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We evaluate the educational returns to General Educational Development (GED) certification using state administrative data. We use fuzzy regression discontinuity (FRD) methods to account for the fact that GED test-takers can repeatedly retake the test until they pass it and the fact that test-takers have to pass all five subtests before receiving the GED. We find that the GED increases the likelihood of postsecondary attendance and course completion substantially but that the GED impact on overall credits completed is modest; the GED causes an average increment of only two credits for men and six credits for women.

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I. Introduction

Many postsecondary institutions require high school graduation or high school equivalency certification for admission to degree-seeking programs. Such certification therefore may be an important path to obtaining labor market skills for high school dropouts. However, the extent of such benefits is not clear, as many of those with certification do not successfully pursue schooling or training options, and dropouts who do not obtain certification often have access to alternative postsecondary educational opportunities.

Until 2014, the General Educational Development (GED) test provided the sole means of high school equivalency certification supported by states, and it was the most widely accepted alternative to a high school diploma for admission to degree-seeking programs at postsecondary institutions. Because GED test-takers can repeatedly retake the test until they pass it, our previous analyses utilize a fuzzy regression discontinuity (FRD) design based on the discontinuity in the first GED test attempt (Jepsen, Mueser, and Troske 2016). This technique provides an estimate of the impact of the GED for individuals who are near the cutoff for passing the GED test, while it also allows us to remove possible bias that results from retaking the test.

In this paper, we provide three extensions to our previous work. First, we investigate the counterintuitive result that the GED is associated with an increase in the likelihood of attending postsecondary education but that the GED does not improve earnings or employment. Specifically, we look at multiple education outcomes to understand in much greater depth how and to what extent the GED improves postsecondary education outcomes.

Second, because GED test-takers need to receive a minimum score on each of the five subtests that make up the GED as well as receive an overall minimum score before obtaining GED certification, we estimate a multiple discontinuity FRD model that includes the lowest subtest score discontinuity in addition to the overall test score discontinuity. We also estimate an FRD model based solely on the discontinuity in passing the GED generated by the overall test score, the model estimated in Jepsen et al. (2016). The two approaches yield similar results.

We find sizable, positive effects of the GED on the likelihood of attendance at a public postsecondary institution: nearly 5 percentage points for men and 10 percentage points for women. The GED effect on course completion is of a similar magnitude, suggesting that completing postsecondary courses taken is not a major challenge for GED test-takers who be-

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gin a course. However, the GED impact on the average amount of human capital obtained is quite low: less than one class for men and just under two classes for women. We find no effect of a GED on receipt of a certificate, diploma, or degree. Fewer than 5% of GED test-takers receive any type of postsecondary award.

Our third contribution is to build on recent work in the regression discontinuity literature that investigates the likelihood that the results may generalize beyond the population of compliers at the discontinuity (DiNardo and Lee 2011; Bertanha and Imbens 2014). For outcomes in the first year after the initial GED test attempt, statistical tests suggest that our results may well be applicable to individuals in the full population of test-takers. Although these statistical tests do not suggest that GED effects on outcomes observed after the first year necessarily apply to the full population, we do find evidence that they very likely apply to individuals near the passing threshold, not just "compliers," which the FRD focuses on.

II. GED Literature

Early work on the GED uses survey data from the National Longitudinal Survey of Youth (NLSY) and the High School and Beyond (HSB) survey. Most of these papers focus on the labor market returns to the GED (see, e.g., Cameron and Heckman 1993; Murnane, Willett, and Boudett 1995, 1999; Tyler 2004; Heckman and LaFontaine 2006; and Heckman, Humphries, and Kautz 2014).

Fewer studies look at the educational returns to the GED. Cameron and Heckman (1993), Tyler, Murnane, and Willett (2003), Heckman and LaFontaine (2006), Heckman, Humphries, and Mader (2011), and Heckman et al. (2014) estimate the raw differences in postsecondary schooling between high school graduates and GED recipients. Murnane, Willett, and Boudett (1997) apply models that use NLSY GED recipients and high school dropouts to estimate the impact of the GED on postsecondary education and training. They include multiple years of data for each person and estimate a random effects probit model to account for person-specific correlations in unobservables. The authors find modest positive effects of GED certification on postsecondary attendance and other training for both men and women, although they find that fewer than half of GED recipients participate at all.

Tyler and Lofstrom (2010) use administrative data on eighth-grade students in Texas to study the effects of the GED on postsecondary education. They compare GED recipients with high school graduates, controlling for differences in the likelihoods of dropping out of high school based on cognitive and noncognitive skills. They find that high school graduates are much more likely to pursue postsecondary education than GED recipients with similar probabilities of dropping out of high school.

Patterson, Song, and Zhang (2009) provide a descriptive analysis of postsecondary education attendance among a random sample of GED test-takers. They find that test-takers who receive GED certification have higher attendance rates than test-takers who do not obtain certification but that 77% of GED test-takers who attend postsecondary institutions only attend for one semester. Nearly 80% of attendees go to public 2-year institutions.

Our analysis provides several contributions to the GED literature. Few papers explicitly study the causal effect of the GED on postsecondary education. Most, such as Heckman et al. (2014), provide descriptive comparisons of educational outcomes between GED recipients and dropouts and/or high school graduates, as opposed to regression-based analyses of the impact of the GED on these outcomes. None of these papers use a regression discontinuity analysis of the GED's effects on education outcomes. The results in Murnane et al. (1997) are limited by a lack of recent data and small samples, roughly 300 GED recipients and 300 high school dropouts of each gender. In contrast, in our analyses we use administrative data from a single state for nearly 100,000 individuals who took the GED between 1995 and 2005. We match these data with education data covering the period 1995–2009, which provides us with education data for several years after individuals took the GED.

We also look in more detail at education outcomes. In addition to the dichotomous attendance decision, we look at course completion, the number of credits earned, and whether an award such as a certificate or degree is received. We also distinguish between attendance at 2-year and 4-year institutions.

We contribute to the RD literature by presenting a model that includes multiple discontinuities in a fuzzy RD setting. Previous RD papers on multiple discontinuities focus solely on sharp rather than fuzzy discontinuities (see, e.g., Papay, Murnane, and Willett 2011; Reardon and Robinson 2012; and Wong, Steiner, and Cook 2013).

III. GED Test and GED Data

Each state maintains a testing program that provides high school equivalency certification for dropouts. Up through 2013, all states used the GED test, and, although passing criteria in the 1990s differed in minor ways across states, such differences had all but disappeared by the turn of the century. The focus here is on the GED test taken by test-takers in Missouri during the period 1995–2005. Although new tests were adopted in 2014 in all states, the basic structure of the testing program, and in particular the ability of test-takers to take the test multiple times, remains unchanged.[1]

[1] Beginning in 2014, a new version of the GED test, which changed the structure of its subtests, became available. This new version was adopted as the exclusive

During the period of our analysis, the GED test consisted of five subtests: reading, writing, social studies, science, and mathematics, with a maximum time for completion set at 7.5 hours. GED certification required minimum scores on each subtest as well as a minimum combined score across the five subjects of 2250 out of a maximum of 4000. Thus, test-takers could score above 2250 on the test but still not obtain GED certification if they failed to obtain the minimum score on each subtest. Test-takers could also score above the minimum on each subtest but still not receive a GED if their combined test score did not equal or exceed 2250. An individual's GED score at any given time was based on a composite of all subtests taken over a 2-year period, where the score on each subtest was the highest score over that period; that is, the score from any given GED subtest attempt contributed to GED certification for 2 years before it expired. Many individuals who failed the test retook the test within 2 years, and they often only retook certain subtests rather than retaking the entire exam.[2]

Prior to 2014, the last revision of the GED occurred in 2002. The 2002 revision altered the certification criteria in several ways. First, the minimum passing subtest score was raised from 400 to 410 (missing subtest scores coded as zeros). Scores from the earlier version could not be combined with the 2002 version, so students who had not passed the exam prior to 2002 had to "start over" and meet the criteria under the new version of the test. In unreported results (available from the authors upon request), we find that the estimated GED impact is qualitatively similar, although less precisely estimated, in each time period (1995–2001 and 2002–5).

Our basic sample consists of any individual who took the GED test for the first time in Missouri between 1995 and 2005.[3] For each individual, we have data on the most recent 10 test scores for each version of the test, 1995 to 2001 and 2002 to 2008. We exclude 86 individuals who took the test 10 or more times in either time period because we do not know when the first attempt occurred. We exclude individuals who took the GED test while incarcerated because their educational outcomes are affected by their incarceration. Individuals who received their GED through the US military's DANTE program are excluded because DANTE program participants who took the test but did not pass are not in the data. Finally, we exclude individuals who took the GED as part of the GED Option program.

measure of high school equivalency by 36 states, but other states substituted alternative high school equivalency tests or allowed test-takers a choice. Alternative tests include the Educational Testing Service HiSET test, and McGraw-Hill's Test Assessing Secondary Completion. Missouri adopted the HiSET test. See Coffey Consulting (2014).

[2] Students could take the test up to six times in any 2-year period.

[3] As discussed in Jepsen et al. (2016), Missouri has labor market and demographic characteristics similar to many US states.

This program, offered in several states, allows high school students at risk of dropping out to use the GED test to help achieve a high school diploma rather than GED certification.

Postsecondary data are available for each public institution in Missouri.[4] The data, provided by the state, are available for each term (spring, summer, or fall) from summer 1994 through spring 2009. We have information on attendance, course completion, number of credits earned, and the receipt of awards such as certificates, associate's degrees, and bachelor's degrees. This information is available separately for 2-year and 4-year institutions.

Because the "final" GED test score—obtained by combining the highest subtests taken over a 2-year period—is the primary factor that determines GED certification, it is an obvious candidate for a conventional regression discontinuity analysis. However, this approach ignores both the facts that some of those whose scores meet the overall test score threshold do not satisfy the minimum on each of the subtest scores and that some individuals retake the test. Justification for this approach rests on the observation that 90%–95% of those whose overall test scores exceeds the threshold also pass the subtest minimum and that only about one in seven test-takers retakes the test.

Jepsen et al. (2016) show that the final test score is not a valid candidate for a regression discontinuity analysis (sharp or fuzzy). Figure 1 shows the distribution of final GED test scores. Specifically, the figure contains fitted values from a local linear regression that is based on a triangular kernel with a bandwidth covering eight scores (80 points), allowing for a discontinuity just below 2250.[5] The log discontinuity in the density of final test scores is close to 1.0, implying that the density to the right of 2250 is nearly three times that of that immediately to the left, a difference that is easily statistically significant at the 0.1% level ($p < .001$). The very high retake probability for those close to the cutoff point causes a dramatic redistribution in the final score. Even though only 16% of individuals retake the test, this small proportion of retakers is sufficient to alter the distribution very dramatically. Jepsen et al. (2016) also demonstrate discontinuities in several demographic variables, such as sex, age, and race. Thus, the central assumptions of the RD model are violated if we take the final test score as the continuous running variable (see Imbens and Lemieux 2008; McCrary 2008).

The analysis here will use the first test score—for all those who first take the test over the period 1995–2005—as the continuous variable underlying

[4] We do not have permission to share individual information, and so we are unable to match these data to data on private schools or to schools in other states.

[5] These methods correspond to those recommended by McCrary (2008).

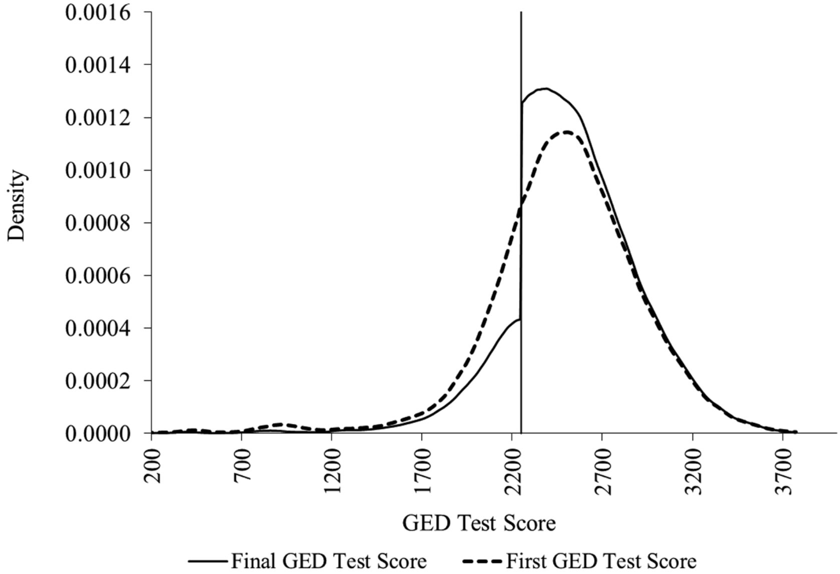

FIG. 1.—Distribution of first and final test scores, 1995–2005

GED certification. Although GED certification is not predicted perfectly by the first score, there is a strong discontinuity in the relationship between first test score and ultimate GED certification, allowing us to apply a fuzzy regression discontinuity (FRD) design.

The FRD design requires that the first test score display continuous relationships with all pre-existing factors that may predict GED certification and postsecondary education outcomes. Figure 1 also presents the distribution of the first test score, again plotting fitted values of a local linear regression allowing for a discontinuity at 2250. In contrast to the final score, there is essentially no discontinuity at the 2250 threshold. Jepsen et al. (2016) also show that there is no discontinuity in the characteristics of individuals around this threshold. The first test score is therefore suitable for a FRD design.

IV. Fuzzy Regression Discontinuity Methods

A. Single Discontinuity Design

Because individuals above the test threshold are appreciably more likely to receive GED certification than those below, these data are appropriate for a FRD design for estimating the GED impact for individuals near that test threshold.[6] In our context, the equation predicting GED certification is written:

$$\begin{aligned}\text{GED} = \alpha_{wl} + \alpha_{wrl}D_r + \sum_{j=1}^{p}\beta_{wlj}[D_l(T - 2250)]^j \\ + \sum_{j=1}^{p}\beta_{wrj}[D_r(T - 2250)]^j + X\eta_w + \varepsilon,\end{aligned} \tag{1}$$

where T is the total score on the first GED test, D_r is a dummy indicating whether that score equals or exceeds the passing threshold, D_l is a dummy indicating whether that score is below the passing threshold, p indicates the order of the polynomial, and X is a vector with the following set of covariates: earnings in four quarters prior to first GED attempt, age, age squared, race, semester of the year (fall, spring, or summer), and dummies for the year the first test was taken. For simplicity, we report the results from the quadratic model where $p = 2$.[7] Greek letters identify estimated parameters, and α_{wrl} indicates the discontinuity at the threshold.

The analogous equation predicting the outcome variable is written:

$$\begin{aligned}Y = \alpha_{yl} + \alpha_{yrl}D_r + \sum_{j=1}^{p}\beta_{ylj}[D_l(T - 2250)]^j \\ + \sum_{j=1}^{p}\beta_{yrj}[D_r(T - 2250)]^j + X\eta_y + \in.\end{aligned} \tag{2}$$

The estimate of the GED's impact is based on the relative size of the regression discontinuities estimated in equations (1) and (2). Assuming that the discontinuity in (1) induces the discontinuity in equation (2), the impact of the GED can be written:

$$\tau = \frac{\alpha_{yrl}}{\alpha_{wrl}}. \tag{3}$$

Hahn, Todd, and van der Klaauw (2001) show that the FRD can be formulated as an instrumental variables (IV) system, where the treatment variable (GED certification here) is instrumented with dummy variables capturing the discontinuity. Equation (1) is the first-stage equation. The outcome variable can be fitted with the following specification:

[6] The formal model presented in this section follows closely from that presented in Imbens and Lemieux (2008), McCrary (2008), and Jepsen et al. (2016).

[7] The results from the cubic model ($p = 3$) are less precisely estimated but show a similar pattern.

$$Y = \alpha_0 + \tau\widehat{\text{GED}} + \sum_{j=1}^{p}\beta_{lj}[D_l(T - 2250)]^j + \sum_{j=1}^{p}\beta_{rj}[D_r(T - 2250)]^j + X\eta + \mu, \tag{4}$$

where $\widehat{\text{GED}}$ is the predicted value from equation (1). If the polynomial is of the same order in equations (1) and (4), estimates of τ based on equations (1)–(3) are numerically identical to those based on equations (1) and (4).

B. Multiple Discontinuity Design

The approach above focuses on the overall GED test score, but it ignores the fact that individuals who have scores at or above 2250 face a discontinuity based on their subtest scores. Furthermore, it ignores the fact that those individuals who have subtest scores that are below the subtest threshold do not obtain GED certification even if their overall scores exceed the threshold, in contrast to those with higher subtest scores. It is possible to identify sharper discontinuities based on both the total score and the lowest subtest score, essentially generalizing the FRD design to multiple dimensions.

If we create separate variables identifying whether GED overall and subtest scores meet these two criteria, the interaction between these measures identifies individuals who receive GED certification on the basis of their initial test performance. The model does not, however, conform to a sharp RD design—even if reinterpreted in two dimensions—because those who fail to meet one of the criteria may still obtain GED certification when they retake the exam. This complication also opens up the possibility that there may be multiple discontinuities that are not present in a sharp RD design. For example, when an individual has not exceeded the overall score threshold, if multiple test-taking cannot occur, the subtest threshold is irrelevant. Given the possibility of retaking the test, a subtest threshold may well influence GED certification even when the overall score falls short because those who meet the subtest criteria will have an easier time meeting the joint criteria on future tries.

Whereas the conventional FRD (or RD) setup focuses only on properly identifying the functional form of a single variable, here the functional form is multivariate. In addition to controlling for the additive impact of the overall and subtest scores, it may be necessary to recognize that the overall score and each subtest score (not just satisfying the criteria) may interact with each other. In the specification below, we therefore include continuous interactions between the overall test score and the lowest subtest score, distinguishing whether either score is above or below the threshold.

Combining these considerations, the specification for the equation predicting GED certification, can be written:

$$\begin{aligned}
\text{GED} = {} & \alpha_{wl} + \sum_{j=1}^{p}\beta_{wllj}[D_{Tl}D_{Sl}(T-2250)]^{j} + \sum_{j=1}^{p}\gamma_{wllj}[D_{Tl}D_{Sl}(S-c)]^{j} \\
& + \phi_{wll}[D_{Tl}D_{Sl}(T-2250)(S-c)] + \alpha_{wrl}D_{Tr}D_{Sl} \\
& + \sum_{j=1}^{p}\beta_{wrlj}[D_{Tr}D_{Sl}(T-2250)]^{j} + \sum_{j=1}^{p}\gamma_{wrlj}[D_{Tr}D_{Sl}(S-c)]^{j} \\
& + \phi_{wrl}[D_{Tr}D_{Sl}(T-2250)(S-c)] + \alpha_{wlr}D_{Tl}D_{Sr} \\
& + \sum_{j=1}^{p}\beta_{wlrj}[D_{Tl}D_{Sr}(T-2250)]^{j} + \sum_{j=1}^{p}\gamma_{wlrj}[D_{Tl}D_{Sr}(S-c)]^{j} \\
& + \phi_{wlr}[D_{Tl}D_{Sr}(T-2250)(S-c)] + \alpha_{wrr}D_{Tr}D_{Sr} \\
& + \sum_{j=1}^{p}\beta_{wrrj}[D_{Tr}D_{Sr}(T-2250)]^{j} + \sum_{j=1}^{p}\gamma_{wrrj}[D_{Tr}D_{Sr}(S-c)]^{j} \\
& + \varphi_{wrr}[D_{Tr}D_{Sr}(T-2250)(S-c)] \\
& + \phi_{w}d_{s0} + X\eta_{w} + \varepsilon,
\end{aligned} \tag{5}$$

where the dummy variable D_{Tl} (D_{Tr}) identifies values below (equal to or above) the cutoff on the overall score, and D_{Sl} (D_{Sr}) identifies values below (equal to or above) the cutoff on the lowest subtest score. Here T continues to designate the total score, and S is the lowest subtest score, with the subtest threshold c.[8] The dummy variable d_{s0} indicates that the lowest subtest score is zero.[9] As above, the subscript w identifies coefficients in the equation predicting certification. The estimated coefficients β_{whkj} and γ_{whkj} (where h and k stand in for either l or r) identify the slopes of the relationship of GED certification with the total score and the lowest subtest score, respectively, allowing different values depending on the scores relative to their thresholds. Discontinuities are estimated by α_{whk}. The interaction term D_{Tr} D_{Sr} identifies individuals who receive a GED based on the initial test, and therefore α_{wrr} is expected to identify a major discontinuity. The smooth interaction terms are fitted with ϕ_{whk}. The test score and subtest score functions are of order p, and we will consider $p = 2$ (quadratic).

In fitting the corresponding outcome function, the structure parallels this closely, except that discontinuities are omitted because they are the excluded instruments used for identifying the model:

[8] For 1995–2001, $c = 400$; for 2002 and after, $c = 410$.

[9] In many instances, test-takers choose to skip at least one subtest; in such cases, the score is coded as zero. As might be expected, the linear relationship assumed for the lowest test score does not apply for scores of zero.

$$
\begin{aligned}
Y = {} & \alpha_l + \tau\widehat{\mathrm{GED}} + \sum_{j=1}^{p}\beta_{llj}[D_{Tl}D_{Sl}(T-2250)]^j + \sum_{j=1}^{p}\gamma_{llj}[D_{Tl}D_{Sl}(S-c)]^j \\
& + \phi_{ll}[D_{Tl}D_{Sl}(T-2250)(S-c)] \\
& + \sum_{j=1}^{p}\beta_{rlj}[D_{Tr}D_{Sl}(T-2250)]^j + \sum_{j=1}^{p}\gamma_{rlj}[D_{Tr}D_{Sl}(S-c)]^j \\
& + \phi_{rl}[D_{Tr}D_{Sl}(T-2250)(S-c)] \\
& + \sum_{j=1}^{p}\beta_{lrj}[D_{Tl}D_{Sr}(T-2250)]^j + \sum_{j=1}^{p}\gamma_{lrj}[D_{Tl}D_{Sr}(S-c)]^j \\
& + \phi_{lr}[D_{Tl}D_{Sr}(T-2250)(S-c)] \\
& + \sum_{j=1}^{p}\beta_{rrj}[D_{Tr}D_{Sr}(T-2250)]^j + \sum_{j=1}^{p}\gamma_{rrj}[D_{Tr}D_{Sr}(S-c)]^j \\
& + \phi_{rr}[D_{Tr}D_{Sr}(T-2250)(S-c)] \\
& + \phi_0 d_{s0} + X\eta_w + \mu .
\end{aligned}
\tag{6}
$$

Estimated coefficients are analogous to those in (5).

Identification comes from the fact that the function in equation (6) is smooth in the overall test score and subtest score in the neighborhood of the thresholds, reflecting our belief that a continuous function will identify the relationship between test scores and earnings in the absence of GED certification, whereas the function determining GED receipt in equation (5) is not. As in the case of the single-dimension FRD model introduced above, the impact estimate is identified solely by the points of discontinuity, and the model fits the other relationships quite flexibly.[10]

An implicit assumption in equations (5) and (6) is that the effect of the lowest subtest is the same across all five subtests. For example, we assume that the discontinuity and its subsequent impact on outcomes is the same for individuals whose lowest subtest is mathematics and those whose lowest subtest is reading. The data indicate that, conditional on failing to pass at least one subtest, test-takers are most likely to fail the math subtest, followed by the writing subtest; test-takers are approximately equally likely

[10] We chose not to impose any constraints on the coefficients because, as shown in appendix table A1, most of these parameters are significant in the first-stage regression. Because the effect estimates obtained in the second stage are often statistically significant (tables 3–6), we believe that the potential benefits of improved precision from reducing the number of parameters are outweighed by the possibility of bias in estimates.

to fail the other three subtests. However, when we modify the specification to allow separate effects for each of the five subtests, the results in the outcome equations are quite similar to those obtained from equations (5) and (6), except that the standard errors in the more flexible model are noticeably larger (likely due to the extra parameters estimated). These results, along with those from the preferred model based on the lowest subtest, are in appendix tables B1–B4 (Appendix B and tables B1–B10 are available online).

As stated previously, our basic sample includes individuals who first take the GED test in the period 1995–2005. We exclude test-takers in 2006–8 because these individuals do not have sufficient education data after their initial GED test score. In addition, the sample is limited to individuals with initial test scores between 1500 and 3000 because there is very little variation in GED receipt outside this range. These limitations eliminate 8% of the cases below the threshold and 12% of the cases above the threshold. For the remainder of the paper, we refer to the regression analysis sample as the full sample. Consistent with previous GED research, all regressions are estimated separately for men and for women.

The outcome variables consist of multiple measures of postsecondary education participation, as measured in each of the first 15 semesters (including summer semesters) after the first GED test attempt. The first dependent variable is a dichotomous variable for postsecondary attendance in each semester after the first GED test attempt. The second dependent variable is a dichotomous variable measuring completion of at least one class (including noncredit classes) in each semester. The third dependent variable is the number of credits completed in each semester. In addition, we also consider the total cumulative number of credits earned across all 15 semesters. This latter variable measures the amount of human capital acquired in postsecondary education. The fifth dependent variable is a dichotomous variable capturing the completion of a postsecondary award such as a certificate, an associate's degree, or a bachelor's degree at any time during the 15 semesters. Finally, we also look at our measures of postsecondary education separately for 2-year and 4-year institutions.

In each case, we identify GED certification at the time when the dependent variable is measured. For example, in examining enrollment in a particular semester, the GED certification is identified at the beginning of that semester. For cumulative outcomes such as total credits, GED certification is measured as of the beginning of the fifteenth semester.

Table 1 contains the descriptive statistics for the regression sample. Most test-takers receive certification, and prior earnings (in current dollars) are low. Approximately one-quarter of men and one-third of women attend postsecondary education and complete a class. The average number of credits earned in the regression sample is 6.5 for men and 11.6 for women. Only 2% of men and under 5% of women receive a postsecondary award.

Table 1
Descriptive Statistics for GED Test Takers, 1995–2005

	Men		Women	
	Mean	SD	Mean	SD
GED certification	.804	.397	.816	.387
Received award	.021	.143	.048	.214
Nonwhite	.216	.411	.199	.399
Age at first test	22.7	8.0	24.9	9.7
Prior earnings ($)	1,702	2,849	1,481	2,338

	Men					Women				
			Credits					Credits		
Semesters since First GED Test	Attend	Complete Class	Mean	SD	Observations	Attend	Complete Class	Mean	SD	Observations
1	.052	.046	.39	1.99	44,378	.079	.072	.62	2.51	41,967
2	.060	.053	.46	2.20	44,378	.094	.084	.73	2.71	41,967
3	.057	.050	.44	2.16	44,378	.096	.087	.76	2.79	41,967
4	.048	.043	.37	2.00	44,378	.082	.074	.64	2.57	41,967
5	.046	.041	.35	1.92	44,378	.076	.070	.59	2.46	41,967
6	.044	.039	.35	1.97	44,378	.076	.070	.60	2.48	41,967
7	.039	.035	.29	1.78	44,378	.067	.061	.51	2.27	41,967
8	.037	.034	.28	1.73	44,378	.063	.057	.47	2.19	41,967
9	.036	.032	.28	1.72	44,378	.064	.059	.49	2.25	41,967
10	.032	.029	.23	1.56	44,378	.059	.054	.43	2.07	41,967
11	.032	.029	.24	1.58	43,290	.056	.052	.42	2.05	40,989
12	.032	.029	.24	1.60	42,404	.057	.052	.43	2.09	40,235
13	.029	.025	.20	1.43	41,178	.054	.049	.39	1.97	39,092
14	.028	.026	.21	1.49	40,087	.052	.047	.37	1.92	38,010
15	.028	.025	.21	1.56	39,332	.050	.046	.37	1.94	37,207
Cumulative	.243	.222	6.52	20.45	39,332	.348	.326	11.62	26.99	37,207

NOTE.—GED certification in the table identifies those who obtained GED certification by the end of our observation period. GED certification in our analyses applies to the beginning of the relevant semester.

V. Results

Figure 2 illustrates the estimation methods underlying equations (1) and (2). The top panel is for men, and the bottom panel is for women. The figure contains the likelihood of GED receipt and the total number of credits received across all semesters, as functions of first GED test score. For both men and women, the discontinuity assumed in equation (1) is clearly present in the data, confirming that those who score just above the threshold

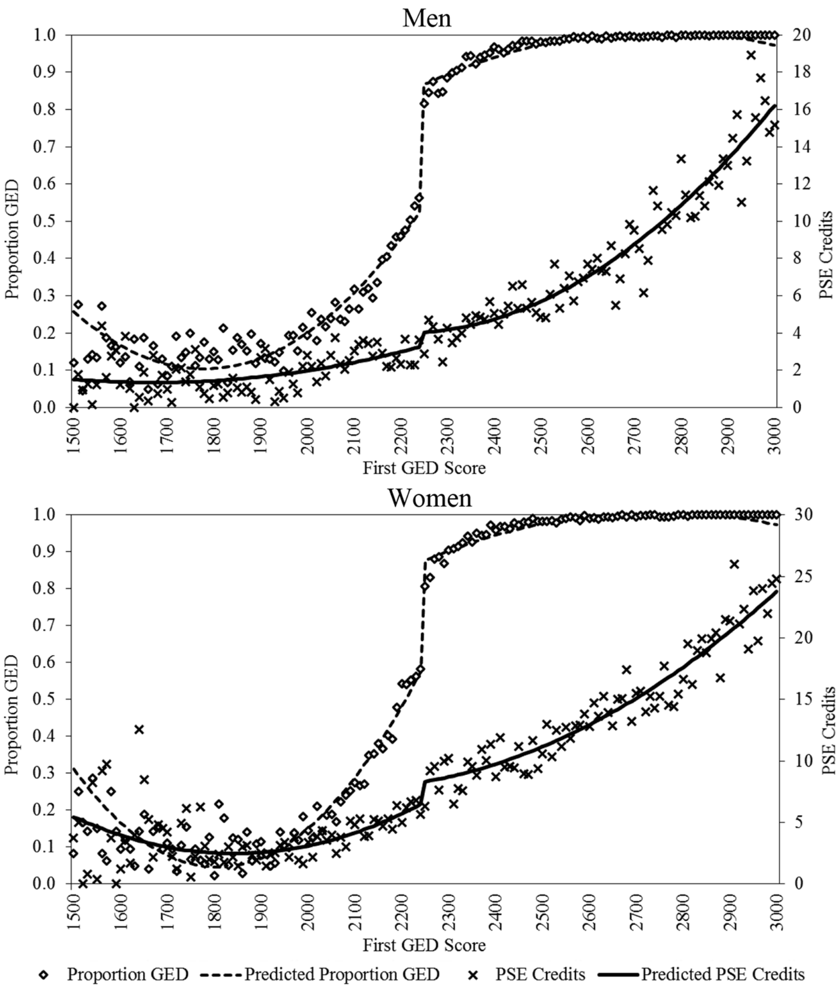

Fig. 2.—Regression discontinuity models predicting GED and postsecondary credits.

on the overall GED score are appreciably more likely to have a GED within 2 years. The graph also illustrates a positive discontinuity in the number of postsecondary credits. The jump in values of the postsecondary credits and the GED receipt variables at the test score threshold provide graphical support for our use of the FRD model, as well as support for a positive effect of the GED on credits obtained.

Table 2 presents estimates of the first stage of the two-stage equation for the ninth semester after the initial GED test. Results for other semesters are available in appendix table B5. The dependent variable is a dichotomous variable for passing the GED test, and the model is estimated as a linear regression. Note that the first-stage estimates for all second-stage outcomes (attendance, completion, and credits) are identical for a given semester because they are all based on the same sample and the same first-stage regression.[11] The discontinuity at the threshold is associated with a 34 percentage point increase in the likelihood that men obtain GED certification, whereas the number for women is 30 percentage points (see estimates for "discontinuity," which is denoted as α_{wrl} in eq. [1]). All the variables are significant at the 1% level (two-sided test).[12]

Table A1 contains results from the multiple discontinuity regression in equation (5). Being above the cutoff for both discontinuities is associated with increases in the likelihood of receiving the GED of 54 percentage points for men and 48 percentage points for women. Even though all students who are above the cutoff for both discontinuities receive the GED, the discontinuity is below 100% because students below the cutoff are able to pass the GED by retaking it. The coefficients for $D_{Tl}\,D_{Sr}$ indicates that, even for those who have not passed the overall score requirement, if the lowest subtest score is just above the threshold this is associated with a 17 percentage point increase (18 for women) in the likelihood of receiving the GED. Similarly, the coefficient on $D_{Tr}\,D_{Sl}$ indicates that being just above the overall threshold increases the chance of GED receipt by about 8 percentage points (2.5 percentage points for women) even for those whose lowest subtest score does not exceed the required minimum.

Table 3 contains parameter estimates for the GED impact based on the single discontinuity as in equation (4) and the multiple discontinuities as in equation (6). The dependent variable is a dummy variable for public post-

[11] The first-stage results vary across semesters because the dependent variable is receipt of the GED at the start of the semester and students retake the GED. In addition, the sample size varies slightly because we do not have a full panel of 15 semesters for individuals first taking the GED test toward the end of our time period (1995–2005).

[12] All significance tests referenced below and in the tables are two-sided tests.

Table 2
Single Regression Discontinuity Equation Parameter Estimates for the Ninth Semester after the First Test, First Stage

	Men		Women	
	Coefficient	SE	Coefficient	SE
D_{Tr} = discontinuity	.3407	.0067**	.3010	.0066**
$D_{Tl}\,(T - 2250)/100$	.1897	.0045**	.2502	.0048**
$D_{Tr}\,(T - 2250)/100$	.0606	.0026**	.0554	.0025**
$[D_{Tl}\,(T - 2250)]^2/100$	.2054	.0070**	.2891	.0079**
$[D_{Tr}\,(T - 2250)]^2/100$	−.0608	.0035**	−.0560	.0034**
Observations	44,378		41,967	
Adjusted R^2	.5975		.6159	
Partial R^2, excluded instruments	.0544		.0468	
F-test on excluded instruments	2,552		2,060	

NOTE.—The dependent variable is GED receipt at the beginning of the ninth semester after the first test. Separate regressions are estimated for men and for women. Each regression also contains controls for earnings in each of the four quarters before the initial GED test, a dummy variable for nonwhite, age, age squared, two dummy variables for the three semesters in a year, a dummy variable for each year the test was taken, and a constant. Variable names refer to the appropriate terms in eq. (1).
* $p < .10$.
** $p < .05$.

secondary attendance in each semester.[13] The impact, τ, is identified by the discontinuity in $\widehat{\mathrm{GED}}$ as shown in the equations. IV models are estimated using least squares regression models in each stage even when the dependent variable is binary. The coefficient and standard error are from a separate regression for each semester and sex. Standard errors are not clustered by GED test score, as suggested by Lee and Card (2008), because such clustering actually produces smaller standard errors.[14]

For men, the GED is positively associated with postsecondary attendance in the first three semesters after taking the GED test, with significant effects in semesters 4 and 5 for the multiple discontinuity model only. The coefficient is 2.8–3.0 percentage points in the first semester, 4.1–4.7 percentage points in the second semester, and 4.5 percentage points in the third semester. For semesters 4 and 5, the coefficient is 1.4–1.8 percentage points in the single discontinuity model and 2.6 percentage points in the multiple discontinuity model. After 2 years (6 semesters), the GED effect is close to zero and is not statistically significant even at the 10% level. The GED

[13] Note that the results in table 3 measure postsecondary attendance in terms of semesters, whereas the results in Jepsen et al. (2016) measure all outcomes, including postsecondary attendance, in terms of quarters.

[14] We do not report Huber-White robust standard errors because using the "robust" command in Stata also produces smaller standard errors than those reported in the tables. Thus, we use the nonclustered, nonrobust standard errors because these standard errors are the largest, allowing us to be conservative in our estimated precision of the GED impact.

Table 3
Estimated GED Impact on Postsecondary Attendance

	Men		Women	
Semesters	Single Discontinuity	Multiple Discontinuities	Single Discontinuity	Multiple Discontinuities
1	.028**	.030**	.055**	.052**
	(.009)	(.008)	(.010)	(.010)
2	.047**	.041**	.096**	.090**
	(.012)	(.010)	(.015)	(.013)
3	.045**	.045**	.075**	.074**
	(.014)	(.012)	(.018)	(.016)
4	.014	.026**	.034*	.043**
	(.014)	(.011)	(.019)	(.016)
5	.018	.026**	.045**	.058**
	(.015)	(.012)	(.020)	(.017)
6	.016	.018	.039*	.041**
	(.015)	(.012)	(.022)	(.018)
7	−.003	−.002	.033	.021
	(.014)	(.012)	(.021)	(.018)
8	.004	−.0003	.020	.033*
	(.014)	(.012)	(.021)	(.017)
9	.013	.003	.016	.031*
	(.014)	(.012)	(.022)	(.018)
10	.006	.003	−.0001	.015
	(.014)	(.011)	(.021)	(.017)
11	.016	.007	−.012	.003
	(.014)	(.011)	(.022)	(.018)
12	.017	.0002	−.009	−.0005
	(.014)	(.012)	(.022)	(.018)
13	.003	.0003	.007	.006
	(.014)	(.011)	(.022)	(.018)
14	.002	.004	.016	.015
	(.014)	(.012)	(.022)	(.018)
15	.003	.008	.002	.020
	(.014)	(.012)	(.022)	(.018)
Any	.086**	.105**	.209**	.187**
	(.035)	(.029)	(.046)	(.037)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (in parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

is associated with roughly a 10 percentage point increase in the likelihood of attendance at any time during the 15 semesters.

For women, the GED impact is larger and persists for more semesters.[15] As with men, the largest coefficient is 2 semesters after the test, with a co-

[15] Recent work on the returns to community colleges, by far the most common postsecondary education choice for GED recipients, finds larger returns for women than for men. For example, see Jepsen, Troske, and Coomes (2014).

efficient of 9.0–9.6 percentage points. In each of the first 6 semesters, the effect is positive and statistically significant at either the 5% or 10% level, and the effects in semesters 8 and 9 are significant only in the multiple discontinuity model. For semesters 10–15, the effect is 2.0 percentage points or less and is never statistically significant at the 10% level. The effect on attending at any point during the 15 semesters is approximately 20 percentage points.

In summary, for both men and women, the GED is associated with an initial increase, sometimes sizable, in postsecondary attendance for individuals near the passing threshold, but this increase fades after 1–2 years.[16] The point estimates are generally similar between the single discontinuity model and the multiple discontinuity model, but the standard errors are slightly smaller in the multiple discontinuity model.[17]

In table 4, the dependent variable is a dummy variable equal to one when individuals complete at least one class (including noncredit classes) during the semester. The GED effects for completing a class are quite similar to the effects for postsecondary attendance, particularly for women. For men, the GED effects are between 2.7 and 4.7 percentage points in the first 3 semesters. Effects for later semesters are below 2.0 percentage points and not statistically significant in the single discontinuity model, whereas, in the multiple discontinuity model, we find statistically significant impact estimates of 2.3–2.4 percentage points in semesters 4 and 5. For women, the effects are between 3.2 and 8.6 percentage points in the first 6 semesters. When the dependent variable is completing a class at any time in the 15 semesters after the first test, the GED impact is 8.8 to 10.4 percentage points for men and 16.6 to 17.8 percentage points for women.

The results for attendance and class completion suggest that, for students with test scores near the cutoff for passing, the GED has sizable impacts on getting high school dropouts into postsecondary classrooms. In table 5, we focus instead on the amount of human capital obtained while enrolled. The dependent variable for the first 15 rows is the number of credits completed

[16] This pattern is to be expected for individuals who take the GED test in order to attend postsecondary education. One would expect these individuals to enroll in postsecondary education soon after receiving GED certification rather than waiting. Relatively few individuals receive GED certification more than 2 years after taking the GED test for the first time, in part because the score is no longer valid after 2 years.

[17] One potential explanation for this pattern of results is selection. Because we measure GED receipt at the start of each semester, the percentage of individuals with a GED increases as more individuals retake and pass the test. However, these "later"-passing test-takers have enrollment probabilities similar to those of individuals who pass on their first attempt—whether measured relative to point of passing or relative to the first test date. Therefore, it seems unlikely that selection due to retaking is driving the decline over time in GED effects on enrollment.

Table 4
Estimated GED Impact on Postsecondary Course Completion

	Men		Women	
Semesters	Single Discontinuity	Multiple Discontinuities	Single Discontinuity	Multiple Discontinuities
1	.027**	.030**	.050**	.049**
	(.008)	(.007)	(.010)	(.009)
2	.047**	.039**	.086**	.080**
	(.012)	(.010)	(.014)	(.013)
3	.044**	.043**	.066**	.069**
	(.013)	(.011)	(.018)	(.015)
4	.013	.024**	.032*	.035**
	(.013)	(.011)	(.018)	(.016)
5	.018	.023**	.038*	.047**
	(.014)	(.011)	(.020)	(.016)
6	.010	.013	.041**	.047**
	(.014)	(.011)	(.021)	(.017)
7	.0002	.001	.033	.018
	(.014)	(.011)	(.021)	(.017)
8	.003	−.001	.023	.029*
	(.014)	(.011)	(.020)	(.017)
9	.006	−.001	.007	.022
	(.014)	(.011)	(.021)	(.017)
10	.005	.004	−.001	.008
	(.013)	(.011)	(.020)	(.017)
11	.013	.004	−.014	.007
	(.013)	(.011)	(.021)	(.017)
12	.018	.003	−.014	.009
	(.014)	(.011)	(.021)	(.017)
13	.003	.0005	.009	.005
	(.013)	(.011)	(.021)	(.017)
14	−.005	.00002	.005	.009
	(.013)	(.011)	(.021)	(.017)
15	.003	.004	−.0001	.017
	(.013)	(.011)	(.021)	(.017)
Any	.086**	.104**	.178**	.166**
	(.035)	(.028)	(.045)	(.037)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (in parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

in each semester. In the bottom row of the table, the dependent variable is the cumulative number of credits earned across all semesters.

Consistent with the results for previous tables, the GED is associated with short-run increases in credits earned. For each of the first 3 semesters after the GED test, the estimated GED impact is 0.23 to 0.40 credits for men and is only marginally significant in a single quarter thereafter. Effects are larger for women, 0.44 to 0.76 credits in the first 3 semesters and between

Table 5
Estimated GED Impact on Postsecondary Credits Completed

	Men		Women	
Semester	Single Discontinuity	Multiple Discontinuities	Single Discontinuity	Multiple Discontinuities
1	.23**	.24**	.45**	.44**
	(.08)	(.07)	(.10)	(.09)
2	.40**	.30**	.75**	.75**
	(.12)	(.10)	(.14)	(.12)
3	.29**	.30**	.74**	.76**
	(.13)	(.11)	(.17)	(.15)
4	.05	.16	.28	.31**
	(.13)	(.11)	(.18)	(.15)
5	.13	.20*	.24	.42**
	(.13)	(.11)	(.19)	(.16)
6	.08	.13	.41**	.43**
	(.14)	(.11)	(.20)	(.17)
7	−.03	.03	.28	.18
	(.13)	(.11)	(.19)	(.16)
8	.08	.01	.08	.24
	(.13)	(.11)	(.19)	(.16)
9	.09	−.004	.12	.28*
	(.13)	(.11)	(.20)	(.16)
10	.09	.06	.03	.01
	(.12)	(.10)	(.19)	(.15)
11	.12	.06	−.26	−.09
	(.12)	(.10)	(.20)	(.16)
12	.15	.08	−.13	.10
	(.13)	(.11)	(.20)	(.16)
13	.003	.07	.02	−.02
	(.12)	(.10)	(.19)	(.16)
14	−.03	.01	−.13	.02
	(.13)	(.10)	(.19)	(.16)
15	.02	.03	−.15	−.05
	(.13)	(.11)	(.20)	(.16)
Cumulative	2.00	1.95	5.99**	5.78**
	(1.69)	(1.42)	(2.65)	(2.15)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (in parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

0.24 and 0.4 credits in semesters 4–6. After this period, the GED effect is statistically significant at the 10% level for only one coefficient. In all the outcomes measured, the GED is associated with a short-term increase in postsecondary attendance and human capital, with no discernable effect after 3 years (9 semesters).

Looking at the cumulative human capital effects, measured by total credits received, the GED impact is approximately two credits for men and six credits for women. However, the effect for men is imprecisely estimated and therefore is not statistically different from zero at the 10% level. Because a typical class is three credits, the effect can be translated into two-thirds of a class for men and nearly two classes for women. Put another way, the typical full-time 2-semester course load in postsecondary education is approximately 30 credits. In terms of years of schooling, the effects are under 0.1 years for men and 0.2 years for women. Thus, the average human capital attainment as measured by credits is extremely modest.

Our final outcome measure is the receipt of an award over the 5 years following the first GED test. Public postsecondary institutions offer a variety of awards, from short-term certificates (usually available only in 2-year institutions) to degrees at the undergraduate and graduate levels. Table 6 contains results for three dependent variables: (i) receiving any type of award, (ii) receiving an award from a 2-year institution, and (iii) receiving an award from a 4-year institution. As indicated in table 1, few GED test-takers receive such awards. Thus, it is not surprising that the GED does not have a consistent statistically significant effect on award receipt. Where the dependent variable is equal to one for the receipt of any type of award, coefficients in table 6 are 0.4–1.3 percentage points for men and 1.5–2.1 percentage points for women, and none of these estimates are statistically significant at even the 10% level. Because most GED test-takers attend 2-year institutions, the effects are generally similar for awards given by 2-year institutions; GED impacts for awards at 4-year institutions are very close to zero (0.3–0.5 percentage points).

In appendix tables A2 to A4, we estimate the GED effects on attendance, course completion, and credits separately for 2-year and 4-year institutions. The tables only contain results from the single discontinuity model (eqq. [1] and [4]); results for multiple discontinuity models are similar and are available from the authors upon request. For both men and women, the GED effects are much stronger for 2-year institutions, very similar to the effects

Table 6
Estimated GED Impact on Postsecondary Award Receipt

	Men		Women	
Award Type	Single Discontinuity	Multiple Discontinuities	Single Discontinuity	Multiple Discontinuities
Any award	.013	.004	.021	.015
	(.012)	(.010)	(.021)	(.017)
2-year award	.011	−.0002	.018	.012
	(.011)	(.009)	(.020)	(.016)
4-year award	.003	.005	.005	.005
	(.007)	(.006)	(.011)	(.009)

NOTE.—Each combination of a coefficient and standard error (in parentheses) is from a separate regression. In each regression, the number of observations is 39,332 for men and 37,207 for women.

in tables 3–5 for overall postsecondary education attendance and credits. As in previous tables, the effects are strongest in the first year (the first 3 semesters) for men and in the first 2 years (6 semesters) for women.

There are some positive statistically significant impact estimates for 4-year schools, particularly for women. The GED is associated with increased 4-year attendance in some semesters in the first 2 years, with coefficients of 0.5–2.0 percentage points; the impact on attendance at any time is 4.6 percentage points. The course completion effects for women at 4-year institutions are slightly weaker, with three statistically significant effects (10% level) in the first 6 semesters. The coefficients are at most 1.7 percentage points for 4-year schools, compared with effects as large as 7.7 percentage points for 2-year schools. For credits, there are significant effects in semester 3 (0.13 credits) and 6 (0.15 credits), although the latter effect is only significant at the 10% level. For men, the few significant results for 4-year schools appear to be the result of randomness rather than evidence of consistent nontrivial impacts of the GED on postsecondary outcomes at 4-year schools.

A. Generalizing Results

As with any FRD design, our effect estimates are for compliers at the threshold, that is, test-takers whose ultimate receipt of GED certification is determined by whether their initial score is above or below the threshold. If the impact is appreciably different for "always-takers" (those who get certification regardless of whether they are above or below the threshold) or "never-takers" (those who fail to obtain certification regardless of whether they are above or below the threshold), this estimate may not reflect their returns. Similarly, if those who obtain scores far above the threshold gain more or less from GED certification, our estimates may be misleading.

Interpreting the FRD as an instrumental variables estimator, we can address the question of whether GED certification is endogenous with a Hausman test. Results are presented in appendix tables B6–B9. When we consider the likelihood of attendance in the first 2 or 3 semesters after taking the test, we find that for both men and women the test generally fails to reject the hypothesis that certification is exogenous.[18] However, for semesters after the initial year, the Hausman test rejects the exogeneity hypothesis at the 10% level more than half of the time, and it rejects exogeneity for our cumulative measure of whether the individual ever attended a postsecondary institution. This means that the attendance differences after the first year between those who obtain certification and others do not represent the

[18] For the first semester after the initial test, about 60% of the cases are classified as compliers. Some 35% of those with scores just above the threshold fail to meet the subtest requirement, and some 5% of those with scores just below the threshold retake the test and are certified by the beginning of the next semester.

causal impact of GED certification. The same pattern of results occurs for course completion and course credits. The Hausman test does not reject the exogeneity assumption for the degree completion measures.

The failure to reject exogeneity in earlier semesters suggests that these results may generalize beyond compliers. Bertanha and Imbens (2014) note that if the assignment to treatment is independent of the outcome, then results obtained in the model will also apply to the full population. In this case, not only will the Hausman test fail to reject the exogeneity, but independence implies a pair of restrictions, which they suggest as a test for the generalizability of the FRD. Specifically, independence implies that untreated compliers and never-takers have the same distribution of the outcome in the neighborhood of the threshold and that treated compliers and always-takers have the same distribution of the outcome. The easiest way to undertake this comparison is to examine the discontinuity in the outcome measure at the threshold conditional on treatment.[19]

As suggested by the Hausman tests, in our model this comparison suggests that independence is likely to be satisfied for early semesters. In most cases, for both men and women, during early semesters we are unable to reject the hypothesis that untreated compliers and never-takers have the same mean outcome and that treated compliers and always-takers have the same mean outcome.[20] Based on this comparison, our finding that the GED leads to substantial increases in postsecondary attendance and course completion in the semesters following the first test appears likely to generalize.

In semesters after the first year, we find that the comparison between treated compliers and always-takers often indicates significant differences, and in each case these suggest that compliers are less likely to attend postsecondary institutions. This negative selection implies that always-takers are more likely to attend postsecondary school by more than 5 percentage

[19] It is easy to show that where α_0 is the discontinuity in the dependent variable for untreated cases at the threshold, the difference in average outcome for never-takers and untreated compliers may be written as

$$Y^0_{NT} - Y^0_C = \alpha_0 / p_{C0},$$

where p_{C0} is the proportion of compliers among untreated cases just below the threshold. Similarly, the difference in average outcome between treated compliers and always-takers may be written as

$$Y^1_C - Y^1_{AT} = \alpha_1 / p_{C1},$$

where α_1 is the discontinuity for treated cases, and p_{C1} is the proportion of compliers among treated cases just above the threshold.

[20] The exception for males is that we observe that, in semester 2, course completion for compliers is lower than that for never-takers, and that in semesters 2 and 3 credits earned for compliers are lower than for never-takers. For females, the exception is that in semester 1 credits earned for compliers are lower than for never-takers.

points among men in some semesters and by over 10 percentage points among women. These findings provide the underlying rationale for use of the FRD design, as the failure of independence implies that the simple difference between treated and untreated cases does not identify the impact of treatment.

Focusing on the later semesters, although these results reject one model in which our results would naturally generalize, failure of this model does not necessarily imply the converse. In particular, it is possible that, even in the presence of the kinds of selection we observe, the effect of the GED does not differ across groups.

There is no direct way to test how GED certification would influence always-takers and never-takers, but DiNardo and Lee (2011) suggest that if we are willing to make distributional assumptions in a simple—but quite general—model of treatment choice, it is possible to estimate the average treatment effect for the full population based on the estimate produced by our FRD. They provide an explicit formula for the average treatment effect in the case where the treatment and instrument are dichotomous, where participation in the treatment is determined by an arbitrary factor that may be correlated with the values of the potential treated and untreated outcomes, which are assumed to vary across individuals, and where unmeasured determinants of the outcome variable and the treatment are assumed normal. Their model allows for the possibility that effects for compliers are very different than for others, reflecting the fact that the choice to receive the treatment may be based on expected benefits.

Because their methods are not adapted to allow for exogenous independent variables, in order to adopt their approach, we re-estimate the effect of GED certification in a model excluding the test score as well as all other covariates. We choose a sufficiently short bandwidth that estimates correspond as closely as possible to those reported above for our preferred models, but for which precision is not too seriously compromised. The basic pattern of estimates produced by this simplified model is essentially the same as we report above for our preferred models, with few differences exceeding a standard error of our reported single-threshold model.[21]

We find that estimates based on the DiNardo and Lee (2011) methods for average treatment effect, which take account of the selection of compliers, differ very little from those we obtain with our simplified FRD model.[22] These results imply that, notwithstanding potentially important differences

[21] For men, we used the band 2210–2240 below the threshold (four data points) and 2250–2290 above the threshold (five data points), and for women we use the band 2150–2240 below (10 data points) and 2250–2350 above (11 data points).

[22] Our estimates are based on equation 13 on page 497 in DiNardo and Lee (2011). See their discussion for a detailed explication of the model and its assumptions. The absolute value of the difference between the FRD estimate we obtain in the simplified model and the estimated average treatment effect based on their

between compliers and others, as suggested by the tests reported above for semesters after the first year, the effects of GED certification for compliers provide a good estimate of effects in the full population whose first test scores are near the passing threshold.

Aside from the important assumptions implicit in these methods, it is worth stressing that they apply to analyses, which, by design, omit test-takers who are far from the threshold. Hence, although these results increase our confidence that our results are likely to apply to the full population of compliers, never-takers, and always-takers near the threshold, they do not indicate the extent to which results may be generalized to the large majority of test takers who receive scores well above the passing threshold.

As noted above, the GED certification during the first year after the initial test passes the independence assumption at the threshold, consistent with the simple model of constant effects across group. One might question how useful this test is for those far from the threshold, as it may appear plausible that high-scorers benefit more from the GED because they are most likely to attend postsecondary schooling. Although we cannot test this possibility directly, we might expect that GED certification would be particularly strongly associated with postsecondary attendance for those with higher initial tests score. In fact, our tabulations show that the relationship between postsecondary attendance and GED certification does not increase with higher test scores.[23]

VI. Conclusion

This paper investigates the relationship between GED receipt and multiple measures of postsecondary education. We use a fuzzy regression discontinuity method to estimate plausibly causal effects of the GED for individuals who have test scores near the threshold for passing the first time they attempt the GED test. We use a single discontinuity model based on the overall test score and a multiple discontinuity model that includes the overall test score and lowest subtest score discontinuities. The results are quite similar for the two approaches.

We find large effects of the GED on the likelihood of attendance and class completion, especially at 2-year institutions. The effects are roughly twice as large for women as for men. For example, the GED increases attendance

model, divided by the standard error in our model, has a median under 0.1, and never exceeds 0.4.

[23] Appendix table B10 provides information on postsecondary attendance and GED receipt by initial test score. The relationship between GED certification and attendance does not vary in a systematic way across those with differing test scores. Of course, among those who obtain test scores substantially above the threshold, only a very small—and possibly unrepresentative—proportion of individuals fail to receive certification.

in semester 2 by 4.7 percentage points for men and 9.6 percentage points for women (table 3). The effects for credits completed are modest. In a given semester, on average, the GED increases credits by no more than 0.4 credits for men and 0.8 credits for women. The cumulative impact on credits for the 5 years following the first test is around two credits (although not statistically different from zero at the 10% level) for men and six credits for women. We do not find that the GED has a statistically significant effect on receipt of a postsecondary award.

We undertook several tests to determine whether our results are likely to generalize beyond the class of individuals for whom the FRD formally applies, compliers with first test scores at the passing threshold for GED certification. Our results suggest that estimates of effects of GED certification on postsecondary attendance in the first year after the initial test are likely to be quite robust and that they may well be applicable to individuals in the full population, including those with scores well above the passing threshold. Estimates of GED effects after the first year may be less broadly applicable, but we find results suggesting that they likely apply at least to the full population of individuals with scores near the passing threshold—not merely compliers.

The pattern of results suggests that the GED is useful in helping individuals enroll in postsecondary institutions. This result is expected given that many postsecondary institutions require a GED (or high school degree) in order to enroll in their programs. However, the GED has much less pronounced effects on the amount of human capital obtained at these institutions. The modest increases in the number of credits earned after 5 years—approximately six credits for women and two credits for men—are unlikely to produce large labor market effects. Our results provide valuable insight into the findings in Jepsen et al. (2016), who report that the GED has a significant positive effect on postsecondary school attendance for several quarters after first taking the GED but little effect on employment or earnings. Combining the results in that paper with the results in this paper, the GED appears to provide little if any "signaling" value. Furthermore, the labor market provides essentially no reward for the small amount of college credits obtained by GED recipients.

Our results are broadly consistent with results reported by Heckman et al. (2014) showing that high school dropouts who take and pass the GED tend to have relatively strong cognitive skills but relatively weak noncognitive skills, accounting for why they are able to pass a standardized test such as the GED but are not able to complete high school or obtain steady employment. Our results show that people who have the ability to pass the GED also have the ability to complete a postsecondary course but not an entire course of study to obtain a degree. Given these results, it is unlikely that the recent changes in the GED would produce different results. It remains the case that understanding how to increase the human capital attainment of GED recipients—through increased postsecondary attendance and increased duration of attendance—is vital to improving their future labor market success.

Appendix A

Table A1
Multiple Discontinuity Regression Equation Parameter Estimates, First Stage

	Men		Women	
	Coefficient	SE	Coefficient	SE
$D_{T_r}D_{S_r}$ = double discontinuity	.544	.009**	.484	.009**
$D_{T_l}D_{S_r}$	.170	.021**	.179	.022**
$D_{T_r}D_{S_l}$	.079	.013**	.025	.014*
$D_{T_l}D_{S_l}\,(T - 2250)\,(S - c)/100{,}000$	−.030	.016*	−.221	.023**
$D_{T_l}D_{S_r}\,(T - 2250)\,(S - c)/100{,}000$	7.958	2.132**	−6.334	1.917**
$D_{T_r}D_{S_l}\,(T - 2250)\,(S - c)/100{,}000$	−.075	.036**	−.160	.068**
$D_{T_r}D_{S_r}\,(T - 2250)\,(S - c)/100{,}000$	−.016	.052	.0002	.053
$D_{T_l}D_{S_l}\,(T - 2250)/100$	.187	.005**	.216	.006**
$D_{T_l}D_{S_l}\,(S - c)/100$	−.146	.020**	.017	.022
$D_{T_l}D_{S_r}\,(T - 2250)/100$	.348	.049**	.434	.047**
$D_{T_l}D_{S_r}\,(S - c)/100$	.139	.223	−.423	.201**
$D_{T_r}D_{S_l}\,(T - 2250)/100$	.059	.011**	.059	.011**
$D_{T_r}D_{S_l}\,(S - c)/100$	.136	.031**	.322	.033**
$D_{T_r}D_{S_r}\,(T - 2250)/100$	.002	.003	.002	.003
$D_{T_r}D_{S_r}\,(S - c)/100$	−.010	.015	−.009	.014
$[D_{T_l}D_{S_l}\,(T - 2250)]^2/100$	.154	.009**	.240	.012**
$[D_{T_l}D_{S_l}\,(S - c)]^2/100$	−.137	.107	.811	.126**
$[D_{T_l}D_{S_r}\,(T - 2250)]^2/100$	.377	.260	.582	.241**
$[D_{T_l}D_{S_r}\,(S - c)]^2/100$	−.052	6.368	1.830	5.331
$[D_{T_r}D_{S_l}\,(T - 2250)]^2/100$	−.061	.023**	−.068	.024**
$[D_{T_r}D_{S_l}\,(S - c)]^2/100$	.263	.112**	1.266	.130**
$[D_{T_r}D_{S_r}\,(S - c)]^2/100$	.001	.006	−.0003	.006
$[D_{T_r}D_{S_r}\,(S - c)]^2/100$	.060	.164	−.006	.163
d_{S0} = lowest subtest score is zero	.052	.109	−.578	.136**
Observations	44,378		41,967	
Adjusted R^2	.6609		.6810	
Partial R^2, excluded instruments	.0948		.0809	
F-test on excluded instruments	716		777	

NOTE.—Dependent variable is GED receipt. Separate regressions are estimated for men and for women. Each regression also contains controls for earnings in each of the 4 quarters before initial GED test, a dummy variable for nonwhite, age, age squared, two dummy variables for the 3 semesters in a year, a dummy variable for each year the test was taken, and a constant. Variable names refer to the appropriate terms in eq. (5).
* $p < .10$.
** $p < .05$.

Table A2
Estimated GED Impact on Postsecondary Attendance, by School Type, Single Discontinuity Model

	Men		Women	
Semesters	2-Year Schools	4-Year Schools	2-Year Schools	4-Year Schools
1	.026**	.002	.049**	.005
	(.008)	(.003)	(.010)	(.004)
2	.039**	.008*	.085**	.012**
	(.012)	(.005)	(.014)	(.006)
3	.040**	.005	.065**	.010
	(.013)	(.005)	(.017)	(.007)
4	.009	.006	.027	.008
	(.013)	(.006)	(.018)	(.007)
5	.009	.010*	.035*	.011
	(.013)	(.006)	(.019)	(.008)
6	.008	.008	.020	.020**
	(.014)	(.006)	(.020)	(.009)
7	−.008	.006	.029	.004
	(.013)	(.006)	(.020)	(.009)
8	−.006	.010	.025	−.004
	(.013)	(.007)	(.020)	(.009)
9	.002	.011	.021	−.005
	(.013)	(.007)	(.020)	(.009)
10	.002	.005	−.000	.001
	(.012)	(.007)	(.019)	(.010)
11	.012	.006	−.012	.000
	(.012)	(.007)	(.020)	(.011)
12	.016	.003	−.011	.003
	(.012)	(.007)	(.020)	(.011)
13	−.002	.006	−.006	.015
	(.012)	(.007)	(.020)	(.011)
14	.001	.001	.020	−.004
	(.012)	(.007)	(.019)	(.011)
15	.004	−.001	.002	.001
	(.012)	(.008)	(.019)	(.011)
Any	.073	.021	.165**	.046*
	(.034)	(.018)	(.045)	(.025)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (in parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

Table A3
Estimated GED Impact on Postsecondary Course Completion, by School Type, Single Discontinuity Model

	Men		Women	
Semesters	2-Year Schools	4-Year Schools	2-Year Schools	4-Year Schools
1	.025**	.002	.046**	.004
	(.008)	(.003)	(.010)	(.003)
2	.040**	.007	.077**	.009*
	(.011)	(.005)	(.014)	(.005)
3	.038**	.006	.055**	.011*
	(.012)	(.005)	(.017)	(.006)
4	.008	.005	.025	.008
	(.012)	(.005)	(.017)	(.007)
5	.009	.009	.031*	.006
	(.013)	(.006)	(.018)	(.007)
6	.002	.008	.025	.017**
	(.013)	(.006)	(.020)	(.008)
7	−.005	.006	.029	.003
	(.013)	(.006)	(.019)	(.008)
8	−.005	.009	.023	.001
	(.012)	(.006)	(.019)	(.008)
9	−.006	.011*	.014	−.006
	(.012)	(.007)	(.019)	(.009)
10	.002	.005	−.005	.003
	(.011)	(.007)	(.018)	(.009)
11	.010	.003	−.014	−.002
	(.011)	(.007)	(.019)	(.010)
12	.017	.002	−.014	.001
	(.012)	(.007)	(.019)	(.011)
13	−.0002	.004	−.002	.011
	(.011)	(.007)	(.019)	(.011)
14	−.005	−.000	.009	−.004
	(.011)	(.007)	(.018)	(.011)
15	.004	−.001	−.001	.004
	(.011)	(.007)	(.018)	(.011)
Any	.070**	.023	.141**	.036
	(.032)	(.018)	(.044)	(.024)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (in parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

Table A4
Estimated GED Impact on Postsecondary Credits Completed, by School Type, Single Discontinuity Model

	Men		Women	
Semesters	2-Year Schools	4-Year Schools	2-Year Schools	4-Year Schools
1	.20**	.03	.42**	.03
	(.07)	(.03)	(.09)	(.04)
2	.35**	.05	.67**	.08
	(.11)	(.05)	(.13)	(.05)
3	.23*	.05	.61**	.13**
	(.12)	(.06)	(.16)	(.07)
4	.01	.04	.23	.05
	(.12)	(.05)	(.17)	(.07)
5	.04	.08	.19	.05
	(.12)	(.06)	(.18)	(.08)
6	.02	.06	.26	.15*
	(.13)	(.07)	(.19)	(.09)
7	−.09	.06	.27	.004
	(.12)	(.06)	(.18)	(.08)
8	−.04	.12*	.08	−.001
	(.11)	(.07)	(.17)	(.09)
9	−.0002	.09	.18	−.07
	(.11)	(.07)	(.18)	(.10)
10	.06	.03	−.01	.04
	(.10)	(.07)	(.16)	(.10)
11	.08	.05	−.14	−.12
	(.10)	(.07)	(.16)	(.11)
12	.17*	−.03	−.13	.003
	(.10)	(.08)	(.17)	(.12)
13	−.04	.04	−.03	.05
	(.09)	(.07)	(.16)	(.11)
14	−.03	−.004	−.06	−.06
	(.10)	(.08)	(.16)	(.12)
15	.06	−.05	−.17	.02
	(.10)	(.09)	(.16)	(.12)
Cumulative	1.27	.73	5.35**	.63
	(1.22)	(1.01)	(2.07)	(1.47)

NOTE.—Semesters are measured as time since first GED test. Each combination of a coefficient and standard error (In parentheses) is from a separate regression. For each semester and gender, the number of observations matches the number of observations in table 1.
* $p < .10$.
** $p < .05$.

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