Estimating the education-earnings equation using geographic variation

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Abstract

We expand on the literature on the causal impact of postsecondary education on earnings by introducing a richer set of location-based measures as instruments for years of education. Utilizing data from the National Longitudinal Study of Youth, 1997, we implement six different sets of instruments based on geographic variation: presence of a four-year or two-year college in the county, inverse log distance to in-state two-year colleges, distance-weighted tuition and distance-weighted enrollment at in-state two-year colleges, and inverse log distance to all colleges. We find that these alternative measures yield differing estimates of the impact of educational attainment on earnings. Using our preferred measure of geographic variation, one additional year of postsecondary attainment results in a 9.7% increase in yearly earnings. We find a larger impact of postsecondary attainment for women, and no measurable impact of postsecondary attainment for men.

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It is a truth widely acknowledged that the best way to earn a better living is to pursue more education. The vast majority of college students now say that being able to get a better job is a very important reason to go to college (Eagan et al., 2014). The goal of much state and federal policy in the area of higher education is to increase both student access and success in order to improve the quality of the workforce (Carnevale et al., 2010). During the period of the late 2000s and into the second decade of the 21st century, serious concerns began to be raised about the value of a college degree (Oreopoulos and Petronijevic, 2013). The key question for policymakers and individuals alike is: to what extent does obtaining more education result in higher earnings?

Identification of the causal impact of education on earnings is known to be difficult in that individuals who pursue more education may be more likely to have a variety of both observable and unobservable characteristics that would lead them to have higher earnings (Card, 1999). This means that in standard regressions of earnings on education, the covariate for education would be correlated with the error term, biasing the results. One common identification strategy has been to use the presence or absence of a college in an individual's local area as an instrument for the number of years of education (Card, 1993; Kane and Rouse, 1995; Carneiro et al., 2011; Carneiro and Heckman, 2002). Other location-based instruments that have been used include characteristics of colleges, such as the average tuition at public colleges in the student's local area (Carneiro and Heckman, 2002).

We expand on this literature in three ways. First, we use a richer set of instruments than in previous estimations. These instruments allow us to test whether the link between the location of colleges and years of education completed remains strong. In addition, this approach allows us to observe variation in local average treatment effects when different instrumental variables are used. Second, we provide estimates from the National Longitudinal Survey of Youth, 1997, (NLSY97) cohort between 2007 and 2010, when the youngest members of the cohort were between 23 and 26 and the oldest members of the cohort were between 27 and 30 (Moore et al., 2000). This was a tumultuous time in labor markets, during which many questioned whether education still had substantial returns. Last, we provide separate estimates for men and women. In many previous studies, the primary sample was males. During this time period, the proportion of women attending and graduating from college exceeded the proportion of men by substantial amounts (Doyle, 2010). We estimate the extent to which higher levels of education has differential payoffs for men and women.

We report both first- and second-stage estimates from two-stage least squares regression (Angrist and Pischke, 2008; Angrist and Krueger, 1999). We find in the first stage that the density of college opportunity has a statistically significant impact on the number of months of education attained, with particularly long-lasting effects for community colleges. We find in the second-stage estimates that the impact of education on earnings, even during the turbulent economic times of the late 2000s remains strong. The results for women show a larger impact of postsecondary attainment on earnings than for the sample as a whole, while the results for men show no observable relationship between postsecondary attainment and earnings.

The outline of this paper is as follows: we provide a brief background, describing previous studies in this area and their findings; we then describe our model and our identification strategy; next we provide a description of the data and our results, followed by a series of specification checks and sensitivity analyses; we conclude by discussing what we have learned from our analysis.

1 Background

We begin by describing the literature on the impact of education on earnings, with a focus on previous studies that have used instrumental variables approaches to estimate this relationship. We then turn to the role of geographic variation in predicting postsecondary attainment.

1.1 Link between education and earnings

Establishing the link between education and earnings has been a very large topic in labor economics over the last thirty years. The observed link between education and earnings in the population as a whole has been well-known for some time. The degree to which this link can be said to be causal has been the focus of most research and theory in this field (Card, 1999).

In their recent review of the returns to education Oreopoulos and Petronijevic (2013) find substantial evidence that education increases earnings, although recent studies have pointed to substantial heterogeneity in results. They also cite the ongoing debate in policy circles and in the popular media regarding whether college is "worth it." This debate is essentially about whether the observed relationship between higher earnings and education is actually a causal relationship. Analysts cite two primary reasons for doubting that the observed association between earnings and education is causal. The first reason is self-selection. The second is signaling (Oreopoulos and Petronijevic, 2013).

Self-selection occurs when those who will likely earn the most also choose to obtain the highest levels of education. Individuals may do this because they know that these investments will pay off more, or simply because they enjoy education more and choose to consume more of it (Card, 2001, 1999; Oreopoulos and Petronijevic, 2013). Analysts can overcome the problem of self-selection either by experimentally altering the amount of education available to one group or by seeking out natural experiments that more-or-less randomly assign some people to more education. The latter is the path that we take in our study, using the impact of geographic variation in college opportunity on educational attainment to mitigate the effects of self-selection.

Signaling is a more subtle problem. Signaling involves using overt behavior to signal private knowledge about an individual (Card, 2001). In the case at hand, individuals would go to college to signal employers that they are productive workers. Employers would respond to this signal by paying college-educated workers more. The impact of this signal, however, should fade over time as employers learn directly about workers. Under this scenario, individuals who go to college do not gain new skills during that time, but rather only signal to future employers the attributes that they already possess (Oreopoulos and Petronijevic, 2013). We do not directly address the signaling debate in our study, but work by Lange (2007) suggests that much of the earnings premium is due to education, as employers learn quickly which employees are productive. Lange estimates that the contribution of signaling to the returns to education are no more than 25% (Lange, 2007).

Many previous studies have attempted to identify the causal impact of schooling on earnings, excluding the effect of self-selection. One of the first analyses to use geographic variation as the basis for an instrumental variable to identify the education earnings equation was Card (1995). Using data from the Young Men Cohort of the National Longitudinal Survey (NLSYM), Card (1995) estimates the impact of educational attainment on earnings for young males. To identify the relationship, Card uses the presence or absence of an accredited four-year institution of higher education in the county where the young person lived at age 17. Card estimates the impact of an additional year of education on earnings as being about 7% using ordinary least squares (OLS), about 13% using geographic proximity of colleges as an instrument, and about 10% when interacting proximity with family background characteristics.

In his 1999 summary of the research on education and earnings, Card surveys the body of evidence that an additional year of education is tied to an increase of earnings on the order of 5-10%. Card concludes that the available evidence suggests that "the average (or average marginal) return to education in a given population is not much below the estimate that emerges from a simple cross-sectional regression of earnings on education," (Card, 1999, p. 1855). Card further suggests that "IV estimates of the return to education based on family background are systematically higher than corresponding OLS estimates and probably contain a bigger upward ability bias than the OLS estimates," (Card, 1999, p. 1855). We conclude from this survey of the work that unlike in other areas, instrumental variables estimates of the link between education and earnings should typically be larger than OLS estimates.

In his work on the link between earnings and education, Hout (2012) suggests another possible reason why OLS estimates may be biased. Instead of ability bias, Hout suggests that institutions of higher education may systematically exclude those who would benefit most in terms of increased lifetime salaries. If the benefit of higher education is highest for those on the margin of attendance (which seems likely), then this mechanism is also likely at work. The combination of these two mechanisms would result in OLS estimates that are considerably lower than instrumental variable estimates.

In his 2001 update, Card discusses progress on estimates of the return to education. Most of the studies reviewed in developed economies also provide estimates of the return to one year of education between 5 and 15%. Card also presents important guidance on the interpretation of instrumental variables estimates, reflecting work done on local average treatment effects by Angrist, Imbens and Rubin (Angrist et al., 1996). Card notes that estimates from instrumental variables approaches should be interpreted as the weighted marginal return to various groups, with weights given by the number of years of schooling induced by a given instrument. This has important implications. Providing multiple instruments in a study can help to establish how much the return to schooling varies across different subgroups with different propensities to complete more schooling.

Card (2001) discusses this issue in the context of schooling reforms that increase the supply of schooling for individuals with a high marginal return—for instance a reform that increased the number of community colleges close to people who could substantially benefit from more postsecondary education:

> [IV estimates] can be interpreted as a weighted average of the marginal returns to education in the population, where the "weight" for any particular "person" is the relative size of the increment in his or her schooling induced by the reform...An IV procedure based on a school reform that leads to bigger changes in the edu-

> cation choices of people with relatively high marginal returns to education will tend to produce an over-estimate of the average marginal return to education. (Card, 2001, p. 1142)

We derive two conclusions from Card's discussion. First, using multiple sets of instruments can help to understand the degree to which instrument variables estimates are sensitive to the populations induced to attend by different estimates. Second, we interpret the results of each instrumental variables estimation carefully, as populations induced will differ depending on the instruments used.

Other researchers have emphasized the importance of updating previous estimates of the return to education. In their review of the literature on returns to education, Oreopolous and Petronijevic state:

> A problem with these estimates is that they apply only to older cohorts affected by college proximity or draft lotteries several decades ago. As such, they are quite outdated, as the fraction and types of individuals enrolling in college has since dramatically changed. It may, therefore, not be prudent to extrapolate these returns and conclude they apply to different types of individuals or more recent cohorts (Oreopoulos and Petronijevic, 2013).

We seek to fill the gap in the literature identified by Oreopolous and Petronijevic by providing more recent estimates of the returns to postsecondary education from a cohort aged 26 to 30 by 2010. Recent changes in the geographic distribution of higher education are incorporated into our results, including the continuing spread of public two-year colleges and the introduction of a wide variety of for-profit institutions.

1.2 Geography and postsecondary attainment

The design of higher education policy to improve college access has been centered on two efforts. First, policymakers have sought through a variety of means to ensure that prices are low (Dynarski, 2002). These efforts have been driven in part by a substantial literature that establishes that individuals are responsive to changes in price (Deming and Dynarski, 2009).

The second pillar of higher education policy to improve college access has been based on geography. In most states, policymakers believed it important that most potential students were close to either a two-year or a four-year public college. During the period of rapid expansion of higher education in the 1960s and 1970s, many states sought to ensure that a public institution of higher education was within easy driving distance of most of the population. This distance-based approach was assumed to improve college access and reduce costs, as students could commute from home and save on residential costs (Kerr, 1991).

In recent times, it has been questioned whether this policy continues to make sense. Hoxby (1997) finds that for academically capable students, there is a much higher likelihood that they will travel farther to college than they did in the 1960s and 1970s. Long (2004) finds that the impact of distance on the conditional probability that a student will attend a given postsecondary institution has decreased over time, although the substantive size of the decrease is fairly small. In addition, many students may not be as place bound due to the impact of new technologies that allow them to attend higher education either entirely online or through hybrid means, attending both in-person and online (Allen and Seaman, 2013). It could be the case that distance is no longer as important a predictor of college attendance as it once was.

Kling (2001) analyzes whether the link between geographic proximity and additional educational attainment demonstrated in Card's work continues to hold using data from the NLSY79. Kling estimates the impact of additional education on earnings for individuals who were between 25 and 33 years old in 1989. Kling provides an interpretation of the instrumental variables estimates based on which subgroups were most affected. He concludes that "most of the individuals affected were from more disadvantaged family backgrounds, particularly with lower parental education," (Kling, 2001, p. 364). In addition, Kling finds that geographic proximity continues to have an impact on postsecondary education, particularly for low-discount-rate individuals. Kling posits that the continued impact of geographic proximity on educational attainment can be attributed to the implicit subsidy provided by locating institutions of higher education closer to individuals.

Recent studies have pointed to the importance of the presence or absence of colleges in a student's local area. Hillman (2014) models the factors that may affect either the presence or number of institutions in a given commuting zone. Hillman (2014) finds that commuting zones that are poorer and/or have a larger proportion of underrepresented minorities are more likely to have few or no college options—so-called "college deserts" (Hillman, 2014). Similarly, Jepsen and Montgomery (2012, 2009) find that increased distance to surrounding community colleges can have a statistically significant negative impact on the enrollment patterns of mature workers.

We build on this recent literature in two ways. First, we develop and deploy a much richer set of measures of distance than previous studies. Rather than simply asking whether young people have at least one college or one college of a certain type within a certain distance of their homes, we instead are able to measure individuals' choice sets by providing a measure of the density of postsecondary opportunities for young people in different parts of the country. We also use distance-weighted measures of college prices and distance-weighted measures of college enrollment to estimate the impact of living closer to more affordable or more accessible higher education options. Second, we estimate not just the impact of distance-based measures on college attendance, but also provide instrumental variable estimates of the impact of college attendance on yearly income. Given that most policymakers support higher education not necessarily as an end in itself but as a means for workforce development, we demonstrate the impact both of geography on college attendance and then the impact of college attendance on earnings.

2 Model specification

We begin by proposing a standard Mincerian model for earnings for individual i in the population:

$$y_i = \alpha + \beta x_i + \boldsymbol{\gamma} \mathbf{c}_i + \epsilon_i, \tag{1}$$

where y_i is log yearly income, x_i is the length of time in education, and $\mathbf{c}_i$ is a set of characteristics of the individual, including a quadratic in age as well as demographic and other characteristics including race, sex, parental education, and some measure of academic ability such as a test score. Our hypothesis is that, consistent with previous literature, the impact of x on y as measured by β will be positive.

A specification such as that contained in (1) is problematic in that individuals might choose to attain more years of education because they are aware of their own higher earnings potential. This would mean that there is endogeneity between college choice and unobserved earnings ability, biasing our estimate of β. An experimental approach to this problem would randomly assign some individuals more education, while leaving those in the control group with less education. While there have been many such experiments, few have been conducted on such a large scale as to establish that the results are generalizable (LaLonde, 1986).

We seek to find characteristics of individuals' environments that might reasonably be related to their overall level of educational attainment, and related to their wages only through the mechanism of educational attainment. Such characteristics should have the property of "somewhat" randomly assigning individuals to more or less educational attainment than they might otherwise have had. We next describe how geographic variation in college opportunity meets this standard on substantive grounds.

2.1 Measuring geographic variation in college choice and prices

Following Card and others, we exploit plausible exogeneity of location at age 17 on post-secondary attainment (Card, 1995; Carneiro et al., 2011). While it is well established that individuals choose where to live based on the perceived quality of local schools, there is no literature that supports the idea that families or individuals choose where to live based on the geographic density of local colleges and universities (Black and Machin, 2011). If individuals do happen to live closer to a number of postsecondary institutions, previous literature and theory supports the idea that they will be more likely to attend. Similarly, if those colleges are lower-priced, the young people living closer to those colleges should be more likely to attend, a result supported by previous research.

We employ three approaches to utilizing geographic variation as an instrumental variable: the presence or absence of colleges in the local area, the inverse log distance to surrounding colleges, and the inverse distance-weighted price and enrollment of college.

One relevant question is whether the advent of more online educational opportunities opportunities has disrupted the link between geographic proximity and educational attainment. If a large part of our sample attends class exclusively online, then the distance between that campus and individuals attending that campus would be more or less irrelevant. During the time period in question (individuals in our sample were 18-24 years old in the late 1990s and early 2000s), exclusively online enrollment was still relatively rare, never exceeding 5 percent of students attending exclusively online for the entire population of students (Radford and Weko, 2011). Even among students who attend online, most attend in-state (Deming et al., 2015). While we do not have information from NLSY97 regarding whether respondents attended exclusively online, we do know that there were no community colleges or public four-year colleges in our sample that offered classes exclusively online. On the other hand, our broadest measure of geographic proximity, which includes all types of postsecondary institutions, does include some institutions that offer exclusively online courses. In any case, if the advent of online course offerings has severed the geographic link between colleges and individuals, we would expect to see little to no relationship between the location of colleges and educational attainment.

2.1.1 Presence or absence of colleges in local area

The most direct measure of geographic variation involves a binary variable indicating the presence or absence of a college within a geographic area. Card (1999) uses the presence or absence of an accredited four-year college within a county. Following Card, we use the presence or absence of a public four-year college within the county where the respondent was living at age 17 in one set of estimates.[1] We also include estimates for the presence or absence of a two-year public college within the county where the respondent was living at age 17.

Measuring the presence or absence of a certain type of postsecondary institution has two advantages: it is straightforward and easy to define. For young people, it should be easy to know whether or not their local area includes a college, which should impact their propensity to attend.

There are, however, multiple drawbacks to such a measure. First, county boundaries are drawn for historic reasons, which differ from state to state. County boundaries are not necessarily sensitive to local labor markets or educational districting. For a given young person, it is more likely that they would be aware that a college is "nearby" rather than a college is within her county.

Presence or absence measures do not include the full set of opportunities available to a young person. A presence or absence measure will be the same for a young person who lives within 20 miles of 10 community colleges or a young person who lives in a large county 30 miles from one community college. We recover this source of variation by providing measures of college access based on spatial statistics that include all of the available colleges in a given

[1] We differ by using the presence of a public four-year as opposed to the presence of any college within a county. We do this as public four-year institutions are much more likely to be less selective and in a position to affect college opportunity in their local area.

state or in the country.

2.1.2 Inverse log distance

We begin with a measure of the density of college choice for an individual. In the simplest case, an individual i would have only one college k to choose from. We hypothesize, following previous research, that the distance d from the residence of a young person i to a college k will be predictive (in the inverse) of the number of years of attendance in postsecondary education for that individual, which we denote as x. It follows from the above that

$$x_i \propto d_{ik}^{-1}. \tag{2}$$

Previous work has considered only the closest college to the individual, or even using a structure as simple as the presence or absence of a four-year college in a young person's labor market as the basis for estimating equation (2). We expand upon this basic model by recognizing that because an individual's postsecondary choice set contains more schools than the closest one, young people who live closer to a large number of postsecondary institutions are more likely than young people who have comparatively fewer proximal options to attend at least one. In addition, we posit that young people who live near a number of postsecondary institutions are more likely to complete more years of education than their peers who live a longer average distance from postsecondary institutions.

We specify our measure w of the density of postsecondary choice for an individual i choosing from among all K postsecondary institutions as

$$w_i = \sum_{k=1}^{K} log(d_{ik})^{-1}, \tag{3}$$

where d_{ik} is the geodesic distance (measured using the Vincenty computational formula[2])

[2]The Vincenty (1975) computational formula improves upon other methods of computing the distance between two points on the surface of the Earth. Rather than assume the Earth to be a perfect sphere, as do solutions derived from the spherical law of cosines and the Haversine formula, Vincenty solutions are the result of iterative calculations that take into account the Earth's non-spherical shape by specifying an

from individual i to college k in miles. Because county of residence is the smallest spatial measure given for each NLSY97 participant, we use the coordinates of each individual's county population center (the population-weighted geographic center) as given by the U.S. Census Bureau as the point of origin when measuring the distance to surrounding colleges. Each distance is transformed to be on the log scale. We take the sum of inverse log distances, shown in (3), so that the resulting measure is larger for individuals with a higher density of postsecondary choice. Figures available in the online supplement offer a visual representation of this computational process and shows the difference between state and national prices and their weighted versions for a single example county. A separate figure, also presented in the online supplement, visualizes the full results of this process in a choropleth map that shows differences in z-scores of the inverse log distance to all public two-year colleges from the population centroid of every county in the lower 48 states.

2.1.3 Inverse distance weighted price and enrollment

Every individual faces an average postsecondary price that is a function of his or her choice set. Without restrictions, the average price for every individual in a given time period would be the same—simply the average price of all postsecondary institutions in the universe of options. To take into account the hypothesis that the real average price for an individual should place more weight on the price of nearby institutions than those far away, we apply distance-based weights to each institution's published tuition in order to calculate an individual's average price. As with the inverse log distance weights, county population centers are used as the finest grained measure of an individual's address. For county i, the weighted average price, WAP, across K postsecondary institutions is determined by

$$WAP_{iy} = \sum_{k=1}^{K} \frac{g_{ik} \cdot price_{ky}}{\sum_{k=1}^{K} g_{ik}}, \tag{4}$$

ellipsoid datum (we use the WGS84 datum). Despite its much greater computational demands, we choose to use the Vincenty method due to our sample's continental scale, which may compound the errors of other formulas.

where $price_{ky}$ is price of institution k in year y and g is a weight for each cell. The weight g is defined as

$$g_{ik} = \left(\frac{d_{ik}}{\sum_{k=1}^{K} d_{ik}} \right)^{-r}, \tag{5}$$

with d_{ik} as the geodesic distance in miles between the county population centroid i and institution k (as computed in (3)) and r as the drop off rate of influence.[3]

For every county in the sample across each sample year, we compute the geodesic distance to each postsecondary institution, creating an $I \times K$ matrix where the sum of each row represents the total distance of all postsecondary institutions from the county and the fraction of each cell over the row total the proportional distance of each institution. So that closer institutions carry more weight than farther ones, weights for each cell, g_{ik}, are computed by dividing the inverse of the proportional distance by the row sum of the inverse proportional distances (5).[4] To compute the weighted average price for each county in each year, WAP_{iy}, these weights are applied to a vector of yearly institutional prices, $price_{ky}$ and summed (4). We merge these county-year estimates with NLSY97 records to create a weighted average price of college for each participant that varies across the country across time.

We repeat the same process to derive measures of distance weighted enrollment by substituting full-time equivalent (FTE) enrollment for price in equation (4). Similar to the measure of distance-weighted price, the measure of distance-weighted enrollment results in higher values for individuals who live closer to a large number of high-enrollment institutions. In the online supplement, we provide a series of choropleth maps that visualize the variation in county-level weighted college price and enrollment across the country. These maps make

[3]The U.S. Census Bureau only provides population center coordinates for the 2000 and 2010 decennial censuses. We split the difference, giving counties the 2000 coordinates in years before 2005, and the 2010 coordinates after. A given cell weight g_{ik} may change slightly from the early to late period of the sample. Even though we recompute the g_{ik} in each sample year, we drop the year subscript for simplicity.

[4]To change the rate at which distance has influence, the exponential term, r, may be modified. At $r = 1$, weights are a linear function of distance; when $r > 1$, weights exponentially decay as distance increases. As r increases, the price of the nearest institutions are up-weighted. In the limit, $r \to \infty$, all weight will be placed on the nearest institution. We use a rate of $r = 2$ to compute weights in these analyses.

readily apparent both the heterogeneity in these measures across the country.

Other authors have found that the distance does not affect enrollment behavior in the same way for all students (Alm and Winters, 2009; Griffith and Rothstein, 2009; DesJardins et al., 1999; Niu and Tienda, 2008). Researchers have found that low SES students are more responsive to distance to the nearest campus or campuses than their higher-income peers. The operationalization of our distance variables does not reflect this finding. In the next section we describe our estimation approach. In our estimation, we interact each distance-based measure with a continuous measure of mother's education. A negative interaction between mother's education combined with a positive main effect for distance variables would indicate a declining impact of the importance of distance as SES increases. This would confirm what has been found in previous research (Avery and Hoxby, 2007).

2.2 Instrumental variables estimation

We begin with a set of first stage equations predicting years of postsecondary attainment, x_i:

$$x_i = \delta + \psi \mathbf{z}_i + \eta \mathbf{c}_i + \mu_i. \tag{6}$$

These equations include a vector of controls $\mathbf{c}_i$ as described above and $\mathbf{z}_i$, a measure of geographic variation interacted with the respondent's mother's education, giving us a total of three excluded instruments in each separate set of estimates.

Our second stage estimates are given by:

$$y_i = \alpha + \beta \hat{x}_i + \boldsymbol{\gamma} \mathbf{c}_i + \epsilon_i, \tag{7}$$

where y_i is log yearly income, $\mathbf{c}_i$ are the same controls as above and $\hat{x}_i$ is the predicted level of college attendance from (6).

We report estimates using the two-stage least squares (2SLS) estimator.[5] Robust standard errors using the Huber-White variance-covariance matrix are reported for all estimates. In the results section we report several empirical tests of our excluded instruments.

2.3 Key assumptions

Angrist and Imbens (1995) establish the two assumptions that are maintained when undertaking two-stage least squares estimation of average causal effects. The first is independence, the assumption that the excluded instruments have no effect on the outcome except through the treatment variable, or in our case that geographic proximity has no impact on earnings except through increased educational attainment. We test this assumption by establishing both that higher levels of geographic opportunity impact educational attainment and that the instruments are uncorrelated with the error term in the second stage.

Second, the assumption of monotonicity must be maintained. Monotonicity implies that assignment to treatment never reduces the level of treatment obtained. As Angrist states regarding the impact of compulsory schooling laws on attendance "monotonicity means that because of compulsory schooling attendance laws, people born in quarters 2-4 complete at least as much schooling as they would have completed had they been born in the first quarter" (Angrist and Imbens, 1995, p. 435). For our case, this would mean that individuals who have increased geographic opportunity to attend higher education have levels of attainment at least as high as those with lower levels of geographic opportunity.

Monotonicity cannot be verified. We note that monotonicity is an untestable assumption but maintain that living closer to more colleges at least does not decrease educational attainment. Without direct tests of this assumption, we must assess its plausibility. How could geographic proximity *lower* educational attainment for any individual? One possibility is that some individuals on the margin of attendance may learn more about college

[5] In analyses not reported in this study we also use the Limited Information Maximum Likelihood (LIML) estimator. Results are substantively very similar. Given that most previous studies use two-stage least squares, we report the results from the more commonly used estimator.

requirements as a result of living close to a college, which discourages them from applying or attending. Another possibility would be that individuals might learn about the campus experience from students and decide that the consumption value of college is negative. Last, individuals living closer to campus may come to realize that attending postsecondary education would not benefit them because of their particular traits or abilities, leading them to be less likely to attend as a result of proximity. All of the evidence of which we are aware points in the other direction. The most likely impact of living closer to more colleges is that individuals learn that college is possible, that costs are not as high as might be expected and that the payoffs are substantial (Avery and Kane, 2004). The focus of most college prep programs is to expose young people to more college campuses on the very plausible assumption that they will find colleges attractive and understand that attendance is possible.

3 Data

The primary data for this study come from the Bureau of Labor Statistics (BLS) National Longitudinal Study of Youth, 1997 (NLSY97), which annually tracked a nationally representative sample of approximately 9,000 persons born between 1980 and 1984 from 1997 to 2012. Questions in each wave of the survey cover a wide range of topics including family, health, social attitudes and behaviors, education, employment, and income. Our analyses take advantage of these rich data to estimate the relationship between education and earnings. Our analytic sample in each year consists of those who reported any earnings and those for whom location data was available at the time they were 17. This reduces our sample size to approximately 3,800 respondents in each year.

In an additional restricted file, BLS provides information on the county of residence for each NSLY97 respondent in each survey wave. Using this location-based information, we are able to assign each respondent with a county-level estimate of college choice for individuals living in that county as well as distance-weighted measures of higher education affordability and enrollment.

Our primary outcome variable is the log of yearly income for those who report earnings. This measure of earnings includes all of the earnings over the course of that year, even for individuals who may not have worked the entire year. We do not restrict our sample to those who are employed during the entire year. We prefer this measure of earnings because it provides the best overall picture of earnings for a given individual. The impact of postsecondary education on earnings involves the cumulative effect of education on employment, followed by higher wages, followed by it being more likely that the individual will work full time. The full cumulative impact of these steps can be most directly observed by examining earnings over the course of a longer time period, during which the individual may have had different employment conditions and wages. As Card (1999) states, "When log annual earnings are regressed on education and other controls, the estimated education coefficient is therefore the sum of the education coefficients for parallel models fit to the log of hourly earnings, the log of hours per week and the log of weeks per year"[p.1808] (Card, 1999). Card (1999) provides a description of the tradeoffs in using various dependent variables for earnings. Despite the tradeoffs inherent in using log yearly income as a dependent variable, Card suggests that yearly income provides a useful benchmark for conducting studies of the impact of education on earnings.

In separate specifications, we provide estimates for the impact of postsecondary schooling on education using log average hourly wages over the course of the previous year. We think that this specification is important because during the time frame in question, the Great Recession affected all labor markets but particularly impacted labor markets traditionally dominated by men (Elsby et al., 2010). For males in our sample, it may be the case that while wages were higher for those with more postsecondary education, difficulty in finding work meant that earnings were no higher or lower for men than for women. If postsecondary education increased the wages an individual could earn but did not increase overall levels of employment, when we should observe substantial differences in our estimates of the impact of education on log yearly income as opposed to log average wages during the course of the year.

Earnings or wages for any individual at any level of education will be affected by the economic characteristics of their labor market. While we specify several controls for the structure of the labor market below, we also acknowledge that mobility may play a role in earnings. More educated individuals are more likely to move to better labor markets (Greenwood, 1969). We view this mobility to better labor markets as an intermediate outcome of increased postsecondary education, and so do not control for these characteristics (Angrist and Pischke, 2008; Angrist and Krueger, 1999).

Our key independent variable of interest is years of postsecondary education completed. Card (1999) again provides a useful discussion of the tradeoffs inherent in different possible ways of operationalizing educational attainment. He suggests years of education as the standard way of measuring the impact of educational attainment on earnings. As the NLSY97 provides us with monthly event history data for postsecondary attendance, our measure reflects fractional years of attendance (e.g., an individual who had attended for four years and six months would be listed as having 4.5 years of postsecondary education).

We include the following controls, which are widely used in the literature regarding both the determinants of college attendance and earnings: year and quarter of birth, race/ethnicity (with four categories: black, Hispanic, multiracial, and non-black, non-Hispanic), sex, an indicator for whether the individual lives in the South, an indicator for whether the individual lives in a Standard Metropolitan Statistical Area (SMSA) as defined by the Census Bureau and a subset of scores on the Armed Services Vocational Aptitude Battery, (ASVAB), that comprise the Armed Forces Qualifications Test (AFQT).

We include year and quarter of birth because of the voluminous literature, beginning with Mincer, that earnings increase as a function of age. In addition, young people in one birth cohort may have faced different labor markets depending on their year and quarter of birth due to the Great Recession (Bell and Blanchflower, 2011).

We include race/ethnicity both because underrepresented minority groups including Black and Hispanic youth face discrimination in the provision of educational opportunity and in the labor market that are consequential for their future earnings and life chances. (Gupta et al., 2006; Ransom and Oaxaca, 2005; Heckman, 2011; Heckman and LaFontaine, 2010; Levin et al., 2007). Sex is included as earnings differ between men and women. We include the ASVAB as an approximate measure of academic ability (Carneiro et al., 2011). Indicator variables for living in the South and living in an SMSA are included to control for broad variations in local labor markets at the time the individual is 17 (Berg and Kalleberg, 2012).

Respondent's mother's education is incorporated in our analyses as an excluded instrument, as previous research demonstrates that parental education is an important predictor of eventual educational attainment (Blundell et al., 2005). In each model specification, mother's education is interacted with the measure of geographic variation in order to form three excluded instruments.

We access data on the geographic location of all postsecondary institutions in the United States (lower 48 plus Washington, D.C.) using data from the Integrated Postsecondary Education Data System (IPEDS) (U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2014). Prices and enrollment measures used to create our distance-weighted measures of price and enrollment are also taken from IPEDS. Price is defined as in-state tuition; enrollment is defined as full-time equivalent (FTE) enrollment (U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2014).

4 Results

We provide first-stage estimates, reporting the predicted impact of geographic variation in college opportunity on education levels. We then describe a series of specification checks undertaken to ensure that the assumptions underlying our identification strategy are supported by the data. Last, we report results from our instrumental variables estimates.[6]

Interpreting our results as local average treatment effects means that these are results for those individuals who could be induced into treatment (college attendance) as a result of the impact of the instruments (Angrist et al., 1996). The instruments in this case are measures of college proximity interacted with mother's education. Those who are induced to attend are those for whom nearby colleges are most attractive—in other words, young persons at the margin of attendance.

4.1 First stage estimates: geographic variation and postsecondary attainment

In this section, we report first-stage estimates from each of our sets of instrumental variables. For each set of instrumental variables, we report two coefficients: the coefficient for the measure of geographic variation and the coefficient for the interaction between mother's education and the measure of geographic variation. These coefficients are reported as a measure of the strength of the association between the geographic measure and years of college completed.

In addition to these coefficients, we report measures of both whether the instruments predict years of education and whether the instruments are related to the error term in the second stage (Sargan, 1958; Stock and Yogo, 2002). The instrumental variables results reported below may not hold if the assumptions underlying our procedure are not correct. There are two critical assumptions that we need to check. First, we need to verify that the excluded instruments themselves have sufficient predictive power to explain variation in the endogenous regressor. Second, we need to establish that the error term in the second stage equation is not correlated with the excluded instruments.

[6] We used the R statistical programming language for most of our data analysis and graphics (R Core Team, 2014). In the R language, we used the packages `dplyr`, `ggplot2`, `ggthemes`, `sandwich`, `lmtest` and `xtable` (Wickham and Francois, 2015; Wickham, 2009; Arnold, 2014; Zeileis, 2004; Zeileis and Hothorn, 2002; Dahl, 2014). Instrumental variables estimates and specification checks were performed in Stata 13 (StataCorp, 2013).

To test the first assumption, we report both the F statistic for the test of excluding the three instruments from the first-stage equation and the minimum eigenvalue as recommended by Stock et al. (2002) and Stock and Yogo (2002). Their work finds that for our particular case, the critical minimum eigenevalue for one endogenous regressor and three excluded instruments at 5% bias is 13.91. To test the second assumption we report the χ^2 and associated p-value from the nR^2 test from Sargan (1958). Table 1 includes the results from the first-stage regressions. We focus most of our discussion on the most recent years of data, while commenting on year-to-year variation when the results merit.

[Table 1 about here.]

Panel 1 of Table 1 shows results for instruments based on the presence or absence of a four-year college in the respondent's county of residence at age 17. The first row of Table 1 shows the coefficient estimate for the presence or absence of a college in the county, while the next row shows the coefficient for the interaction between the presence of a four-year college and the respondent's mother's education, measured in years. All estimates reported in Table 1 come from a regression which also controls for the variables described in Section 3, along with the main effect for respondent's mother's education. We omit reporting all coefficient estimates for these control variables for the sake of space.

The results from the first panel of Table 1 demonstrate that in the first years of our results, young people who lived in a county with a four-year college completed more years of postsecondary education than those who did not. In 2007, individuals who had a four-year college in their county at age 17 had completed on average 0.56 more years of college, or about 7 months. The 95% confidence interval for this estimate is bounded by [0.006,1.13], indicating a lack of precision. In later years, the 95% confidence interval includes zero, signaling further lack of precision. Jointly, the three instruments of presence or absence of a four-year college in the county, mothers education and the interaction of a four-year college in the county are significant in every year. We estimate the F statistic for these excluded instruments to be 41.4 in 2007 and 27.9 in 2010. To measure the strength of these excluded instruments we also include the minimum eigenvalue from Stock et al. (2002). All minimum eigenvalues reported in Panel 1 of Table 1 exceed the values for 5% for two stage least squares estimates as reported in Stock et al. (2002).

We also report the results of the Sargan overidentification test in Panel 1 of Table 1. These results are not statistically significant in any year, indicating that the instruments meet the condition of being unrelated to the error term in the second stage equation. Overall, we conclude that living in a county with a four-year institution impacts earnings only through the mechanism of increased educational attainment.

In the second panel of Table 1, we report similar results for public two-year colleges. Overall, the patterns for the instrument of two-year colleges are very similar to the patterns for four-year colleges. Having a two-year college in the county at age 17 is associated with higher levels of educational attainment in 2007, but the results become less precise over time. The joint test of significance for the excluded instruments is highly significant, with an F statistic of 45.4 in 2007 and 31.1 in 2010. The overidentification test does not return a statistically significant result in any year. The coefficient estimate for the presence or absence of a two-year college in the county at age 17 in 2007 is larger than the estimate reported for the presence or absence of a four-year college, with a point estimate of 0.82 bounded by a 95% confidence interval of [0.16,1.48].

In the third panel of Table 1, we report results for the first stage for estimates using the first of our new instrumental variables: inverse log distance to in-state public 2-year institutions. The coefficient estimate for the main effect for this excluded instrument for 2010 is estimated to be 0.12, with a 95% confidence interval bounded by [0.08,0.15]. Unlike the estimates for the presence or absence measures, the confidence interval for this coefficient does not cross zero in any year. This indicates that living closer to a larger number of community college is associated with increased levels of educational attainment. We further find that the interaction between inverse log distance to community colleges and other's education is negative. This results means that higher SES individuals (as measured by mother's education) are less sensitive to the presence of a large number of nearby public 2-year colleges when compared with their lower-SES peers. This finding is consistent with previous research (Griffith and Rothstein, 2009).

The F statistic for these excluded instruments ranges from 58.9 in 2007 to 43.6 in in 2010. The overidentification test is not statistically significant in any year. These results provide strong support for our proposed new instrument that includes the entire set of in-state two-year colleges. The measure of inverse log distance to two-year colleges is a significant predictor of educational attainment in every year. It is unrelated to the error term in the second stage, indicating that the only way this variable impacts earnings is through increased educational attainment. This measure appears to be more predictive of attainment, as measured by the precision with which we estimate the coefficient and the larger F statistics in these results.

In the final three panels of Table 1, we report estimates for three other possible measures of geographic variation: distance-weighted price, distance-weighted enrollment and inverse log distance to all colleges. Distance-weighted tuition has a statistically significant and negative coefficient, while the main effect for distance-weighted enrollment is not significant. Last, the inverse log distance measure to all colleges, public and private, in-state and out-of-state, shows a negative main effect, but a large and positive interaction with mothers education. This indicates that living closer to more colleges in general has a stronger predicted impact on attendance for those with higher levels of maternal education. The F statistics for all three possible measures of geographic variation are large and statistically significant, and the minimum eigenvalues exceed the values shown in Stock et al. (2002). However, the values for these are not as large as the values for inverse log distance to community colleges shown in the third panel.

We derive several observations from our first-stage estimates. First, the presence of a two-year or four-year institution has a positive association with enrollment, and both variables meet the requirements for an instrumental variable. This indicates that the approach laid out by Card still provides a valid basis for instrumental-variables estimates of the impact of educational attainment on earnings. Several of our proposed measures of geographic variation also meet these criteria, including distance-weighted enrollment, distance-weighted price, and the inverse log distance to all colleges. The strongest predictor among our proposed excluded instruments is inverse log distance to in-state public two-year colleges. This is shown both in the size of the coefficient, the precision of the coefficient estimate, and the F statistic for the excluded instruments. The finding that those who live near more in-state community colleges complete more years of postsecondary education is consistent with the policy emphasis in many states of placing these institutions near to as many potential students as possible.

4.2 Second stage results: impact of education on earnings

In this section, we report estimates from the second stages for each of our sets of instrumental variables. Table 2 includes the second-stage estimates for each set of excluded instruments described above. As Card notes, all of our estimates in this section are local average treatment effects which identify the impact of education on earnings for the subset of the sample that is induced to complete more years of school by that particular set of instruments (Card, 2001). Our discussion of results will focus on which students are likely to be affected by different types of geographic variation.

[Table 2 about here.]

The third row of Table 2 shows the impact of an additional year of postsecondary education on the log yearly income for the excluded instrument of whether or not there is a public four-year college in the individual's county. The results indicate that for most of the years of the study there is not an observable effect of an additional year of education on earnings in the complete sample. Understood as a local average treatment effect, this indicates that there was not an observable difference in earnings between those who were induced to attend college by the presence of a nearby four-year institution and those who were not. The following rows in Table 2 show estimates for the presence or absence of a two-year college in the individuals county. Similar to the results for public four-year institutions, these estimates are not statistically significant in three of the four years.

The results for the excluded instrument of inverse log distance to community colleges in the state, on the other hand, show a positive and statistically significant effect in both 2008 and 2010. By 2010, the results indicate that an additional year of postsecondary education resulted in a 9.7% increase in earnings, an estimate bounded by [0.01,0.18]. This indicates that for individuals who are induced to attend higher education by being nearby to a large number of community colleges, earnings are on average about 9.7% higher. For an individual with just a high school diploma earning $25,000 per year, these estimates suggest that an additional year of postsecondary education would result in additional earnings of $2,547. This estimate is bounded by a range of [$251, $4,930]. These results show that for those who are induced to attend postsecondary education by the presence of nearby two-year colleges, there are substantial impacts on earnings.

Turning to our remaining proposed measures of geographic variation, the results for inverse log distance to all colleges and distance-weighted tuition, with the exception of 2008, are not statistically significant in most years. The results using the instrument of distance-weighted enrollment at community colleges do show a measurable impact of attainment on earnings, particularly by 2010. The results for 2010 indicate that for this group, one additional year of postsecondary education is associated with an increase in log yearly income of 11%, with a 95% confidence interval bounded by [0.01,0.21]. From these results we conclude that those who are induced to complete more years of postsecondary education by the nearby presence of more high-enrollment public-two year colleges have higher earnings than those who are not.

Based on our second-stage estimates, we find that coefficient estimates do differ depending on the excluded instruments utilized. In our results, the largest impacts are for the excluded instruments of inverse log distance to public two-year colleges and distance-weighted enrollment of two-year colleges. These results point to the role of community colleges in ensuring increased earnings among young persons on the margins of attendance.

4.2.1 Estimates for men and women

Many of the original estimates of the impact of education on earnings focused only on men. In this section, we provide separate estimates from both the first-stage and second-stage equations, first for men then for women. The results show stark differences, with postsecondary education strongly associated with higher earnings for women in our sample, but generally no observable impact for men. Due to space limitations, we do not present tables for these subanalyses; full tables for the separate results for men and women are available in the online supplement.

Though we again perform analyses using each of our possible measures of geographic variation, the first-stage results for the subsample of women generally follow those reported in Table 1, with inverse log distance to public two-year colleges providing the best prediction of additional years of education. Our second-stage results indicate that the payoff for an additional year of postsecondary education is much larger for women than for the entire sample. When using the presence of a four-year college as an excluded instrument, the estimates suggest that an additional year of education results in earnings that are 23% higher. Using the presence of a two-year college within the county, we find that earnings for women are 10.7% higher for each additional year of educational attainment. With our preferred instrument of inverse log distance to all in-state public two-year institutions, we find that one additional year of attainment increases earnings by 15.1%. Results for the remaining three instruments based on geographic variation all offer similar estimates, with an approximate increase in yearly income of 15% for each year of attainment among women in the sample. Our results indicate that among the women in the sample induced to attend higher education by virtue of living closer to more community colleges, a woman making $25,000 per year would realize an average increase in earnings of approximately $4,075 for an additional year of education. These findings indicate a considerable increase in earnings for women, at the high end of the range reported inn Card (2001).

First-stage results for men results vary somewhat from the patterns shown in Tables 1 and those found for women. First, the set of instruments for the presence of a four-year college no longer meet the criteria for overidentification. The test for overidentification for this instrument returned a p-value of 0.03, indicating a statistically significant relationship between the excluded instruments and the error term in the second stage. This finding indicates that the instrument originally proposed by Card for a sample of men does not meet the criteria for overidentification in our sample. The set of excluded instruments for presence or absence of a two-year college pass all of the standard tests, but is not statistically significant on its own.

Among men, we continue to find that inverse log distance to all in-state community colleges predicts attainment. The coefficient for inverse log distance is statistically significant and positive, and the tests for both overidentification and the strength of instruments show that this set of measures identifies the relationship between attainment and earnings. Of the remaining proposed instrumental variables, distance-weighted enrollment and distance-weighted tuition meet the criteria for excluded instruments. Inverse log distance to all colleges fails to meet the criteria for an excluded instrumental variable.

Unlike for women we fail to find a measurable impact of postsecondary attainment on log yearly earnings for men. For any of the second stage results, we find that the coefficients are not statistically significant. While this does not indicate that there is no relationship between postsecondary attainment and earnings for men, it does indicate a lack of measurable impact during the time period covered in our sample for men who were induced to attend through the mechanism of nearby community colleges.

We summarize our results overall as follows. First, the inverse log distance to all community colleges provides the strongest predictor of educational attainment among the proposed measures of geographic variation. Among all of the measures of geographic variation proposed, this measure consistently shows a statistically significant relationship with educational attainment and meets the criteria both for overidentification and for strong instruments. When using this instrument, we find that in the overall sample that an additional year of postsecondary education results in an increase of log yearly income of 9.7%, with a confidence interval bounded by [0.01,0.18]. This result is complicated by our findings for men and women. The coefficient for the impact of education on earnings using this same set of excluded instruments for women shows an impact of 15.1% for women, with a confidence interval bounded by [0.03,0.27]. For men, this same coefficient using the same set of excluded instruments has a point estimate of 0.068, with a confidence interval that includes zero and is bounded by [0.05,0.18].

5 Sensitivity tests

The prior results section includes what we consider to be the most important sensitivity test, namely, how sensitive the results are to the choice of instruments. As we have shown, we find that the results are in fact sensitive to the choice of instruments, with instruments based on inverse log distance to the nearest community college showing the most consistent ability to identify the relationship between attainment and log yearly income. Beyond our choice of instruments, our findings also may be sensitive to several other choices we made in estimating results.

First, we use log yearly income, while other measures of earnings have been utilized in the literature. We test the sensitivity of our results by first providing estimates for our models with a dependent variable of log hourly wages as opposed to log yearly income. We report these findings in the online supplement. For the full sample, these results show a substantively similar pattern in both the first and second stage. These results do not show the same disparity in estimates between men and women, but they are not well identified in the split sample. Second, we do not operationalize our independent variable in terms of degree attainment, but instead use years of education. While such a specification is possible, it diverges from standard methods used in the literature (Card, 1999). When degree attainment has been used by other authors, it is many times assumed that a certain degree indicates a certain number of years of attendance–for instance, an associates degree indicates two years of attendance (Card, 1999). This assumption is not supportable given changes in attendance patterns over time, so we prefer our specification. Finally, we do not include indicators of degree attainment (*e.g.,* associates degree, bachelors degree in our models). To do so would be to control for an intermediate outcome of educational attainment (Angrist and Pischke, 2008). While the "sheepskin" effect is of interest, our purpose here is to measure the impact of additional postsecondary education on earnings, regardless of degree obtained.

6 Conclusion

We find first that college attendance is sensitive to proximity-based measures. Young people who live closer to more institutions are more likely to attend higher education. In particular, the density of community college opportunity appears to play a large role in the level of educational attainment in the population. More than simply having at least one college in ones local area, living close by to a large number of community colleges is associated with an increase in educational attainment. In our measures, going from the 1st quartile to the 3rd quartile on our measure of the inverse log distance of in-state community colleges is associated with a predicted increase in educational attainment of about 7 months.

With the advent of both a national market in higher education and the widespread availability of online courses, it has been suggested that location no longer matters in determining college attendance. Our results show a quite different picture. Instead, young persons who live closer to more affordable colleges are more likely to attain higher levels of education, an association that increases over time. In particular, the density of nearby community colleges appears to play a key role in educational attainment.

For the group induced to attend higher education by the density of community colleges, the impact of additional education on earnings is statistically significant and substantively large. In the general sample, for individuals who are induced to attend higher education by the presence of more in-state community colleges, yearly earnings were 9.7% higher–an increase of about $2,547 per year above mean yearly income.

We find that the payoff for more postsecondary education was higher for women than men. In our preferred estimates, an additional year of postsecondary education for women induced to attend higher education by the presence of many nearby community colleges results in an increase in earnings of 15.1%, or about $4,075 per year above mean earnings. While average yearly income in our sample was still lower for women than for men, the payoff for more postsecondary education for women was higher. Recent years have seen an ongoing discussion of the gender gap in higher education. Women now constitute 55% of undergraduate enrollment. Our results help to shed light on this disparity–since the payoff for women is higher, it follows that more women would attend postsecondary education.

We fail to find any measurable increase in yearly income for men induced to attend higher education by the presence of a large number of nearby community colleges. We do not conclude that there is no payoff for men for increased educational attainment but rather that we cannot detect such a payoff. In any case, the increase in earnings for additional educational attainment for this group of men is likely to be lower than for women. The great recession had a bigger impact on many male dominated industries, including manufacturing (Elsby et al., 2010). Our results may mirror the broader trend in society of males—including more educated males—struggling in a changing labor market.

The generation that entered the workforce for the first time in the late 2000s faced one of the worst labor markets in decades. Many struggled to find work and even among those who did find work, pay was lower than what they could have expected even a few years before (Elsby et al., 2010). It is no surprise that many began to question the importance of postsecondary education during a time when so many college graduates were struggling to find good-paying jobs. Our results suggest that even during this time, the earnings advantage for postsecondary education remained. Young people who lived in areas with a high concentration of community colleges were more likely to go to college, and those who attained more years of education earned more.

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List of Tables

Table 1: 2SLS first stage estimates for log yearly income for all subjects

	2007	2008	2009	2010
Public 4-Year in County	0.5604	0.4139	0.1364	0.1889
	(0.2888)	(0.306)	(0.3306)	(0.338)
... × Mother's education	-0.0318	-0.0228	-0.0006	-0.0036
	(0.0217)	(0.0229)	(0.0248)	(0.0253)
Endogeneity: F p-value	0.122	0.2304	0.0689	0.708
Overidentification: χ^2 p-value	0.39	0.7504	0.6799	0.5934
First Stage F	41.3819	35.4891	32.781	27.8778
First stage Min. Eigenvalue	48.9857	42.4025	39.3282	33.7787
N	3892	4026	3744	3777
Public 2-Year in County	0.8195	0.5514	0.734	0.4888
	(0.339)	(0.356)	(0.3917)	(0.3952)
... × Mother's education	-0.0536	-0.0319	-0.042	-0.0209
	(0.0255)	(0.0268)	(0.0294)	(0.0296)
Endogeneity: F p-value	0.2204	0.1604	0.0969	0.8191
Overidentification: χ^2 p-value	0.6162	0.8413	0.9614	0.1094
First Stage F	45.3506	38.3893	37.8155	31.1127
First stage Min. Eigenvalue	49.0984	42.7465	40.8744	35.1024
N	3892	4026	3744	3777
Inverse Log Distance to In-State Pub. 2yr	0.1152	0.1269	0.1249	0.1232
	(0.0173)	(0.0181)	(0.02)	(0.0203)
... × Mother's education	-0.0077	-0.0086	-0.0083	-0.0082
	(0.0013)	(0.0013)	(0.0015)	(0.0015)
Endogeneity: F p-value	0.4595	0.064	0.2184	0.4781
Overidentification: χ^2 p-value	0.2884	0.5862	0.3931	0.8263
First Stage F	58.8715	58.4783	50.6743	43.5653
First stage Min. Eigenvalue	62.4609	58.3953	52.365	45.9725
N	3892	4026	3744	3777
Distance-Weighted Tuition; In-State Pub. 2yr	-0.2385	-0.2429	-0.1988	-0.2883
	(0.1124)	(0.1196)	(0.1297)	(0.13)
... × Mother's education	0.0116	0.0114	0.01	0.0119
	(0.0085)	(0.009)	(0.0097)	(0.0098)
Endogeneity: F p-value	0.1513	0.1317	0.0924	0.6139
Overidentification: χ^2 p-value	0.9146	0.8053	0.9896	0.365
First Stage F	43.1271	40.0409	35.0488	34.6193
First stage Min. Eigenvalue	50.4854	45.1229	40.2734	38.6751
N	3892	4026	3744	3777

Continued on next page...

... table 1 continued

	2007	2008	2009	2010
Distance-Weighted Enrollment: In-State Pub. 2yr	0.0376	0.029	0.0206	0.0239
	(0.0215)	(0.0226)	(0.0242)	(0.0249)
... × Mother's education	-0.0016	-0.001	-0.0003	0
	(0.0017)	(0.0017)	(0.0019)	(0.0019)
Endogeneity: F p-value	0.1474	0.157	0.0796	0.8348
Overidentification: χ^2 p-value	0.9505	0.1504	0.9873	0.179
First Stage F	42.0477	36.9755	34.3534	30.3613
First stage Min. Eigenvalue	49.7756	43.3276	40.3062	36.0631
N	3892	4026	3744	3777
Inverse Log Distance to All Colleges in Country	-0.0069	-0.0073	-0.0051	-0.0063
	(0.003)	(0.0031)	(0.0035)	(0.0035)
... × Mother's education	0.0006	0.0006	0.0005	0.0005
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Endogeneity: F p-value	0.3125	0.1298	0.1195	0.3813
Overidentification: χ^2 p-value	0.2415	0.6638	0.4701	0.0145
First Stage F	40.9179	37.7759	34.3365	29.42
First stage Min. Eigenvalue	49.154	43.5365	39.9014	34.0326
N	3892	4026	3744	3777

NOTE: The critical minimum eigenevalue for one endogenous regressor and three excluded instruments at 5% bias is 13.91.

Table 2: 2SLS second stage estimates for log yearly income for all subjects

	2007		2008		2009		2010	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Years of college	0.035		0.059		0.063		0.065	
	(0.01)		(0.009)		(0.01)		(0.009)	
Public 4yr in County		-0.038		0.129		-0.042		0.084
		(0.049)		(0.057)		(0.058)		(0.049)
Public 2yr in County		-0.025		0.14		-0.035		0.056
		(0.05)		(0.057)		(0.059)		(0.047)
Inverse Log Distance: In-State Pub. 2yr		0.002		0.153		-0.001		0.097
		(0.043)		(0.051)		(0.05)		(0.044)
Inverse Log Distance: All Colleges		-0.033		0.147		-0.037		0.091
		(0.048)		(0.058)		(0.059)		(0.05)
Distance-Weighted Tuition: In-State Pub. 2yr		-0.033		0.143		-0.038		0.076
		(0.048)		(0.058)		(0.057)		(0.05)
Distance-Weighted Enroll.: In-State Pub. 2yr		-0.015		0.147		-0.028		0.11
		(0.05)		(0.058)		(0.058)		(0.051)