analyses, I calculate each of these variables in terms of change (time 2 – time 1).

Missing Values

Other analyses of this dataset (e.g. Grossman and Rhodes 2002; Rhodes et al. 2002) use marginal mean imputation to substitute mean values for missing data. Allison (2002), among others, recommends against using this method to avoid producing biased estimates. Thus, to deal with missing data, I employ multiple imputation using the ICE command in Stata 10 (Royston 2004). Each imputation model includes the control and other independent variables listed in each of the main regression tables. I exclude cases that require imputed dependent variables from the analysis, as these cases may bias the estimates (von Hippel 2007). I impute interaction values using an approach recommended by Allison (2002) in which I first create all relevant interaction variables and then impute values for any missing variables. In total, I create ten datasets for combined use in the analysis. The ICE command corrects standard errors due to the resulting adjusted sample size.

Analytic Strategy

In the first stage of the analysis, I run three sets of OLS regression models (see the generalized form below in Equation 1). The first set examines the effects of relationship time, trust, social class difference, and closure on each of the four dependent variables (Hypotheses 1, 2, 4, and 6). The second set adds in type of racial match (Hypothesis 3). The third set examines the interaction of race and type of racial match (or race and type of class match) to determine if there are any differences in the effects of type of tie (Hypothesis 5).

$$Y_{\Delta Outcome} = \beta_0 + \beta_1 RelationshipTime + \beta_2 Trust1 + \beta_3 Trust2 + \beta_4 Trust3 + \beta_5 ClassMatch + \beta_6 Closure + \beta_7 RaceMatch + \beta_8 X + \varepsilon \quad (1)$$

Equation 1 estimates the causal effects of these social capital variables if there are no significant differences in the youths assigned to different groups of mentors (such as same-race versus cross-race groups). Experimental research randomly assigns participants to a treatment condition specifically for this reason. If assignment is random and there are no significant differences between groups, the ignorable treatment assignment or conditional independence assumption has been met (Guo and Fraser 2010; Heckman 2005; Morgan and Harding 2006; Rosenabum and Rubin 1983). However, if there are significant differences between groups or any reason to suspect that assignment to a treatment condition is not random, the coefficients from Equation 1 likely will be biased.

In the data I examine, assignment to a mentor or a control group during data collection was random. However, once youth were assigned to the mentor group, assignment to *any* mentor was not random. Caseworkers and parents had some influence over selection into these pairs and caseworkers recorded information about the basis of the selection. First, caseworkers automatically matched pairs on the basis of gender. Next, the "match reason" variable explains that caseworkers matched 47 cases (12.4%) because a pair "live near one another," 278 cases (73.5%) because a pair was "interested in the same things," and 40 cases (10.6%) because a pair was of the "same race or ethnicity."[5] These decisions were made by BBBSA program staff and based on preferences indicated by youths and their families and adult volunteers (Tierney, Grossman and Resch 2000). Since matches between youths and mentors (assignment to treatment) were not made at random, Equation 1 may be misspecified. Thus, I must eliminate the possibility that any effects may be biased due to selection into a relationship.

Since this research attempts to identify the causal effect of social capital, I consider same-race matches made explicitly because of individual preferences a potential problem of selection bias.[6] Prior research (e.g. Ensher and Murphy 1997; Rhodes et al. 2002; Thomas 1989, 1990; Zirkel 2002) highlights the importance of this aspect of social capital and thus suggests that this influence in the selection process should be correlated with the other social capital measures and the outcome variables and thus bias the estimates. The results could potentially be biased because the two groups (same-race versus cross-race) are distinctly different in multiple ways. Although the prior research does not clearly articulate the mechanisms, this may occur because the adults who are best-equipped to be mentors volunteer for the program specifically to help youths similar to themselves. These mentors may be more committed to creating successful outcomes in youths. The most involved mentors may be the most persistent in their attempts to influence what type of youths they are matched to. Additionally, these involved mentors may have the power to avoid the most deeply troubled youths, adapt to specific goals of youths and their families, or provide more concrete assistance to youths. Alternatively, motivated parents may work harder to get their child assigned to a mentor to serve as a same-race role model. Since youths in the program come from mostly single-parent homes, their parents may request a same-race mentor to serve as a type of substitute father or mother. Whatever the case may be, racial preference is one of the possible assignment reasons representing selection into relationships and prior research suggests this may bias the estimates of the unadjusted models.

The information on match reasons in mentor assignment presents a unique opportunity to examine these relationships in more detail and adjust for the bias that results from selection into these relationships using propensity score weights. Propensity scores are simply an estimated probability of receiving some defined treatment. To create the scores, researchers use variables that may lead to selection into groups and thus bias the treatment effect (Gangl 2010; Guo and Fraser 2010; Rosenbaum 1987; Rosenbaum and Rubin 1983). These scores are then used as weights in a regression model. As other scholars note (Guo and Fraser 2010; McCaffrey, Ridgeway, and Morral 2004; West, Biesanz, and Pitts 2000), there is no definitive way to select covariates for the propensity score prediction model. Researchers may start with pertinent variables and include polynomials and interactions until no significant differences between groups exist (Dehejia and Wahba 1999), include all variables that have a significant bivariate relationship with the treatment effect (Guo and Fraser 2010; Hirano and Imbens 2001; Rosenbaum 2002) or include variables as guided by theoretical importance (Guo and Fraser 2010). Essentially, however, the method of using propensity score weights is only as good as the selection of the variables considered to be a potential source of bias. If propensity score models are incorrectly specified, estimates and standard errors will be biased, perhaps even more so than models that do not adjust for selection (Freedman and Berk 2008). Additionally, propensity score weights offer no help when selection occurs due to unobserved factors (Rubin 1997; Winship and Morgan 1999).

I use propensity scores to address the selection bias that may remain from the non-random matching of youths and mentors. I consider the match of a youth to a same-race mentor as the treatment and the match of a youth to a cross-race mentor as the control. To create the propensity scores, I first model a series of bivariate relationships between the type of racial match and all theoretically applicable covariates. Similar to the technique of Hirano and Imbens (2001), I then include in the propensity score prediction model all variables with a significant relationship to the racial match variable at $p < 0.15$.[7] Finally, using the pscore command in Stata (Becker and Ichino 2002), I estimate a logistic regression that predicts the probability of assignment to a same-race match given the vector (x) of covariates :

$$p(X) = \Pr(\text{ RaceMatch} = 1 \mid X) \tag{2}$$

I use the propensity scores obtained from this model as sampling weights in the final regression models predicting academic and deviant behavioral outcomes. Youths in same-race relationships (treatment) are given a weight of 1 and youths in cross-race relationships (control) are given a weight of P/(1-P) (Guo and Fraser 2010:197). Each model is shown both with and without propensity score weight to assess the adjustment for selection into mentoring relationships based on race-matching. I examine R-squared and Bayesian information criterion (BIC) values to assess model fit.

To examine the robustness of the PSW models, I calculate the Impact Threshold for Confounding Variables (ITCV) (Frank 2000). While some research (e.g. McCaffrey, Ridgeway, and Morral 2004) uses Rosenbaum's (2002) bounds sensitivity analysis, the most recent studies use the ITCV statistic both generally (Augustine, Cavanagh, and Crosnoe 2009; Cheng, Martin, and Werum 2007; Frank et al. 2011; Harding 2009) and in combination with propensity score weights (Crosnoe 2009; Frank et al. 2008). Although this robustness check cannot assess whether there is an unmeasured confounding variable nor can it control for an unmeasured confounding variable, it does provide a statistic that indicates to what degree a potential confounding variable would have to be correlated with both the independent and dependent variables to change the significance level of the independent variable. The equation for the ITCV with covariates is:

$$\text{ITCV} = [r_{xy} - r^{\#}_{xy} / 1 - r^{\#}_{xy}] * [\text{sqrt}(1-R^2_{xg})*(1-R^2_{yg})] \quad (3)$$

where $r^{\#}_{xy} = t / \{\text{sqrt}\,[(n - q - 1) + t^2]\}$, R^2_{xg} is the R^2 value from the independent variable regressed on the covariates, R^2_{yg} is the R^2 value from the dependent variable regressed on the covariates, t is the critical t-value (1.96), n is the sample size, and q is the number of model parameters (excluding the intercept) (see Frank 2000 for the full derivation of this equation).

The ITCV represents the product of the predicted correlations between (a) confounder and independent variable and (b) confounder and dependent variable, thus the square root of the ITCV gives the predicted correlation of each. For instance, an ITCV of 0.25 indicates a confounder would need a correlation of at least 0.5 with both the dependent and independent variables to alter the significance level of the independent variable in the regression model. I calculate ITCV values for all significant social capital variables in the PSW models and report them in the text of the results section.

RESULTS[8]

Propensity Score Weights

Table 2 shows the logistic regression model predicting same-race match that I use to create the propensity score weights. The results indicate that blacks and Hispanics are less likely to be in a same-race relationship and youth matched due to same-race preference or request and parent referral to program are more likely to be in a same-race relationship. In Table 3, I examine covariate imbalance before and after calculating the propensity score weights using weighted simple regression (Guo and Fraser 2010). In this analysis, the treatment variable is the single independent variable and the regression is estimated both without and with the propensity score weights. If the regression coefficients are not significant when using the propensity score weights, the results indicate that the propensity score weights have corrected for covariate imbalance. Table 3 shows there are no significant differences between youths with a same-race mentor and youths with a cross-race mentor with the inclusion of the propensity score weights.[9] Based on this evidence, the propensity score weights appear to be a reasonable way to adjust for selection into mentoring relationships.

(Table 2 about here)

(Table 3 about here)

Change in GPA

Table 4 explores how the different aspects of a mentoring relationship affect a youth's change in GPA. Net of the independent variables used to control for a youth's characteristics, the mentoring relationship components that influence social capital predict the change in GPA. OLS regressions estimate these relationships in models 1, 3, and 5, while models 2, 4, and 6 use propensity score weights. The table presents both coefficients and standard errors.

(Table 4 about here)

The results from Table 4 for model 1 reveal that relationship time has a positive and significant effect on change in GPA. This suggests that the longer a match with a mentor is and the more time spent together, both in terms of number and length of meetings, the greater the positive effect on change in GPA from time 1 to time 2. The interpretation of this logged composite independent variable suggests that doubling the amount of time spent with a mentor results in an increase of 0.128 in a youth's GPA from time 1 to time 2, holding all else constant. Additionally, the first trust variable has a positive and significant effect ($\beta = 0.174$) on change in GPA. In this model, a mentor of higher social class and closure have small and non-significant effects on GPA change. Model 2 is the same as model 1 except with the addition of propensity score weights. In this model, the effect of relationship time decreases and becomes non-significant while the effects of the first and second trust variables increase. The propensity score weighted model suggests that the relationship time coefficient is upwardly biased by the non-random assignment of youths to racially matched pairs. Additionally, these results provide evidence that the trust coefficients are downwardly biased by the non-random assignment of youths to racially matched pairs.

Figure 1 is based on predicted values generated from model 2. It shows that for youths of all races, both trust for a mentor and a large amount of time spent between youth and mentor increases the predicted change in GPA from time 1 to time 2. For white and black youths in mentoring relationships with no trust and low relationship time, the predicted change in GPA reverses signs.

(Figure 1 about here)

Although the first two models in Table 4 show some support of both the relationship time and trust theories, additional models test other theories of social capital. In hypothesis 3, I predict that same-race matching will moderate the effect of trust. Models 3 (OLS) and 4 (PSW) of Table 4 show that adding the type of race-match into these models has no effect on the coefficients of the trust and relationship time variables. Finally, I run two additional models that include interactions for the type of racial match and the race of youth and mentor. These models (5 and 6) show no significant effects for the type of racial match or the interaction of racial match and race on change in GPA. Thus, there appears to be no direct or indirect effect of race-matching on change in GPA.

Both R-squared and BIC (lower is better) statistics suggest that the fit of the PSW models is better than the unweighted OLS models, although the differences in BIC statistics (< 2) suggest only weak evidence of a better fit (Raftery 1995). The ITCV for the trust-reliable variable is 0.070 and the ITCV for the trust-promises variable is 0.082. In other words, a confounder would have to have a correlation of 0.265 (square root of 0.070) with the trust-reliable variable and change in GPA for the causal inference of trust's effect on GPA to change. Likewise, a confounder would have to have a correlation of 0.286 with the trust-promises variable and change in GPA for the causal inference of trust's effect on GPA to change. An inspection of correlations among the variables used in the analysis and other variables available in the dataset suggests that a correlation this high among these variable is unlikely: no measured variable meets these thresholds.

Change in Homework Hours

Table 5 shows that the results of the models predicting change in homework hours are somewhat similar to the results found in the models predicting change in GPA. In the basic OLS model (model 1), relationship time has a positive ($\beta = 0.600$), although marginally significant ($p \leq 0.10$) effect on the change in time spent on homework. Again, this coefficient implies that the longer a match with a mentor is, along with the more time spent together, the greater the positive effect on change in hours spent on homework from time 1 to time 2. A mentor of higher social class, trust, and closure indicators all are non-significant. Model 2 shows the results of the propensity score weighted model. Compared to the OLS model (1), the coefficient for relationship time is now significant at the $p \leq 0.05$ level and still maintains a positive effect on change in homework hours. This model suggests that the relationship time coefficient is *downwardly* biased by the non-random assignment of youths to racially matched pairs ($\beta = 0.600$ in model 1 and $\beta = 0.855$ in model 2). Additionally, the coefficient for closure is now marginally significant ($p \leq 0.10$) and has a positive effect ($\beta = 1.612$) on change in homework hours.

Based on Raftery's (1995) guidelines for model fit, the difference in BIC statistics (2.73) suggests positive evidence of a better fit with the PSW model. The ITCV for the relationship time variable is 0.026 and the ITCV for the closure variable is 0.066. Thus, a confounder would have to have a correlation of 0.161 with the relationship time variable and change in time spent on homework for the causal inference to change. A confounder would have to have a correlation of 0.257 with the closure variable and change in time spent on homework for the causal inference to change. An inspection of correlations among the variables in the dataset suggests that a correlation this high among these variable is possible. Thus, I suggest that, in this case, the propensity score weighted models fail to completely account for the bias from selection into these relationships.

(Table 5 about here)

Models 3 and 4 of Table 5 show that relationship time still has a positive ($\beta = 0.572$ and $\beta = 0.869$, respectively) and significant ($p \leq 0.10$ and $p \leq 0.05$, respectively) effect on change in homework hours with the addition of the type of race match variable. The closure variable still maintains a significant and positive effect as well in the PSW model (4). The final models (5 and 6) predicting change in hours spent on homework show no significant effects for the type of racial match or the interaction of racial match and race. Thus, once again there appears to be no direct or indirect effect of race-matching on the dependent variable.

Figure 2 shows that for youths of all races, both closure between mentor and parent and a large amount of time spent between youth and mentor increases the predicted change in hours spent on homework from time 1 to time 2.

(Figure 2 about here)

The results from all of the models predicting academic outcomes (either change in GPA or change in homework hours) are somewhat consistent. Overall, these models indicate that relationship time has a strong and positive effect on academic outcomes. Trust also has a significant effect on change in GPA, while closure has a marginally significant effect on change in homework hours. Furthermore, there is no evidence that this variable is moderated through the type of racial match a youth is placed in. Having a mentor of higher social class has no significant effect in any of the models. Additionally, the propensity score weighted models do give some indication that there may be a small amount of selection bias influencing the OLS coefficients, albeit only in size and not direction. Next, I continue this analysis by turning to the models that examine the effects of these variables on change in deviant behavior.

Change in Alcohol Usage

Table 6 shows the results of the models predicting change in alcohol usage. The results from Table 6 for model 1 reveal that only the second trust variable has a significant effect on change in alcohol usage. This negative effect ($\beta = -0.693$) suggests that trust in a mentor reduces alcohol usage from time 1 to time 2. In this model, relationship time, a mentor of higher social class, and closure all have small and non-significant effects on change in alcohol usage. Model 2 is the same as model 1 except with the addition of propensity score weights. In this model, the effect of the second trust variable becomes only marginally significant ($p < 0.10$) due to an increase in the standard error. The difference in BIC statistics (4.55) suggests positive evidence of a better fit with the PSW model. The ITCV for the relationship time variable is 0.038. In other words, a confounder would have to have a correlation of 0.194 with the relationship time variable and change in alcohol usage for the causal inference to change. An inspection of correlations among the variables in the dataset suggests that a correlation this high among these variable is possible.

(Table 6 about here)

Figure 3 is based on predicted values generated from model 2. It shows that for youths of all races, both trust for a mentor and a large amount of time spent between youth and mentor reduces the predicted increase in alcohol usage from time 1 to time 2.

(Figure 3 about here)

The models that include the type of racial match (model 3 for OLS and model 4 for PSW) do not change the story. However, it is of interest to note that the same-race match coefficient is larger in size when compared to the trust and relationship time variables, suggesting that there may be an effect but the limited sample size presents a precision problem. Models 5 and 6 continue the inquiry into the effects of the type of racial match and model 5 shows that there are some significant effects on change in alcohol usage. The second trust variable maintains a negative ($\beta = -0.672$) and significant ($p \leq 0.05$) effect. The results also indicate there are differential effects of the type of racial match on change in alcohol usage. For whites, a same-race mentor has a negative effect on change in alcohol usage ($\beta = -1.787$). For blacks, a cross-race mentor has an overall negative effect on change in alcohol usage ($\beta = -1.865$), while a same-race mentor has no significant effect on change in alcohol usage (the test of the two coefficients, $\beta = -1.865 + 1.913$ is non-significant). These results imply that only white mentors have a significant effect on the reduction of alcohol usage in youths. Although these coefficients change somewhat in the PSW model (6), the increase in standard errors once again suggests a precision problem as a result of the small sample size.

Change in Drug Usage

In the final series of models, presented in Table 7, I examine how the different aspects of a mentoring relationship affect a youth's change in drug usage. The results from Table 7 for model 1 reveal that relationship time has a negative and significant effect ($\beta = -0.149$) on change in drug usage from time 1 to time 2. This indicates that longer matches with a mentor contribute to a decline in drug usage in a youth. Additionally, the closure and third trust variables have negative and marginally significant ($p \leq 0.10$) effects on change in drug usage. In the PSW model (2), only relationship time ($\beta = -0.168$), retains significance. The difference in BIC statistics (5.73) suggests positive evidence of a better fit with the PSW model. The ITCV for the relationship time variable is 0.162. In other words, a confounder would have to have a correlation of 0.402 with the relationship time variable and change in drug usage for the causal inference to change. This is the highest ITCV among all of the robustness checks and it is highly unlikely that a confounder would have correlations this high.

(Table 7 about here)

Figure 4 shows that for youths of all races, both closure between mentor and parent and a large amount of time spent between youth and mentor reduces the predicted increase in drug usage from time 1 to time 2. For white and black youths in mentoring relationships with both closure and high relationship time the predicted change in drug usage reverses signs.

(Figure 4 about here)

Models 3 and 4 in Table 7, which include the type of racial match, show similar results. Once I include race*racial match interactions in models 5 and 6, the same-race match variable has a negative ($\beta = -0.950$) and significant ($p \leq 0.05$) effect in the OLS model but a non-significant effect in the PSW model. Additionally, the main effects for black and Hispanic are negative and marginally ($p < 0.10$) significant. These results suggest that white mentors are able to reduce drug usage among all types of youths, while there are no additional effects of same-race mentors for black and Hispanic youths. Although these results are interesting, once again I believe that the small sample size limits my ability to fully explore and comprehend these interaction effects.

In summary, the results from all of the models predicting deviant behavioral outcomes (either change in alcohol usage or change in drug usage) are somewhat consistent. These models show that measures of trust have consistently negative effects on changes in deviant behavior. There is some weak evidence of an effect from the type of racial match and interaction effects with youths' race on these outcomes. The results also indicate that relationship time has a negative effect on change in drug usage in all models and closure has a negative effect on change in drug usage in the OLS models. Throughout all of these models, having a mentor of higher social class has no significant effect. Finally, the propensity score weighted models consistently indicate that there may be some selection bias influencing the OLS coefficients, particularly the relationship time and trust variables, in size but not direction.

DISCUSSION

The current literature on social capital leaves researchers to question what characteristics of a relationship are important in producing beneficial outcomes. A variety of theories and a number of empirical studies suggest different characteristics: the amount of time individuals spend together, their levels of trust, their racial similarity, their social class difference, or intergenerational closure. Additionally, research struggles with causation when examining social capital due to concerns of bias from selection into relationships. This research addresses these issues by examining how relationship characteristics operate within a dyadic relationship to produce academic and deviant behavioral outcomes. Using data from mentoring relationships in the BBBSA program, the analysis uses propensity score weights to reduce the impact of selection bias that has plagued prior studies.

The results lend strong support to Coleman's (1988) hypothesis on social capital in both the OLS and propensity score weighted models. The measure of relationship time has an effect in at least some models for every variable except changes in alcohol usage and the measures of trust have an effect for every dependent variable except changes in hours spent on homework. Some of the results that examine more direct monitoring processes (time spent on homework and drug usage) illustrate the importance of closure between parent and mentor in extracting benefits from a relationship. Perhaps the biggest surprise in this respect is that closure does not affect changes in alcohol usage. These findings lead me to conclude that even though the amount of time spent between individuals is important in building social capital, it is clearly more complex than just placing two individuals together for extended periods of time.

These findings have broad implications for any research that examines other relationships between youths and adults. Youths are more receptive to both adults who show they care based on their time commitments and adults they feel they can trust. Surprisingly, racial similarity does not affect trust levels between individuals. Other relationships may be stunted by a lack of trust, such as those between authority figures and students in school. If the mentors who are most effective at curbing deviant behavior and fostering academic growth in youths are also those most trusted by youths, perhaps principals, teachers, and other school staff might work harder to inspire trusting relationships in their schools. Might youths respond to other important people they feel they can trust as well? Although the answers uncovered in this research are preliminary, future studies should examine additional outcomes.

One shortcoming of the data in unraveling the issue of race and trust is the lack of a measure of expected trust or perceived feeling about a mentor at time 1. From time 1 to time 2, youths undergo a transformation from generalized trust (a measure of trust for people similar to themselves) to specialized trust (a measure of trust for a specific person) (Smith 2010). Perhaps racial similarity matters in the early phases of a relationship but not long term. Future research should focus on measuring and examining trust in a variety of relationships and continue to address these question of race and trust.

Surprisingly, having a mentor of higher social class has no effect on any of the outcomes I examine in these data. For this age group, social class might just be less important in fostering beneficial outcomes than time spent together and levels of trust. As discussed earlier, a mentor of higher social class is likely to lead to information or opportunities normally unknown within an individual's social world. Thus, a mentor of higher social class could be more important for providing disadvantaged youths with information regarding college and employment that they may not otherwise have access to. Although these benefits might have shown up in a dataset that includes adult outcomes, such as college attendance or job placement, these data did not include an adult follow-up wave. Future research should test these possibilities more fully with a dataset that follows youths throughout their post-secondary years.

Additionally, social class difference may be a simplified way of measuring *embedded* levels or the *availability* of potential benefits from social capital. Consider again Portes' (1998:6) definition of social capital: “the *ability* of actors to secure benefits by virtue of membership in social networks or other social structures” [emphasis added]. The way that researchers currently handle the conceptualization of social capital is problematic. It is imperative for researchers to recognize that there are at least two important, yet substantively different, aspects of mobilized social capital. First, there are the aspects of a relationship or network that increase or decrease the *ability* of an individual to extract benefits or value from a relationship, as Portes (1998) contends. I use this conceptualization of social capital in testing my hypotheses. Second, there are also the aspects of a relationship or network that increase the *availability* of potential benefits or value to be extracted. It is this conceptualization of social capital that has been examined in most of the literature on network ties and job opportunities (Granovetter, 1973; Lin, Ensel and Vaughn 1981). Future researchers should be cautious in clarifying exactly what they envision social capital to be. In fact, there are many benefits to be gained from a close examination of these issues that leads to a more clear and precise vocabulary on social capital. Although some literature has begun to untangle the mess created by the glut of work on social capital (see Brunie 2009; Lin 2008), researchers still have a long way to go.

These results lead me to conclude that individual selection is important to understanding social capital. Observational research, which is not free from selection bias, can only examine what people already select individually. Comparison of the OLS and propensity score weighted models, which adjusts for selection into the relationships, reveals that these choices make a small difference. However, our understanding of the contribution of bias from selection into relationships on social capital needs further examination with larger sample sizes and more variation in the pair types.

Furthermore, when institutions create relationships between individuals with no choice from participants (random assignment), actors should consider the goals behind creation of the relationships. Pairs made for the purpose of general support and assistance may see greater success when matching similar individuals. Conversely, assignment between distinctly different individuals may be helpful if the goal is to pair individuals to expand their knowledge, networks, or opportunities. Additionally, the amount of time spent between the two individuals may be an important factor in light of the consistently significant findings in the present research. Future research on social capital should more closely examine how selection into relationship contributes to this effect.

All of these issues leave researchers with many questions to consider in future studies. Still, social capital research is important since many fields have much to gain from learning how, why, and under what conditions people extract value from relationships and networks. Much of the prior research on social capital struggles with differing definitions, issues of selection, and a lack of unifying theory on social capital. This study attempts to fill in those gaps, but future research should continue to make uncovering a more complete model of social capital a top priority.

Table 1: Descriptive Statistics

Demographic Characteristics	Youths		Mentors			
Male	204	57.46%	203	57.18%		
Female	151	42.54%	152	42.82%		
White	174	49.01%	263	74.08%		
Black	148	41.69%	71	20.00%		
Hispanic	33	9.30%	13	3.66%		
Mean age (in years)	12.13		29.41			
Household receives public assistance	151	42.54%				
Location - Columbus	90	25.35%				
Location - Houston	46	12.96%				
Location - Minneapolis	7	1.97%				
Location - Philadelphia	38	10.70%				
Location - Phoenix	49	13.80%				
Location - Rochester	34	9.58%				
Location - Wichita	69	19.44%				
Location - San Antonio	22	6.20%				
Learning disability	54	15.21%				
1 or more siblings	312	87.88%				
Household income (mentor)						
< $10,000			18	5.07%		
$10,000 - $24,999			103	29.01%		
>= $25,000			234	65.92%		
N =	355		355			
Mentoring Relationship Characteristics	Total		White Youths		Black Youths	
Mean length of match (in days)	323.26		340.12		310.45	
Mean meeting frequency (per month)	3.27		3.36		3.07	
Mean meeting length (in hours per meeting)	3.77		3.91		3.53	
Relationship time (log)	4.60		4.75		4.41	
Mentor is higher social class	265	74.65%	126	72.41%	115	77.70%
Mentor is equal or lower social class	90	25.35%	48	27.59%	33	22.30%
Cross-race match	113	31.83%	8	4.60%	79	52.38%
Same-race match	242	68.17%	166	95.40%	69	46.62%
Trust - reliable	325	91.55%	163	93.68%	133	89.86%

Table 1: Descriptive Statistics (Continued)

Mentoring Relationship Characteristics	Total		White Youths		Black Youths	
Trust - promises	269	75.77%	139	79.89%	105	70.95%
Trust - acceptance	325	91.55%	158	90.80%	138	91.22%
Closure between mentor and parent	53	14.93%	28	16.09%	23	15.54%

Academic Characteristics / Deviant Behavior	Total	White Youths	Black Youths
GPA (t1)	2.78	2.72	2.86
GPA (t2)	2.73	2.68	2.78
Change in GPA	-0.04	-0.04	-0.08
Hours spent per week on homework (t1)	3.23	3.72	2.68
Hours spent per week on homework (t2)	4.97	5.33	4.61
Change in hours spent on homework	1.75	1.61	1.94
Times drank alcohol within last year (t1)	0.34	0.40	0.15
Times drank alcohol within last year (t2)	0.93	1.10	0.64
Change in alcohol usage	0.59	0.71	0.49
Times used drugs within last year (t1)	0.06	0.10	0.00
Times used drugs within last year (t2)	0.23	0.24	0.17
Change in drug usage	0.16	0.14	0.17

Table 2: Propensity Score Logistic Regression Model Predicting Same-Race Match

Black	-7.141***
	(1.971)
Hispanic	-8.395***
	(1.946)
Reason matched: same-race	2.198*
	(1.017)
Parent referred youth	1.702+
	(0.975)
Constant	4.089
	(4.011)
Observations	355
Pseudo R-squared	0.831

Note: Unstandardized coefficients. Standard errors in parentheses. Model also controls for whether a youth's household receives public assistance, location, self-reported relationship with parent, history of abuse, parent/guardian's employment status, goals for a youth in the program, mentor's age, income, and education level, whether mentor has his/her own children, and reason matched: interested in the same things (all non-significant in this model, although significant in the bivariate model).
+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 3: Covariate Imbalance Tests With Propensity Score Weights

	Same-Race Regression Coefficient p-Value without propensity score	Same-Race Regression Coefficient p-Value with propensity score
Black	0.000***	0.579
Hispanic	0.000***	0.109
Youth household receives public assistance	0.000***	0.217
Parent referred youth	0.097+	0.326
Youth has history of any type of abuse	0.026*	0.919
Parent/guardian works full-time	0.051+	0.950
Mentor's age	0.005**	0.410
Mentor's household income >= $25,000	0.042*	0.133
Mentor's education > HS degree	0.018*	0.446
Mentor has own children	0.010**	0.497
Observations	355	355

Note: Unstandardized coefficients are calculated in weighted simple regressions using the listed variable as the only independent variable and the treatment variable (same-race match) as the dependent variable.
+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 4: Models Predicting Change in GPA

	(1) OLS	(2) PSW	(3) OLS with same-race	(4) PSW with same-race	(5) OLS with interactions	(6) PSW with interactions
Black	0.015	0.005	0.027	0.003	0.001	-0.086
	(0.115)	(0.144)	(0.133)	(0.143)	(0.358)	(0.680)
Hispanic	0.110	0.327	0.130	0.334	-0.023	-0.053
	(0.192)	(0.324)	(0.224)	(0.382)	(0.391)	(0.720)
Relationship time	0.128*	0.110	0.128*	0.112	0.124*	0.117
	(0.059)	(0.074)	(0.059)	(0.075)	(0.059)	(0.077)
Mentor is higher	0.040	0.189	0.040	0.188	0.044	0.177
social class	(0.134)	(0.137)	(0.134)	(0.137)	(0.134)	(0.138)
Trust - reliable	0.174*	0.230*	0.175*	0.230*	0.179*	0.234*
	(0.076)	(0.107)	(0.076)	(0.107)	(0.076)	(0.107)
Trust - promises	0.088	0.169*	0.087	0.169**	0.089	0.169**
	(0.057)	(0.067)	(0.058)	(0.066)	(0.058)	(0.066)
Trust - acceptance	-0.015	0.018	-0.016	0.018	-0.016	0.018
	(0.084)	(0.102)	(0.084)	(0.102)	(0.085)	(0.102)
Closure between	-0.061	-0.082	-0.061	-0.081	-0.064	-0.081
mentor and parent	(0.067)	(0.090)	(0.067)	(0.089)	(0.067)	(0.089)
Same-Race match			0.025	-0.089	-0.030	-0.121
			(0.140)	(0.281)	(0.350)	(0.609)
Same-Race*Black					-0.011	0.179
					(0.392)	(0.712)
Same-Race*Hispanic					0.603	0.501
					(0.551)	(0.931)
Constant	-0.092	-0.323	-0.109	-0.301	0.034	-0.272
	(0.742)	(0.838)	(0.749)	(0.872)	(0.814)	(0.991)
Observations	352	352	352	352	352	352
R-squared	0.082	0.098	0.082	0.098	0.088	0.099
BIC	1059.62	1057.89	1065.37	1063.72	1076.85	1073.43

Note: Unstandardized coefficients. Standard errors in parentheses. Models 1, 3, and 5 use OLS regression. Models 2, 4, and 6 use OLS regression with propensity score weights. All models also control for location, age, gender, number of siblings, whether the youth has a learning disability, and whether the youth's family receives public assistance.

+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 5: Models Predicting Change in Hours Spent on Homework

	(1) OLS	(2) PSW	(3) OLS with same-race	(4) PSW with same-race	(5) OLS with interactions	(6) PSW with interactions
Black	0.201	0.099	-0.301	0.105	1.001	0.439
	(0.640)	(0.787)	(0.741)	(0.788)	(2.013)	(1.983)
Hispanic	0.685	-1.043	-0.167	-1.197	1.494	0.528
	(1.075)	(1.125)	(1.249)	(1.132)	(2.197)	(1.902)
Relationship time	0.600+	0.855*	0.572+	0.869*	0.562+	0.873*
	(0.327)	(0.398)	(0.327)	(0.404)	(0.331)	(0.412)
Mentor is higher	0.058	0.011	0.037	-0.001	0.079	0.006
social class	(0.740)	(0.758)	(0.737)	(0.759)	(0.740)	(0.768)
Trust - reliable	-0.293	0.646	-0.310	0.649	-0.219	0.639
	(1.131)	(0.913)	(1.125)	(0.913)	(1.130)	(0.918)
Trust - promises	-0.032	-0.434	0.105	-0.420	0.073	-0.419
	(0.722)	(0.807)	(0.729)	(0.813)	(0.732)	(0.828)
Trust - acceptance	-0.663	-0.388	-0.612	-0.371	-0.639	-0.375
	(1.073)	(1.042)	(1.073)	(1.045)	(1.076)	(1.048)
Closure between	0.794	1.612+	0.824	1.626+	0.839	1.620+
mentor and parent	(0.879)	(0.860)	(0.877)	(0.859)	(0.877)	(0.867)
Same-Race match			-1.044	-0.560	0.322	-0.295
			(0.784)	(0.913)	(1.969)	(1.608)
Same-Race*Black					-1.380	-0.352
					(2.202)	(2.169)
Same-Race*Hispanic					-3.431	-0.875
					(3.095)	(2.609)
Constant	2.431	2.932	3.298	3.477	1.760	1.813
	(3.624)	(3.959)	(3.677)	(3.869)	(4.061)	(4.200)
Observations	351	351	351	351	351	351
R-squared	0.061	0.109	0.067	0.109	0.070	0.110
BIC	2187.94	2185.21	2192.23	2190.47	2202.84	2200.74

Note: Unstandardized coefficients. Standard errors in parentheses. Models 1, 3, and 5 use OLS regression. Models 2, 4, and 6 use OLS regression with propensity score weights. All models also control for location, age, gender, number of siblings, whether the youth has a learning disability, and whether the youth's family receives public assistance.

+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 6: Models Predicting Change in Alcohol Usage

	(1) OLS	(2) PSW	(3) OLS with same-race	(4) PSW with same-race	(5) OLS with interactions	(6) PSW with interactions
Black	-0.155	-0.108	-0.284	-0.097	-1.865*	-2.979
	(0.276)	(0.369)	(0.320)	(0.358)	(0.871)	(3.087)
Hispanic	-0.495	-1.222	-0.711	-1.576	-2.009*	-3.611
	(0.474)	(1.222)	(0.546)	(1.386)	(0.955)	(3.081)
Relationship time	-0.130	-0.126	-0.132	-0.095	-0.097	-0.058
	(0.142)	(0.194)	(0.143)	(0.195)	(0.143)	(0.204)
Mentor is higher	-0.020	-0.063	-0.028	-0.092	-0.109	-0.150
social class	(0.316)	(0.375)	(0.317)	(0.363)	(0.315)	(0.363)
Trust - reliable	-0.526	-0.686	-0.525	-0.680	-0.494	-0.626
	(0.475)	(0.489)	(0.475)	(0.478)	(0.475)	(0.451)
Trust - promises	-0.693*	-0.715+	-0.656*	-0.696+	-0.672*	-0.708+
	(0.306)	(0.372)	(0.310)	(0.369)	(0.309)	(0.371)
Trust - acceptance	-0.221	-0.360	-0.208	-0.340	-0.177	-0.309
	(0.478)	(0.615)	(0.479)	(0.583)	(0.479)	(0.551)
Closure between	0.132	0.429	0.138	0.438	0.131	0.397
mentor and parent	(0.425)	(0.482)	(0.423)	(0.488)	(0.422)	(0.494)
Same-Race match			-0.270	-1.312	-1.787*	-2.650
			(0.339)	(1.607)	(0.851)	(3.039)
Same-Race*Black					1.913*	3.008
					(0.949)	(3.078)
Same-Race*Hispanic					0.912	2.439
					(1.344)	(3.612)
Constant	-1.237	-1.982	-1.022	-1.032	0.193	0.301
	(1.582)	(2.181)	(1.604)	(2.545)	(1.768)	(3.632)
Observations	351	351	351	351	351	351
R-squared	0.081	0.102	0.083	0.108	0.096	0.120
BIC	1625.01	1620.46	1630.15	1625.84	1638.74	1633.95

Note: Unstandardized coefficients. Standard errors in parentheses. Models 1, 3, and 5 use OLS regression. Models 2, 4, and 6 use OLS regression with propensity score weights. All models also control for location, age, gender, number of siblings, whether the youth has a learning disability, and whether the youth's family receives public assistance.

+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

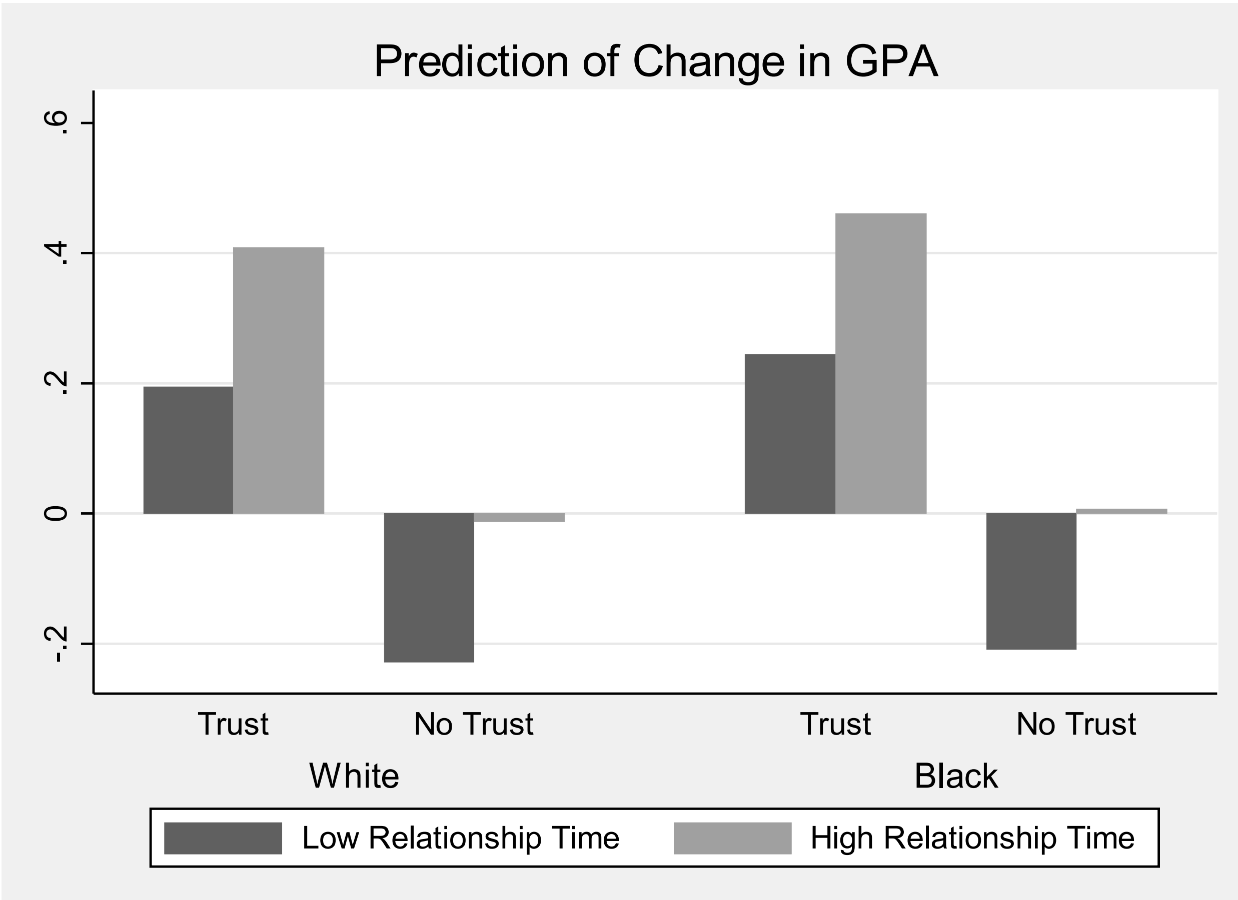
Table 7: Models Predicting Change in Drug Usage

	(1) OLS	(2) PSW	(3) OLS with same-race	(4) PSW with same-race	(5) OLS with interactions	(6) PSW with interactions
Black	-0.023	-0.137	-0.146	-0.130	-0.808+	-1.239
	(0.146)	(0.193)	(0.170)	(0.187)	(0.458)	(1.627)
Hispanic	0.190	0.603	-0.019	0.427	-0.887+	-1.474
	(0.248)	(0.704)	(0.288)	(0.799)	(0.500)	(1.558)
Relationship time	-0.149*	-0.168*	-0.157*	-0.176*	-0.154*	-0.172*
	(0.075)	(0.074)	(0.075)	(0.074)	(0.075)	(0.074)
Mentor is higher	0.039	0.132	0.036	0.123	0.018	0.096
social class	(0.159)	(0.158)	(0.158)	(0.152)	(0.159)	(0.143)
Trust - reliable	0.036	0.294	-0.036	0.299	-0.018	0.278
	(0.095)	(0.194)	(0.095)	(0.195)	(0.094)	(0.186)
Trust - promises	-0.033	0.006	-0.019	0.020	-0.018	0.015
	(0.070)	(0.152)	(0.071)	(0.134)	(0.070)	(0.139)
Trust - acceptance	-0.194+	-0.141	-0.189+	-0.126	-0.186+	-0.101
	(0.100)	(0.348)	(0.099)	(0.312)	(0.099)	(0.272)
Closure between	-0.184+	-0.128	-0.185+	-0.107	-0.188+	-0.098
mentor and parent	(0.090)	(0.232)	(0.090)	(0.215)	(0.089)	(0.211)
Same-Race match			-0.254	-0.650	-0.950*	-1.449
			(0.179)	(0.833)	(0.447)	(1.575)
Same-Race*Black					0.691	1.163
					(0.500)	(1.616)
Same-Race*Hispanic					0.858	2.472
					(0.704)	(1.881)
Constant	0.946	0.167	1.688+	0.606	2.543*	1.389
	(0.749)	(1.247)	(0.951)	(1.549)	(1.028)	(2.021)
Observations	355	355	355	355	355	355
R-squared	0.064	0.092	0.070	0.112	0.087	0.116
BIC	1231.19	1225.46	1235.82	1230.87	1243.94	1239.59

Note: Unstandardized coefficients. Standard errors in parentheses. Models 1, 3, and 5 use OLS regression. Models 2, 4, and 6 use OLS regression with propensity score weights. All models also control for location, age, gender, number of siblings, whether the youth has a learning disability, and whether the youth's family receives public assistance.

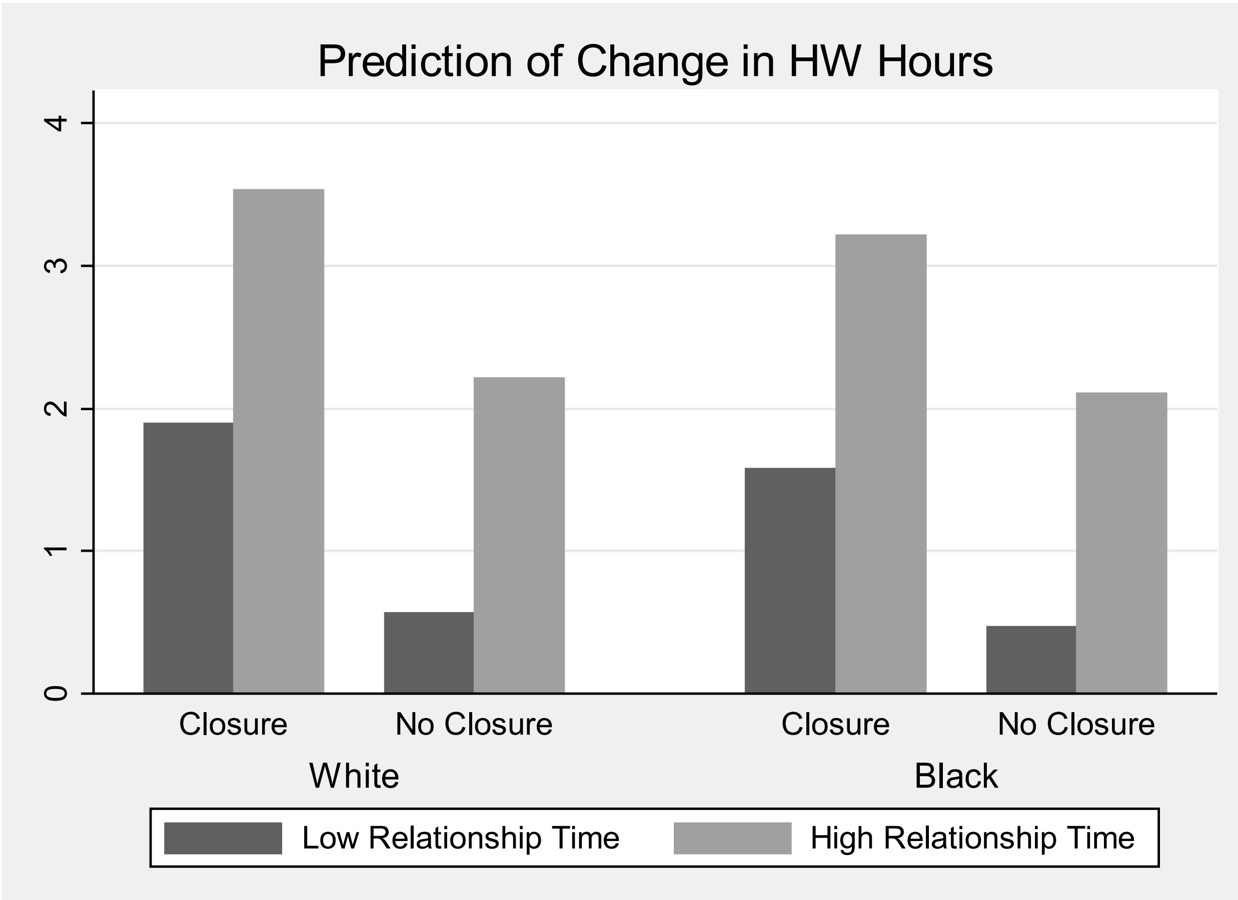
+ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Figure 1



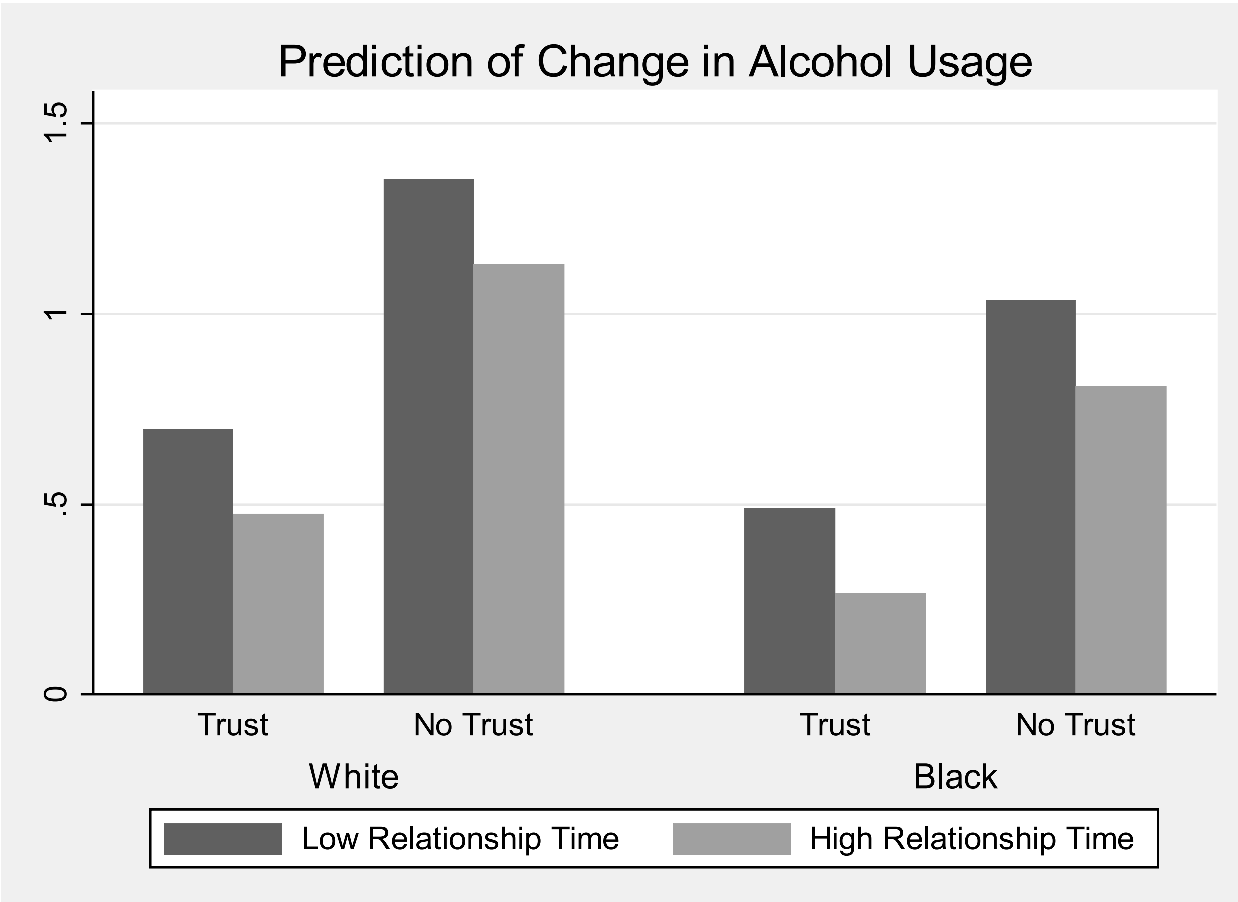
Note: Predicted values based on PSW regressions from Table 4, model 2. Low relationship time indicates the composite of relationship time variable is equal to one standard deviation below the mean. High relationship time indicates the composite of relationship time variable is equal to one standard deviation above the mean.

Figure 2



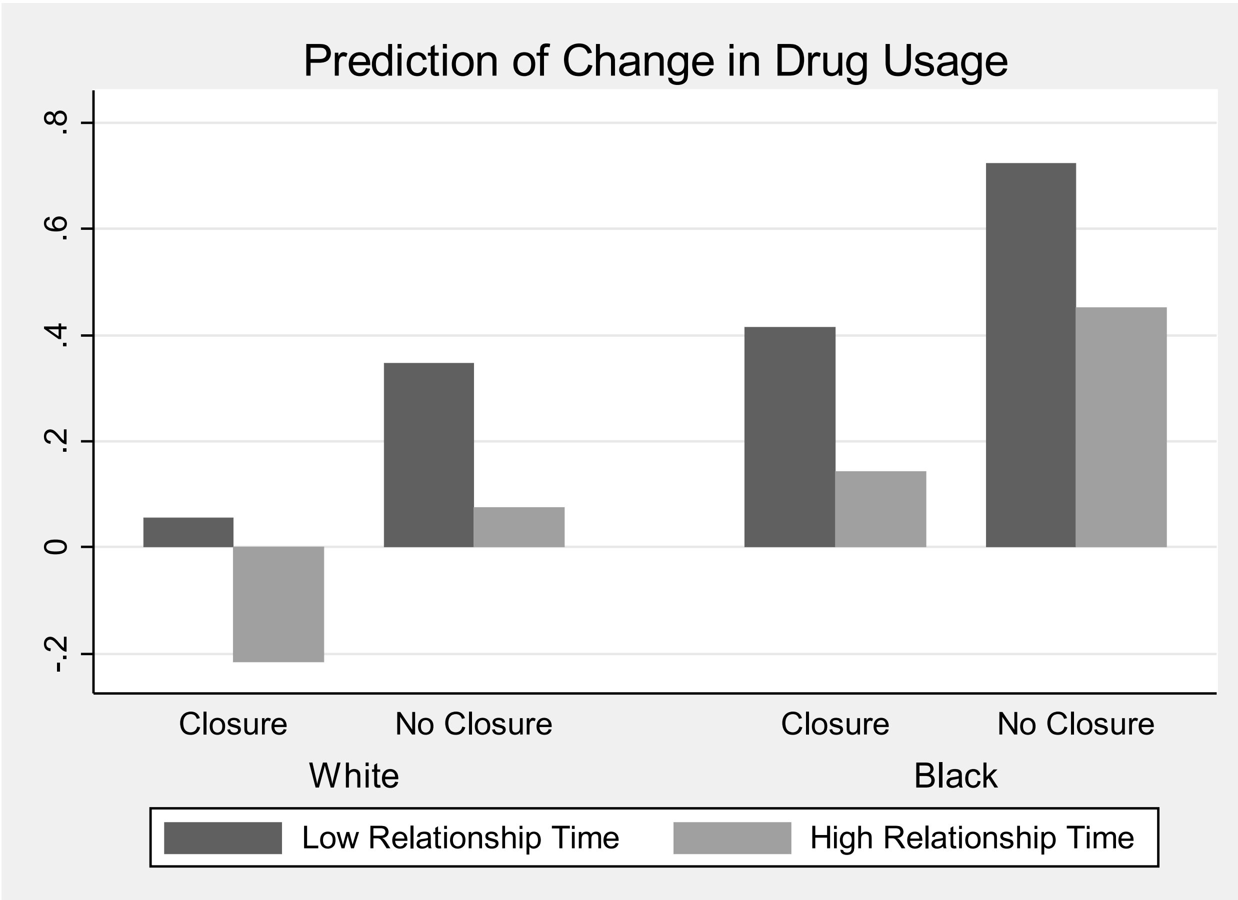
Note: Predicted values based on PSW regressions from Table 5, model 2. Low relationship time indicates the composite of relationship time variable is equal to one standard deviation below the mean. High relationship time indicates the composite of relationship time variable is equal to one standard deviation above the mean.

Figure 3



Note: Predicted values based on PSW regressions from Table 6, model 2. Low relationship time indicates the composite of relationship time variable is equal to one standard deviation below the mean. High relationship time indicates the composite of relationship time variable is equal to one standard deviation above the mean.

Figure 4



Note: Predicted values based on PSW regressions from Table 7, model 2. Low relationship time indicates the composite of relationship time variable is equal to one standard deviation below the mean. High relationship time indicates the composite of relationship time variable is equal to one standard deviation above the mean.

NOTES

1. The measure of parent-child connectivity was a composite of answers to eight questions asked to both children and parents regarding frequency of discussion of education and school issues.
2. However, Centola and Macy (2007) argue that Granovetter's use of the term weak tie has two meanings. In this article, I use the term weak tie to indicate what Centola and Macy describe as a long tie, or ties “between otherwise distant nodes [which] provide access to new information.” (2007:704).
3. For a more complete description of the data design and collection, see Tierney, Grossman and Resch, 2000.
4. However, I am only concerned with the group matched with mentors in this study and only those pairs are part of any of the analysis. Prior research has examined the treatment effect of being assigned to a mentor versus the control waiting list (see, for instance, Tierney, Grossman and Resch 1995).
5. The remaining 13 cases (3.44%) are missing on this variable.
6. Similarly, if caseworkers had made explicit matches due to class preferences (either similarities or differences) among participants I would run additional propensity score weighted models to adjust for that selection into relationships.
7. These variables are race, match reason, reason for a youth's referral to the program, whether a youth's household receives public assistance, location, self-reported relationship with parent, history of abuse, parent/guardian's employment status and income, goals for a youth in the program, mentor's age, income, and education level, and whether mentor has his/her own children.
8. In addition to the six models for each dependent variable presented in Tables 4 through 7, I also examined the differential effect of weak social class ties by race and the interactive effect of strong (same-race) and weak (social class) ties. These variables are not significant in any of the models for any of the dependent variables, thus I do not include the results here. These results are available from the author upon request.
9. Alternate specifications (available from author upon request) using only theory and information from prior research to predict selection into the treatment group resulted in remaining imbalances between same-race and cross-race groups. However, covariate balance was achieved once I used a model that included all variables with significant bivariate relationships with the treatment variable. These results strongly suggest the importance of variable selection when creating a propensity score prediction model.

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