

## Labor-Market Returns to the GED Using Regression Discontinuity Analysis

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### Abstract:

We evaluate the labor-market returns to General Educational Development (GED) certification using state administrative data. We develop a fuzzy regression discontinuity (FRD) method to account for the fact that GED test takers can repeatedly retake the test until they pass it. Our technique can be applied to other situations where program participation is determined by a score on a “retake-able” test. Previous regression discontinuity estimates of the returns to GED certification have not accounted for retaking behavior, so these estimates may be biased. We find that the effect of GED certification on either employment or earnings is not statistically significant. GED certification increases postsecondary participation by up to four percentage points for men and up to eight percentage points for women.

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## **I. Introduction**

Labor-market opportunities for high school dropouts have declined substantially in recent years. Certification on the General Educational Development (GED) test provides potential benefits to dropouts. Dropouts with GED certification may be able to signal to employers that they have higher skills than the “average” dropout. Many postsecondary institutions require high school graduation or GED certification for admission to degree-seeking programs.

In this paper, we evaluate the labor-market returns to GED certification in state administrative data. We develop a fuzzy regression discontinuity (FRD) method to account for the fact that GED test takers can repeatedly retake the test until they pass it. This method estimates the local average treatment effect (LATE) for test takers around the cutoff for passing the GED. Our technique, based on the discontinuity generated by the score from multiple test scores, can be applied to other situations where program participation is determined by a score on a “retake-able” test, including the original application of regression discontinuity in Thistlewaite and Campbell (1960). Other examples of retake-able tests where this technique can be applied include civil service exams, the bar exam, votes for unionization, and licensure exams such as drivers’ licenses. Previous regression discontinuity estimates of the returns to a GED have not accounted for retaking behavior, so these estimates may be biased.

We find that the estimated effects of GED certification on either employment or earnings are generally small and not statistically significant. GED certification increases postsecondary participation in the months following certification by up to four percentage points for men and up to eight percentage points for women. Finally, the results from our preferred FRD model often differ from results of a sharp regression discontinuity (SRD) design, which ignore the ability of students to retake the test.

## II. Relation to Previous Literature

Early work on the GED analyzed survey data from the National Longitudinal Survey of Youth (NLSY) and High School and Beyond (HSB) survey. Cameron and Heckman (1993) show that male GED recipients have lower earnings than high school graduates in a cross-section of NLSY data. They estimate models that account for the selection that occurs because wage data are not available for nonworkers, and individuals with missing wage data are unlikely to be similar to individuals with wage data on all dimensions. Heckman and LaFontaine (2006) use more recent NLSY data (through 2000) as well as two other data sets, and they find no economic returns to GED certification. Cao, Stromsdorfer, and Weeks (1996) produce similar results for women using NLSY data as well as data from Washington State.

Murnane, Willett, and Boudett (1995, 1999) extend the work on the GED based on a panel analysis of the NLSY data, comparing male GED recipients to other high school dropouts. They include multiple years of data for each person and include either person-level random effects or fixed effects to account for person-specific correlation in unobservables. The authors find positive effects of the GED on hourly wage growth. Boudett, Murnane, and Willett (2000) use the same approach and find positive effects of the GED on annual earnings for women in the NLSY.

Murnane, Willett, and Tyler (2000) use High School and Beyond (HSB) data to allow the effect of the GED on earnings to vary by cognitive ability (as measured by 10<sup>th</sup> grade math scores). Using OLS models on males in the 1992 follow-up study, they find that labor-market gains associated with the GED are concentrated among recipients with low cognitive skills. Using the same model, Tyler, Murnane, and Willett (2003) find similar results for women in the HSB data.

Tyler, Murnane, and Willett (2000a, 2000b) use administrative data from the Social Security Administration (SSA) to study the effects of the GED on earnings. Using grouped data cells (to satisfy SSA data privacy requirements), they estimate differences in mean outcomes for individuals near the passing threshold in each state, thereby exploiting differences across states and over time in passing thresholds. Tyler, Murnane, and Willett (2000a) compare mean earnings by GED score for individuals aged 16-21 who took the GED in 1989 or 1990 in New York and Florida. They find a consistent, positive association between GED certification and annual earnings for nonwhite males, white females, and nonwhite females. Tyler, Murnane, and Willett (2000b) look at GED test takers aged 16 to 21 who last took the GED in 1990 in 42 states. They use method-of-moments estimators based on estimated differences in mean outcomes. The authors find positive effects of GED certification on earnings for whites (males and females) but not for nonwhites. However, Rubinstein (2003) suggests that estimates of GED impacts based on this approach could be biased because differences across states in passing standards are endogenous.

Recent GED research on earnings has utilized administrative earnings records matched with records of GED test takers to compare GED recipients with dropouts who took but did not pass the GED. For example, Tyler (2004) uses administrative data for Florida men, and he finds positive long-run earnings effects. Lofstrom and Tyler (2008) use administrative data for Texas men, but they find no impact of the GED on earnings—identified through the state’s 1997 increase in the passing standard—possibly due to the low GED threshold that existed prior to the 1997 change.

Both these papers use several techniques including regression discontinuity (RD) analysis. OLS models – even with pre-GED earnings – are unlikely to capture all the differences

in skills and motivation that affect labor market success between test takers who receive the GED and test takers who do not. The student fixed effects models control for all time-invariant determinants of earnings, but they are less useful for those who obtain GED certification prior to full-time labor market participation, and they cannot capture changes over time experienced by individuals that affect both GED receipt and earnings. Although RD models offer the potential of overcoming such problems due to unmeasured factors, the validity of RD rests on several assumptions that are not adequately considered in these analyses. In particular, we show below that students' ability to retake the test if they do not pass seriously compromises the validity of estimates based on RD models that use last test score as the forcing variable as these papers do. Lofstrom and Tyler (2008) conduct a robustness test where they limit the sample to students who take the test only once, but we show below that the sample of single test takers does not satisfy conditions for implementation of a valid regression discontinuity design.

Based on both a summary of the academic literature on the GED and their own analysis, Heckman, Humphries, and Mader (2011) argue that the test has few if any benefits in terms of labor-market outcomes. They infer that there are substantial non-cognitive differences between GED recipients and traditional high school graduates, and they suggest that the availability of the GED may induce individuals to drop out and forgo valuable non-cognitive benefits of school attendance.

Our analysis provides several contributions to the GED literature. First, the inferences that can be drawn from HSB and NLSY are limited by a lack of recent data and small samples. Both data sets contain only information on men and women in their 20s and 30s, and Heckman, Humphries, and Mader (2011) is the only study with earnings outcomes since 2001. Each data set has a sample of roughly 300 GED recipients and 300 high school dropouts of each gender. In

contrast, in our analyses we will use administrative data from a single state for over 100,000 individuals who took the GED between 1995 and 2005. We will match these data with earnings data covering the period 1993-2009, providing us with earnings for several years before and after individuals took the GED. The extended follow-up period allows us to examine the persistence of the impact of GED certification on earnings.

Second, as noted above, the previous GED research using regression discontinuity analysis failed to account for the ability of students to retake the GED. Our analysis illustrates how estimates that do not explicitly account for retaking are not valid, and we provide a technique based on multiple GED test scores to produce valid regression discontinuity estimates. We also implement models that illustrate how the multidimensional character of the GED certification procedure can be used to improve the precision of impact estimates.

Third, nearly all the previous work focuses on the returns of the GED for men, with the studies for women based solely on NLSY, HSB, and grouped SSA data. As discussed previously, the NLSY and HSB survey data comprise small samples of dropouts and GED recipients, and there are concerns about potential endogeneity in the models using SSA data.

Our paper also provides a valuable contribution to the RD literature by presenting a valid RD approach for situations where the treatment is based on a test score, and individuals can retake the test in order to improve their scores. The seminal paper on RD, Thistlewaite and Campbell (1960), is an evaluation of a merit scholarship program where retaking and general manipulation of the running variable are issues. Their Table 1 shows that the merit test score density is not smooth on both sides of the passing threshold, suggesting that their regression discontinuity results may not be valid.

Little previous work has addressed the issue of test retaking with respect to RD models. Pantal, Podgursky, and Mueser (2006) show that retaking the ACT to satisfy a scholarship criterion is a significant issue, and they use initial ACT scores as instruments in their RD analysis of a college scholarship program in Missouri. Similarly, Martorell and McFarlin (2011) use the initial remedial education scores in a FRD analysis of college remediation in Texas in order to eliminate bias due to test retaking, although their analysis does not address the methodological significance of this choice. Cellini, Ferreira and Rothstein (2010) implement an RD model examining the impact of school funding using municipal bond referenda that allows for multiple referenda. Although the underlying methodological issue is similar to that which we address, their methods of estimation rely on assumptions that are not applicable in our context. We also present estimates that exploit the multidimensional character of the GED certification criteria, which is based on both total and subtest scores. Although there has been increased interest in developing such models (Papay, Murnane, and Willett, 2011; Reardon and Robinson, 2012), current applications, especially those using an FRD design, are very limited.

### **III. GED Test and GED Data**

Nationwide, nearly 700,000 people took the GED test in 2008, and 73 percent of these received GED certification. The GED test is a seven-and-a-half hour test consisting of five subtests (reading, writing, social studies, science, and mathematics). The version of the GED introduced in 2002—and referred to as the 2002 GED—replaced the previous version, which had been in place since 1988; the next version of the GED is scheduled for release in 2014 (GED Testing Service 2013). Subject to certain constraints, states set their own criteria for certification based on test performance, but differences between states are minor. As recently as the 1990s, there were some differences across states in the score required for certification, but such

differences were not very great. The standards for passing are currently all but universal across states.

To obtain GED certification, test takers in our data must obtain a minimum score on each of the five subtests and must obtain a total test score of at least 2250 out of a maximum of 4000. Certification is based on a composite based on the highest score on each subtest taken over the prior two years, i.e., each subtest score is “valid” for two years before it expires. Many individuals with scores below the required thresholds retake the test—often several times—within two years, and they often retake only certain subjects rather than retaking the entire exam.<sup>1</sup> Scoring of tests is done at a center outside the state.

Advent of the 2002 version of the GED test altered the certification criteria in several ways. First, the minimum permitted subtest score prior to 2002 was 400, and this was raised to 410 (missing subtest scores are coded as zeros). Further, scores from earlier versions could not be combined with the 2002 version, so students who had taken the exam prior to 2002 but had not passed it had to meet the criteria based on their scores on the new version of the test. For this reason, and also because it was widely believed that the new test version would impose higher standards, we explore the sensitivity of our findings by estimating separate models for each time period (1995-2001 and 2002-2005).

Our basic sample consists of any individual who took the GED test for the first time in the state between 1995 and 2005.<sup>2</sup> For each individual taking the test within this period, we have access to data on the most recent ten test scores taken for each version of the test, whenever the tests were taken. We exclude individuals who have taken either version of the test ten or more

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<sup>1</sup> Individuals can take the test up to six times in any two-year period. Note that a given version of the test includes multiple forms that are normed to the same scale, so when a student retakes the exam, the particular questions are different.

<sup>2</sup> We draw on interviews with state agency personnel in our description of the state GED data and procedures.

times because we cannot identify the first test; there were 86 individuals excluded for this reason. We exclude individuals who took the GED test while incarcerated because their labor-market outcomes are likely constrained by their incarceration.<sup>3</sup> We exclude individuals with missing information on gender or race. Individuals who received their GED through the DANTE program, which provides state certification for tests taken by military personnel outside the state, are also excluded because test scores are not reported for program participants who took the GED test through the military program. Finally, we exclude individuals who took the GED as part of the GED Option program. 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. Descriptive statistics for the regression sample are in Appendix Table 1.<sup>4</sup>

Quarterly earnings in all UI-covered jobs are available as reported by employers in states' unemployment insurance programs for the state and a neighboring state. Very few of the state's residents commute to states other than these two. We use data through the second quarter of 2009.

Although our data pertain to a single state, this state is quite typical of the U.S. The industrial structure is similar to that of the U.S. as a whole, and earnings and wages are within 10 percent of the U.S. average. The proportion of the population that is African-American is slightly below the national average. The proportion Hispanic is substantially below the U.S. average but similar to that of most states.

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<sup>3</sup> Tyler (2004) also points out that GED recipients with criminal records may have different labor-market returns to a GED due to their criminal history.

<sup>4</sup> As discussed later, the regression sample used in our main analysis below is limited to individuals with test scores between 1500 and 3000, whereas samples in Tables 1 and 2 and in Figure 1 include scores outside this range.

Table 1 provides a tabulation of the GED scores, and an indicator of whether the test was later retaken, for individuals taking the exam for the first time in the period of our study 1995-2005. The overwhelming majority of individuals in our study—nearly 80 percent—obtain a score above the total passing threshold of 2250. It is therefore important to keep in mind that a regression discontinuity design will provide a LATE impact estimate for those near the threshold, individuals whose test performance is substantially below the median.

The table also shows the proportion of the test takers who retake the test within the period of our study. The bottom line in the table (right column) indicates that only about 16 percent of the test takers take the test more than once. Previous studies using RD methods have pointed to such small proportions to justify analyses that ignore test retaking. However, the overall likelihood of retaking the test is misleading in the case at hand. The large majority of scores that satisfy the GED passing criteria with the first test are not relevant for the RD analysis because they are far from the passing threshold. The right-hand column shows that for those who do not pass, test retaking is very common. Among those with scores in the range 2200-2240, just below the passing threshold, almost 70 percent retake the GED test, and, for those with lower scores, more than half of the initial test takers retake the test. Of those who just barely meet the threshold (those with total scores 2250-2290), more than a fifth retake the test, reflecting their need to satisfy the minimum required score on each of the five subtests.

In the analysis that follows, we will define GED certification in two ways. First, when we present basic statistics on GED certification, we measure GED certification as having received GED certification during the entire sample period, i.e. by the end of 2008. This definition is the most inclusive and avoids the challenges of reporting multiple measures of GED certification. In practice, the vast majority of people who ultimately receive certification receive

it within two years of first taking the test. Second, when we look at the effect of GED certification on quarterly earnings, employment, and postsecondary education, we measure GED certification at the start of the quarter in which the outcome is measured. For example, when the dependent variable is quarterly earnings 12 quarters after the initial GED test, GED certification is measured as of the start of the 12<sup>th</sup> quarter.

### ***Test Score: Examining Discontinuities***

The discussion above makes clear that individuals whose scores are close to the passing threshold are very likely to retake the GED test, yet it is the “final” test score—obtained by combining the highest subtests taken over a two-year period—that determines GED certification. Consequently, the final test score is an obvious candidate for a conventional regression discontinuity analysis. Such an approach ignores both the fact that some individuals retake the test and that some whose scores meet the overall test score threshold do not satisfy the minimum on each of the subtest scores.

Figure 1 presents the distribution of the final test scores for individuals who took the GED test in 1995-2005. The sample of test takers is slightly different from that considered above because individuals may have taken their first test prior to this period. The vertical axis identifies the number of individuals who obtain a given test score as a proportion of the total number, so the “bin size” for density calculations is a single score (possible test scores are multiples of 10). The trend line fits a local linear regression that is based on a triangular kernel with a bandwidth covering eight scores (80 points), allowing for a potential discontinuity at the threshold 2250.<sup>5</sup>

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<sup>5</sup> These methods correspond to those recommended by McCrary (2008).

The discontinuity in the density for the final test score is extraordinary. The log discontinuity is close to 0.92, implying that the density to the right of 2250 is approximately two and one-half times that immediately to the left, a difference that is easily statistically significant. Even though only 16 percent of individuals retake the test, the very high retake probability for those close to the cutoff point causes a dramatic redistribution in the final score.

Given that the final test score displays a marked discontinuity, it would appear highly likely that there would be discontinuities in the values for relevant characteristics. Those who choose to retake the test would be expected to differ in various ways, causing those with scores just above the threshold to differ systematically from those below. In order to test for a discontinuity in a demographic variable  $X$  (which we define below), we fit a fourth order polynomial in the test score, allowing for the function to change discontinuously at 2250:

$$X = \alpha_{xl} + \alpha_{xlr} D_r + \sum_{j=1}^4 \{ \beta_{xlj} [D_l(score - 2250)]^j + \beta_{xrj} [D_r(score - 2250)]^j \} + v.$$

$D_r$  ( $D_l$ ) is a dummy variable indicating whether that score equals or exceeds (is below) the passing threshold, and  $score$  is the final score on the GED test.  $\beta_{xlj}$  and  $\beta_{xrj}$  are estimated coefficients that capture the relationship between the GED score and the outcome variable, and the coefficient  $\alpha_{xlr}$  identifies the extent of any discontinuity, providing an estimate of the mean difference on the dependent variable between those just above the threshold and those just below.

Table 2, column 1, provides estimates for this parameter, where the variable  $X$  is one of the following: gender (male), race (nonwhite), age, whether the test taker took the test more than

once, and earnings in the quarter prior to taking the test.<sup>6</sup> There are several statistically significant differences. The proportion of males is 1.8 percentage points lower above the threshold, which is not quite statistically significant. The proportion of nonwhites is approximately three percentage points higher above the threshold than below, a difference that is easily statistically significant. Those just above the threshold are also slightly younger and have lower prior earnings than those just below. Finally, we see that those above the threshold are slightly less likely to have retaken the test. This reflects the fact, indicated in Table 1, that those whose first test is below the threshold have much stronger incentives to retake the test. Many of them will not achieve a score that exceeds the threshold. A countervailing force—which reduces the size of the discontinuity on this measure—reflects the fact that many individuals exceed the threshold by virtue of taking the test repeated times. It is clear that 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).

One strategy to avoid this problem would be to limit consideration to the cases in which individuals have not taken the test a second time. As noted above, Lofstrom and Tyler (2008) limit their sample in this way as a robustness check for their RD estimation approach. Figure 2 presents the distribution of scores for individuals who took the test for the first time in the period 1995-2005 and did not take the test a second time through 2008. The most notable observation is that a marked discontinuity is present just as in the final test score—in fact, measured in log form, the discontinuity size is slightly larger for this sample. This similarity indicates that the discontinuity identified in the final score is not primarily a result of the fact that the final score

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<sup>6</sup> The sample in the first column is the set of individuals taking the test for the *last* time between 1995 and 2005. The second column is the subset of individuals in the first column who only take the test once. The sample in the third is the set of individuals taking the test for the *first* time between 1995 and 2005.

combines scores from previous tests. Rather, it occurs because of selection, with scores just below the threshold depleted because individuals with these scores are very likely to retake the test.

A simple alternative is to use the first test score as the continuous variable underlying 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 employment outcomes. Table 2 (column 3) shows that there is no discontinuity in the characteristics of individuals around this measure. Figure 3 presents the distribution of the first test score, using the same method to identify discontinuities as for the densities above. The figure shows that, in contrast to the final score and the score for those taking the test only once, there is essentially no discontinuity in the density at the 2250 threshold. This measure is therefore suitable for a FRD design.

Although the analysis based on the first test provides an unbiased estimate of the impact of the GED, it ignores information implicit in later test scores. For example, of those who take the test a second time, a portion will get scores that are just above the threshold of 2250, and a portion will get scores that are just below. As with the first test, the threshold will not perfectly identify whether the test taker obtains a GED, but passing a threshold is associated with a discontinuous shift in the probability of ultimately obtaining a GED degree. Hence, the full distribution of scores from second tests should satisfy the basic assumptions necessary for the FRD. The same logic allows use of later test scores as well, as long as all retaken test scores are properly classified by order of the attempt, i.e., parity or the number of prior tests taken.

For those retaking the test, the threshold is only relevant for an individual who obtains a greater score than that on the prior test, and so in analyses of later tests we focus on the compound score to that point and include only an individual whose compound score after taking a given test is greater than the previous score. We also omit all those individuals' retaken test attempts whose prior scores are above the threshold. Although this is a selected sample of test scores, the observed distribution of scores is expected to satisfy necessary continuity conditions at the threshold. This approach could be used to provide separate estimates of program impact based on each test, but, in the present analyses, the primary estimates we present constrain impacts to be the same in order to improve statistical power.

#### **IV. Applying Fuzzy Regression Discontinuity Methods**

The analysis will focus on first tests taken between 1995 and 2005, and second and third tests taken within two years of taking the first test. The diagnostics suggest that the each GED test score, properly identified by parity, is not subject to manipulation or selection effects.<sup>7</sup> Because those at or above the test threshold are appreciably more likely to receive GED certification than those below, these data are appropriate for a fuzzy regression discontinuity (FRD) design. For simplicity, we begin by describing our formal model as applied to an analysis based on the first test. Later, we discuss the model we actually estimate, where we include second and third test attempts. In the subsequent section, we expand the model to take advantage of the multidimensional character of the GED certification criteria. We also present results for models that predict earnings measures that are temporally aggregated in order to improve estimate precision.

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<sup>7</sup> In particular, as in the case of the first test scores, our diagnostics suggest the sample of second test scores described above is not subject to manipulation or selection effects, and likewise for the sample of third test scores.

The equation predicting GED certification is written:<sup>8</sup>

$$(1) \quad GED = \alpha_{gl} + \alpha_{glr}D_r + \sum_{j=1}^p \beta_{glj}[D_l(T - 2250)]^j + \sum_{j=1}^p \beta_{grj}[D_r(T - 2250)]^j + X\eta_g + \varepsilon$$

where  $T$  is the total score on the first GED test,  $D_l$  ( $D_r$ ) is a dummy indicating whether that score is below (equals or exceeds) the passing threshold,  $p$  indicates the order of the polynomial, and  $X$  is a set of covariates (earnings in four quarters prior to first GED attempt, age, age squared, race, year of first GED test, and quarter of the year – winter, spring, summer or fall). In these equations focusing on the first test attempt, units are individuals who take a first GED test, and individual subscripts are suppressed. The subscript  $g$  identifies coefficients predicting GED certification, so  $\beta_{glj}$  and  $\beta_{grj}$  identify the relationship of the first GED test score with certification, below and above the 2250 threshold, respectively. The estimated parameter  $\alpha_{glr}$  indicates the discontinuity at the threshold.

If we fit the same structure predicting the outcome variable, we can write:

$$(2) \quad Y = \alpha_{yl} + \alpha_{ylr}D_r + \sum_{j=1}^p \beta_{ylj}[D_l(T - 2250)]^j + \sum_{j=1}^p \beta_{yrj}[D_r(T - 2250)]^j + X\eta_y + \nu,$$

where the subscript  $y$  identifies coefficients in the equation predicting the outcome measure. The estimate of program impact is based on the relative size of the regression discontinuity estimated in equation (1) and that estimated in equation (2). Assuming that the discontinuity in (1) induces the discontinuity in equation (2), the impact of the program can be written:

$$(3) \quad \tau = \alpha_{ylr} / \alpha_{glr}.$$

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<sup>8</sup> The formal model presented here follows closely from that presented in Imbens and Lemieux (2008). See also McCrary (2008) and Lee and Lemieux (2010).

Figure 4 provides a graph that illustrates the estimation methods underlying equations (1) and (2).<sup>9</sup> Here the focus is on earnings in quarter 12. The discontinuity assumed in equation (1) is clearly present in the data, confirming that those who score at or just above the threshold on the overall GED score are appreciably more likely to have a GED within two years than those scoring just below. The graph for earnings does not show a discontinuity at this point, suggesting that there is little impact on quarter 12 earnings.

As Imbens and Lemieux (2008) observe (see also Hahn, Todd and van der Kaauw, 2001), the FRD can be formulated as an instrumental variables system, where the treatment variable (GED certification in our case) is instrumented with the continuous measure and dummy variables capturing the discontinuity. Equation (1) is then the auxiliary equation. The outcome variable can be fitted with the following specification:

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

where  $\widehat{GED}$  is the predicted value from equation (1). Since the polynomial is of the same order in equations (1) and (4), estimates of  $\tau$  based on equations (1) through (3) are numerically identical to those based on equations (1) and (4). Values away from the discontinuity have no effect on the estimate of impact estimate  $\tau$ , except insofar as they influence the estimate of the extent of the discontinuity.

In order to improve precision, rather than estimating the model on a single test, we perform the analysis using up to three tests, so units of analysis are individuals by test score. The two-stage system implied by equations (1) and (4) is revised as follows:

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<sup>9</sup> The figure shows the results from the specification that excludes covariates. The figure based on a regression controlling covariates has the same pattern as Figure 4.

$$(5) \quad GED = \alpha_{gkl} + \alpha_{gklr} D_r + \sum_{j=1}^{p(k)} \beta_{gklj} [D_{kl}(T_k - 2250)]^j + \sum_{j=1}^{p(k)} \beta_{gkrj} [D_{kr}(T_k - 2250)]^j \\ + \phi_{gk1} T_{k-1} + \phi_{gk2} T_{k-1}^2 + X\eta_{gk} + \varepsilon_k$$

$$(6) \quad Y = \alpha_{kl} + \tau \widehat{GED} + \sum_{j=1}^{p(k)} \beta_{klj} [D_{kl}(T_k - 2250)]^j + \sum_{j=1}^{p(k)} \beta_{krj} [D_{kr}(T_k - 2250)]^j \\ + \phi_{k1} T_{k-1} + \phi_{k2} T_{k-1}^2 + X\eta_k + \nu_k$$

where we have added the subscript  $k$  to identify the parity of the test (e.g.,  $k=1$  is the first test,  $k=2$  is the second test), and  $T_k$  is the score associated with test  $k$ . As before, subscript  $g$  identifies the parameters for the GED certification equation. We have added test parity subscripts to  $\alpha$  and  $\beta$ , so that they are estimated separately for each of the three tests. As noted above, the sample for  $T_k$  for  $k=2, 3$  includes only cases where  $T_k > T_{k-1} < 2250$ . The specification controls for prior test score for the second and third tests, but in the case of the first test, no prior test is available, i.e., we take  $\phi_{g11} = \phi_{g12} = \phi_{11} = \phi_{12} = 0$ .  $D_{kl}$  ( $D_{kr}$ ) is a dummy indicating whether the total score on parity  $k$  is below (equals or exceeds) the passing threshold, and  $X$  is the same set of covariates as in equation (1).

The equation is estimated flexibly by test parity, as  $\tau$  is the only parameter constrained to be same across all test parities (i.e. test score attempts).<sup>10</sup> In other words, we assume that the effect of getting a GED after taking any of the tests is the same, but we recognize that crossing a threshold has a different effect on the likelihood of getting a GED depending on the parity of the test, and that the relationship between test performance and earnings above and below the threshold depends on the test parity. Imposing a constant GED impact by test parity has little substantive effect on the size and significance of the GED coefficients. Appendix Table 2

<sup>10</sup> Although not shown explicitly, equations (5) and (6) contain a set of parameters for each test parity except for GED impact ( $\tau$ ). For example, the equations contain 3 spring quarter estimates: the spring quarter for the first test attempt, spring quarter in the second test attempt, and spring quarter for the third test attempt.

presents the results when we estimate separate models by test parity for the multidimensional model presented in the subsequent section. In all models, the estimated GED impacts for the second and third test parity are very imprecise due to the small sample of repeat test takers.

Because the model includes second and third test attempts, the above specification allows each individual to be included in the analysis up to three times. The dependent variable is the same when the individual case is repeated. In each test parity for a given individual, the prediction is based on a different test score because the independent variables vary by test parity. We account for clustering on individuals in calculating standard errors. For simplicity, we report the results from a model using a quadratic specification for the first test ( $p(1)=2$ ) and a linear specification for the second and third tests ( $p(2)=p(3)=1$ ). Estimates based on higher order polynomials are less precise but show a similar pattern.

As noted above, our basic sample includes individuals who first take the GED test in 1995 to 2005. We exclude test takers in 2006 through 2008 because these individuals do not have sufficient earnings and 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 the observed relationship between test score and GED receipt is irregular below 1500 (many of these individuals do not take all the subtests), and because initial experiments indicated that the truncation improved estimate precision without altering the substantive conclusions. This approach eliminated 8 percent of the cases below the threshold and 12 percent of the cases above the threshold. About 37 percent of those with scores below 1500 ultimately obtain certification; virtually all those with scores over 3000 are certified. For the remainder of the paper, we will refer to the regression analysis sample as the full sample. In keeping with previous GED research, all regressions are estimated separately for men and women.

We estimate a separate regression for each of our three dependent variables in each quarter after the initial GED test attempt. The first dependent variable is quarterly earnings. The second measure is employment, a dichotomous variable equal to one for individuals with positive earnings in the quarter. An analysis of employment is insightful when studying disadvantaged populations with low employment levels such as GED test takers. The final measure is an indicator of whether the individual enrolled in public postsecondary education in the state at any time during the quarter. Earnings and employment outcomes are available for 30 quarters after the initial GED attempt, whereas postsecondary education is available for 16 quarters after the initial GED attempt. So, we estimate 30 separate quarterly regressions for earnings and employment and 16 separate regressions for postsecondary attendance.

Table 3 presents estimates based on equation (5), the first stage of the two-stage equation, applied to quarter 12.<sup>11</sup> In Table 3, the dependent variable is a dichotomous variable for passing the GED test, and the model is estimated with clustered standard errors for each individual. Note that the first-stage estimates for the three second-stage outcomes (quarterly income, employment, and postsecondary education) are identical because they are all based on the same sample and the same first-stage regression. The discontinuity at the threshold for the first test is associated with a 34 percentage point increase in the likelihood that men obtain GED certification. The discontinuity increases to 47 percentage points for the second attempt and 40 percentage points for the third attempt. For women, the discontinuities are 30 percentage points for the first attempt, 47 percentage points for the second attempt, and 46 percentage points for the third attempt. All the discontinuity variables are significant at the one-percent level (two-sided test).

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<sup>11</sup> The results from the first-stage equation vary from quarter to quarter because the dependent variable is GED certification as of the beginning of the quarter and because the sample size varies depending on the number of GED test attempts as of the beginning of the quarter. For brevity, the table contains the results for quarter 12 after the initial GED test. The results from other quarters show a very similar pattern.

Parameter estimates for the GED impact from the basic model in equation (6), estimated separately for men and women, are in the leftmost columns of Tables 4 through 6. As mentioned previously, we consider three dependent variables: quarterly earnings, employment, and postsecondary school attendance. The first two columns in each table contain the estimated impact,  $\tau$ , and its standard error, as identified by the discontinuity in  $\widehat{GED}$  from the basic FRD. Each coefficient (and standard error) is from a separate regression where the outcome applies to the indicated quarter.

In Table 4, the dependent variable is quarterly earnings, where quarters are measured from 1 to 30 quarters after the initial GED test attempt. The quarter in which the individual first attempts the GED is labeled quarter 0. In the basic model, although the estimated coefficients vary from quarter to quarter, only 2 of the 30 coefficients reported are statistically significant at the five-percent level (two-sided test) for men; one is statistically significant at the ten-percent level for women. Thus, in most cases, we cannot reject the hypothesis that the GED has no effect on quarterly earnings. For men, the GED does appear to be associated with higher quarterly earnings of \$230 to \$240 in quarters 5 and 6 following the initial GED test. The estimates have nontrivial standard errors, especially in later quarters where the sample size is smaller because individuals who took the GED in the later years do not have earnings data from all 30 quarters.

One obvious factor that may reduce employment for GED recipients would be enrollment in postsecondary education. In unreported results, we reproduced our earnings analysis limiting the sample to those not enrolled in public postsecondary education during that quarter. The results from this sample were nearly identical to the results reported in the tables. We also estimated effects taking the dependent variable as log earnings rather than earnings, limiting

consideration to those with positive earnings in the quarter. Impact estimates in this specification were qualitatively similar to those in our base analyses.<sup>12</sup>

In Table 5 the dependent variable is a dichotomous variable for employment, measured as having positive earnings in the quarter. None of the basic FRD coefficients in either table are statistically significant at the five percent level (two-sided test). As with earnings, the results for employment are not sensitive to the inclusion of individuals attending postsecondary education during the quarter.

Table 6 presents results for postsecondary enrollment in the state's public institutions. For men, the basic model indicates that GED certification is associated with increased postsecondary enrollment of two to four percentage points in the first five quarters after the test. We also see a positive effect for men of as much as three percentage points in quarters 9 to 11. In other quarters, the effect is small and not statistically significant. For women, the effect is much larger. GED certification is associated with an increased likelihood of postsecondary attendance for the first eight quarters after the initial GED attempt. The effect size is eight percentage points in the first quarter after the test, and it declines to three percentage points in the eighth quarter after the test. In subsequent quarters, the effect continues to decline, and it is not statistically different from zero.

The fact that passing the GED is associated with increased postsecondary education attendance but is not associated with higher earnings or employment can be explained by the low levels of postsecondary education obtained by GED recipients. Jepsen, Mueser, and Troske

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<sup>12</sup> Focusing on only those not in secondary education or those employed may induce bias in estimates because of selection. However, the biases for analyses limited to those employed are likely to be small since the GED does not predict employment (see employment results below). If omitting those in postsecondary schooling imposes a bias, this would imply that postsecondary attendance influences earnings but not employment. The potential bias is further limited by the relatively short duration of enrollment for individuals in postsecondary education in our data (Jepsen, Mueser, and Troske, 2010).

(2010) show that passing the GED is associated with an increase of approximately two credit hours for men and five credit hours for women.

All reported estimates suffer from sizable standard errors as is typical in IV models. As noted above, in an effort to improve the estimation equations, these results are from models that control for demographic characteristics, employment prior to taking the GED, and other factors. The exclusion of these measures increased the standard errors by as much as one third in the quarters immediately following the first GED test, but the pattern of results were nearly identical to the reported results. Because the test changed in 2002 (and prior test scores were no longer accepted at that point), we fitted models allowing the slope of the test score on GED certification and the dependent variable to differ by period. We also fitted the full model separately for the period prior to and after the implementation of the new test in 2002. In none of these models were results substantively different from those we report.

Lee and Lemieux (2010) suggest using multiple methods, both parametric and nonparametric, for conducting regression discontinuity analysis. In response, we also fitted estimates based on a local linear regression approach using software developed by Fuji, Imbens, and Kalyanaraman (2009), which, in essence, specifies a linear regression on each side of the threshold. In this approach, the choice of bandwidth is critical. Power improves as bandwidth increases, but, if there is any nonlinearity in the relationship between the running variable and the outcome, larger bandwidths induce greater bias. Because standard formulas for optimal bandwidth were unstable, we obtained estimates for a large number of bandwidths, varying from as few as 30 points (four data points), to as many as 750 points (up to 76 data points). In order to get a sense of whether nonlinearities were biasing our results, we examined graphs of the data and the estimated functions, as well as examining how estimates varied with bandwidth. We

found that the appropriate bandwidth varied across cases considered. In no case were our final results based on these analyses seriously at variance with those presented here; nor were the impact estimates more precise.

### ***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. Individuals who have subtest scores that are below the subtest threshold do *not* obtain the GED if their overall scores exceed the threshold, whereas those with higher subtest scores (and overall scores at or above 2250) do obtain the GED. 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 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 in addition to the overall and subtest scores mentioned above, which are not present in a sharp RD design. For example, when an individual has not exceeded the *overall* score threshold, if test retaking cannot occur, the *subtest* threshold is irrelevant. However, given the possibility of retaking the test, a subtest threshold may well influence the likelihood of 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 when they retake the test.

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 the lowest subtest score (not just the criteria) may interact with each other. In the specification below, we therefore include continuous interactions between the overall test and subtest scores, distinguishing scores above and below the threshold.

For simplicity, we again present the specification for the equation predicting GED certification based on the first test score. The model we actually estimate includes additional parameters for second and third test parity analogous to those in equations (5) and (6):

$$\begin{aligned}
(7) \quad GED = & \alpha_{gl} + \sum_{j=1}^p \beta_{gllj} [D_{Tl} D_{Sl} (T - 2250)]^j + \sum_{j=1}^p \gamma_{gllj} [D_{Tl} D_{Sl} (S - c)]^j \\
& + \phi_{gll} [D_{Tl} D_{Sl} (T - 2250)(S - c)] \\
& + \alpha_{grl} D_{Tr} D_{Sl} + \sum_{j=1}^p \beta_{grlj} [D_{Tr} D_{Sl} (T - 2250)]^j + \sum_{j=1}^p \gamma_{grlj} [D_{Tr} D_{Sl} (S - c)]^j \\
& + \phi_{grl} [D_{Tr} D_{Sl} (T - 2250)(S - c)] \\
& + \alpha_{glr} D_{Tl} D_{Sr} + \sum_{j=1}^p \beta_{glrj} [D_{Tl} D_{Sr} (T - 2250)]^j + \sum_{j=1}^p \gamma_{glrj} [D_{Tl} D_{Sr} (S - c)]^j \\
& + \phi_{glr} [D_{Tl} D_{Sr} (T - 2250)(S - c)] \\
& + \alpha_{grr} D_{Tr} D_{Sr} + \phi_{g0} d_{s0} + X\eta_g + \varepsilon,
\end{aligned}$$

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.  $T$  continues to designate the total score, and  $S$  is the lowest subtest score, with the subtest threshold  $c$ .<sup>13</sup> The dummy variable  $d_{s0}$  indicates that the lowest subtest score is zero.<sup>14</sup>

As above, the subscript  $g$  identifies coefficients in the equation predicting certification. The

<sup>13</sup> For 1995-2001,  $c=400$ ; for 2002 and after,  $c=410$ .

<sup>14</sup> In many instances, test takers choose to skip at least one subtest. As might be expected, the linear relationship assumed for the lowest test score does not apply for scores of zero.

estimated coefficients  $\beta_{gxxj}$  and  $\gamma_{gxxj}$  (where  $x$  stands in for either  $l$  or  $r$ ) identify the slope 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  $\alpha_{gxx}$ . The interaction term  $D_{T_r}D_{S_r}$  identifies individuals who receive a GED based on the initial test, and therefore  $\alpha_{grr}$  is expected to identify a major discontinuity. The smooth interaction terms between total score and lowest subtest score are fitted with  $\phi_{gxx}$ . Note that when both the total and lowest subtest scores are above their respective thresholds, the actual scores are not relevant because GED certification is certain, so coefficients  $\beta_{grrj}$ ,  $\gamma_{grrj}$  and  $\phi_{grr}$  are not fitted, effectively constraining their values to be zero. The test score and subtest score functions are of order  $p$ , and we will consider  $p=2$  (quadratic).<sup>15</sup>

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. The outcome equation is therefore written as:

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<sup>15</sup> Again, we fit only the linear model for the test score threshold for the second and third test attempts. Imposing linearity improves precision of the estimates but has no substantive effect on the estimated GED coefficient.

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

Estimated coefficients are analogous to those in (7). The exceptions are  $\beta_{rrj}, \gamma_{rrj}$  and  $\phi_{rr}$  in (8), for which the analogous parameters are taken to be zero in equation (7)—reflecting the fact that all individuals with such scores receive GED certification. In (8) we must capture the relationship between the scores and the outcome when the GED criteria are satisfied.

Identification comes from the fact that the function in equation (8) is mostly smooth, reflecting our belief that a continuous function will identify the relationship between test scores and earnings, whereas the function determining GED receipt in equation (7) 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.

As a way of increasing power, we also fit this structure using a more parsimonious functional form. First, we omit the smooth interaction terms ( $\phi$ 's). For those below the overall test score threshold, we also constrain the slope of the overall test score to be the same whether or not the lowest subtest score is above the threshold, i.e., we constrain  $\beta_{gllj} = \beta_{glrj}$ , designating this constrained parameter  $\beta_{gl0j}$ . Analogously, we assume that, when the subtest threshold is not

met, the slope of the subtest score is the same whether or not the overall score is above the threshold, i.e.,  $\gamma_{glj} = \gamma_{grlj}$ , designating this parameter  $\gamma_{g0lj}$ . Incorporating these changes, we write a revised version of (7) as:

$$\begin{aligned}
 (9) \quad GED &= \alpha_{gl} + \sum_{j=1}^p \beta_{gl0j} [D_{Tl}(T - 2250)]^j + \sum_{j=1}^p \gamma_{g0lj} [D_{Sl}(S - c)]^j \\
 &+ \alpha_{grl} D_{Tr} D_{Sl} + \sum_{j=1}^p \beta_{grlj} [D_{Tr} D_{Sl}(T - 2250)]^j \\
 &+ \alpha_{glr} D_{Tl} D_{Sr} + \sum_{j=1}^p \gamma_{glrj} [D_{Tl} D_{Sr}(S - c)]^j \\
 &+ \alpha_{grr} D_{Tr} D_{Sr} + \phi_{g0} d_{S0} + X\eta_g + \varepsilon
 \end{aligned}$$

The reduced version of equation (8) is specified analogously, except that we also constrain  $\beta_{rlj} = \beta_{rrj}$ , designating the constrained parameter  $\beta_{r0j}$ , and  $\gamma_{rrj} = \gamma_{lrj}$ , designated  $\gamma_{0rj}$ .

$$\begin{aligned}
 (10) \quad Y &= \alpha_l + \tau \widehat{GED} + \sum_{j=1}^p \beta_{l0j} [D_{Tl}(T - 2250)]^j + \sum_{j=1}^p \gamma_{0lj} [D_{Sl}(S - c)]^j \\
 &+ \sum_{j=1}^p \beta_{r0j} [D_{Tr}(T - 2250)]^j + \sum_{j=1}^p \gamma_{0rj} [D_{Sr}(S - c)]^j \\
 &+ \phi_0 d_{S0} + X\eta + \nu
 \end{aligned}$$

For both multidimensional models, we fit equations that make use of the first three test scores, modifying estimation equations (7)-(10) to allow separate parameters by parity of test. As described in our discussion of the one-dimensional model, we control for prior test score for the second and third test, and omit retake scores that are outside the range in which the discontinuity is relevant.

The third through sixth columns of Tables 4 through 6 present results from the two models presented above, again estimated as single system. As discussed previously, the first two columns contain results from the basic model. Generally, standard errors in the full

multidimensional model are quite similar to those in the unidimensional (i.e. “basic”) model. The reduced model presented in columns (5) and (6) yields standard errors that are substantially smaller than those in the basic model (columns (1) and (2)). The impact estimates in both multidimensional models for earnings and employment yield substantive conclusions that are almost identical. Of estimates of effects on income over the 30 quarters, as in the unidimensional model, two are statistically significant and positive for men, whereas none are statistically significant for women. Effects for employment across men and women are statistically significant in only three cases, and these are negative.

Estimates of the impact on educational enrollment (Table 6) also display greater precision for the reduced multidimensional models. For men, estimates for quarters 1-4 are similar or slightly smaller than in the unidimensional model, and neither multidimensional model yields statistically significant impacts on school attendance in any subsequent quarter. In the case of women, estimates for all models are basically consistent for the first eight quarters, but the reduced model suggests that there is a larger impact on enrollment in quarters 9-11.

To address the volatility of quarterly labor market outcomes for this low-skilled population, we also estimate reduced multidimensional models where we consider aggregate measures of earnings and employment based on one to two years of data. Table 7a contains the results from these specifications for earnings, where the dependent variable in each row is the sum of quarterly earnings for the listed quarters. Table 7b contains the results for employment, where the dependent variable is the number of quarters employed for the one- or two-year period. In each table, the top panel is for men and the bottom panel is for women. The earnings coefficients are small and not statistically significant except for a positive effect for women in years 6 and 7, which is statistically significant at the ten-percent level. The employment

coefficients are almost always negative, although they are generally small and not statistically significant. The exception is that men have a significantly lower (at the ten-percent level) employment of 0.199 quarters in years 4 and 5.<sup>16</sup>

In Table 8, we look at the effect of the GED on subgroups of the population based on three demographic characteristics measured at the time of the first GED attempt: race, age, and highest grade completed. In addition to coefficients and standard errors, the table also includes t-statistics (in absolute value) for differences in coefficients between whites and nonwhites, age 20 or less and over 20, and grade 10 or less and grade 11 or more. The table shows that there are few differences between subgroups that are statistically significant at the ten-percent level and none significant at the five-percent level. For quarters 1-4 and quarters 21-28, nonwhite women register smaller impacts of GED on employment than white women, but nonwhite women register greater impacts on postsecondary attendance. In general, the returns to the GED do not appear to differ systematically by race, age, or highest grade completed.

## **VI. Comparison with SRD Model**

As discussed previously, our FRD model differs substantially from the RD models previously estimated for the GED. Specifically, previous work estimates a sharp regression discontinuity (SRD) based on the last test attempt of the GED. Therefore, in this section, we estimate SRD models of the GED in order to compare the results between methods. The comparison of models using the same sample of GED test takers is more informative than comparing our results directly with those of previous work, which looked at different time periods and states.

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<sup>16</sup> We obtained estimates corresponding to those in Tables 7a and 7b using the single dimension model and the full multidimensional model. Results were substantively similar to those presented, although precision was usually reduced. We also undertook analyses of postsecondary enrollment using methods presented here. Although precision was increased, results were essentially unchanged.

To the extent possible, we fit a model corresponding to that of Tyler (2004). We limit the sample to individuals who passed the subtest requirement. This requirement is needed in order to make sure that the discontinuity is sharp. With this restriction, those who obtain a score of 2250 or higher on their last attempt receive GED certification, and those who score below 2250 do not receive GED certification. We also limit the sample to individuals whose final test score is between 2200 and 2300, which is analogous to the sample used in Tyler (2004).

We estimate the following SRD model in equation (11) below:

$$(11) \quad Y = \alpha + \beta PassGED + \gamma GEDLAST + X\eta + \nu$$

$Y$  is the outcome of interest: earnings, employment, or education.  $PassGED$  is a dummy variable for receiving a score of 2250 or higher on the final attempt.<sup>17</sup>  $GEDLast$  is the score on the last GED attempt, and  $X$  is a set of covariates. This model is estimated using OLS. The main difference between the model in equation (11) and the model estimated by Tyler is that Tyler uses an average of the first and last GED score, whereas we use only the final test score.

Figures 5 and 6 allow us to compare the SRD and FRD results for men and women, respectively. The solid line and box marker in each graph contains the estimated effect  $\tau$  for the FRD model, as captured by the reduced multidimensional model presented in Tables 4-6. The dashed line and triangle marker is for a sharp regression discontinuity (SRD). Estimates that are statistically significant at the five-percent level (two-sided test) are shaded in black; estimates that are significant at the ten-percent level (two-sided test) are shaded in gray; and estimates that are not significant at the ten-percent level (two-sided test) are not shaded.

The figures show that the pattern of results differs by model and gender. For men's earnings, the SRD model has earnings impacts above \$200 per quarter for men in a majority of

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<sup>17</sup> Because a GED test score is "valid" for up to two years, this score is the sum of the highest subgroup scores in the two-year period up to the last GED attempt.

quarters starting with quarter 17, although the coefficients are not significantly different from zero at the 10 percent level. In contrast, the FRD model estimates seldom exceed \$100, and are statistically significant in only two quarters. For women, the SRD estimates of the earnings impact increase dramatically over the period of the study, from levels that are initially negative in excess of \$200, to positive impacts exceeding \$400, with most of them easily statistically significant. In contrast, none of the earnings impact estimates in the FRD are statistically significant, and most are less than \$100.

The differences between models for employment are more dramatic, as illustrated by the middle panels of Figures 5 and 6. The SRD model estimates much larger positive employment impacts than the FRD model, especially for women. Except for most of the first eight quarters, the SRD results for women suggest that the GED is associated with increased employment probability, whereas the FRD model suggests, if anything, negative impacts.

The SRD and FRD models produce different patterns of results for education as well. For both men and women, the FRD model estimates decline over time and eventually become statistically insignificant and close to zero 12 quarters after the initial GED attempt. In contrast, the SRD results increase over time, and they produce statistically significant education effects in most quarters starting with quarter 8 for men and quarter 11 for women.

The potential difference in results by model is noteworthy given our concerns about the validity of the SRD model. We have shown that the last test score is not a valid running variable for conducting an RD analysis. Our analysis suggests that conclusions drawn from RD models that do not take into account manipulation of the running variables—due here to a test that can be retaken—may be unreliable.

## VII. Conclusion

In this paper we have demonstrated how one can apply a valid regression discontinuity approach—fuzzy regression discontinuity with multiple thresholds—to a situation where a treatment is based on a test score and individuals can manipulate the test score by retaking the test. We use this technique to estimate the effect of the GED test, which is subject to manipulation because test takers can retake the test multiple times in a two-year period. Using the FRD methodology we find that, for persons near the threshold for passing the test, the effect of passing the GED is small and statistically insignificant. We do find a positive association between passing the GED and postsecondary enrollment of up to four percentage points for men and eight percentage points for women. Given that less than 12 percent of the population of GED test takers enrolls in postsecondary institutions in any given quarter, this impact is substantial. However, these effects decline over time, becoming insignificant after five quarters for men and after 11 quarters for women.

Our results are robust to implementing the FRD technique as a local linear model or as an instrumental variables model. Our results are also robust to the exclusion of demographic variables as well as prior earnings. However, our results are sensitive to the choice of the FRD approach as opposed to the SRD approach. The fragility of our results to the choice of technique demonstrates the importance of ensuring that the underlying assumptions of the RD estimator are met in the data. Using SRD when not appropriate may lead to the wrong conclusion.

In common with other analyses based on an RD methodology, our results formally apply only to those near the test threshold. Such individuals are in the bottom quartile in terms of performance on the GED test, so the average experience could differ if GED signaling was of greater importance for those with high ability. Also, our analysis does not capture any direct

effects of student studying on labor market outcomes. If those who study for the GED — whether or not they pass it—obtain valuable skills that improve their labor market opportunities, such benefits will not be captured in our analysis. Although the typical GED test taker spends fewer than 40 hours studying for the test, a small number of test takers put in substantial time studying, and our approach could omit benefits they receive.

For high school dropouts near the GED passing thresholds, our findings do not support the view that GED certification is of use in helping them escape their disadvantaged labor market status. Perhaps most troubling, a substantial portion of high school dropouts indicate that they dropped out because they believed it was easier to obtain a GED than complete high school (Heckman et al., 2008). Insofar as additional time in school would have benefited those who drop out, the GED may have reduced the labor market success of GED test takers. At the very least, the results in this paper lend further support to the growing consensus that the GED is simply not a substitute for a high school diploma.

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Table 1: Test Performance and Test Retaking: First Time Test Takers, 1995-2005

Score Range <sup>1</sup>	Number	Distribution (%)	Retake (%)
0-990	1,009	1.0%	65.7%
1000-1490	897	0.9%	51.7%
1500-1740	1,410	1.5%	37.6%
1750-1990	4,787	4.9%	42.9%
2000-2090	4,223	4.4%	52.9%
2100-2140	2,798	2.9%	57.0%
2150-2190	3,423	3.5%	62.0%
2200-2240	3,946	4.1%	68.9%
2250-2290	4,398	4.5%	20.9%
2300-2340	4,879	5.0%	14.0%
2350-2490	16,343	16.9%	6.8%
2500-2740	24,967	25.8%	1.6%
2750-3000	15,171	15.7%	0.4%
3010-4000	8,632	8.9%	0.2%
<b>Total</b>	<b>96,883</b>	<b>100.0%</b>	<b>16.1%</b>

<sup>1</sup> Only test scores that are multiples of 10 are awarded.

Table 2: Discontinuity in Estimates for the Distribution of Test Takers' Characteristics, 1995-2005.

		Final Test Score (1)	One-Time Test Takers (2)	First Test (3)
Male	Coefficient	-0.018	-0.035	0.010
	(Standard error)	(0.012)	(0.016)	(0.011)
	t-statistic	-1.5	-2.2	1.0
Nonwhite	Coefficient	0.032	0.035	0.006
	(Standard error)	(0.010)	(0.012)	(0.008)
	t-statistic	3.3	3.0	0.8
Age	Coefficient	-1.077	-1.329	-0.340
	(Standard error)	(0.219)	(0.278)	(0.191)
	t-statistic	-4.9	-4.8	-1.8
Retake test	Coefficient	-0.029		-0.504
	(Standard error)	(0.008)		(0.006)
	t-statistic	-3.6		-80.7
Prior earnings	Coefficient	-320.50	-321.95	-53.03
	(Standard error)	(242.07)	(313.38)	(210.26)
	t-statistic	-1.3	-1.0	-0.3
	Observations	95,160	81,296	96,883

Note: Prior earnings are measured as the total earnings in the four quarters (i.e. year) before the GED attempt.

Table 3: Regression Discontinuity Equation Parameter Estimates,  
First Stage for Quarter 12

	Men		Women	
	Coefficient	Standard Error	Coefficient	Standard Error
<i>First test attempt</i>				
Discontinuity	<b>0.33984</b>	<b>(0.00709)</b>	<b>0.30127</b>	<b>(0.00710)</b>
Linear - left	<b>0.00190</b>	<b>(0.00005)</b>	<b>0.00250</b>	<b>(0.00005)</b>
Linear - right	<b>0.00061</b>	<b>(0.00003)</b>	<b>0.00055</b>	<b>(0.00003)</b>
Square - left	<b>0.00205</b>	<b>(0.00007)</b>	<b>0.00289</b>	<b>(0.00008)</b>
Square - right	<b>-0.00061</b>	<b>(0.00004)</b>	<b>-0.00056</b>	<b>(0.00004)</b>
<i>Second test attempt</i>				
Discontinuity	<b>0.47387</b>	<b>(0.01098)</b>	<b>0.46770</b>	<b>(0.01041)</b>
Linear - left	<b>0.00123</b>	<b>(0.00006)</b>	<b>0.00127</b>	<b>(0.00006)</b>
Linear - right	0.00004	(0.00003)	<b>0.00013</b>	<b>(0.00004)</b>
Previous score	<b>-0.00080</b>	<b>(0.00026)</b>	-0.00019	(0.00030)
Previous score squared	<b>2.0E-07</b>	<b>(6.1E-08)</b>	5.1E-08	(7.1E-08)
Dummy for second attempt	<b>0.69914</b>	<b>(0.27528)</b>	-0.00596	(0.32522)
<i>Third test attempt</i>				
Discontinuity	<b>0.39571</b>	<b>(0.02228)</b>	<b>0.45537</b>	<b>(0.02080)</b>
Linear - left	<b>0.00161</b>	<b>(0.00016)</b>	<b>0.00198</b>	<b>(0.00015)</b>
Linear - right	0.00017	(0.00010)	0.00015	(0.00009)
Previous score	0.00012	(0.00031)	<b>0.00102</b>	<b>(0.00026)</b>
Previous score squared	-2.4E-08	(8.3E-08)	<b>-3.0E-07</b>	<b>(7.4E-08)</b>
Dummy for third attempt	-0.33545	(0.30313)	<b>-1.03227</b>	<b>(0.24406)</b>
Observations	51,637		48,961	
Number of Individuals	44,378		41,967	
Adjusted R-squared	0.58		0.60	

Notes: Bold terms represent coefficients that are statistically significant at the five-percent level (two-sided test). Squared terms are measured in thousands. Standard errors are clustered by individual. Each regression also includes earnings in the four quarters prior to first GED attempt, race, age, age squared, dummy variables for year of first GED test, and quarter of the year (winter, spring, summer or fall).

Table 4a: Estimated GED Impact on Earnings for Alternative FRD Designs, Men

Quarters since 1st GED test	Basic		Full		Reduced		Mean Earnings
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	-36.2	(66.9)	82.0	(59.1)	27.3	(42.8)	\$2,048
2	71.2	(80.1)	63.9	(77.2)	5.4	(56.0)	\$2,190
3	78.8	(90.8)	74.4	(87.0)	-2.4	(63.1)	\$2,255
4	9.0	(103.9)	127.0	(99.4)	-5.8	(73.0)	\$2,333
5	<b>228.2</b>	<b>(114.6)</b>	<b>281.2</b>	<b>(106.1)</b>	<b>199.3</b>	<b>(78.7)</b>	\$2,404
6	<b>238.9</b>	<b>(120.6)</b>	<b>296.5</b>	<b>(114.8)</b>	<i>124.2</i>	<i>(86.2)</i>	\$2,470
7	210.5	(131.8)	<i>224.1</i>	<i>(123.7)</i>	103.5	(92.6)	\$2,507
8	133.1	(139.2)	-8.8	(131.7)	63.6	(96.7)	\$2,565
9	131.7	(144.8)	118.8	(136.2)	70.0	(100.1)	\$2,607
10	125.2	(155.9)	-143.0	(145.4)	-60.8	(106.3)	\$2,657
11	242.2	(156.9)	-28.4	(147.0)	27.2	(108.5)	\$2,661
12	70.0	(167.7)	60.1	(155.0)	35.3	(114.2)	\$2,723
13	-16.7	(174.8)	-7.4	(159.0)	-97.5	(118.0)	\$2,766
14	-42.4	(179.3)	-47.6	(161.9)	-98.6	(120.1)	\$2,781
15	-11.8	(182.6)	77.7	(167.1)	-32.2	(123.7)	\$2,795
16	-129.6	(185.2)	59.1	(169.6)	-114.8	(126.2)	\$2,835
17	-11.6	(188.0)	71.7	(174.9)	-44.1	(127.8)	\$2,858
18	-147.9	(194.7)	-65.9	(179.2)	-93.4	(130.5)	\$2,888
19	38.7	(193.4)	-27.3	(178.0)	-13.8	(131.2)	\$2,904
20	-45.9	(201.5)	-13.9	(183.7)	-74.7	(137.1)	\$2,933
21	72.7	(206.7)	-61.6	(191.4)	59.5	(140.2)	\$2,971
22	178.1	(218.5)	-24.6	(199.9)	77.1	(146.6)	\$3,016
23	11.8	(224.6)	98.7	(207.7)	97.4	(150.3)	\$3,018
24	34.8	(232.2)	-7.7	(214.3)	-66.8	(158.2)	\$3,049
25	217.4	(226.2)	233.3	(214.4)	115.5	(155.5)	\$3,078
26	50.6	(231.2)	303.0	(221.6)	74.5	(161.1)	\$3,104
27	-32.0	(232.8)	78.6	(226.0)	-36.5	(163.8)	\$3,090
28	39.3	(233.5)	190.7	(227.4)	164.1	(165.5)	\$3,135
29	-51.4	(261.5)	196.1	(251.2)	110.4	(173.9)	\$3,178
30	-90.0	(252.8)	-24.8	(246.3)	-28.9	(177.2)	\$3,211

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 4b: Estimated GED Impact on Earnings for Alternative FRD Designs, Women

Quarters since 1st GED test	Basic		Full Multidimensional		Reduced Multidimensional		Mean Earnings
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	-56.8	(59.7)	-2.8	(54.7)	29.1	(37.7)	\$1,725
2	-40.5	(71.2)	-14.9	(67.9)	-17.5	(48.2)	\$1,864
3	21.4	(80.2)	45.7	(80.6)	-21.2	(58.9)	\$1,921
4	68.1	(89.8)	64.0	(92.6)	9.3	(62.2)	\$1,996
5	2.3	(94.9)	-19.6	(98.9)	-37.5	(69.9)	\$2,058
6	41.5	(102.6)	-19.3	(107.7)	-47.0	(71.6)	\$2,109
7	-49.9	(112.8)	-105.4	(119.4)	-45.0	(76.6)	\$2,155
8	-18.7	(116.7)	-103.7	(126.2)	-103.0	(80.7)	\$2,227
9	-72.1	(125.2)	-45.7	(133.2)	-79.3	(85.2)	\$2,261
10	5.6	(131.1)	-40.3	(140.8)	-70.0	(88.3)	\$2,300
11	17.0	(135.8)	-18.3	(148.1)	-5.1	(93.5)	\$2,312
12	37.8	(140.0)	6.5	(150.2)	-30.4	(97.0)	\$2,359
13	5.6	(144.7)	67.8	(155.4)	45.0	(99.3)	\$2,382
14	-7.3	(151.4)	39.3	(162.7)	39.6	(103.2)	\$2,398
15	110.0	(149.4)	121.6	(157.6)	68.8	(102.1)	\$2,413
16	181.7	(151.6)	76.4	(160.1)	71.5	(103.2)	\$2,434
17	116.0	(159.1)	2.5	(163.8)	39.4	(107.0)	\$2,457
18	102.8	(164.0)	-8.7	(167.0)	22.6	(109.5)	\$2,483
19	125.0	(162.6)	-67.5	(168.7)	36.4	(109.2)	\$2,473
20	211.5	(169.4)	-9.5	(170.4)	57.3	(111.7)	\$2,477
21	<b>294.2</b>	<i>(169.9)</i>	-38.2	(174.4)	148.6	(115.0)	\$2,500
22	267.7	(190.4)	-80.2	(197.0)	111.1	(126.0)	\$2,527
23	111.4	(178.2)	-60.4	(188.0)	143.6	(122.2)	\$2,517
24	204.8	(182.1)	76.6	(192.7)	97.1	(129.6)	\$2,555
25	242.3	(182.1)	130.7	(191.7)	200.9	(127.1)	\$2,566
26	60.1	(190.2)	7.0	(201.6)	64.1	(131.2)	\$2,598
27	88.7	(191.0)	-126.8	(207.2)	68.6	(134.3)	\$2,576
28	127.6	(191.5)	-34.3	(205.3)	91.6	(135.3)	\$2,604
29	135.8	(200.5)	-204.3	(224.9)	132.2	(141.2)	\$2,604
30	-128.9	(205.2)	-113.2	(233.0)	15.5	(143.7)	\$2,633

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 5a: Estimated GED Impact on Employment for Alternative FRD Designs, Men

Quarters since 1st GED test	Basic		Full Multidimensional		Reduced Multidimensional		Mean Employ.
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	0.013	(0.017)	0.015	(0.015)	0.006	(0.010)	62.1%
2	-0.015	(0.018)	-0.020	(0.017)	-0.015	(0.012)	62.6%
3	0.016	(0.019)	-0.002	(0.019)	-0.012	(0.013)	62.1%
4	-0.014	(0.020)	-0.010	(0.020)	-0.017	(0.014)	61.7%
5	0.000	(0.021)	-0.003	(0.021)	-0.005	(0.015)	61.7%
6	-0.008	(0.022)	0.003	(0.022)	-0.024	(0.015)	61.1%
7	-0.010	(0.023)	-0.006	(0.022)	-0.013	(0.016)	60.7%
8	0.007	(0.024)	-0.005	(0.023)	0.001	(0.016)	60.5%
9	0.004	(0.024)	-0.020	(0.024)	-0.019	(0.017)	60.0%
10	-0.009	(0.025)	-0.015	(0.024)	-0.021	(0.017)	59.4%
11	0.000	(0.025)	-0.027	(0.024)	-0.016	(0.017)	58.7%
12	-0.022	(0.026)	-0.006	(0.025)	-0.022	(0.018)	58.3%
13	<i>-0.045</i>	<i>(0.026)</i>	-0.020	(0.025)	<i>-0.032</i>	<i>(0.018)</i>	57.5%
14	-0.036	(0.026)	-0.022	(0.025)	<i>-0.032</i>	<i>(0.018)</i>	56.9%
15	-0.002	(0.026)	-0.013	(0.025)	-0.023	(0.018)	56.4%
16	-0.011	(0.027)	-0.005	(0.026)	-0.019	(0.018)	56.1%
17	-0.018	(0.027)	-0.005	(0.026)	-0.016	(0.018)	55.6%
18	-0.013	(0.027)	-0.019	(0.026)	-0.024	(0.018)	55.5%
19	-0.007	(0.027)	-0.025	(0.026)	-0.025	(0.019)	55.2%
20	0.004	(0.027)	0.001	(0.026)	-0.025	(0.019)	54.6%
21	-0.017	(0.028)	-0.041	(0.027)	-0.031	(0.019)	54.5%
22	-0.011	(0.028)	<b>-0.054</b>	<b>(0.028)</b>	-0.032	(0.020)	54.5%
23	-0.027	(0.029)	-0.010	(0.028)	-0.029	(0.020)	53.9%
24	-0.027	(0.029)	-0.016	(0.028)	-0.022	(0.020)	53.6%
25	-0.021	(0.029)	-0.001	(0.029)	<i>-0.038</i>	<i>(0.020)</i>	53.4%
26	-0.038	(0.029)	0.016	(0.029)	-0.017	(0.021)	53.3%
27	<i>-0.052</i>	<i>(0.029)</i>	-0.005	(0.030)	<i>-0.040</i>	<i>(0.021)</i>	52.8%
28	-0.033	(0.030)	0.000	(0.030)	-0.017	(0.021)	52.7%
29	-0.026	(0.030)	0.008	(0.030)	-0.006	(0.022)	52.7%
30	<i>-0.057</i>	<i>(0.030)</i>	-0.018	(0.030)	-0.022	(0.022)	52.5%

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 5b: Estimated GED Impact on Employment for Alternative FRD Designs, Women

Quarters since 1st GED test	Basic		Full Multidimensional		Reduced Multidimensional		Mean Employ.
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	-0.005	(0.017)	-0.001	(0.016)	-0.004	(0.011)	63.1%
2	-0.016	(0.018)	-0.015	(0.018)	-0.008	(0.012)	64.1%
3	0.002	(0.020)	-0.004	(0.020)	-0.004	(0.014)	64.2%
4	-0.010	(0.021)	0.004	(0.022)	-0.003	(0.014)	64.6%
5	0.001	(0.022)	0.023	(0.023)	-0.005	(0.015)	64.4%
6	-0.025	(0.023)	0.001	(0.024)	-0.019	(0.016)	64.3%
7	-0.012	(0.024)	0.004	(0.025)	-0.016	(0.017)	64.0%
8	-0.017	(0.024)	-0.014	(0.026)	-0.024	(0.017)	64.0%
9	<i>-0.045</i>	<i>(0.025)</i>	-0.021	(0.027)	<b>-0.043</b>	<b>(0.017)</b>	63.9%
10	-0.020	(0.025)	-0.026	(0.027)	<b>-0.037</b>	<b>(0.018)</b>	63.5%
11	-0.011	(0.026)	-0.009	(0.028)	-0.015	(0.018)	62.7%
12	0.001	(0.027)	0.019	(0.028)	-0.009	(0.018)	62.5%
13	0.000	(0.027)	0.003	(0.029)	-0.010	(0.019)	62.2%
14	0.003	(0.028)	0.021	(0.029)	0.004	(0.019)	61.9%
15	0.033	(0.028)	0.034	(0.030)	0.009	(0.019)	61.3%
16	0.046	(0.029)	0.035	(0.030)	0.019	(0.019)	60.8%
17	0.041	(0.029)	0.033	(0.030)	0.007	(0.019)	60.5%
18	0.006	(0.029)	-0.009	(0.030)	-0.021	(0.020)	60.2%
19	-0.018	(0.029)	-0.019	(0.031)	<i>-0.035</i>	<i>(0.020)</i>	59.6%
20	0.036	(0.030)	-0.001	(0.031)	-0.007	(0.020)	59.3%
21	-0.002	(0.031)	-0.029	(0.032)	-0.009	(0.021)	58.8%
22	0.004	(0.031)	-0.039	(0.032)	-0.012	(0.021)	58.4%
23	-0.011	(0.031)	-0.046	(0.033)	-0.008	(0.021)	58.0%
24	-0.011	(0.032)	-0.013	(0.033)	-0.004	(0.022)	57.9%
25	0.040	(0.032)	0.009	(0.034)	0.021	(0.022)	57.5%
26	0.020	(0.032)	0.033	(0.035)	0.003	(0.022)	57.5%
27	0.000	(0.032)	-0.005	(0.035)	-0.005	(0.023)	57.0%
28	0.026	(0.033)	0.037	(0.035)	0.007	(0.023)	56.7%
29	0.011	(0.033)	0.001	(0.036)	0.004	(0.023)	56.4%
30	0.027	(0.033)	0.021	(0.037)	0.023	(0.023)	56.2%

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 6a: Estimated GED Impact on Education for Alternative FRD Designs, Men

Quarters since 1st GED test	Basic		Full Multidimensional		Reduced Multidimensional		Mean Education
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	<b>0.039</b>	<b>(0.007)</b>	<b>0.038</b>	<b>(0.007)</b>	<b>0.029</b>	<b>(0.005)</b>	7.7%
2	<b>0.032</b>	<b>(0.008)</b>	<b>0.038</b>	<b>(0.007)</b>	<b>0.027</b>	<b>(0.006)</b>	7.2%
3	<b>0.022</b>	<b>(0.008)</b>	<b>0.030</b>	<b>(0.008)</b>	<b>0.022</b>	<b>(0.006)</b>	6.7%
4	<b>0.023</b>	<b>(0.008)</b>	<b>0.030</b>	<b>(0.008)</b>	<b>0.024</b>	<b>(0.006)</b>	6.4%
5	<b>0.024</b>	<b>(0.008)</b>	<b>0.023</b>	<b>(0.009)</b>	<b>0.016</b>	<b>(0.007)</b>	6.0%
6	<i>0.016</i>	<i>(0.009)</i>	<i>0.015</i>	<i>(0.009)</i>	0.004	(0.007)	5.5%
7	0.002	(0.009)	-0.001	(0.009)	-0.003	(0.007)	5.2%
8	0.006	(0.009)	-0.002	(0.009)	0.004	(0.007)	5.0%
9	<b>0.025</b>	<b>(0.008)</b>	0.013	(0.009)	<i>0.011</i>	<i>(0.006)</i>	4.8%
10	<b>0.031</b>	<b>(0.008)</b>	0.005	(0.009)	0.009	(0.006)	4.5%
11	<b>0.023</b>	<b>(0.008)</b>	0.002	(0.008)	0.007	(0.006)	4.2%
12	0.013	(0.008)	0.001	(0.009)	0.002	(0.006)	4.1%
13	0.004	(0.009)	-0.004	(0.008)	-0.006	(0.006)	3.8%
14	0.011	(0.008)	0.003	(0.008)	-0.001	(0.006)	3.6%
15	0.006	(0.008)	-0.002	(0.009)	-0.002	(0.006)	3.5%
16	0.002	(0.008)	-0.001	(0.008)	0.001	(0.006)	3.3%

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 6b: Estimated GED Impact on Education for Alternative FRD Designs, Women

Quarters since 1st GED test	Basic		Full Multidimensional		Reduced Multidimensional		Mean Education
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	
1	<b>0.080</b>	<b>(0.009)</b>	<b>0.077</b>	<b>(0.009)</b>	<b>0.065</b>	<b>(0.007)</b>	12.0%
2	<b>0.077</b>	<b>(0.009)</b>	<b>0.068</b>	<b>(0.010)</b>	<b>0.064</b>	<b>(0.007)</b>	11.7%
3	<b>0.056</b>	<b>(0.010)</b>	<b>0.073</b>	<b>(0.011)</b>	<b>0.057</b>	<b>(0.008)</b>	10.9%
4	<b>0.053</b>	<b>(0.010)</b>	<b>0.055</b>	<b>(0.011)</b>	<b>0.049</b>	<b>(0.008)</b>	10.4%
5	<b>0.051</b>	<b>(0.011)</b>	<b>0.051</b>	<b>(0.012)</b>	<b>0.049</b>	<b>(0.008)</b>	9.7%
6	<b>0.038</b>	<b>(0.011)</b>	<b>0.042</b>	<b>(0.012)</b>	<b>0.042</b>	<b>(0.008)</b>	9.2%
7	<b>0.035</b>	<b>(0.012)</b>	<b>0.029</b>	<b>(0.013)</b>	<b>0.041</b>	<b>(0.009)</b>	8.9%
8	<b>0.032</b>	<b>(0.012)</b>	<b>0.029</b>	<b>(0.013)</b>	<b>0.037</b>	<b>(0.009)</b>	8.4%
9	<i>0.021</i>	<i>(0.012)</i>	<i>0.023</i>	<i>(0.014)</i>	<b>0.031</b>	<b>(0.009)</b>	8.0%
10	0.011	(0.013)	0.015	(0.013)	<b>0.023</b>	<b>(0.009)</b>	7.7%
11	0.018	(0.012)	0.013	(0.013)	<b>0.024</b>	<b>(0.009)</b>	7.4%
12	0.014	(0.012)	-0.001	(0.013)	0.013	(0.009)	7.0%
13	0.004	(0.012)	0.001	(0.013)	0.010	(0.009)	6.6%
14	0.002	(0.013)	-0.009	(0.013)	0.008	(0.009)	6.4%
15	-0.003	(0.013)	-0.005	(0.013)	0.010	(0.009)	6.1%
16	-0.002	(0.012)	0.004	(0.013)	0.012	(0.009)	5.9%

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 7a: Estimated GED Impact for Total Earnings  
Multidimensional Reduced Model

Quarters since 1st GED test	Coeff.	Standard Error	Mean Earnings	Coeff. As Pct Of Mean	Std. Err. As Pct Of Mean
Men					
1-4	42.9	(162.9)	8,750	0.5%	1.9%
5-12	459.4	(584.3)	20,470	2.2%	2.9%
13-20	-626.2	(855.1)	22,813	-2.7%	3.7%
21-28	496.5	(1109.1)	24,594	2.0%	4.5%
Women					
1-4	34.5	(145.1)	7,465	0.5%	1.9%
5-12	-226.3	(483.2)	17,717	-1.3%	2.7%
13-20	386.7	(706.2)	19,514	2.0%	3.6%
21-28	<i>1612.9</i>	<i>(913.6)</i>	20,532	7.9%	4.4%

Table 7b: Estimated GED Impact for Total Quarters Employed  
Multidimensional Reduced Model

Quarters since 1st GED test	Coeff.	Standard Error	Mean Employ.	Coeff. As Pct Of Mean	Std. Err. As Pct Of Mean
Men					
1-4	-0.012	(0.032)	2.461	-0.5%	1.3%
5-12	-0.123	(0.091)	4.768	-2.6%	1.9%
13-20	<i>-0.199</i>	<i>(0.115)</i>	4.472	-4.4%	2.6%
21-28	-0.188	(0.135)	4.295	-4.4%	3.1%
Women					
1-4	-0.007	(0.034)	2.547	-0.3%	1.3%
5-12	-0.127	(0.091)	5.101	-2.5%	1.8%
13-20	-0.031	(0.121)	4.890	-0.6%	2.5%
21-28	0.054	(0.145)	4.672	1.2%	3.1%

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 8: Estimated GED Impact for Subgroups, Reduced Multidimensional Model

Quarters since 1st GED test	Nonwhite		White		Diff.	20 or Under		Over 20		Diff.
	Coeff.	Std. Err.	Coeff.	Std. Err.	T-Stat.	Coeff.	Std. Err.	Coeff.	Std. Err.	T-Stat.
Men										
Total Earnings										
1-4	253	(269)	-43.1	(201)	0.9	262	(183)	-122	(283)	1.1
5-12	917	(939)	346	(721)	0.5	653	(710)	1031	(962)	0.3
13-20	516	(1418)	-999	(1046)	0.9	787	(1072)	-1517	(1388)	1.3
21-28	<i>3127</i>	<i>(1849)</i>	-123	(1343)	1.4	1417	(1407)	-50.7	(1766)	0.6
Quarters Employed										
1-4	-0.003	(0.066)	-0.020	(0.037)	0.2	0.042	(0.043)	-0.070	(0.048)	1.7
5-12	-0.258	(0.183)	-0.051	(0.105)	1.0	-0.059	(0.122)	-0.138	(0.137)	0.4
13-20	-0.181	(0.224)	-0.190	(0.133)	0.0	0.031	(0.153)	<b>-0.371</b>	<b>(0.173)</b>	1.7
21-28	-0.100	(0.269)	-0.227	(0.155)	0.4	-0.074	(0.177)	-0.242	(0.205)	0.6
Quarters Enrolled in Postsecondary Education										
1-4	<b>0.127</b>	<b>(0.036)</b>	<b>0.061</b>	<b>(0.018)</b>	1.7	<b>0.060</b>	<b>(0.023)</b>	<b>0.095</b>	<b>(0.021)</b>	1.1
5-12	0.031	(0.083)	0.043	(0.038)	0.1	-0.004	(0.052)	0.074	(0.049)	1.1
Women										
Total Earnings										
1-4	-46.1	(297)	83.2	(167)	0.4	113	(183)	-42.3	(215)	0.6
5-12	-160	(958)	-355	(570)	0.2	-123	(651)	-386	(691)	0.3
13-20	-19.3	(1415)	595	(818)	0.4	248	(996)	520	(985)	0.2
21-28	840	(1848)	<b>2075</b>	<b>(1057)</b>	0.6	589	(1295)	<i>2177</i>	<i>(1270)</i>	0.9
Quarters Employed										
1-4	<i>-0.118</i>	<i>(0.071)</i>	0.026	(0.039)	1.8	-0.043	(0.051)	0.016	(0.046)	0.9
5-12	-0.251	(0.174)	-0.080	(0.109)	0.8	-0.175	(0.136)	-0.079	(0.123)	0.5
13-20	-0.063	(0.223)	-0.007	(0.145)	0.2	-0.081	(0.187)	0.017	(0.160)	0.4
21-28	-0.358	(0.279)	0.213	(0.173)	1.7	-0.100	(0.225)	0.111	(0.193)	0.7
Quarters Enrolled in Postsecondary Education										
1-4	<b>0.273</b>	<b>(0.056)</b>	<b>0.155</b>	<b>(0.024)</b>	1.9	<b>0.131</b>	<b>(0.036)</b>	<b>0.204</b>	<b>(0.028)</b>	1.6
5-12	<b>0.424</b>	<b>(0.111)</b>	<b>0.188</b>	<b>(0.054)</b>	1.9	<b>0.195</b>	<b>(0.080)</b>	<b>0.254</b>	<b>(0.062)</b>	0.6

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3.

Table 8 (Continued): Estimated GED Impact for Subgroups, Reduced Multidimensional Model

Quarters since 1st GED test	Grade 10 or less		Grade 11 or more		T-Stat.
	Coeff.	Std. Err.	Coeff.	Std. Err.	
Men					
Total Earnings					
1-4	25.4	(211.1)	534.4	(351.6)	-1.2
5-12	341.5	(773.8)	1966.9	(1258.3)	-1.1
13-20	-1059.7	(1118.4)	1079.1	(1931.3)	-1.0
21-28	-108.3	(1354.5)	3730.8	(2368.1)	-1.4
Quarters Employed					
1-4	-0.027	(0.044)	<i>0.109</i>	(0.064)	-1.8
5-12	-0.145	(0.123)	-0.029	(0.186)	-0.5
13-20	-0.230	(0.152)	-0.165	(0.242)	-0.2
21-28	-0.184	(0.168)	-0.154	(0.268)	-0.1
Quarters Enrolled in Postsecondary Education					
1-4	<b>0.089</b>	<b>(0.020)</b>	0.026	(0.035)	1.5
5-12	0.040	(0.046)	0.053	(0.081)	-0.1
Women					
Total Earnings					
1-4	145.8	(193.8)	62.6	(304.9)	0.2
5-12	130.8	(637.9)	-456.1	(1008.0)	0.5
13-20	<i>1521.4</i>	(912.7)	-346.2	(1471.3)	1.1
21-28	<b>2829.1</b>	<b>(1104.5)</b>	-463.9	(1778.9)	1.6
Quarters Employed					
1-4	-0.027	(0.046)	-0.020	(0.069)	-0.1
5-12	-0.088	(0.122)	-0.286	(0.181)	0.9
13-20	0.128	(0.159)	-0.380	(0.231)	1.8
21-28	0.175	(0.178)	-0.270	(0.270)	1.4
Quarters Enrolled in Postsecondary Education					
1-4	<b>0.161</b>	<b>(0.028)</b>	<b>0.138</b>	<b>(0.047)</b>	0.4
5-12	<b>0.234</b>	<b>(0.064)</b>	<b>0.219</b>	<b>(0.104)</b>	0.1

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual.

Figure 1: Test Score Distribution for Final Test, 1995-2005

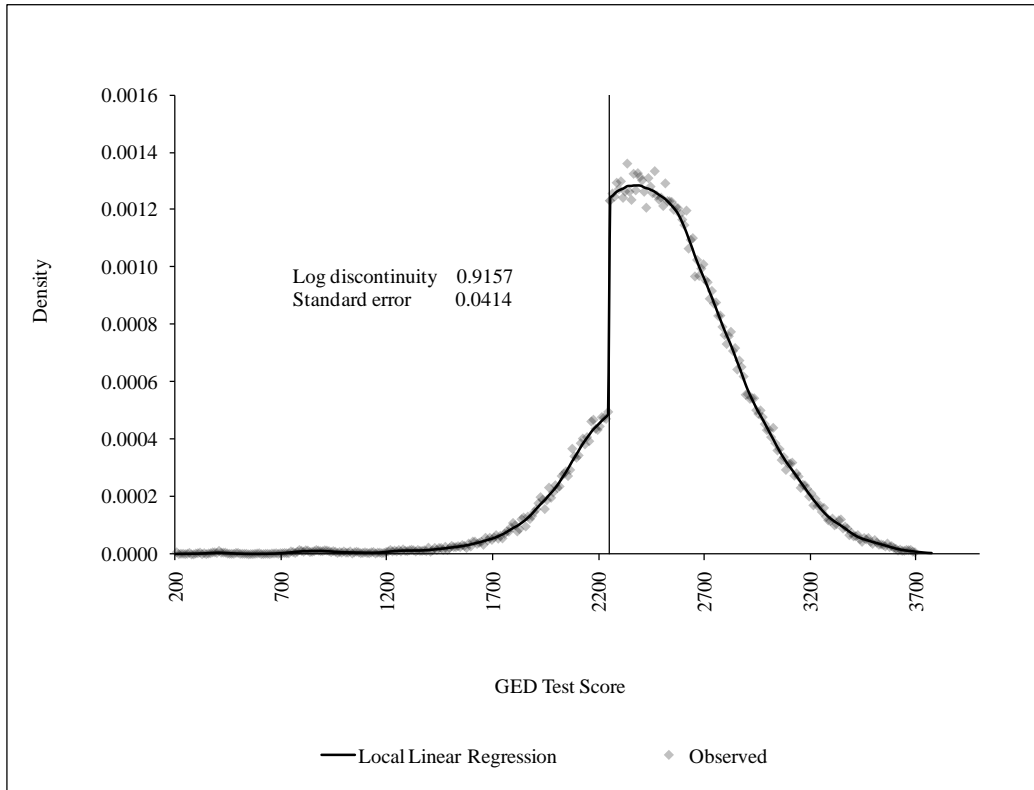


Figure 2: Test Score Distribution for Single-test Takers, 1995-2005

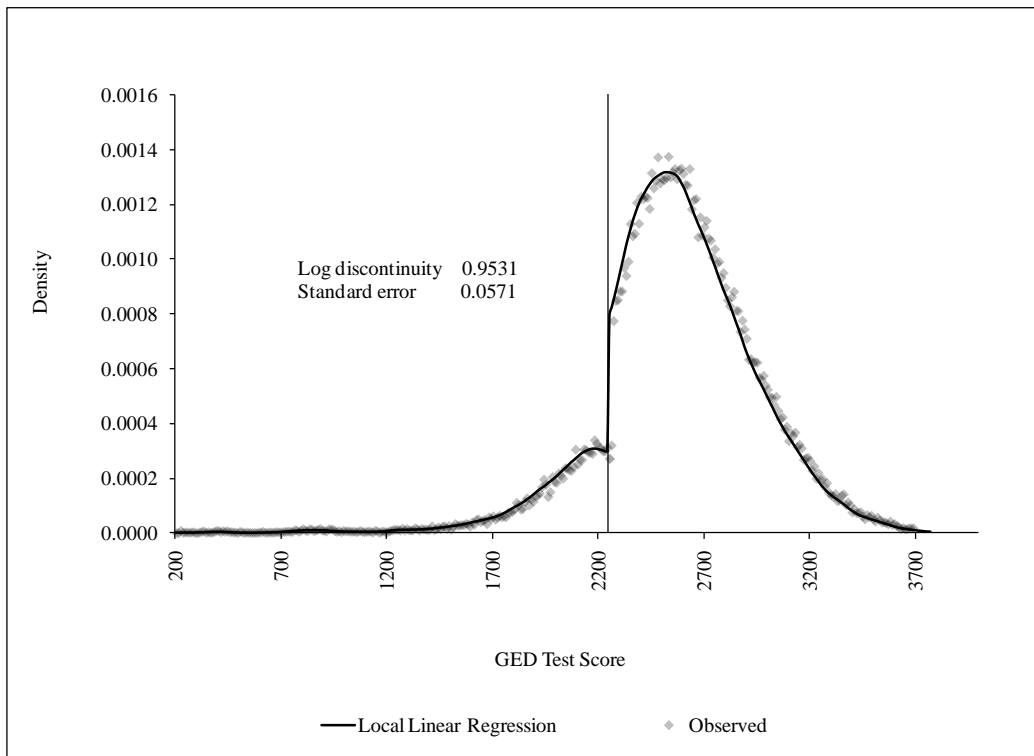


Figure 3: Test Score Distribution for First Test, 1995-2005

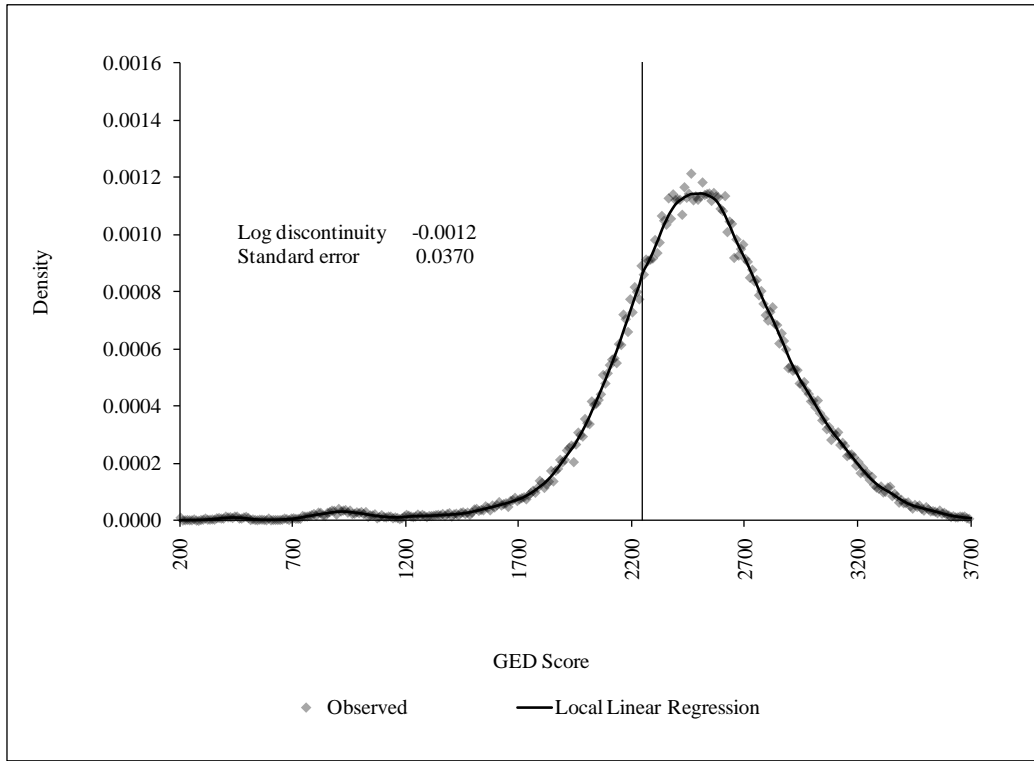


Figure 4: Regression Discontinuity Models Predicting GED and Quarterly Earnings, Men

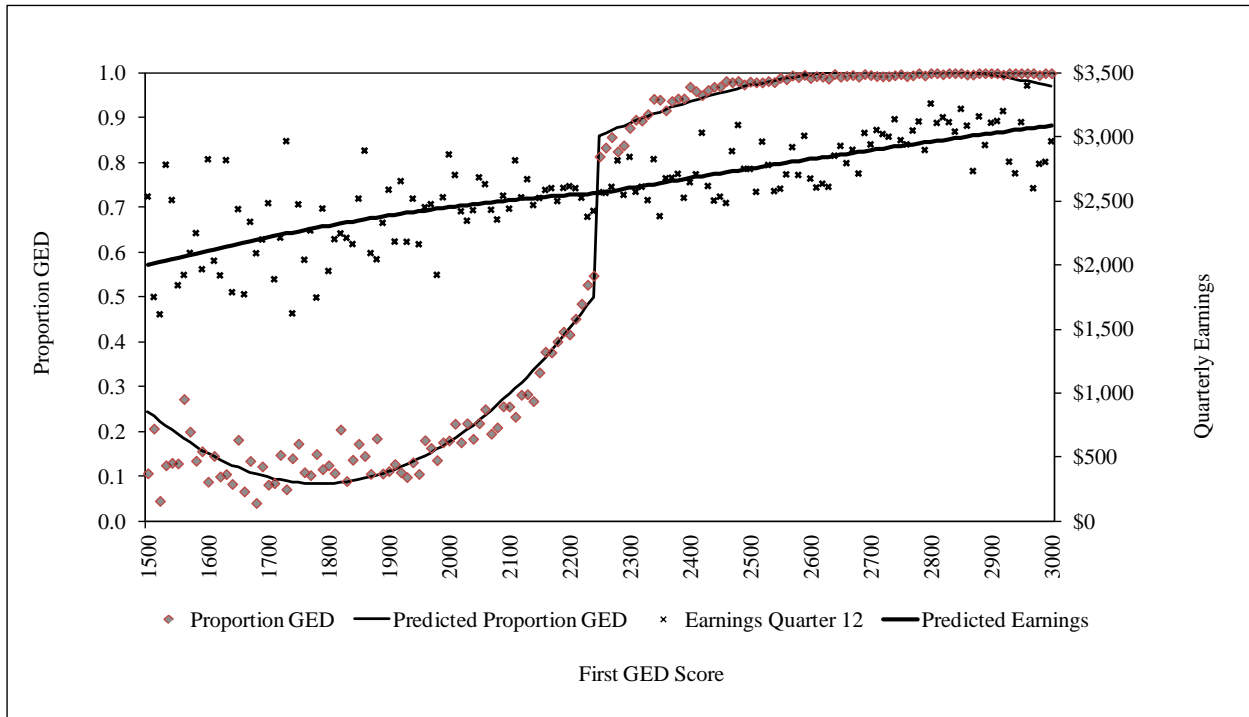


Figure 5: Estimated Multidimensional Reduced FRD and SRD GED Impacts for Men

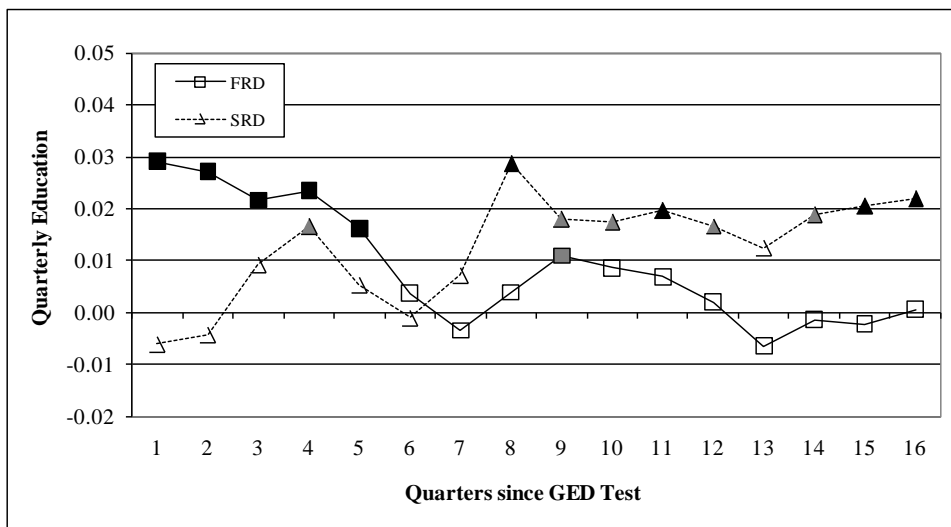
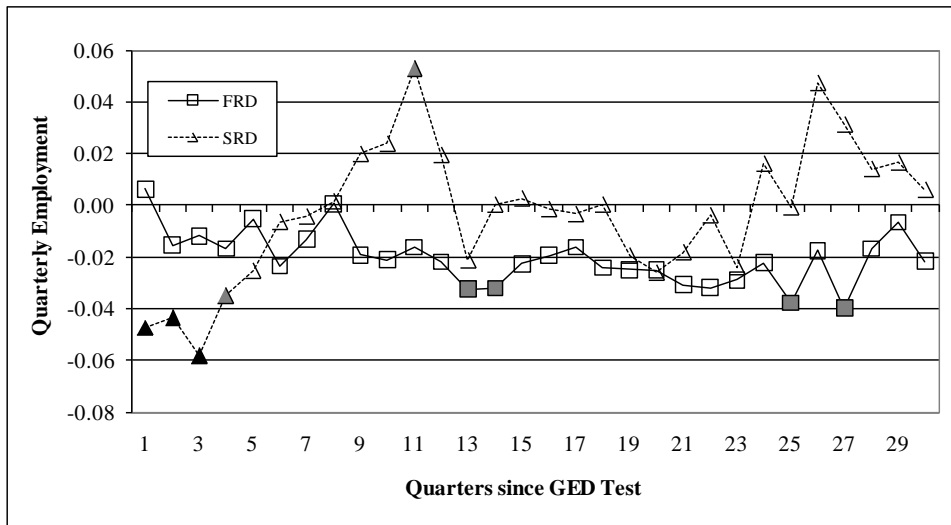
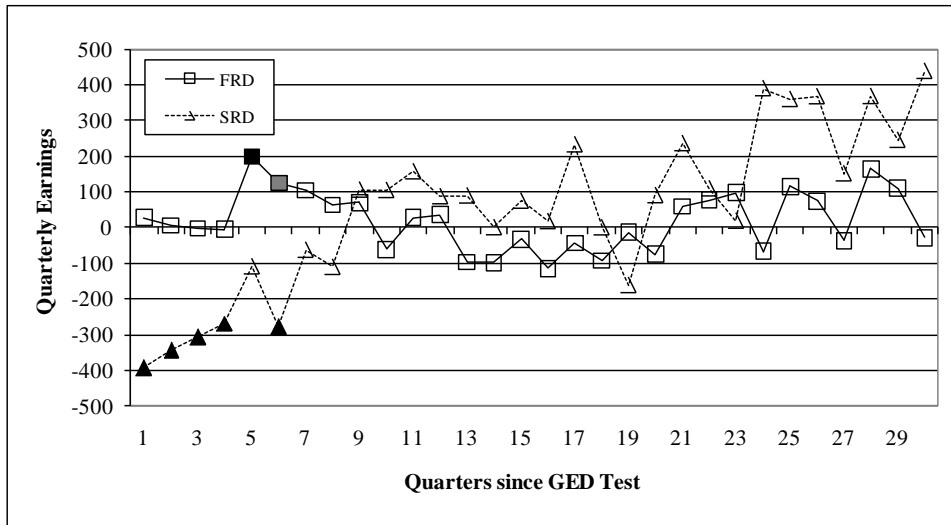
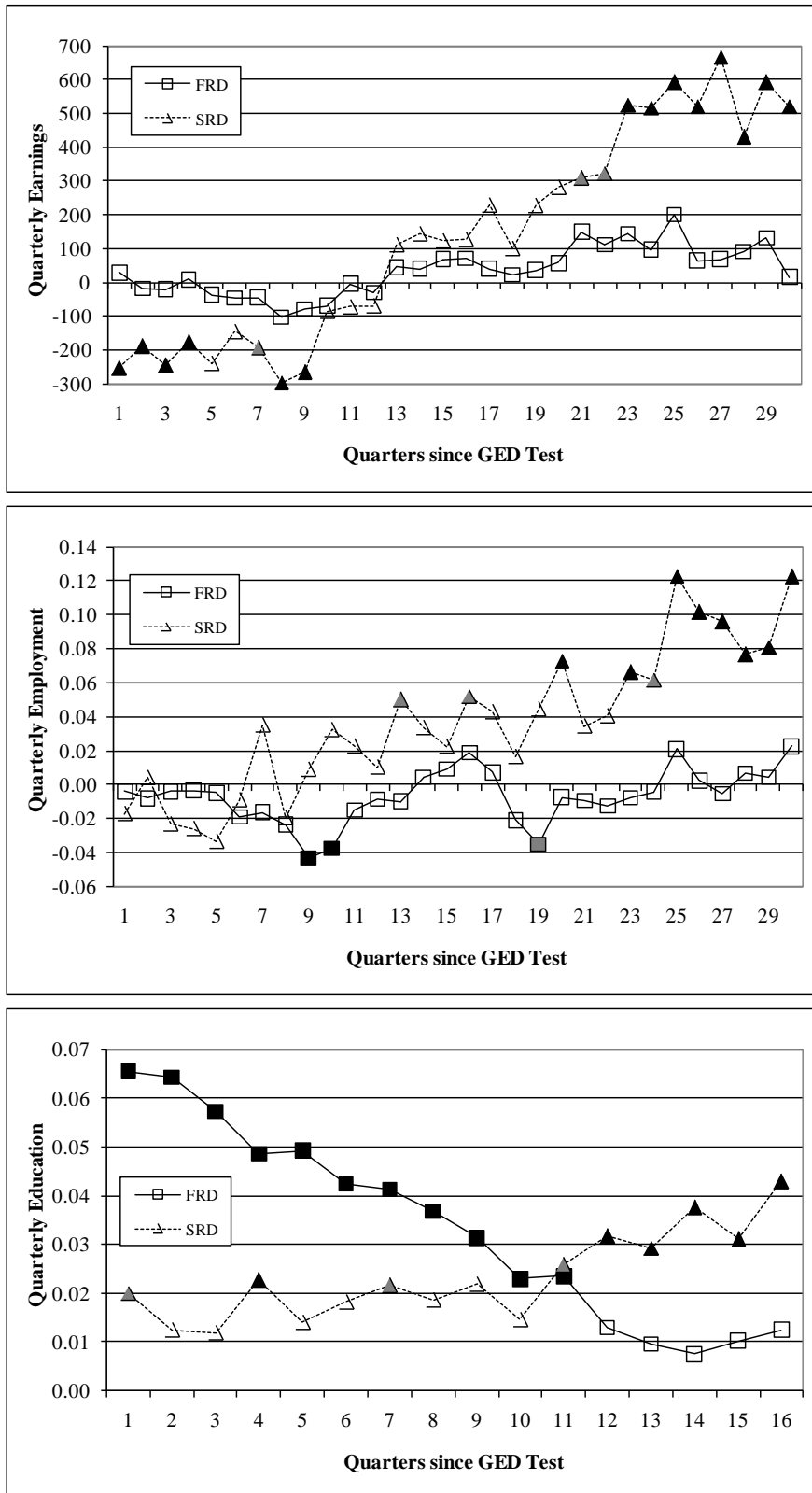


Figure 6: Estimated Multidimensional Reduced FRD and SRD GED Impacts for Women



Appendix Table 1: Descriptive Statistics

	Men					Women				
Year first GED test										
1995-2000	62.6%					65.1%				
2001	12.7%					13.1%				
2002-2005	14.1%					14.0%				
Nonwhite	21.6%					19.9%				
GED Certification	80.4%					81.6%				
Observations	44,378					41,967				
Quarters										
since 1st	Earnings		Employ.	Educ.		Earnings		Employ.	Educ.	
GED test	Mean	Std. Dev.	Pct	Pct	Obs.	Mean	Std. Dev.	Pct	Pct	Obs.
1	2,048	2,862	62.1	7.7	44,378	1,725	2,237	63.1	12.0	41,967
2	2,190	2,980	62.6	7.2	44,377	1,864	2,345	64.1	11.7	41,967
3	2,255	3,043	62.1	6.7	44,378	1,921	2,639	64.2	10.9	41,965
4	2,333	3,131	61.7	6.4	44,378	1,996	2,484	64.6	10.4	41,967
5	2,404	3,173	61.7	6.0	44,377	2,058	2,537	64.4	9.7	41,964
6	2,470	3,251	61.1	5.5	44,377	2,109	2,550	64.3	9.2	41,967
7	2,507	3,352	60.7	5.2	44,377	2,155	2,611	64.0	8.9	41,963
8	2,565	3,374	60.5	5.0	44,376	2,227	2,733	64.0	8.4	41,967
9	2,607	3,407	60.0	4.8	44,378	2,261	2,714	63.9	8.0	41,966
10	2,657	3,515	59.4	4.5	44,378	2,300	2,790	63.5	7.7	41,964
11	2,661	3,574	58.7	4.2	44,378	2,312	2,799	62.7	7.4	41,967
12	2,723	3,625	58.3	4.1	44,378	2,359	2,913	62.5	7.0	41,967
13	2,766	3,682	57.5	3.8	44,378	2,382	2,895	62.2	6.6	41,967
14	2,781	3,728	56.9	3.6	44,378	2,398	2,899	61.9	6.4	41,966
15	2,795	3,906	56.4	3.5	44,378	2,413	2,948	61.3	6.1	41,966
16	2,835	3,830	56.1	3.3	44,378	2,434	2,974	60.8	5.9	41,967
17	2,858	3,850	55.6		44,377	2,457	3,152	60.5		41,966
18	2,888	3,905	55.5		44,377	2,483	3,056	60.2		41,967
19	2,904	3,936	55.2		43,647	2,473	3,054	59.6		41,336
20	2,933	3,995	54.6		42,919	2,477	3,081	59.3		40,661
21	2,971	4,064	54.5		41,918	2,500	3,111	58.8		39,799
22	3,016	4,138	54.5		41,178	2,527	3,226	58.4		39,092
23	3,018	4,316	53.9		40,483	2,517	3,172	58.0		38,400
24	3,049	4,390	53.6		39,783	2,555	3,302	57.9		37,726
25	3,078	4,223	53.4		38,966	2,566	3,288	57.5		36,843
26	3,104	4,264	53.3		38,261	2,598	3,306	57.5		36,171
27	3,090	4,428	52.8		37,595	2,576	3,279	57.0		35,521
28	3,135	4,341	52.7		36,944	2,604	3,336	56.7		34,860
29	3,178	4,374	52.7		35,983	2,604	3,359	56.4		34,364
30	3,211	4,426	52.5		35,146	2,633	3,392	56.2		33,982

Note: GED certification is measured as having ever received GED certification.

Appendix Table 2a: Estimated GED Impact on Earnings for FRD Design  
 Reduced Multidimensional Model, Separate Regressions by Test Parity

Quarters since 1st GED test	Men			Women		
	First Test	Second Test	Third Test	First Test	Second Test	Third Test
1	28.8	-61.1	n/a	32.2	-186.8	n/a
2	42.8	-107.7	-809.8	13.3	-131.8	-536.2
3	-21.0	-1.5	363.2	39.8	-157.2	-137.6
4	4.5	19.0	-315.7	2.5	-34.7	342.4
5	<b>235.9</b>	184.8	-178.7	-25.4	-124.2	282.7
6	<b>232.6</b>	-49.0	-222.0	-22.3	-104.2	1.3
7	<i>201.7</i>	-1.3	-424.7	25.1	-157.5	-91.5
8	181.7	-175.3	-82.0	-74.9	-172.8	-18.0
9	<b>271.0</b>	-325.9	-198.5	18.6	-234.7	-105.6
10	-36.9	-34.3	-400.5	-62.1	-165.9	239.1
11	-7.3	61.3	220.0	96.1	-121.2	-229.0
12	22.6	-21.5	394.1	77.7	-233.1	14.0
13	-54.4	-225.7	8.8	<i>256.6</i>	-207.6	-454.9
14	-29.0	-231.9	-257.9	<b>357.7</b>	-323.3	<b>-848.6</b>
15	38.2	-288.5	352.0	<b>325.1</b>	-184.8	<b>-798.8</b>
16	1.8	-386.0	-176.7	209.6	-77.4	-343.2
17	10.5	-263.7	347.5	140.3	-49.6	-352.1
18	29.2	<i>-421.3</i>	47.8	154.3	-163.4	-217.8
19	43.5	-216.7	277.0	170.8	-182.5	-117.2
20	3.5	-295.7	86.2	168.7	-74.8	-280.9
21	164.3	-172.4	-37.5	<i>269.9</i>	-25.7	-94.9
22	199.7	-194.2	-49.0	<i>299.4</i>	-299.7	335.6
23	264.4	-325.9	159.4	<i>298.9</i>	-146.2	103.9
24	2.9	-285.7	175.3	186.5	-61.2	28.8
25	307.8	-370.7	175.6	69.9	<b>472.7</b>	137.0
26	252.5	-465.5	549.7	-9.7	154.9	304.1
27	0.6	-318.6	824.7	-2.2	96.1	548.7
28	<b>422.7</b>	-530.3	287.5	42.4	-20.4	<i>942.6</i>
29	301.7	-534.7	842.4	-10.6	208.1	<i>1004.6</i>
30	132.1	<i>-638.6</i>	865.5	-79.0	86.8	496.0

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3. n/a = Not applicable (N=0)

Appendix Table 2b: Estimated GED Impact on Employment for FRD Design  
 Reduced Multidimensional Model, Separate Regressions by Test Parity

Quarters since 1st GED test	Men			Women		
	First Test	Second Test	Third Test	First Test	Second Test	Third Test
1	0.007	-0.017	n/a	-0.005	0.099	n/a
2	-0.006	-0.043	<i>-0.269</i>	-0.001	-0.040	0.121
3	-0.015	-0.010	0.032	-0.002	-0.018	0.104
4	-0.008	-0.039	0.001	0.002	-0.016	0.001
5	0.004	-0.023	-0.017	0.006	-0.034	0.032
6	-0.008	<b>-0.063</b>	0.000	-0.003	-0.038	-0.062
7	-0.009	-0.019	-0.030	0.005	-0.048	-0.043
8	0.004	-0.011	0.016	-0.003	-0.048	-0.068
9	-0.025	-0.030	0.086	-0.011	<b>-0.098</b>	-0.033
10	-0.022	-0.020	-0.016	-0.027	<i>-0.057</i>	-0.032
11	-0.025	-0.024	0.104	-0.003	-0.035	-0.020
12	-0.030	-0.037	<i>0.125</i>	0.020	-0.042	-0.075
13	-0.037	-0.025	-0.020	0.004	-0.014	-0.092
14	-0.014	<b>-0.071</b>	-0.058	<b>0.051</b>	-0.037	<b>-0.172</b>
15	-0.017	<i>-0.060</i>	0.086	0.040	-0.018	-0.108
16	-0.009	-0.058	0.040	0.020	0.023	-0.009
17	-0.015	-0.035	0.057	0.004	0.018	-0.010
18	-0.012	<b>-0.084</b>	0.119	0.005	<i>-0.069</i>	-0.023
19	-0.015	<i>-0.063</i>	0.044	-0.009	<b>-0.081</b>	-0.049
20	-0.011	-0.060	-0.022	0.004	-0.028	-0.012
21	-0.033	-0.035	0.017	0.009	-0.052	0.024
22	-0.025	-0.061	0.026	-0.012	-0.038	0.093
23	-0.007	<b>-0.104</b>	0.078	-0.002	-0.042	0.095
24	-0.009	-0.062	0.016	-0.007	-0.006	0.029
25	-0.006	<b>-0.101</b>	-0.108	0.019	0.003	0.116
26	0.012	<b>-0.093</b>	-0.001	0.000	-0.004	0.053
27	-0.016	<b>-0.106</b>	-0.023	-0.002	-0.039	0.108
28	0.019	<b>-0.110</b>	-0.010	-0.011	0.012	0.125
29	0.016	-0.062	-0.012	-0.007	0.008	0.086
30	-0.003	<i>-0.082</i>	0.040	0.002	0.011	<b>0.240</b>

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3. n/a = Not applicable (N=0)

Appendix Table 2c: Estimated GED Impact on Education for FRD Design  
 Reduced Multidimensional Model, Separate Regressions by Test Parity

Quarters since 1st GED test	Men			Women		
	First Test	Second Test	Third Test	First Test	Second Test	Third Test
1	<b>0.029</b>	0.026	n/a	<b>0.066</b>	0.055	n/a
2	<b>0.030</b>	0.018	-0.055	<b>0.056</b>	<b>0.095</b>	0.128
3	<b>0.022</b>	0.014	<b>0.062</b>	<b>0.055</b>	<b>0.071</b>	-0.025
4	<b>0.019</b>	<b>0.027</b>	<b>0.070</b>	<b>0.047</b>	<b>0.056</b>	0.027
5	0.012	0.019	0.050	<b>0.045</b>	<b>0.054</b>	<i>0.065</i>
6	0.001	0.003	0.037	<b>0.042</b>	<b>0.040</b>	0.052
7	-0.001	-0.011	0.013	<b>0.030</b>	<b>0.052</b>	<b>0.077</b>
8	0.003	0.000	0.030	<b>0.026</b>	<b>0.050</b>	<i>0.062</i>
9	0.009	0.009	0.043	<b>0.032</b>	<i>0.030</i>	0.033
10	0.009	0.010	0.002	<i>0.023</i>	0.021	0.028
11	0.005	0.015	-0.006	<i>0.022</i>	<i>0.030</i>	0.013
12	-0.002	0.011	0.004	0.002	0.024	0.042
13	-0.011	0.004	-0.003	0.004	0.017	0.017
14	-0.001	-0.004	0.007	0.005	0.019	-0.019
15	0.001	-0.014	0.016	-0.002	<i>0.030</i>	0.023
16	0.004	-0.008	0.003	0.009	0.017	0.015

Notes: Coefficients in bold are statistically significant at the five-percent level (two-sided test), and coefficients in italics are statistically significant at the ten-percent level (two-sided test). Each coefficient is from a separate regression. Standard errors are clustered by individual. Control variables are listed in the notes to Table 3. n/a = Not applicable (N=0)