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Higher Education and Health Investments: Does More Schooling Affect Preventive Health Care Use?◆

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Abstract

While it is well-known that individuals with higher levels of education consume more preventive medical care, there are several potential explanations for this stylized fact. These explanations include causal and non-causal mechanisms, and distinguishing among explanations is relevant for accessing the importance of educational spillovers on lifetime health outcomes as well as uncovering the determinants of preventive care. In this paper, we use regression analysis, sibling fixed effects, and matching estimators to examine the impact of education on preventive care. In particular, we use a cohort of 10,000 Wisconsin high school graduates that has been followed for nearly 50 years and find evidence that attending college is associated with an increase in the likelihood of using several types of preventive care by approximately five to fifteen percent for college attendees in the early 1960s. We also find that greater education may influence preventive care partly through occupational channels and access to care. These findings suggest that increases in education have the potential to spillover on long-term health choices.

Keywords

preventive care; education; college attendance

Introduction

It is well-known that individuals with higher levels of education are healthier than individuals with lower levels of education. For example, Cutler and Lleras-Muney (2008) report sizable correlations between education and mortality, heart disease, diabetes, lost days of work, smoking, alcohol consumption, and self-reported poor health. The effects of increasing education by four years on these outcomes are comparable in magnitude to the gender gap or the black-white gap in these outcomes. Education is also correlated with the use of preventive care services; Cutler and Lleras-Muney (2007, 2008) document that individuals with higher levels of education obtain more flu shots, vaccines, mammograms, Pap smears, and colonoscopies.

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There are three general explanations for the observed correlation between education and health: (1) reverse causality—poor health leads to low levels of schooling, (2) education causally improves health, and (3) additional factors lead to a spurious correlation between education and health. It is important to establish whether the relationship between education and health choices is causal or merely represents a correlation in order to assess the total social benefit of education and to determine the potential impact of education policies on health.

To date, there have been relatively few credible attempts to estimate the causal effects of education on health. Research that has used experimental or quasi-experimental designs has typically focused on a small set of health outcomes such as mortality and smoking (e.g., Lleras-Muney 2005; deWalque 2007; Grimard and Parent 2007; Clark and Royer 2009).[1] However, it might be the case that education affects health in additional domains that are important for policy priorities. For instance, because of the relatively low costs and high long term benefits, increasing a broad set of prevention practices is one of the nine current priorities for the US Department of Health and Human Services in increasing the health of the nation.[2] Additionally, the use of various preventive care services, as opposed to smoking or curative treatment which also have consumption value, is a behavior that is closer to a pure investment in health capital (Kenkel 1994).[3] Thus, determining the nature of the relationship between education and preventive care use is an important part of understanding health investment decisions.

We add to the literature that assesses the effect of education on health by examining whether individuals who attended college in the late 1950s and early 1960s were more likely to receive physical examinations, dental examinations, flu shots, and cholesterol tests in the early 2000s. In addition to extending the literature by examining a broad set of preventive health care choices, this paper also implements several estimators to assess the robustness of the findings and examines competing hypotheses for the links between education and health. Specifically, we utilize data in the Wisconsin Longitudinal Study (WLS), which contains rich information that can be used to examine competing hypotheses such as reverse causality and omitted variables. In particular, this dataset contains extensive information on usually unobserved variables, such as IQ measured at age 18 and basic proxy measures of time preference. To combat issues of reverse causality, we are also able to control for measures of childhood health status. Additionally, since the dataset follows siblings across 50 years, we control for important unobserved family background factors by using sibling fixed effects methods. Finally, as an additional robustness check, we use matching to estimate the impact of college attendance on the demand for preventive services.

Our results suggest that the effect of college attendance on health decisions in old age is large in magnitude and consistent across preventive care choices. We find increases in each of our four measures of preventive care choices (receiving a physical examination, dental examination, flu shot, and cholesterol test) of between five and eight percentage points or approximately ten percent. Further, we investigate the potential mechanisms linking education with later preventive health care choices and find evidence that the effects operate primarily through occupational pathways; specifically we find suggestive evidence that a fraction of the returns to college attendance flow through general measures of occupational prestige. There is also some evidence that individuals who attended college are more likely

[1]Related work by Chou et al. (in press) uses a natural experiment in Taiwan to estimate the causal effects of parental education on children's health. Currie and Moretti (2003) examine the impact of mothers' education on smoking during pregnancy and low birth weight.

[2]http://www.hhs.gov/secretary/priorities/; accessed May 2007.

[3]While some measures of prevention, such as exercising, may have both consumption and investment qualities, the preventive care measures we use in this paper are arguably purely investments.

to receive preventive care due to greater access to health care. In contrast, we find limited evidence that marital status, health insurance, income, or wealth are primary mechanisms. These results suggest increases in college attendance during the past 40 years could have had large positive impacts on health investments and public health.

Background

In Grossman's (1972) model of the demand for health, individuals invest in health capital because health is an important determinant of the amount of time available for market and nonmarket activities and health is valued as a consumption commodity. Cropper (1977) extends this model to incorporate uncertainty; individuals demand preventive care to decrease their probability of illness.[4] Preventive care may also decrease the severity of illness without influencing the probability of illness (Kenkel 1994). Many forms of health investments have consumption as well as investment aspects; however, many types of preventive care use are an input in the production of health capital that is almost entirely driven by investment motives (Kenkel 1994).

In this analysis, we focus on four specific measures of preventive care use: receiving a flu shot, cholesterol screening, physical examination, and dental examination. Flu shots and cholesterol screening are among the top ten priorities for effective clinical preventive services based on preventable burden and cost effectiveness (Maciosek et al. 2006).[5] Each year in the United States, approximately 36,000 people die from the flu and more than 200,000 people are hospitalized due to complications from the flu.[6] The Center for Disease Control and Prevention's Advisory Committee on Immunization Practices recommends that adults aged 50 years and older receive a flu shot (or influenza vaccination) annually to reduce the probability of contracting the flu.[7] The U.S. Preventive Services Task Force strongly recommends routine cholesterol screening for all adults aged 45 years and older to identify increased risk of coronary heart disease (Berg 2001). Routine physical examinations enable physicians to counsel patients about healthy lifestyles and determine whether additional preventive services are appropriate.[8] Routine dental examinations are important for the early detection of oral cancers and periodontal disease and professional cleaning may reduce the probability of periodontal disease.[9]

According to the model of the demand for health (Grossman 1972), an increase in education is expected to increase investment in health. A consistent conclusion in the public health and economics literatures is that education is correlated with the use of preventive health care for adults (e.g., Kenkel 2000). Cutler and Lleras-Muney (2008) estimate that each year of schooling is associated with an increase of 1.7 percentage points in the likelihood of receiving a flu shot. Mullahy (1999) and Xakelis (2005) reach similar conclusions for adults aged 65 years and older. Centers for Disease Control and Prevention (1990) and Sambamoorthi and McAlpine (2003) find that individuals with more schooling are more likely to receive a cholesterol screening. Manski (1998) finds that higher levels of schooling are associated with visiting a dentist. However, these studies focus on establishing correlations between schooling and preventive care rather than causality.[10]

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[4]For other extensions to the Grossman model that incorporate uncertainty, see Grossman (2000). For additional literature that distinguishes preventive from curative care, see Kenkel (2000). See also the seminal work by Ehrlich and Becker (1972), who termed a broad class of preventive care and actions as self-protection.

[5]Other preventive services included childhood immunization, daily aspirin use, and screens and counseling for tobacco use.

[6]See http://www.cdc.gov/flu/about/disease/index.htm, accessed March 26, 2008.

[7]See http://www.cdc.gov/flu/protect/keyfacts.htm, accessed on March 25, 2008.

[8]We do not analyze whether individuals received a blood pressure screening because nearly all sample respondents in the WLS report receiving a blood pressure test in the past 12 months.

[9]See http://www.ahrq.gov/ppip/50plus/checkups.htm#dental and http://www.cdc.gov/nohss/guideDV.htm, accessed on March 26, 2008.

There are a variety of explanations for the correlation between education and preventive care use, which represent both causal and non-causal mechanisms.[11] Education and preventive care use may be correlated because poor childhood health reduces educational attainment and leads individuals to reduce their adult health investments. For example, Case, Fertig, and Paxson (2005) show that children who are sick or malnourished are more likely to miss additional days of school, have lower school performance, and complete fewer years of schooling. As suggested by Ehrlich and Chuma (1990), individual's initial stock of health, or childhood health, influences later health investments. Thus, individuals who were in poor health in childhood may also be less likely to use preventive health care.

Alternatively, there are potentially omitted factors that jointly affect educational outcomes and preventive care use. In a seminal paper by Fuchs (1982), variation in individuals' discount rates was hypothesized to account for part of the correlations found between education and health outcomes. Unmeasured ability differences across individuals could also determine both years of completed schooling and health outcomes. Commonly unobserved family or environmental factors could also jointly affect health and education outcomes, including family resources and neighborhood disadvantage.[12] Importantly, each of these competing hypotheses can be tested in our data, which allows increased confidence that our results represent causal effects of education on preventive health care choices in old age and directs our attention to examining potential mechanisms for the relationships we uncover.

There are a variety of mechanisms through which education may affect the use of preventive health care. One primary pathway is through occupational choice. Individuals with higher levels of education are more likely to be able to choose occupations that confer higher social prestige and monetary rewards (Card 1999). Over time, these advantages in prestige and income may accumulate, and individuals in higher paying occupations may be more likely to utilize preventive care because of higher costs associated with illness (Mullahy 1999). In support of this potential mechanism, income, wealth, and employment characteristics such as job control have been shown to be related to later health choices (Smith 1999). These occupations are also more likely to offer health insurance coverage and easier access to a regular source of medical care, which increases preventive care through reductions in costs to the consumer (DeVoe et al. 2003; Powell-Griner, Bolen, and Bland 1999). Alternatively, higher wages may lead individuals to under-consume some health inputs, such as preventive care, due to their higher time costs of investing (Ehrlich and Yin 2006). Importantly, our data include measures of income, wealth, health insurance coverage, access to care, firm size, job tenure, and an overall measure of occupational characteristics (prestige) that allow us to begin to examine these potential channels.

Another potential mechanism is that education increases allocative efficiency and improves the choices of health inputs (Kenkel 1991; 1994). This could occur if more educated individuals are better informed or are more able to process available information about preventive medical care. For example, Scott (2002) finds that individuals with low levels of health literacy are less likely to receive a flu shot or utilize other forms of preventive care. We examine this potential mechanism by using data on cognition tests in later life, which

[10]For example, Mullahy (1999) focuses on the impact of labor market behavior and perceived risks of infection on receiving a flu shot and does not attempt to determine whether the estimated correlation between schooling and receiving a flu shot represents a causal relationship.

[11]For a more general discussion about the mechanisms between education and health, broadly construed, see Cutler and Lleras-Muney (2008) and Grossman and Kaestner (1997).

[12]For example, Case, Fertig, and Paxson (2005) provide evidence that maternal education is associated with an individual's self reported health status at age 42. Additionally, Wolfe and Behrman (1987) find no education effect on a health outcome after controlling for family factors

allows us to examine whether educated individuals are more able to process available information but likely does not capture whether individuals are better informed.[13], [14]

An additional mechanism is that education may influence health status broadly (Cutler and Lleras-Muney 2008). Individuals in worse health may be more likely to seek a flu shot because the consequences of influenza are more severe for less healthy individuals (Mullahy 1999). Finally, education could improve the efficiency of an individual's health production function (Grossman 1972). This change in efficiency would lower the costs of health capital (relative to consumption). If the price elasticity of demand for health capital was greater than one, the individual would demand more health capital and health inputs (such as preventive care) (Kenkel 1994).[15]

Data

In this study, we use data from the Wisconsin Longitudinal Study (WLS) to examine the impact of college attendance on preventive health care use. The WLS is a longitudinal study of a one-third random sample of the graduating high school class of 1957 in Wisconsin.[16] Survey information from 10,317 of the graduates was collected in 1957, 1964, 1975, 1992–1993, and 2003–2004. The WLS sample also includes information from a randomly selected sibling that was collected in 1977, 1993–1994, and 2005–2007. The WLS includes extensive information about schooling, social background, labor market experiences, and health.[17] The sample is roughly representative of white, non-Hispanic American men and women who have completed at least a high school education.[18] Along several measures, Wisconsin is an "average" or "typical" state. For example, the proportion of individuals aged 60–70 who reported receiving a physical exam in the previous 12 months in the 2006 Behavioral Risk Factor Surveillance System (BRFSS) data was 80%, which was not statistically different for individuals living in Wisconsin versus other states. Likewise, we find no statistical difference in the likelihood of receiving a flu shot (53%) for residents of Wisconsin compared to residents of other states. We also find that the rate of college attendance in Wisconsin for these cohorts is only slightly lower than the national average using the BRFSS data (50% vs. 54%, p-value < 0.05).[19]

Important features of the WLS for this study are the longitudinal nature of the data set that combines information about the preventive health care choices of elderly individuals with information about the family economic characteristics prior to college attendance. Whether an individual has received a flu shot, cholesterol test, physical exam, and dental exam are available in the most recent survey wave for the original WLS respondents and their siblings. [20]

[13]We also examine whether marital status is a potential mechanism linking education with preventive care choices. While this mechanism could suggest one channel through which information could be provided, we find little evidence for our measures of marital status, including spouse's education level.

[14]Additional specifications that control for previous self-reported health status, measured in the early 1990s, do not influence our results for any of the preventive care measures (see Table 6).

[15]We are not able to directly test this potential mechanism.

[16]Cameron and Heckman (1998) present evidence that a focus on high school graduates will likely bias downward the effects of early life conditions. The reader should view the results with this caveat in mind.

[17]Full information can be found online: http://www.ssc.wisc.edu/wlsresearch/

[18]As noted in the WLS Handbook (2007, p.14), "among Americans aged 50 to 54 in 1990 and 1991, approximately 66 percent were non-Hispanic white persons who completed at least 12 years of schooling. Some strata of American society are not well represented. The WLS sample is mainly of German, English, Irish, Scandinavian, Polish, or Czech ancestry. It is estimated that about 75 percent of Wisconsin youth graduated from high school in the late 1950s – everyone in the primary WLS sample graduated from high school; about seven percent of their siblings did not graduate from high school. Minorities are not well-represented: there are only a handful of African American, Hispanic, or Asian persons in the sample. … About 19 percent of the WLS sample is of farm origin, and that is consistent with national estimates of persons of farm origin in cohorts born in the late 1930s. … In 1964, 1975, and again in 1992, about two-thirds of the sample lived in Wisconsin, and about one-third lived elsewhere in the U.S. or abroad."

[19]Source: Authors' calculations using BRFSS data.

While the WLS contains information on 10,317 original respondents and their siblings, we must constrain our analysis sample in order to take advantage of the use of sibling fixed effects.[21] In 2004, 7,732 original respondents completed the survey for a response rate of 75 percent; however, only 6,845 respondents or 66 percent of the original respondents completed the mail questionnaire that included the preventive care questions.[22] Of the 7,928 siblings of the original respondents, 4,004 or 51% completed the mail questionnaire in 2005.[23] We drop individuals without any health outcome information or schooling information, leaving a sample of 10,037 observations that includes 6,419 original respondents, but this sample size varies with the health outcome.[24] We then limit our sample to respondents with a sibling in the sample. Our analysis sample consists of 2,789 original respondents and their 2,789 siblings for a total of 5,578 observations. In order to maximize our sample size, we impute missing values of the family background variables and include missing-value indicator variables in our specifications.[25]

We present means and standard deviations of the full sample of 10,037 individuals with non-missing preventive care and education data and our analysis sample of 5,578 individuals in Table 1. This table provides evidence that our analysis sample is quite similar to the dropped sample of individuals. Fifty three percent of individuals in the analysis sample attended college. Fifty seven percent of these individuals received a flu shot and between 77 and 80 percent received a physical exam, dental exam, and cholesterol test in the last 12 months.

Methods

In this paper, we use a variety of empirical strategies to extend the scope of previous examinations of the causal impact of education on health choices, focusing on whether education increases individuals' use of preventive health care. First, we examine the

[20]The specific wordings for the preventive care questions are: "In the last 12 months, have you had a complete health exam or physical?", "In the last 12 months, have you had a routine dental check-up?", "In the last 12 months, have you had a flu shot?", and "In the last 12 months, have you had a cholesterol test?". Similar questions are asked in the National Health Interview Survey (NHIS) and BRFSS, and the NHIS includes a physical examination as routine or preventive care. These variables may be subject to measurement error due to the one year recall period; however, this would increase the standard errors without affecting the consistency of the estimates if recall bias is random.

[21]Importantly, we include results in the appendix that show that our baseline results are similar for the full sample and the analysis sample of sibling pairs. We define the full sample as the 10,037 individuals with information about college attendance and at least one measure of preventive care use.

[22]Among the 3,472 respondents who did not complete the mail questionnaire in 2004, 1,288 were deceased, 785 were not able to be contacted, and 1,399 refused to complete the questionnaire (WLS 2009).

[23]Among the 3,924 respondents who did not complete the mail questionnaire in 2004, 1,226 were deceased, 1,365 were not able to be contacted, and 1,333 refused to complete the questionnaire (WLS 2009). For comparison, the response rate of survey respondents in the 1988 wave of the Panel Study of Income Dynamics who lived in the original 1968 households is 56.1 percent (PSID User Guide, available at http://psidonline.isr.umich.edu/Guide/ug/chap5.html).

[24]College attendance and years of schooling completed are gathered from the 1992–1993 and 1993–1994 survey years. After removing observations with missing data for preventive health care use, 601 observations are removed due to missing schooling data. Comparing the individual and family characteristics of the original WLS respondents to those individuals remaining in our sample after this restriction suggests that the WLS respondents in our sample are similar to those excluded from the analysis sample in many ways, but that there are a few exceptions. In particular, the respondents in our sample are 6.9 percentage points more likely to be female, 1.8 percentage points more likely to have lived with both parents in high school, and have an IQ 3.6 points higher, on average, than the original WLS respondents excluded from our sample. Regressions of whether the survey respondent is dropped from the sample on pre-college attendance individual and family characteristics suggest that gender and IQ are related to whether the original WLS respondent remains in our sample. In our estimates, IQ is not predictive of preventive care use. Further, although gender is predictive of preventive care use, interaction terms between gender and college attendance are never statistically significant in OLS and fixed effects specifications.

[25]We impute missing values using linear regression based on the full sample of 10,037 observations that includes individuals without siblings in the sample. We impute mother's education for 78 observations, father's education for 228 observations, family income for 452 observations, the number of siblings for 13 observations, age for 623 observations, birth order for 15 observations, living with both parents for 399 observations, poor childhood health for 32 observations, missed school for one month for 137 observations, and IQ for 581 observations. We also assign siblings with missing values the value of the non-missing sibling for living with both parents and assign sibling pairs with missing values the imputed value of the graduate for mother's education, father's education, and family income; these missing values will difference out in the fixed effects model. Our results are robust to using mean imputation and adding dummy variables to denote that the value is missing, as opposed to regression-based imputation.

determinants of the use of preventive care using regression analysis. We estimate the use of preventive care, P_i, as a function of an individual's educational level, E_i, individual and family characteristics, X_i, and an idiosyncratic shock, ε_i:

$$P_i=\alpha_0+\alpha_1 E_i+\alpha_2 X_i+\varepsilon_i. \quad (1)$$

Individual and family characteristics included in X are mother's education, father's education, family income during high school, number of siblings, sex, age, birth order, whether the individual lived with both parents during high school, and a dummy variable indicating whether the individual is in the graduate sample (vs. the sibling sample).[26] Including a wide array of family background characteristics measured prior to college attendance is important due to the influence of family background on education and health outcomes (Case et al. 2005; Wolfe and Behrman 1987).

Next, to explore the possibility that the observed correlation that exists between education and the use of preventive care services is the result of reverse causality from health to education, we include measures of childhood health (whether at least one month of school was missed due to illness and an indicator variable for poor or fair self-reported health in childhood).[27] We thus augment the above equation to include past health, $H_{i,t-1}$:

$$P_{i,t}=\beta_0+\beta_1 H_{i,t-1}+\beta_2 E_i+\beta_3 X_i+\varepsilon_i. \quad (2)$$

To explore the possibility that third factors lead to a spurious correlation between education and preventive care use, we augment the previous demand equation with additional characteristics that may jointly influence both education and preventive care use. We include the Henmon-Nelson measure of IQ as a proxy for innate ability.[28] We also include measures of whether the individual planned to attend college when they were 16 years old and whether the student discussed future plans with teachers, counselors, and parents as measures of the discount rate prior to college attendance.

Next, we use a family fixed effects estimator that compares the preventive care use of siblings with differing levels of education. To implement this strategy, we compare the use of preventive services of WLS graduates in 2003–4 to their siblings' use of preventive services using the 2005–6 data by adding a family fixed effect, μ_f, to the previous equation:

$$P_{i,f,t}=\delta_0+\delta_1 H_{i,f,t-1}+\delta_2 E_{i,f}+\delta_3 X_{i,f}+\mu_f+\varepsilon_{i,f}. \quad (3)$$

By controlling for a wide array of exogenous individual characteristics that influence educational attainment and might differ between siblings, in addition to any fixed family characteristics that determine educational attainment, we hope to identify the nature of the relationship between education and the use of preventive services.[29]

[26]Family income is collected from the public records of the Wisconsin Tax Department data (WLS Handbook 2007). Family income during 1957 through 1960 is averaged by the WLS to reduce measurement error and create a variable closer to the permanent income of the family during the high school years. Family income is converted to 2004 dollars using the Consumer Price Index for all urban consumers. The other family and individual variables are derived from the survey responses in 1957.

[27]These measures of childhood health are derived from questions asked of respondents in the latest survey wave, which introduces the possibility of substantial recall error. On the other hand, significant events, such as illness for at least one month, are less likely to be subject to recall error.

[28]This variable is based on tests of mental ability conducted for all high school students in the state by the Wisconsin State Testing Service in 9th and 11th grade (Hauser 2005). We use the recommended measure constructed by the WLS that consists of the 11th grade score and a transformation of the 9th grade score if the 11th grade score is missing.

This estimate is derived by comparing sibling pairs that consisted of one sibling who attended college and one sibling who did not. The identifying assumption is that the underlying reasons why one sibling attended college and the other did not are (conditionally) uncorrelated with later preventive care use. In Table 2 we provide descriptive statistics for the siblings who are discordant, as well as comparisons with concordant sibling pairs. This table shows that sibling pairs in which neither sibling attended college are less advantaged along many characteristics than discordant siblings and sibling pairs who both attended college. Within the discordant siblings, the sibling who attended college is more likely to be male, have a higher IQ, but is also slightly more likely to be in poor health as a child. What is essential for our identification strategy is that we capture important differences between siblings in our measurable characteristics. Our results below suggest that there would need to be a critical measure of individual heterogeneity between siblings that is both correlated with college attendance and later health that explains more of the variance in preventive care use than our measured characteristics, such IQ, time preferences, childhood health, to eliminate the estimated impact of college attendance on preventive care use.

In addition to unmeasured between-sibling heterogeneity, another concern about our strategy is that unobserved parental investments that differ among siblings influence both college attendance and preventive care use. To examine this possibility, we examine additional specifications that include the interaction of two proxy variable for parental investments – birth order and living with both parents during high school – and college attendance. We focus on birth order and whether these individuals lived with both parents because these variables are related to the amount of time that parents spend with their children, which is an important measure of parental investment (Price 2008). Our results are robust to these additional specifications for all measures of preventive care use and no interaction term is ever significant, which minimizes the potential that unobserved parental investments are influencing the estimates of the impact of college attendance.

Finally, as an additional robustness check we use matching estimation methods to estimate the impact of college attendance on the use of preventive services, which relax the parametric assumption of linearity embedded in the previous specifications and relaxes the need for control variables to be exogenous as long as they are balanced between "treatment groups" (e.g., Black and Smith 2004). Specifically, we use the bias-corrected nearest neighbor matching estimator described in Abadie and Imbens (2002) as well as several alternative propensity-score matching estimators, such as stratification, nearest neighbor, and kernel matching.[30] These techniques compare the preventive care use of individuals with similar observable characteristics, but whose college attendance choices differed. If individuals choose whether to attend college based on the extensive list of observable

[29] A limitation of the fixed effects strategy is the exaggeration of the influence of measurement error, which could bias the estimate of δ_2 towards zero. Additionally, while the fixed effects strategy is implemented to reduce endogenous variation in college attendance, exogenous variation may also be reduced (Bound and Solon 1999). Further, moving from equation (2) to equation (3) limits the source of variation that identifies the coefficient for college attendance to the 1870 siblings who are discordant in their college attendance choice provide identifying variation—sibling pairs who both attend college or neither attend college no longer help identify the coefficient. We do find evidence that limiting the sample to include only siblings who were discordant in their college attendance slightly increases the point estimates. Results from additional specifications that limit the sample to include only discordant sibling pairs and do not include fixed effects suggest that the increase shown in Table 4 from the fixed effects specification is driven by the change in the composition of the sample; although, these additional estimates are never statistically different from the OLS results in columns (2) and (5) of Tables 3 and 4 at the five percent level of significance and are only statistically significant at the ten percent level for receiving a physical exam and a dental exam. Additionally, these results from the discordant pairs' sample show that the use of fixed effects, per se, only leads to a small change in our estimates. This finding further demonstrates the robustness of the OLS results.

[30] We estimate these matching estimators for the full sample of observations, including individuals without a sibling in the sample, in the common support and the trimmed sample of observations with propensity scores in the range of [0.1, 0.9], which is the optimal subsample for estimating the average treatment effect on the treated under a wide range of distributions (Crump et al. 2006).

characteristics that we can match on in the WLS, then matching estimates the causal effect of college attendance on preventive care use.

Results

We present results for several preventive care choices that are suggested for near-elderly males and females, including physical examinations, dental examinations, flu shots, and cholesterol tests. All estimates are from linear probability models and the standard errors are clustered to allow for arbitrary correlation within families and for heteroskedasticity.[31]

While we focus on the effects of attending college on these preventive care choices, results for years of schooling are qualitatively similar and available from the authors. Briefly, our sibling fixed effects results for years of schooling are robust and our OLS results for years of schooling are qualitatively similar but less precisely estimated. For example, our sibling fixed effects results suggest that an additional year of schooling increases the probability of receiving a physical exam by 1.1 percentage points, a dental exam by 1.3 percentage points, a flu shot by 1.7 percentage points, and a cholesterol test by 0.8 percentage points.[32] One potential explanation for the lower estimates in examining years of schooling versus college attendance is that individuals who attended college, who differ in both education and accumulated wealth, have a greater and non-linear incentive to pursue self-protective measures than individuals with less than college attainments (see Ehrlich 2000 and Ehrlich and Yin 2006 for further discussion and evidence). On the other hand, the time costs associated with seeking preventive care may favor the less educated (Ehrlich and Yin 2006).

Results that examine the associations between college attendance and receiving a physical examination are shown in Table 3. Column 1 presents results from estimating equation (1), which controls for pre-determined individual and family characteristics. The results suggest that attending college is associated with a 3.1 percentage point increase in receiving a physical examination.[33] Females are found to be more likely to receive a physical exam (by nearly 5 percentage points), as are older individuals. No family background characteristics are statistically significant. In column 2, we add measures of usually unobserved heterogeneity that alternative hypotheses predict will lead to both higher educational attainment and better health care decisions. IQ measured at age 18 is not predictive of receiving a physical examination in old age. Individuals with poor self-rated childhood health are 7 percentage points less likely to receive a physical examination. However, the association between college attendance and physical examination receipt is not influenced by the addition of these control variables. Including variables that measure individuals' plans for the future also does not influence the relationship between college education and receiving a physical examination.[34] Column 3 estimates a family fixed effects specification and finds evidence that college attendance increases physical examination receipt (controlling for all common family factors) by 6.1 percentage points.

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[31]Similar estimates are obtained from a logit model and Chamberlain's conditional logit model.

[32]Our results for years of schooling are similar to the results reported by Cutler and Lleras-Muney (2007, 2008) and Mullahy (1999) for receiving a flu shot.

[33]These results are based on the sample of individuals with a sibling; the p-value from a Wald test for the null hypothesis that the college attendance estimate from the analysis sample is equivalent to the estimate from the full sample is 0.76.

[34]These results are shown in Appendix Table 2. There are two variables that we include to proxy for an individual's discount rate prior to college attendance. The first variable measures whether the individual planned to attend college when they were 16 years old. The survey question was asked of graduates in 1975 and of siblings in 1977. The second variable is the sum of the individual's response about the extent to which they discussed future plans with teachers, counselors, and parents. This survey question was asked in 1957 of graduates only. Individuals who discussed future plans with teachers, counselors, and parents were more likely to receive a physical examination; however, including this measure of an individual's discount rate does not influence the estimated relationship between college attendance and receiving a physical exam. The results are similar for the three other measures of preventive care use, as shown in Appendix Tables 3 through 5.

Results examining the link between college attendance and dental examination receipt are presented in columns 4 through 6 of Table 3 and largely follow the results for physical examinations. Like previous results, females are nearly 5 percentage points more likely to receive a dental examination than males. Individuals with higher IQs at age 18 are also more likely to receive a dental examination in old age. The results show that individuals who attended college are between 6.3 and 10.7 percentage points more likely to receive a dental examination.

In Table 4, we examine the association between receipt of a flu shot in old age and college attendance. Our results are structured much like the results for physical examinations. In columns 1 through 3 of Table 4, our results show that college attendance is robustly linked to receiving a flu shot in old age; the association for the sibling sample remains between 5.9 and 7.5 percentage points across the specifications. Controlling for several usually omitted variables, such as IQ, early child health status, and later health status all seem to slightly strengthen the association we find.

Finally, columns 4 through 6 of Table 4 present our results examining the relationship between college attendance and receiving a cholesterol examination in old age. We find that individuals who attend college are approximately 2 to 5 percentage points more likely to receive a cholesterol examination.

The results in Table 5 are based on various matching estimators. The top panel includes all individuals in the full sample, including individuals without siblings, in the common support. The bottom panel is the subsample of individuals with propensity scores in the range of [0.1, 0.9]. In general, the results in Table 5 are consistent across the different matching estimators and are similar to the results shown in the previous tables. Attending college is estimated to increase the likelihood of receiving a physical exam by approximately five percentage points, a dental exam by approximately eight percentage points, a flu shot by approximately five percentage points, and a cholesterol test by approximately three percentage points.

Inspecting the Mechanisms

In this section, we examine several potential mechanisms that could link educational attainment during young adulthood with preventive health care choices in old age. We focus on several alterative hypotheses for which we have information in the data, including (1) links between education, occupation, and preventive care, (2) long term links between education, cognition, and preventive care, (3) links between education, adult health status, and preventive care, and (4) links between education, marital status, and preventive care. For our hypothesis that occupation may link education and preventive care, we are also able to broadly distinguish between several potential mechanisms tied with occupation, including prestige, income, assets, health insurance, and access to health care. While our data contain information related to several potential mechanisms linking education to preventive care, we are not able to fully capture all potential pathways. [35] A few pathways of note that should be the subject of future research include social relations/networks, proximity to family, and retirement/employment dynamics. Our results must be viewed within the limitations of the measures available in our data.

[35]The WLS contains information about cognitive ability, but not knowledge specifically related to health. Kenkel (1991) finds that differences in health knowledge can explain some, but not most, of the relationship between education and smoking, drinking, and exercise. Additionally, Cutler and Lleras-Muney (2008) find that health knowledge explains about 10 percent of the relationship between years of schooling and health behaviors.

Our basic strategy for inspecting potential mechanisms is to examine the change in our previous results in our preferred sibling fixed effects empirical models after controlling for our outlined mechanisms.[36] We generally add our mechanism controls in chronological order. [37] Table 6 presents the estimate of the influence of college attendance on the use of each preventive care measure and documents the change in the estimate as additional variables are added.[38] The first row of Table 6 replicates the fixed effects results shown in Tables 2 and 3. The second row displays the results from fixed effects specifications that also include the Nakao-Treas occupational prestige rating from the individual's current or last occupation.[39] The third row adds a set of indicator variables denoting the type, if any, of health insurance in 1992–4 to the above specification. The fourth row adds three measures of access to health care: whether the individual has had any difficulty obtaining access to care, whether the individual has a usual source of health care, and a scale of access to health care satisfaction.[40] The fifth row adds marital status. The sixth row adds total household income. The seventh row adds total assets. The eighth row adds a cognition score.[41] The ninth row adds an individual's self-reported health status from the prior survey wave. Because the order in which these additional variables are entered in the equation could influence the estimates, we present results that highlight each potential mechanism individually. The tenth row includes variables from the baseline fixed effects specification and health insurance type in 1992–4. Similarly, the eleventh through sixteenth rows includes variables from the baseline specification and separately add the access to care variables, total household income, marital status, total assets, cognition, and self-reported health status from the prior survey wave.

Broadly, we interpret the results to suggest that the most important mechanism linking education with preventive care choices in old age is occupational prestige, and we find modest links with access to care and very small changes after controlling for health insurance, income, assets, or cognition at midlife. Our measure of occupational prestige generally reduces the total effect of education on the health choices by 10 to 20 percent. Controlling for access to care reduces the impact of college attendance by 5 to 15 percent.[42]

There are a variety of reasons why a broad measure of occupational prestige might be a mechanism through which college attendance influence preventive care use. More prestigious occupations may provide employees with health insurance benefits or more generous health insurance plans. We do not find that controlling for health insurance influences the impact of education, but we are not able to measure the benefits of the employer-provided health insurance options. We use firm size as a crude proxy for the generosity of health insurance options and find that firm size has little impact on the

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[36]Our results are quite similar if we do not include sibling fixed effects and are available upon request.

[37]Cutler and Lleras-Muney (2007, 2008) use a similar strategy to examine the relationship between years of schooling and health behaviors.

[38]The full results for each specification are available upon request from the authors.

[39]The Nakao-Treas prestige rating is the percentage of respondents in the 1989 General Social Survey who ranked an occupation in the top half of a nine point scale of the prestige of the occupation. Thus, this measure is a proxy for respondents' views of the social standing of occupations. We standardized this rating to have a mean of zero and a standard deviation of one to ease the interpretation of the coefficient. The reader should view the results with the caveat that this proxy is imperfect and potentially measured with error.

[40]The access to health care satisfaction is a scale running from 1 (poor) to 5 (excellent) that is the average response from questions that ask: "Thinking about your own health care, how would you rate the convenience of location of the doctor's office? The hours when the doctor's office is open? Your access to specialty care if you need it? Your access to hospital care if you needed it? Your access to medical care in an emergency? Arrangements for making appointments for medical care by phone? The length of time spent waiting at the office to see the doctor? The length of time you wait between making and appointment for routine care and the day of your visit? The availability of medical information or advice by phone? Your access to medical care whenever you need it? The services available for getting prescriptions filled?"

[41]The measure of cognition is derived from six items from the Weschler Adult Intelligence Scale.

[42]Ayyagari and Sloan (2009) link education with measures of self-rated health for diabetics in the HRS data and attempt to examine potential pathways. Using a different set of potential mechanisms (self-control, social support, etc), they also are unable to fully explain the pathways.

relationship between education and preventive care choices. More prestigious occupations may provide employees with higher income and assets; however, we find little influence of income and assets on the impact of college attendance. Additionally, more prestigious occupations may have lower turnover and high employee turnover may lead to underinvestment in health by companies that are unlikely to receive as large of a return from their investment if the employee leaves the firm (Fang and Gavazza 2007). To explore this possibility we control for job tenure but find little impact on the relationship between education and preventive care use; however, we do not have information about industry or occupation-specific measures of turnover. Other reasons why occupational prestige might be an influential mechanism are that more prestigious occupations may have more job control, which would allow individuals greater flexibility in their work schedule to be able to seek preventive care, and that more prestigious occupations may have non-monetary rewards, which leads to greater invest to reduce the non-monetary costs of illness. Unfortunately, data limitations prohibit definitive conclusions about exactly why occupational prestige is a mechanism through which college attendance influences preventive care use.

Although we find that health insurance is predictive of preventive health care choices, health insurance does not influence the relationship between college attendance and preventive care use. Measuring health insurance with an insurance summary variable denoting whether the individual had any type of insurance in 1992–4 or in 2003–7 does not influence the college attendance results. However, an important caveat to these results is that health insurance coverage is nearly universal for this sample. Thus, we also examine categories of health insurance: employer-provided, privately-purchased, other insurance, and no insurance. Controlling for the types of health insurance, as shown in Table 6, has little impact on the influence of college attendance.

We use health insurance information from 1992–4 as a measure of health insurance status prior to Medicare because the original respondents of the WLS are between the ages of 63 and 67 when preventive care use is measured. As noted by Card, Dobkin, and Maestas (2004), Medicare eligibility could change individuals' incentives to utilize preventive health care, where individuals without health insurance prior to age 65 or individuals with less generous insurance than Medicare postpone preventive health care use until they become Medicare eligible. Because health insurance is correlated with education, the incentives associated with Medicare eligibility may differ for individuals who attended college and individuals who did not. Although Card, Dobkin, and Maestas (2004 Although Card, Dobkin, and Maestas (2008) conclude that individuals do not delay medical procedures or preventive care in anticipation of Medicare eligibility[43], we further investigate the potential influence of Medicare eligibility on the influence of college attendance on preventive care use in Appendix Table A6. In particular, we find that controlling for health insurance information in 2003–7, Medicare eligibility, or employment/retirement status has little influence on the impact of college attendance.[44]

[43]For example, Card, Dobkin, and Maestas (2004) note that a potential threat to the validity of their regression discontinuity design, which is based on the age 65 eligibility threshold, is that individuals may "delay certain medical procedures until after age 65 in anticipation of Medicare coverage," but they find "no evidence of anticipatory behavior" (Card, Dobkin, and Maestas 2004, page 6).

[44]Employment/retirement status may influence the impact of college attendance on preventive care use because employment is correlated with health insurance status. Additionally, retired individuals have more time available to seek preventive care, but also have lower costs of foregone wages associated with becoming ill from not receiving preventive care (Mullahy 1999). Further, if less educated individuals with less desirable occupational characteristics retire at an earlier age, then these individuals may delay preventive care until becoming eligible for Medicare. However, we do not find that employment/retirement status at the time of preventive care use has an influence on the estimated impact of college attendance. We also do not find that high school graduates are less likely to be employed in 2004 than college attendees.

Conclusion

In this paper, we use a rich dataset of individuals and their siblings who have been followed over fifty years to assess the potential effects of college attendance on preventive care choices in old age. We focus on college attendance because there have been multiple policies over the last several decades that have attempted to improve rates of college attendance and college attendance continues to be an important policy area. Previous policies have been justified both by appealing to the need to enhance the stock of the nation's human capital as well as the many potential non-market benefits of increasing schooling (Haveman and Wolfe 1984), including health benefits. Specifically, Cutler and Lleras-Muney (2008) suggest that there may be substantial health returns to education policies that promote college attendance because increasing levels of education may lead to different thinking and decision-making patterns in health-related choices. They also suggest that the monetary value of the rate of return to education in terms of health may be as high as half the return to education on earnings. In this paper, we examine this conjecture that there are important spillover effects of increasing education in the context of increasing one domain of health—preventive health care choices.

Broadly, our results suggest that increases in college attendance in the late 1950s/early 1960s led to large increases in preventive health care use such as the receipt of flu shots, physical examinations, dental examinations, and cholesterol tests. We provide evidence against standard alternative hypotheses such as reverse causality and several types of omitted variables, including differences in ability, differences in time preferences, or unobserved family-level factors. Other factors, such as determinants of preventive care by gender as well as an examination of the links between education and health care choices for gender-specific preventive care is left for future research.

We also extend the literature by examining the potential mechanisms linking college attendance with preventive care choices at old age, particularly focusing on occupation-related factors and cognition. Our results suggest that measures of occupational prestige and access to care may link college attendance to preventive care choices and that health insurance, income, assets, marital status, several job characteristics, and cognition likely play a limited role. Some limitations of our data include the low proportions of non-white individuals and high school drop-outs, attrition from the sample, measurement error in the data, and the focus on a cohort from one state. Our methods are also unable to control for all potential sources of individual heterogeneity. However, the results are quite robust across a number of specifications and inclusion of a variety of controls, and overall suggest important health benefits to college attendance for this cohort of individuals who have been followed for over a half a century.

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Table 1

Summary Statistics of Full and Sibling Samples

	Full Sample		**Sibling Sample**	
	Mean	**Std. Deviation**	**Mean**	**Std. Deviation**
Flu shot in 2004	0.581	0.493	0.569	0.495
Physical exam in last 12 months in 2004	0.763	0.425	0.768	0.422
Dental exam in last 12 months in 2004	0.786	0.410	0.795	0.403
Cholesterol test in last 12 months in 2004	0.781	0.414	0.784	0.411
Years of schooling completed	13.705	2.384	13.822	2.442
Ever attended college	0.498	0.500	0.525	0.499
Mother’s years of schooling in 1957	10.532	2.795	10.601	2.750
Father’s years of schooling in 1957	9.802	3.413	9.881	3.450
Family income during high school ($10,000s)	3.979	2.140	4.023	2.172
Number of siblings	3.280	2.488	3.352	2.393
Female	0.542	0.498	0.536	0.499
Age in 2004	64.260	4.074	64.197	4.802
Birth order	2.544	1.830	2.541	1.732
Lived with both parents in high school	0.916	0.278	0.931	0.254
Graduate from Class of 1957	0.640	0.480	0.500	0.500
Self-reported health is poor or fair in childhood	0.037	0.189	0.038	0.190
Missed school for >= 1 month b/c of health as child	0.082	0.272	0.084	0.276
IQ score during high school	102.602	14.532	103.432	14.457
Planned to attend college at age 16	0.435	0.496	0.447	0.497
Employer prestige for last or current job in 2004	0.000	1.000	0.037	1.023
Covered by any type of health insurance in 1992–4	0.972	0.166	0.977	0.150
Employer Provided Health Insurance (1992–4)	0.887	0.317	0.888	0.315
Privately Purchased Health Insurance (1992–4)	0.067	0.251	0.072	0.259
Other Health Insurance, including Medicaid (1992–4)	0.017	0.130	0.016	0.127
Covered by any type of health insurance in 2004	0.973	0.162	0.976	0.153
Employer Provided Health Insurance (2004)	0.467	0.499	0.486	0.500
Medicare (2004)	0.397	0.489	0.390	0.488
Privately Purchased Health Insurance (2004)	0.061	0.240	0.060	0.238
Other Health Insurance, including Medicaid (2004)	0.016	0.126	0.014	0.119
Difficulty obtaining health care in 2004	0.089	0.285	0.090	0.286
Access to health care satisfaction in 2004	3.650	0.671	3.655	0.669
Usual source of care in 2004	0.957	0.195	0.959	0.191
Total household income in 2004 ($10,000s)	6.520	7.683	6.752	7.791
Total household assets in 2004 ($100,000s)	5.920	10.732	6.161	10.828
Cognition score in 2004	6.658	2.223	6.733	2.241
Sample Size	10037		5578	

Notes: The sample sizes are for the sample of individuals with at least one non-missing measure of preventive health care. The sample size for the full sample for flu shot is 10,001, for physical exam is 10,002, for dental exam is 10,006, and for cholesterol test is 9,994. The sample size for the sibling sample for flu shot is 5,578, for physical exam is 5,556, for dental exam is 5,564, and for cholesterol test is 5,556. All dollar values are converted to 2004 dollars using the Consumer Price Index for All Urban Consumers.

Source: Wisconsin Longitudinal Study.

Table 2

Descriptive Statistics Stratified by Sibling Pair-Type

Sibling Pair Type:	Both No College		No College/Discordant		Discordant		College/Discordant		Both College	
	N=1716		N=935		N=1870		N=935		N=1992	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Maternal Education	9.50	2.38			10.43	2.64			11.71	2.73
Paternal Education	8.43	2.62			9.41	2.98			11.58	3.76
Family Income	3.05	1.72			3.60	1.96			4.85	2.67
Number Sibs	4.00	2.70			3.36	2.33			2.79	2.00
Female	0.59	0.49	0.60	0.49	0.53	0.50	0.47	0.50	0.49	0.50
Age	64.79	4.85	64.53	4.70	64.06	4.93	63.59	5.10	63.81	4.59
Birth Order	2.85	1.97	2.41	1.58	2.56	1.72	2.70	1.83	2.26	1.46
Both Parents	0.92	0.27	0.93	0.25	0.93	0.26	0.93	0.26	0.94	0.24
Poor Child Health	0.04	0.19	0.03	0.18	0.04	0.20	0.05	0.21	0.04	0.19
Miss School	0.08	0.27	0.08	0.27	0.08	0.27	0.09	0.28	0.09	0.28
IQ	96.49	12.98	99.58	13.30	102.69	13.76	105.81	13.51	109.97	13.36
Plan College	0.16	0.37	0.23	0.42	0.39	0.49	0.54	0.50	0.75	0.43

Notes: The descriptive statistics are based on the following samples for each column. Column 1/2: neither sibling attended college, 3/4: sibling who did not attend college in a discordant pair, 5/6: discordant siblings combined, 7/8: sibling who did attend college in a discordant pair, 9/10: both siblings attend college.

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Table 3

Estimates of the Impact of College Attendance on Receiving a Physical and Dental Exam

Outcome	Physical Exam	Physical Exam	Physical Exam	Dental Exam	Dental Exam	Dental Exam
Sample	**Pair**	**Pair**	**Pair**	**Pair**	**Pair**	**Pair**
Fixed Effects?	**No**	**No**	**Yes**	**No**	**No**	**Yes**
Attended College	0.031** (0.012)	0.033** (0.013)	0.061*** (0.020)	0.107*** (0.012)	0.099*** (0.012)	0.063*** (0.018)
Mother's Education	−0.001 (0.003)	−0.001 (0.003)		0.001 (0.002)	0.001 (0.002)	
Father's Education	0.002 (0.002)	0.002 (0.002)		0.003 (0.002)	0.002 (0.002)	
Family Income	−0.002 (0.002)	−0.002 (0.002)		0.005*** (0.002)	0.005*** (0.002)	
Number of Siblings	0.000 (0.003)	0.001 (0.003)		−0.003 (0.003)	−0.003 (0.003)	
Female	0.047*** (0.012)	0.047*** (0.012)	0.040** (0.016)	0.044*** (0.011)	0.043*** (0.011)	0.048*** (0.015)
Age	0.008*** (0.001)	0.008*** (0.001)	0.004 (0.003)	−0.003** (0.001)	−0.003* (0.001)	−0.005* (0.003)
Birth Order	−0.002 (0.005)	−0.002 (0.005)	−0.015 (0.009)	0.000 (0.005)	0.001 (0.005)	−0.001 (0.010)
Live with Both Parents	0.005 (0.023)	0.005 (0.023)	0.054 (0.044)	0.019 (0.023)	0.017 (0.023)	0.037 (0.043)
WLS graduate	0.021* (0.011)	0.017 (0.012)	0.017 (0.013)	0.025** (0.011)	0.021* (0.011)	0.023* (0.012)
Poor Childhood Health		−0.073** (0.032)	−0.115*** (0.041)		−0.005 (0.028)	0.017 (0.040)
Missed School as Child		0.006 (0.021)	0.017 (0.028)		0.005 (0.020)	−0.013 (0.026)
IQ		−0.000 (0.000)	−0.000 (0.001)		0.001** (0.000)	0.001* (0.001)
Constant	0.208** (0.102)	0.250** (0.114)	0.470** (0.233)	0.809*** (0.098)	0.721*** (0.109)	0.881*** (0.227)
Observations	5556	5556	5556	5564	5564	5564
R-squared	0.02	0.02	0.02	0.04	0.04	0.02
P-value Diff w/Full	0.761			0.934		
P-value Diff w/IQ		0.603			0.028	

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the first column for each outcome for the pairs sample is equal to the coefficient estimate from a similar specification for the full sample. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the first column is equivalent to the estimate reported in the second column for each outcome.

*** p<0.01,

** p<0.05,

* p<0.1.

Table 4

Estimates of the Impact of College Attendance on Receiving a Flu Shot and Cholesterol Test

Outcome	Flu Shot	Flu Shot	Flu Shot	Cholesterol Test	Cholesterol Test	Cholesterol Test
Sample	**Pair**	**Pair**	**Pair**	**Pair**	**Pair**	**Pair**
Fixed Effects?	**No**	**No**	**Yes**	**No**	**No**	**Yes**
Attended College	0.059*** (0.014)	0.062*** (0.015)	0.075*** (0.022)	0.024** (0.012)	0.026** (0.013)	0.049*** (0.019)
Mother's Education	−0.002 (0.003)	−0.002 (0.003)		−0.003 (0.002)	−0.003 (0.002)	
Father's Education	0.003 (0.002)	0.003 (0.002)		−0.001 (0.002)	−0.001 (0.002)	
Family Income	0.000 (0.002)	0.000 (0.002)		−0.002 (0.002)	−0.001 (0.002)	
Number of Siblings	−0.009** (0.004)	−0.009** (0.004)		−0.005 (0.003)	−0.005 (0.003)	
Female	0.040*** (0.013)	0.040*** (0.013)	0.033* (0.018)	−0.023** (0.011)	−0.023** (0.011)	−0.023 (0.016)
Age	0.025*** (0.001)	0.025*** (0.001)	0.020*** (0.003)	0.009*** (0.001)	0.008*** (0.001)	0.003 (0.003)
Birth Order	0.007 (0.005)	0.007 (0.005)	−0.013 (0.010)	0.004 (0.005)	0.003 (0.005)	−0.011 (0.009)
Live with Both Parents	−0.022 (0.027)	−0.022 (0.027)	−0.063 (0.050)	0.029 (0.024)	0.027 (0.024)	0.041 (0.045)
WLS graduate	0.101*** (0.013)	0.098*** (0.013)	0.111*** (0.014)	0.009 (0.011)	0.003 (0.011)	−0.003 (0.012)
Poor Childhood Health		−0.003 (0.035)	−0.028 (0.045)		−0.043 (0.032)	−0.057 (0.043)
Missed School as Child		0.008 (0.024)	0.023 (0.032)		−0.007 (0.021)	0.001 (0.029)
IQ		−0.000 (0.000)	0.000 (0.001)		−0.000 (0.000)	−0.001 (0.001)
Constant	−1.137*** (0.112)	−1.085*** (0.124)	−0.735*** (0.251)	0.256** (0.105)	0.311*** (0.115)	0.644*** (0.231)
Observations	5578	5578	5578	5556	5556	5556
R-squared	0.07	0.07	0.08	0.01	0.01	0.01
P-value Diff w/Full	0.149			0.983		
P-value Diff w/IQ		0.459			0.579	

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the first column for each outcome for the pairs sample is equal to the coefficient estimate from a similar specification for the full sample. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the first column is equivalent to the estimate reported in the second column for each outcome.

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

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Table 5

Matching Estimates of the Impact of College Attendance on Preventive Care Use

Outcome	Physical Exam	Dental Exam	Flu Shot	Cholesterol
Sample	**Full, Common Support**	**Full, Common Support**	**Full, Common Support**	**Full, Common Support**
Nearest Neighbor Matching (bias-corrected)	0.052*** (0.013)	0.075*** (0.012)	0.050*** (0.014)	0.054*** (0.013)
Stratification Matching	0.054*** (0.020)	0.080*** (0.011)	0.052** (0.022)	0.071*** (0.018)
Kernel-Based Matching	0.047*** (0.015)	0.092*** (0.011)	0.056*** (0.013)	0.047*** (0.013)
Nearest Neighbor Matching	0.051*** (0.020)	0.083*** (0.012)	0.073*** (0.025)	0.069*** (0.020)
Sample Size	9984	9989	9985	9979
Sample	Trimmed	Trimmed	Trimmed	Trimmed
Nearest Neighbor Matching (bias-corrected)	0.050*** (0.012)	0.082*** (0.011)	0.047*** (0.013)	0.038*** (0.011)
Stratification Matching	0.044*** (0.012)	0.105*** (0.012)	0.057*** (0.014)	0.034*** (0.011)
Kernel-Based Matching	0.042*** (0.013)	0.102*** (0.010)	0.052*** (0.012)	0.032*** (0.012)
Nearest Neighbor Matching	0.042*** (0.016)	0.109*** (0.015)	0.059*** (0.020)	0.031** (0.015)
Sample Size	9374	9380	9369	9366

Notes: Heteroskedasticity-robust standard errors in parentheses. The sample in the top panel includes individuals from the full sample in the common support. The sample in the bottom panel is the subset of individuals from the full sample in the common support with propensity scores in the range [0.1, 0.9]. The first row of estimates is based on the bias-adjusted nearest neighbor matching with replacement estimator developed by Abadie and Imbens (2002). These estimates are based on a minimum of three matches per observation; similar results are obtained using a minimum of two and four matches per observation.

*** p<0.01,

** p<0.05,

* p<0.1.

Table 6

Examining the Mechanisms through which College Attendance Influences Preventive Care Use

Outcome	Physical Exam	Dental Exam	Flu Shot	Cholesterol Test
Baseline	0.061*** (0.020)	0.063*** (0.018)	0.075*** (0.022)	0.049*** (0.019)
plus Occupational Prestige	0.047** (0.021)	0.052*** (0.019)	0.060*** (0.022)	0.044** (0.019)
plus Health Insurance Type	0.046** (0.021)	0.050*** (0.019)	0.061*** (0.022)	0.042** (0.019)
plus Access to Care	0.042** (0.020)	0.050*** (0.019)	0.058*** (0.022)	0.040** (0.019)
plus Marital Status	0.043** (0.020)	0.050*** (0.019)	0.059*** (0.022)	0.042** (0.019)
plus Income	0.043** (0.020)	0.048** (0.019)	0.059*** (0.022)	0.041** (0.019)
plus Assets	0.043** (0.020)	0.047** (0.019)	0.058*** (0.022)	0.040** (0.019)
plus Cognition	0.045** (0.021)	0.046** (0.019)	0.058** (0.023)	0.049** (0.019)
plus Self Reported Health	0.047** (0.021)	0.045** (0.019)	0.060*** (0.023)	0.050** (0.019)
Baseline with Health Insurance Type	0.058*** (0.020)	0.059*** (0.018)	0.074*** (0.022)	0.047*** (0.019)
Baseline with Access to Care	0.056*** (0.020)	0.061*** (0.018)	0.071*** (0.022)	0.046** (0.018)
Baseline with Income	0.060*** (0.020)	0.059*** (0.018)	0.073*** (0.022)	0.048** (0.019)
Baseline with Marital Status	0.062*** (0.020)	0.064*** (0.018)	0.076*** (0.022)	0.052*** (0.019)
Baseline with Assets	0.060*** (0.020)	0.060*** (0.018)	0.074*** (0.022)	0.048** (0.019)
Baseline with Cognition	0.062*** (0.020)	0.061*** (0.019)	0.073*** (0.022)	0.058*** (0.019)
Baseline with Self Reported Health	0.063*** (0.020)	0.062*** (0.018)	0.078*** (0.022)	0.051*** (0.019)
Observations	5556	5564	5578	5556

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. Each cell in this table is the estimated coefficient for college attendance from separate regressions that also control for sex, age, birth order, whether the individual lived with both parents during high school, a dummy variable indicating whether the individual is in the graduate sample (vs. the sibling sample), an indicator variable for poor childhood self-reported health status, an indicator variable for missing at least one month of school as a child due to health problems, IQ, and family fixed effects. The baseline results are the fixed effects results shown in Tables 2 and 3. Each row that begins with the title "plus" report estimates that add the denoted variable to the specification estimated in the row directly above. The categories of health insurance type are employer-provided, privately-purchased, other insurance, and no insurance. The access to care variables are the three measures: difficulty obtaining health care, access to health care satisfaction, and usual source of care.

*** p<0.01,

** p<0.05,

* p<0.1.

Table A1

Estimates of the Impact of College Attendance on the Use of Preventive Care Using the Full Sample

Outcome	Physical Exam	Physical Exam	Dental Exam	Dental Exam	Flu Shot	Flu Shot	Cholesterol Test	Cholesterol Test
Sample	**Full**	**Full**	**Full**	**Full**	**Full**	**Full**	**Full**	**Full**
Fixed Effects?	**No**	**No**	**No**	**No**	**No**	**No**	**No**	**No**
Attended College	0.033*** (0.009)	0.038*** (0.010)	0.107*** (0.009)	0.097*** (0.009)	0.046*** (0.010)	0.048*** (0.011)	0.024*** (0.009)	0.027*** (0.010)
Mother's Education	0.001 (0.002)	0.001 (0.002)	0.000 (0.002)	−0.000 (0.002)	−0.001 (0.002)	−0.001 (0.002)	−0.003 (0.002)	−0.003 (0.002)
Father's Education	−0.000 (0.002)	0.000 (0.002)	0.003** (0.001)	0.003* (0.001)	0.004** (0.002)	0.004** (0.002)	−0.001 (0.001)	−0.001 (0.001)
Family Income	−0.001 (0.002)	−0.001 (0.002)	0.005*** (0.001)	0.005*** (0.001)	0.000 (0.002)	0.000 (0.002)	0.001 (0.001)	0.001 (0.001)
Number of Siblings	0.001 (0.002)	0.001 (0.002)	−0.006*** (0.002)	−0.006** (0.002)	−0.007** (0.003)	−0.007** (0.003)	−0.003 (0.002)	−0.003 (0.002)
Female	0.049*** (0.009)	0.050*** (0.009)	0.050*** (0.008)	0.048*** (0.008)	0.050*** (0.010)	0.050*** (0.010)	−0.021** (0.008)	−0.021** (0.008)
Age	0.008*** (0.001)	0.008*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	0.025*** (0.001)	0.025*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
Birth Order	0.001 (0.003)	0.001 (0.003)	0.004 (0.003)	0.004 (0.003)	0.007* (0.004)	0.007* (0.004)	0.005 (0.003)	0.005 (0.003)
Live with Both Parents	−0.006 (0.016)	−0.006 (0.016)	0.002 (0.016)	0.001 (0.016)	−0.039** (0.019)	−0.038** (0.019)	0.012 (0.016)	0.011 (0.016)
WLS graduate	0.016* (0.009)	0.011 (0.010)	0.023** (0.009)	0.019** (0.009)	0.102*** (0.010)	0.102*** (0.011)	0.017* (0.009)	0.011 (0.009)
Poor Childhood Health		−0.048** (0.024)		0.010 (0.022)		−0.004 (0.026)		−0.041* (0.024)
Missed School as Child		−0.002 (0.016)		−0.026* (0.016)		0.016 (0.018)		0.000 (0.016)
IQ		−0.001* (0.000)		0.001*** (0.000)		−0.000 (0.000)		−0.000 (0.000)
Constant	0.170** (0.084)	0.247*** (0.092)	0.851*** (0.080)	0.746*** (0.088)	−1.122*** (0.091)	−1.096*** (0.099)	0.227*** (0.085)	0.286*** (0.093)
Observations	10002	10002	10006	10006	10001	10001	9994	9994
R-squared	0.01	0.01	0.04	0.04	0.05	0.05	0.01	0.01

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model.

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

Table A2

Including Plans for the Future in Estimates of the Impact of College Attendance on Receiving a Physical Exam

Sample	Graduates	Graduates	Pair	Pair	Pair	Pair
Fixed Effects?	No	No	No	No	Yes	Yes
Attended College	0.044^{***} (0.012)	0.036^{**} (0.014)	0.033^{**} (0.013)	0.036^{**} (0.014)	0.061^{**} (0.028)	0.061^{**} (0.029)
Mother's Education	0.002 (0.002)	0.003 (0.002)	−0.001 (0.003)	−0.001 (0.003)		
Father's Education	−0.000 (0.002)	−0.001 (0.002)	0.002 (0.002)	0.002 (0.002)		
Family Income	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)		
Number of Siblings	−0.003 (0.003)	−0.002 (0.003)	0.001 (0.003)	0.000 (0.003)		
Female	0.048^{***} (0.011)	0.042^{***} (0.011)	0.047^{***} (0.012)	0.047^{***} (0.012)	0.040^{*} (0.023)	0.040^{*} (0.023)
Age	0.010 (0.007)	0.010 (0.007)	0.008^{***} (0.001)	0.008^{***} (0.001)	0.004 (0.004)	0.004 (0.004)
Birth Order	0.005 (0.004)	0.005 (0.004)	−0.002 (0.005)	−0.001 (0.005)	−0.015 (0.013)	−0.015 (0.013)
Live with Both Parents	−0.001 (0.020)	−0.001 (0.020)	0.005 (0.023)	0.005 (0.023)	0.054 (0.062)	0.054 (0.062)
WLS graduate	0.000 (0.000)	0.000 (0.000)	0.017 (0.012)	0.024 (0.017)	0.017 (0.018)	0.021 (0.029)
Poor Childhood Health	−0.046 (0.031)	−0.044 (0.031)	-0.073^{**} (0.032)	-0.073^{**} (0.032)	-0.115^{**} (0.059)	-0.115^{*} (0.059)
Missed School as Child	0.008 (0.020)	0.008 (0.020)	0.006 (0.021)	0.006 (0.021)	0.017 (0.040)	0.017 (0.040)
IQ	-0.001^{**} (0.000)	-0.001^{***} (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.001)	−0.000 (0.001)
Planned to Attend College at Age 16		0.006 (0.014)		−0.009 (0.015)		−0.000 (0.028)
Discussed Plans for the Future		0.019^{***} (0.007)				
Constant	0.190 (0.466)	0.084 (0.466)	0.250^{**} (0.114)	0.237^{**} (0.115)	0.470 (0.330)	0.465 (0.334)
Observations	6402	6402	5556	5556	5556	5556
R-squared	0.007	0.010	0.017	0.017	0.020	0.020
P-value Diff vs. Pairs Basic				0.549		
P-value Diff vs. Grad Basic		0.218	0.380			

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the fourth column is equivalent to the estimate reported in the first column. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in that column is equivalent to the estimate reported in the first column.

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

Table A3

Relationship between College Attendance and Receiving a Dental Exam Including Plans for the Future

Sample	**Graduates**	**Graduates**	**Pair**	**Pair**	**Pair**	**Pair**
Fixed Effects?	**No**	**No**	**No**	**No**	**Yes**	**Yes**
Attended College	0.090*** (0.012)	0.088*** (0.013)	0.099*** (0.012)	0.099*** (0.013)	0.063** (0.026)	0.066** (0.027)
Mother's Education	−0.002 (0.002)	−0.002 (0.002)	0.001 (0.002)	0.001 (0.002)		
Father's Education	0.003 (0.002)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)		
Family Income	0.004** (0.002)	0.004** (0.002)	0.005*** (0.002)	0.005*** (0.002)		
Number of Siblings	−0.008*** (0.003)	−0.008*** (0.003)	−0.003 (0.003)	−0.003 (0.003)		
Female	0.047*** (0.010)	0.043*** (0.011)	0.043*** (0.011)	0.043*** (0.011)	0.048** (0.021)	0.047** (0.021)
Age	0.003 (0.007)	0.003 (0.007)	−0.003* (0.001)	−0.003* (0.001)	−0.005 (0.004)	−0.005 (0.004)
Birth Order	0.004 (0.004)	0.005 (0.004)	0.001 (0.005)	0.001 (0.005)	−0.001 (0.013)	−0.000 (0.013)
Live with Both Parents	0.017 (0.020)	0.018 (0.020)	0.017 (0.023)	0.017 (0.023)	0.037 (0.062)	0.037 (0.062)
WLS graduate	0.000 (0.000)	0.000 (0.000)	0.021* (0.011)	0.025 (0.016)	0.023 (0.018)	0.052* (0.028)
Poor Childhood Health	0.007 (0.028)	0.010 (0.028)	−0.005 (0.028)	−0.005 (0.028)	0.017 (0.056)	0.020 (0.056)
Missed School as Child	−0.042** (0.020)	−0.042** (0.020)	0.005 (0.020)	0.005 (0.020)	−0.013 (0.037)	−0.014 (0.037)
IQ	0.001*** (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001 (0.001)	0.001 (0.001)
Planned to Attend College at Age 16		−0.002 (0.013)		0.001 (0.014)		−0.016 (0.027)
Discussed Plans for the Future		0.011* (0.006)				
Constant	0.385 (0.474)	0.313 (0.474)	0.721*** (0.109)	0.717*** (0.110)	0.881*** (0.322)	0.844*** (0.325)
Observations	6403	6403	5564	5564	5564	5564
R-squared	0.036	0.038	0.040	0.040	0.019	0.021
P-value Diff vs. Pairs Basic				0.912		
P-value Diff vs. Grad Basic		0.784	0.443			

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the fourth column is equivalent to the estimate reported in the first column. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in that column is equivalent to the estimate reported in the first column.

*** p<0.01,

** p<0.05,

* p<0.1.

Table A4

Including Plans for the Future in Estimates of the Impact of College Attendance on Receiving a Flu Shot

Sample	Graduates	Graduates	Pair	Pair	Pair	Pair
Fixed Effects?	**No**	**No**	**No**	**No**	**Yes**	**Yes**
Attended College	0.041*** (0.014)	0.041*** (0.016)	0.062*** (0.015)	0.069*** (0.016)	0.075** (0.031)	0.086*** (0.032)
Mother's Education	−0.001 (0.003)	−0.001 (0.003)	−0.002 (0.003)	−0.002 (0.003)		
Father's Education	0.006*** (0.002)	0.006*** (0.002)	0.003 (0.002)	0.004 (0.002)		
Family Income	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.001 (0.002)		
Number of Siblings	−0.009*** (0.003)	−0.009*** (0.003)	−0.009** (0.004)	−0.009** (0.004)		
Female	0.046*** (0.012)	0.039*** (0.013)	0.040*** (0.013)	0.040*** (0.013)	0.033 (0.025)	0.031 (0.026)
Age	0.020** (0.008)	0.020** (0.008)	0.025*** (0.001)	0.025*** (0.001)	0.020*** (0.005)	0.020*** (0.005)
Birth Order	0.009** (0.004)	0.009** (0.004)	0.007 (0.005)	0.008 (0.005)	−0.013 (0.015)	−0.012 (0.015)
Live with Both Parents	−0.036 (0.022)	−0.036 (0.022)	−0.022 (0.027)	−0.021 (0.027)	−0.063 (0.071)	−0.062 (0.071)
WLS graduate	0.000 (0.000)	0.000 (0.000)	0.098*** (0.013)	0.130*** (0.019)	0.111*** (0.020)	0.148*** (0.032)
Poor Childhood Health	0.005 (0.033)	0.005 (0.033)	−0.003 (0.035)	−0.002 (0.035)	−0.028 (0.064)	−0.024 (0.064)
Missed School as Child	0.029 (0.023)	0.030 (0.023)	0.008 (0.024)	0.007 (0.024)	0.023 (0.046)	0.020 (0.046)
IQ	−0.000 (0.000)	−0.001 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.001)	0.000 (0.001)
Planned to Attend College at Age 16		−0.011 (0.016)		−0.022 (0.016)		−0.043 (0.031)
Discussed Plans for the Future		0.017** (0.008)				
Constant	−0.675 (0.549)	−0.741 (0.550)	−1.085*** (0.124)	−1.135*** (0.125)	−0.735** (0.356)	−0.769** (0.358)
Observations	6397	6397	5578	5578	5578	5578
R-squared	0.014	0.015	0.071	0.072	0.079	0.082
P-value Diff vs. Pairs Basic				0.241		
P-value Diff vs. Grad Basic		0.974	0.149			

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the fourth column is equivalent to the estimate reported in the first column. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in that column is equivalent to the estimate reported in the first column.

*** p<0.01,

** p<0.05,

*p<0.1.

Table A5

Including Plans for the Future in Estimates of the Impact of College Attendance on Receiving a Cholesterol Test

Sample	Graduates	Graduates	Pair	Pair	Pair	Pair
Fixed Effects?	**No**	**No**	**No**	**No**	**Yes**	**Yes**
Attended College	0.032*** (0.012)	0.027** (0.014)	0.026** (0.013)	0.031** (0.014)	0.049* (0.026)	0.051* (0.027)
Mother's Education	−0.003 (0.002)	−0.003 (0.002)	−0.003 (0.002)	−0.003 (0.002)		
Father's Education	−0.002 (0.002)	−0.002 (0.002)	−0.001 (0.002)	−0.000 (0.002)		
Family Income	0.001 (0.002)	0.001 (0.002)	−0.001 (0.002)	−0.001 (0.002)		
Number of Siblings	−0.004 (0.003)	−0.003 (0.003)	−0.005 (0.003)	−0.005 (0.003)		
Female	−0.017 (0.010)	−0.024** (0.011)	−0.023** (0.011)	−0.023** (0.011)	−0.023 (0.022)	−0.023 (0.022)
Age	0.015** (0.007)	0.015** (0.007)	0.008*** (0.001)	0.008*** (0.001)	0.003 (0.004)	0.004 (0.004)
Birth Order	0.007** (0.004)	0.008** (0.004)	0.003 (0.005)	0.004 (0.005)	−0.011 (0.013)	−0.011 (0.013)
Live with Both Parents	0.020 (0.020)	0.020 (0.020)	0.027 (0.024)	0.027 (0.024)	0.041 (0.064)	0.042 (0.064)
WLS graduate	0.000 (0.000)	0.000 (0.000)	0.003 (0.011)	0.013 (0.016)	−0.003 (0.017)	0.027 (0.027)
Poor Childhood Health	−0.050* (0.030)	−0.049 (0.030)	−0.043 (0.032)	−0.042 (0.032)	−0.057 (0.062)	−0.055 (0.062)
Missed School as Child	0.009 (0.019)	0.009 (0.020)	−0.007 (0.021)	−0.007 (0.021)	0.001 (0.041)	−0.000 (0.041)
IQ	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.001 (0.001)	−0.001 (0.001)
Planned to Attend College at Age 16		−0.005 (0.013)		−0.014 (0.014)		−0.010 (0.027)
Discussed Plans for the Future		0.023*** (0.006)				
Constant	−0.142 (0.456)	−0.237 (0.457)	0.311*** (0.115)	0.291** (0.116)	0.644* (0.328)	0.601* (0.332)
Observations	6391	6391	5556	5556	5556	5556
R-squared	0.005	0.007	0.014	0.014	0.013	0.014
P-value Diff vs. Pairs Basic				0.354		
P-value Diff vs. Grad Basic		0.511	0.680			

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. The p-value in the second to last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in the fourth column is equivalent to the estimate reported in the first column. The p-value in the last row is calculated for the null hypothesis that the coefficient estimate for college attendance reported in that column is equivalent to the estimate reported in the first column.

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

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Table A6

Alternative Specifications that Examine the Influence of Medicare Eligibility

	(1)	(2)	(3)	(4)	(5)
A. Physical Exam					
Attended College	0.061*** (0.020)	0.061*** (0.020)	0.060** (0.023)	0.057*** (0.020)	0.062*** (0.020)
Eligible for Medicare		0.024 (0.021)	0.022 (0.026)		
Attended College x Eligible for Medicare			0.004 (0.031)		
Health Insurance Types in 2004				X	
Currently Employed					−0.026 (0.017)
B. Dental Exam					
Attended College	0.063*** (0.018)	0.063*** (0.018)	0.039* (0.021)	0.062*** (0.018)	0.063*** (0.018)
Eligible for Medicare		−0.001 (0.020)	−0.034 (0.027)		
Attended College x Eligible for Medicare			0.066** (0.030)		
Health Insurance Types in 2004				0.068 (0.045)	
Currently Employed					0.013 (0.016)
C. Flu Shot					
Attended College	0.075*** (0.022)	0.076*** (0.022)	0.062** (0.025)	0.075*** (0.022)	0.076*** (0.022)
Eligible for Medicare		0.035 (0.023)	0.015 (0.029)		
Attended College x Eligible for Medicare			0.039 (0.036)		
Health Insurance Types in 2004				0.143*** (0.049)	
Currently Employed					−0.026 (0.020)
D. Cholesterol Test					
Attended College	0.049*** (0.019)	0.049*** (0.019)	0.053** (0.023)	0.047** (0.019)	0.050*** (0.019)
Eligible for Medicare		0.000 (0.020)	0.005 (0.025)		
Attended College x Eligible for Medicare			−0.011 (0.030)		
Health Insurance Types in 2004				0.102** (0.042)	
Currently Employed					−0.016 (0.017)

Notes: Heteroskedasticity-robust standard errors that allow for clustering within families in parentheses. Estimates are calculated using a linear probability model. Column (1) is the fixed effects results shown in Tables 3 and 4. Column (2) adds whether the individual is eligible for Medicare, which is measured as age 65 years and older. Column (3) adds an interaction term of college attendance and Medicare eligibility. Column (4) adds the type of health insurance at the time of preventive care use (Medicare, employer-based, privately-purchased, and other) to column (1). Column (5) adds employment status to Column (1).