

NBER WORKING PAPER SERIES

HOW FINANCIAL AID AFFECTS PERSISTENCE

Eric Bettinger

Working Paper 10242

<http://www.nber.org/papers/w10242>

NATIONAL BUREAU OF ECONOMIC RESEARCH

1050 Massachusetts Avenue

Cambridge, MA 02138

January 2004

Special thanks goes to Rob Sheehan and Andy Lechler for helpful comments and for providing the data. I am also grateful for comments from David Cooper, Jim Rebitzer, Bridget Long, Jon Guryan, and especially Caroline Hoxby. All errors are my own. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

©2004 by Eric Bettinger. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

How Financial Aid Affects Persistence
Eric Bettinger
NBER Working Paper No. 10242
January 2004
JEL No. I2

ABSTRACT

The Pell Grant program is the largest means-tested financial assistance available to postsecondary students across the United States, yet researchers have only limited evidence on the causal effects of these grants. This paper examines the effect of Pell grants on student persistence after the first year. The paper uses unique, student-level data from all public colleges in Ohio. The data include detailed financial data which allow me to identify small discontinuities in the Pell grant formula. I exploit these discontinuities to identify the causal effects of the voucher. The results based on discontinuity approaches suggest that Pell grants reduce college drop-out behavior. The results in this paper support other evidence that find a relationship between need-based aid and college completion (e.g. Dynarski 2002, Turner and Bound 2002).

Eric Bettinger
Department of Economics
266 Peter B. Lewis Building
Case Western Reserve University
11119 Bellflower Road
Cleveland, OH 44106-7235
and NBER
epb4@weatherhead.cwru.edu

The Pell Grant program is the largest means-tested financial assistance available to postsecondary students across the United States. Students from all types of degree granting post-secondary institutions can apply for Pell grants. In 2000-01, the federal government awarded almost \$8 billion in Pell grants among more than 3.8 million students, roughly one-third of all college students (College Board 2001). President Bush's 2003 budget allocates over \$10.9 billion dollars for an estimated 4.5 million Pell grant recipients (DOE 2002) potentially representing a 32.4 percent increase in the number of students receiving Pell grants since the 1990-91 school year. Yet despite this continued expansion of Pell, researchers have only limited evidence on the causal effects of these grants.

Most Pell-related research focuses on the effects of Pell Grants on enrollment decisions, specifically focusing on initial enrollment and choice amongst colleges (see Kane 1999, Ehrenberg and Sherman 1984, Leslie and Brinkman 1987, Seftor and Turner 2002). However, there is surprisingly little research measuring the causal effect of Pell grants on student outcomes in college (e.g. persistence, graduation). Regardless of whether Pell grants affect initial enrollment patterns, Pell grants may independently affect student outcomes.

Moreover, studying the effects of need-based aid on student outcomes may also be important since Pell-eligible students are more likely to be on the margin of "stopping-out."¹ At Ohio 4-year colleges in 1999-2000, 18 percent of full-time freshmen who were *not* eligible for Pell Grants withdrew from college by the next year while 28 percent of students who were eligible for a Pell grant did not enroll the following year. It is an open

¹ "Stopping-out" refers to students who withdraw from school after their first year. These students are not "drop-outs" since many of these students do not leave school permanently and their undergraduate credit hours do not "expire." I use these terms interchangeably throughout the paper.

question whether Pell grants and other need-based aid programs affect these margins. This paper attempts to resolve these questions. Using unique student data from Ohio, this paper measures the causal relationship between need-based aid and student retention.

A study of the effects of need-based aid on student retention may be of interest to both policymakers and educational researchers. As Sarah Turner argues elsewhere in this volume, policymakers have often paid more attention to improving student access to college rather than improving student retention once in college. However, as college enrollment rates continue to increase while completion rates do not, both policymakers and researchers have begun focusing more heavily on indicators of student retention (e.g. DesJardins, Ahlburg, McCall 1999, St. John, Hu, Tuttle 2000, St. John, Hu, Weber 2000), and the relationship between financial need and persistence is central to many of these studies (e.g. DesJardins, Ahlburg, MccCall 2002, St. John, Musoba, Simmons 2003).

There are a number of reasons why more research has not investigated the effects of Pell grants on student collegiate outcomes. One reason is that researchers have difficulty distinguishing between the effects of family characteristics and the effects of Pell grants. Pell grants are a means-tested program. Comparisons between Pell recipients and non-Pell recipients (e.g. Wei and Carroll 2002) may be difficult to interpret since Pell recipients are poorer and may be more likely to drop-out even in the absence of need-based aid. To correct for such bias, researchers must sufficiently control for family characteristics.

Additionally, identifying the effects of Pell grants is difficult since much of the variation in the size of students' Pell grants is correlated with students' college enrollment decisions. For example, college choice and the size of a students' Pell grant

are directly connected. Students who attend more expensive (and often higher quality) schools are eligible for larger Pell grants than students at other colleges or universities. Pell grants are also more generous for full-time rather than part-time students. Even in the absence of Pell grants, students who benefit most from college are more likely than other students to attend more expensive schools and to attend full-time. However, since Pell grant awards are systematically higher for these same students, it may be difficult to identify the effects of the Pell grant separate from college enrollment effects. To avoid this bias, researchers must exploit variation in Pell grants that is independent of college choice (e.g. discontinuities in the Pell formula).

A final reason that researchers have been unable to identify the effects of Pell grants on outcomes is the absence of accurate data, in particular, the absence of accurate persistence and detailed financial data. Some researchers have measured persistence at a particular university; however, in these data, researchers cannot distinguish between a student who transferred to another school and one who withdraws from college. Other survey-based data rely on students' self-reports of their college experience. These data may not be as reliable as administrative data since students may not recall or do not wish to report small periods of time when they withdrew from college.

Financial data is equally as difficult to obtain. Most of the students who receive Pell grants do not attend elite, expensive institutions, nor do they have substantial family support. Pell recipients (and much of the variation in their awards) typically come from less expensive colleges and their family contributions are much smaller. Moreover, the variation in Pell grants is typically small. Exact financial data are necessary both to identify the small variations in Pell grants and to employ creative identification strategies.

Survey data (e.g. High School and Beyond, National Educational Longitudinal Survey) do not offer the level of detail necessary to identify accurately the level of students' Pell grants.

To examine the effects of Pell, this paper presents evidence from data gathered by the Ohio Board of Regents (OBR). These data do not have the shortcomings of other datasets and offer a level of detail on both persistence and financial variables that is not available in other data. Since 1998, OBR has collected comprehensive data on college enrollment in Ohio's public 2- and 4-year colleges. As a result, the OBR data tracks students within and across schools. With the data, researchers can distinguish between students who withdraw from school and students who transfer to other Ohio schools. Moreover, through collaborative agreements, OBR has expanded the data to include students' ACT scores and data from the Free Application for Federal Student Aid (FAFSA). The FAFSA data are the exact data used by institutions to determine the amount of students' Pell grant eligibility.

The level of detail in the financial data also facilitates the use of statistical tools that are impractical using other data. In particular, the level of detail allows researchers to identify small discontinuities in the Pell grant formula. These discontinuities may be exploited to identify the causal effects of the voucher. While this paper may not completely resolve biases from college choice/enrollment or family background, the discontinuity analysis may be the best available method for dealing with such biases.

The paper presents evidence on the effects of Pell grants using both panel and cross-sectional variation.² The panel specifications suggest that need-based financial aid

² It is important to distinguish between the effects of Pell grants in general and the effects of Pell grants conditional on initial enrollment. This paper focuses on estimating the effect of persistence conditional on

reduces students' stop-out behavior. In identifying this effect, the paper shows that students who receive Pell grants after their first year are a unique subset of students who applied for financial aid in their first year. Failure to control for this selection may confound causal estimates of the Pell grant program.

The paper also presents evidence relying on cross-sectional variation. The paper estimates the effects of Pell grants close to existing discontinuities in family size. The results based on discontinuity approaches suggest that Pell grants reduce college drop-out rates; however, the results are not robust to alternative specifications.

Section 1 of this paper presents a simple economic model of student persistence under uncertainty. Section 2 of the paper explains the OBR data in greater detail. Section 3 of the paper presents the empirical strategies and results. Section 4 discusses policy implications of the results and concludes.

I. Economic Model

Economists often model educational attainment as investment in human capital. Even basic economics classes teach that students will choose an education level that maximizes the expected present discounted value (PDV) of future wage payments less the expected PDV of educational costs. There have been a number of permutations to this model – factoring in scholarship aid, allowing the returns to education to vary, and showing how predicted education levels vary with expectations (Manski 1993). This paper investigates the relationship between financial aid and outcomes. Rather than use a

a student having enrolled. I discuss below the relationship between the conditional effects of Pell and the unconditional effects.

traditional human capital model, the paper models students' dropout behavior using a multi-stage investment model.

Multi-stage investment models are particularly useful in cases where the agent must reevaluate the project after an initial period of time. For example, Myers and Majd (1990) investigate optimal abandonment rules for firms. Dixit and Pindyck (1994) review other examples of multi-stage investments.

The phenomenon of interest – students' stop-out behavior – is similar to these multi-stage investments. In the initial period, students must decide whether or not to attend the first year of college. After completion of the first year, students must then reevaluate whether or not to complete the next year. About 20 percent of first-time freshmen withdraw from 4-year colleges after the first year.

To formalize the model, let person i 's wage at time t (w_{it}) be modeled as a function of years of college (s_t) and ability (a_i) which is not perfectly known to the student. Let the cost of education at time t (c_t) be the difference between announced tuition (T_t) and financial aid. Financial aid contains two components: the need-based component is a function of initial wealth (I_0) and the number of children attending college at time t (n_t); the merit-based component is a function of perceived ability at time t . Let $E_t[\cdot]$ denote the expectation operator conditional on information at time t .

$$w_{it} = f(s_{it}, a_i) \tag{1}$$

$$c_t = T_t - g(I_0, n_t) - h(a_i) \tag{2}$$

A student will attend a 1st year of college if the expected value of increased lifetime earnings for that year exceeds the cost of attending college (including foregone earnings).

$$E_0\left(\sum_{t=2}^T R^{t-1} [f(s_{it}=1, a_i) - f(s_{it}=0, a_i)]\right) > E_0(f(s_{i1}=0, a_i) + T_1 - g(I_0, n_1) - h(a_i)) \quad (3)$$

At the start of the first year, a student will indicate an intention to attend a second year as well so long as

$$E_0\left(\sum_{t=3}^T R^{t-2} [f(s_{it}=2, a_i) - f(s_{it}=1, a_i)]\right) > E_0(f(s_{i2}=1, a_i) + T_2 - g(I_0, n_2) - h(a_i)) \quad (4)$$

We could solve the decision rules for the maximum tuition level that a student would be willing to pay. For simplicity, let's assume that tuition is fully known one year in advance.

$$E_0(T_1^*) = T_1^* = E_0(g(I_0, n_1) + h(a_i) - f(s_{i1}=0, a_i) + \sum_{t=2}^T R^{t-1} [f(s_{it}=1, a_i) - f(s_{it}=0, a_i)]) \quad (5)$$

and

$$E_0(T_2^*) = E_0(g(I_0, n_2) + h(a_i) - f(s_{i2}=1, a_i) + \sum_{t=3}^T R^{t-2} [f(s_{it}=2, a_i) - f(s_{it}=1, a_i)]) \quad (6)$$

These tuition levels are likely the formulae that students use to make any decisions about the second year of school that must be made during the first year. For example, a student wanting to transfer to another university must file that application during the first year. Also, students who want financial aid in their second year must file applications during their first year. With these types of decisions in mind, there are a few insights that come from comparing these two tuition values:

1. For a given level of ability, if the returns to schooling are linear (or even concave) in schooling and scholarship aid does not change, then the maximum tuition that a student will pay falls over time. Hence, many students may rationally choose to get only one year of school.

2. Even if the returns to schooling are convex and scholarship aid does not change, then the maximum tuition a student is willing to pay may still decrease over time leading to more planned attrition.³
3. Even expected changes in financial aid can alter the maximum that students would be willing to pay leading to students to plan on withdrawing or transferring.
4. Since students must apply for 2nd year financial aid during their first year, they will do so only if they perceive that their benefits exceed costs in both periods.⁴

There are also a number of decisions about the second year that can be made after the first year – for example, the decision to withdraw from college altogether. Students make these decisions after gaining another year of information by which to base their decisions. The student will choose to attend another year if the expected value of the increase in lifetime earnings for the 2nd year exceeds the cost of attending college that year (including foregone earnings).

$$E_1\left(\sum_{t=3}^T R^{t-2} [f(s_{it}=2, a_i) - f(s_{it}=1, a_i)]\right) > E_1(f(s_{i2}=1, a_i) + T_2 - g(I_0, n_2) - h(a_i)) \quad (7)$$

We could rewrite this decision rule solving for the maximum tuition levels that the student would be willing to pay in order to actually attend a given year of college:

³ Holding scholarship aid constant and as $T \rightarrow \infty$, the maximum tuition rises only if the following inequality is satisfied:

$$(1-r)E_0[f(s_{it}=2, a_i) - f(s_{it}=1, a_i)] > E_0[f(s_{it}=1, a_i) - f(s_{it}=0, a_i)].$$

If in the extreme case, there is a “sheepskin” effect of a degree (i.e. returns only to a 2- or 4-year degree), then the inequality is always satisfied. Typical models of sequential investment show that the willingness to pay increases over time. The key difference is the usability of capital. Students may be able to drop out of colleges and use a year of college in the labor market.

⁴ There may be a small group who apply for financial aid even though they expect not to attend the second year. There is an option value to applying for financial aid since ability is not known perfectly (see discussion by Sarah Turner elsewhere in this volume).

$$T_2^* = E_1(g(I_0, n_2) + h(a_i) - f(s_{i2} = 1, a_i) + \sum_{t=3}^T R^{t-2} [f(s_{it} = 2, a_i) - f(s_{it} = 1, a_i)]) \quad (8)$$

Notice that the difference between equation (8) and (6) is the information set. Students have a chance to update their expectations with information from their first year of school. As the model stands, the updating comes in terms of ability. Similar to the model in Manski (1993), students discover their ability by attending college. Knowing the ability then changes the willingness to pay.

We could have also changed this model by introducing uncertainty in the financial aid formula. Unexpected changes in financial aid might lower the maximum tuition price that students might be willing to pay. For example, if a student's expected financial aid offer falls, the maximum that a student would be willing to pay declines. The student may wish to transfer to a cheaper school or drop-out altogether.

A simple insight of the model is that changes in financial aid matter. Previous work on the effects of financial aid has looked at relationships between student outcomes and both changes and levels of aid. Recent work by Wetzel, O'Toole, and Peterson (1999) look at changes in financial aid for students at Virginia Commonwealth University. They find that increases in need-based financial aid likely improved student retention. Other work by Singell (2001) looks at the effects of the level of financial aid in the first year. He finds that the higher students' levels of need-based financial aid, the more likely the student is to graduate.

While the model in this paper suggests that decisions about enrollment in the second year rely on financial aid changes rather than levels, there may be reasons that the level of financial aid in the first year matters. If the level of financial aid in the first year creates some inertia or helps to shape expectations about the financial aid offer in the

second period, the level may affect the student in the next year. One example of this type of effect is the application for 2nd year financial aid. The higher a student's Pell grant in the first year, the more likely the student will apply for a 2nd year award. If students expect to get a low 2nd year award, they may never even apply for financial aid.

The level of financial aid may even have deleterious consequences on the student. The model implicitly assumes that financial aid does not change students' behavior in other ways. But for example, if a student receives financial aid, he or she may be more "detached" from college. The student may not fully engage and take college seriously since his/her money is not "on the line." In this way, Pell grants eliminate the "sunk cost fallacy" for the student.⁵ Since Pell grant recipients did not make this initial investment (the Federal government did instead), they may not have as strong of an incentive to work hard in school as students who made this initial investment themselves. As a result, Pell recipients may perform worse. The model may capture some of this through the "updates" on students' abilities. Controlling for students' performance in school gives a clear indicator of whether they are exerting effort or not. The empirical results will investigate this hypothesis more fully.

Although they are outside of the scope of this paper, there are other outcomes in which we might be interested that are related to either the level or change in financial aid. For example, we might be interested in how financial aid affects the number of credits that a student successfully attempts. Students without financial aid may be reluctant to take loans and may spend more time working on the side. On the other hand, students without financial aid may want to "cram" in more credits per semester to try to reduce the

⁵ The "sunk cost fallacy" suggests that people often devote greater resources and more effort in areas where they have already made an investment.

number of semesters they have to attend (and as a result the total cost of college). We might also be interested in knowing how GPA's vary with financial aid. In particular, if the level of financial aid affects hours attempted, completed or grade point averages, it might also affect students' perception of their abilities and, in the context of the model above, affect their likelihood of completing college.

II. Data

The data for this project come from the Ohio Board of Regents (OBR). Through a collaborative agreement with the OBR, the OBR has allowed me to access anonymous student data from Ohio's public institutions. The data are provided by the respective institutions to the OBR and include information on student demographics, enrollment, credit hours completed, and grade point averages.

OBR has collaborative arrangements with other agencies that allow them to expand the data. For example, OBR links the student records to ACT and SAT records. Most Ohio students take the ACT exam, and the ACT records include the highest test score of the student and the most recent responses to the ACT survey (which includes student-reported data on high school performance). OBR also links students to their respective FAFSA. The FAFSA data include detailed information about the finances of both students and their families. From the FAFSA, the variable of most interest is the "estimated family contribution" that colleges use to award grants based on financial need.

One important limitation of the data is that they only include information about need-based financial aid. From FAFSA data, we know students' eligibility for federal grants and loans. We also know students' eligibility for Ohio's Instructional Grant

program, a state-run need-based financial aid award. The data do not include information about merit-based financial aid. Ohio institutions are reluctant to divulge merit-based awards since these rewards are central to their recruitment strategies. While I do not observe merit aid, I observe students' GPA's once in college, their ACT scores, and their (self-reported) high school GPA's. If these variables adequately control for student ability and if colleges determine need- and merit-based awards separately, then not knowing students' merit-based awards should not affect the estimated results.

Another limitation of the data is that they only include students attending Ohio public universities. Students from Ohio that attend universities in other states, including the nation's elite schools, and students that attend private schools in Ohio are excluded from the sample.⁶ These exclusions are both a weakness and a strength of these data. Excluding elite students makes it so the results may not be generalizable to all college students; however, excluding elite students gives us the opportunity to describe how financial aid affects students at non-elite schools. These non-elite schools educate the majority of college students and may be places where financial constraints are more binding.

Another concern related to the inclusion of Ohio public institutions alone is the measurement of drop-out behavior. Students who transfer from Ohio public institutions to institutions located in other states are indistinguishable in the data from students who withdraw from Ohio public universities. This potential bias, however, should be very

⁶ Ohio State University and Miami University are the top ranked public universities in Ohio. In the 2004 version of US News and World Reports' college rankings, they rank 60th and 64th respectively among national universities with doctoral programs. Other high ranking institutions in Ohio (e.g. Oberlin) are private colleges.

small since the percentage of students who likely transferred makes up a small fraction of the total number of observed dropouts.⁷

I focus entirely on the incoming freshman class in 1999-2000 school year. These are the first students for whom FAFSA data are available through the OBR. I include students who enrolled in any college, including community colleges, for the first time in 1999, and I track these students through the 2000-2001 school year.

Table 1 provides summary statistics for the sample. At 4-year institutions, about 10 percent of incoming full-time freshman are from other states, and students are much less likely to be commuter students than at 2-year colleges. At 2-year colleges, which include local and state-run community colleges and technical colleges, about 2 percent of all students live on campus. Similar to other national surveys, the average age of first time freshman at 2-year colleges is considerably higher than at 4-year colleges, and students complete fewer semester hours in their first year (13 at 4-year colleges as compared to 11 at 2-year colleges).

Seventy-five percent of incoming freshman at Ohio's 4-year colleges took the ACT exam while only 45 percent of students at 2-year colleges took the exam. The 4-year college students performed better than the 2-year college students. Throughout the paper, I will at times restrict the sample to students who took the ACT exam. Not only do I know these students test scores, but I also have additional (self-reported) data on these students' high school experiences.

⁷ The Integrated Postsecondary Education Data System (IPEDS) tracks the number of transfers at each institution but does not record the state of residence of transfer students although it does track the states of residence for incoming freshman. Assuming that transfer students are geographically representative of the incoming freshman class, then one would expect around 650 Ohio students to transfer to the non-Ohio schools with substantial Ohio enrollments. If we further assume that *all* 650 transfer students just finished their first year of school, then about 4.3 percent of observed dropouts are actually transfer students.

Throughout the paper, I will also restrict the sample at times to those students who filed a FAFSA in both Fall 1999 and Fall 2000. About 65 percent of 4-year students and 63 percent of 2-year students submitted FAFSA's in 1999; however, only 49 percent and 40 percent respectively filed FAFSA's in 2000. As explained below, not observing FAFSA data for many applicants leads to substantial biases in the results using panel identification. The average, uncovered financial need is small across all students, but conditional on it being positive, the uncovered financial need is slightly greater than \$1400 for students at 4-year schools.

Table 2 shows some basic least-squares regressions of student stop-out behavior on the level of students' financial aid. These regressions are not meant to show the causal effect of Pell grants, but rather to demonstrate associations between the stop-out behavior, financial aid awards and other covariates. These regressions are also useful in understanding the types of biases present in the data. Comparing the various specifications will help identify important biases.

Column 1 shows a regression of whether a student drops out or not regressed on the student's financial aid award. The regression includes fixed effects that control for the school that the student attends. The estimated coefficient is positive and significant suggesting that larger awards are positively associated with drop-out behavior. As mentioned before, however, these coefficients are significantly biased for a number of reasons. For example, when we include controls for an individual's socio-economic background and personal characteristics in Columns 2, the estimated relationship drops significantly.⁸ The estimated relationship drops dramatically (from .033 to .006) and is

⁸ The sample sizes fall across columns in Table 2. The first column includes all students in the sample. The second column includes only those students for whom demographic data are available. Columns 3 and

still significant. Column 5 is similar to Column 2 except that I focus only on students who took the ACT exam, including controls for a student's high school performance and entrance exam scores. The estimated coefficient is similar to Column 2 but is no longer significant. The other rows in Columns 2 and 5 suggest that wealthier students are less likely to stop-out; out-of-state students are more likely to drop-out; older students and men are more likely to withdraw; and students living on campus and students who took the ACT (and performed well on it) are less likely to stop-out.

In Column 3, I add controls for students' grades during their freshman years of school. As previously mentioned, Pell may have had a negative effect since students with Pell may have had less of a financial commitment to schooling and may not have worked as hard. Including grade point average should control for these students and may further weaken the estimated relationship between financial aid and stop-out behavior. As shown in Table 2, the estimated relationship is smaller than in Columns 1, 2, and 5. The result is also not statistically different than zero. In Column 6, I estimate a similar regression for students who took the ACT exam. Again, the estimated relationship is indistinguishable from zero.

In Column 4, I estimate the relationship controlling for personal and family characteristics and grades during a student's first year. I exclude the fixed effects for students' campuses of attendance. These fixed effects also control for differences in quality, price, and other unobservable campus characteristics (e.g. the strength of a campus freshman intervention programs). These fixed effects control for the fact that students attending lower quality schools (who also receive smaller financial aid awards

4 further restrict the sample to students who had a freshman GPA reported to the Ohio Board of Regents. Columns 5 and 6 are based on the subsample of students who took the ACT exam.

since tuition is smaller) are more likely to withdraw than students attending better schools (who receive higher financial aid awards for similar reasons). Without these fixed effects, we would expect the estimated relationship between financial aid and student stop-out behavior to be even smaller and maybe even negative. This is exactly what Column 4 of Table 2 shows. The estimated relationship suggests that higher financial aid awards are negatively associated with student stop-out behavior.

III. Estimating the Causal Effects

There are three sources of variation that economists can use to identify the effects of Pell grants: time series, panel, and cross-sectional. In this section, I discuss the feasibility of each of these identification strategies using the Ohio Board of Regents data. I also present the basic empirical results for each identification strategy.

Each strategy aims at identifying the effects of Pell grants *conditional* on initial enrollment. However, Pell grants may affect enrollment, and as a consequence, some students who would not be enrolled without Pell grants would be included in the analysis making the parameter estimated in this paper more difficult to interpret. If Pell affects enrollments, then the parameter estimated in this paper would be a combination of two different effects – 1) the effect of Pell grants on the persistence behavior of students who would have attended college in the absence of the Pell and 2) the effect of Pell grants on the persistence behavior of students who would not have attended school without the Pell grant.

Under some circumstances, the latter effect does not matter. For example, any potential bias depends on the degree to which Pell grants affect enrollment. If the Pell

grant has no effect, then the parameter estimated in this paper represents only the effect of the Pell grant on all students eligible for Pell grants. If the Pell grant has a small effect, than any bias in the estimated parameter is likely to be small. Most of the research on Pell grants and enrollment suggest that the Pell has had either no effect or a very small positive effect on enrollment (see Kane 1999, Leslie and Brinkman 1987).

Additionally, if the unobservable factors that can potentially bias any estimate of the effect of Pell grants on persistence are similar for those people for whom Pell influenced enrollment decisions and those people for whom they did not, then the effect of Pell grants estimated in this paper should be the same for both groups. For example, suppose that unobservable family characteristics affect both the size of students' Pell grants and their likelihood of dropping out. We typically think that these unobserved characteristics likely bias our estimate of the effects of Pell grants downward. If the bias is the same for students for whom Pell did and did not affect initial enrollments, then the bias should be symmetric across both groups, and while the overall parameter may be biased by these unobservables, the overall parameter is not made up of two components. If we can control for these unobservables in our empirical design, we can estimate a single parameter that is easily interpreted. However, if the determinants of persistence are not constant across groups, then the parameter will remain a combination of the two aforementioned effects.

A. Time Series Identification

One way to identify the effects of Pell grants is to compare changes in students' outcomes after systematic changes in Pell grants occur. For example, the Pell grant program began in 1973. Previous work by Kane (1996) compares low-income student

enrollment rates before and after the Pell program was established. Kane finds that college rates grew about 2.6 percentage points slower for low-income students than other groups, suggesting that the Pell grant had little effect. Other systematic changes in Pell grant formulae are described in Mortenson (1988). For the study at hand, I am presenting evidence for a single cohort, so time-series variation will not be useful in identifying the effects of Pell.

B. Panel Identification

Another way to identify the effects of Pell grants is to look at changes in students' Pell grants over time. While this seems like a promising strategy since the OBR data contain two years of data for a single cohort, there are a number of reasons that this strategy might be limited.

To see the limitations and possibilities of this identification strategy, we need to understand how variations over time are generated for a single individual. There are really three basic reasons that a student's Pell grant would change from one year to the next. First, the generosity of the Pell grant may change. This could be the result of systematic changes in the Pell formula or by a change in college tuition. Such changes are likely to be exogenous, and if they generate enough variation, they may help researchers to accurately identify the effects of Pell grants. Unfortunately, there is little variation over time in the period of time that the OBR data are available. From the 1999-2000 school year to the 2000-2001 school year, the maximum Pell grant increased from \$3125 to \$3300, a 5.6% increase. Over the same time, tuition at Ohio schools increased by 5% across the board (OBR 2001).

Another source of variation comes from changes in students' college choices. Students may transfer to another school after the first year. The corresponding change in tuition will generate variation in students' Pell grants. Unfortunately, this source of variation does not help identify the effects of Pell grants. Students who transfer may have different abilities than those students who do not transfer. For example, a student with high ability may transfer from a two- to a four-year college to gain access to more opportunities. This student's Pell grant would automatically increase. However, this increase is correlated with the student's ability and may confound causal estimates of the Pell grant. Another reason why using variation from transfer behavior may be misleading is that the size of students' Pell grants may affect transfer behavior making it even more difficult to interpret and identify the effects of Pell grants using variation caused by student transfer behavior. Thus, changes in Pell grants resulting from transfer decisions will not generate variation in Pell grants that can be legitimately used to identify the effect of Pell grants alone.

A final reason that students' Pell grants may change is due to changes in students' circumstances. Some changes may be legitimate sources of variation. For example, a family of four with one child in college may have a second child come of college age causing the existing college student's Pell grant to increase. Similarly, a change in family size (e.g. birth of another child or separation) may increase a student's Pell grant. Even the natural aging of parents should increase students' Pell grants although only slightly. However, there are other changes in family circumstances which may not be legitimate sources of variation. For example, changes in income due to unemployment or health shocks may reduce family income and consequently increase students' Pell grants from

year to year. These sources of variation may also affect the likelihood that a student persists in college.

For panel identification strategies to be successful, variation in the Pell grants must come from sources that are exogenous from changes in students' stop-out behavior. As mentioned above, the most legitimate changes come from changes in the Pell formula, changes in tuition, and changes in family size or sibling attendance. I can use changes from these "legitimate" sources as instruments for actual changes in financial aid.

Constructing the instrument from changes in the Pell formula and tuition is straightforward. I simply impute what students' Pell grants would have been during the 2000-2001 school year assuming that their financial and family information is unchanged from the 1999-2000 school year. The imputed 2000-01 Pell grant does not include variation from changes in students' (or their families') circumstances. It only includes variation arising from changes in the Pell grant formula and tuition.

Imputing student data not only allows me to isolate exogenous variation, but it also allows me to estimate data for many students for whom financial data are missing. In the 1999-2000 school year, 35,233 students filed FAFSA's. However, 12,143 of these students did not file FAFSA's in the 2000-2001 school year (hereafter referred to as the "non-filers"). These non-filers are not a random subset of all students. These non-filers include 2/3 of all students who withdrew from college after the 1999-2000 school year. For these individuals, I am missing financial data and information about changes in their siblings' college attendance for the 2000-2001 school year. Since the imputation assumes that students' financial information is unchanged from their first to second year of college, I can estimate data for these non-filers.

If I had data for all non-filers, I could estimate out the causal effect of Pell grants by using the imputed grant as an instrument for the actual grant. The instrumental variable estimate would be an unbiased estimate of the effect. Unfortunately, since the actual data are not available for non-filers, I can only estimate reduced-form regressions of stop-out behavior on the imputed Pell grant. Since there is a significant, positive relationship between students' imputed Pell grants and their actual Pell grants, the reduced-form estimates of the relationship between imputed Pell and stop-out behavior should give us a sense of the sign and significance of the effect of actual Pell grants, but the reduced-form estimates will not give a precise estimate of the magnitude of such an effect.

Table 3 contains the reduced-form regressions regressing student stop-out behavior against the imputed increase in a student's Pell grant from one year to the next measured in thousands of dollars. For students who withdrew or transfer, I impute the Pell grant students would have received if they remained at the same institution as their initial enrollment. Column 1 shows the results with fixed effects for school of attendance but no covariates. Column 2 shows the results without fixed effects for college of enrollment but with covariates for gender, age, campus living conditions, whether the student took the ACT exam, and grade point average in the students' first years. Column 3 includes both fixed effects and covariates.

As Column 1 shows, students whose Pell grants increase are less likely to dropout. Without covariates, the coefficient suggests that a \$1,000 increase in a student's Pell grants leads to an 8.6 percentage point decrease in the likelihood that the student withdraws. With covariates, the estimated coefficient implies that a \$1,000 increase in a

student's Pell grant corresponds to a 9.2 percentage point decrease in the likelihood that students withdraw. These estimates suggest strongly and consistently that increases in financial aid decrease the likelihood that students withdraw from school.

Column 4 repeats the analysis focusing only on the students whose initial college enrollment was at a 4-year campus. As before, the estimated coefficient is negative and significant. A \$1,000 increase in students' imputed Pell grants corresponds to a 6.4 percent reduction in the likelihood that students withdraw from college.

Column 5 reports estimates when non-filers are excluded from the analysis. As mentioned before, the students who filed FAFSA's in both years are a non-random subset of all students. Now the estimate is positive and significant. A \$1000 increase in a student's financial aid corresponds to a 2 percentage point increase in the likelihood that a student withdraws. I include the estimate of Column 5 to provide some hint of what the bias may be from excluding the "non-filers" in the previous columns. When we include the "non-filers," we get significant, negative relationships between increases in students' Pell grants and the likelihood that students drop out; however, when these students are omitted, the estimates are positive and significant.

One might be able to further refine the estimates of students' Pell grants in the cases where data are missing by using information about students' siblings. If ages or graduation dates were known or could be approximated, I could include this information in the estimation of what students' Pell grants would have been in the 2000-2001 school year. Unfortunately, little information is available about students' siblings for the non-filers.⁹

⁹ Some information about the family (parental age, family size in 1999-2000, number of children in college in 1999-2000, parental marital status) may help predict changes in the number of children attending

What conclusion should be drawn from the panel identification specifications? First, panel identification has only limited power to actually identify the effects of Pell grants. Much of the variation created over time in a student's Pell grant comes from sources which may also affect the probability that the student withdraws from school. It would be inappropriate to use this type of variation to identify the effects of Pell. Second, the fact that many students, especially those who plan to withdraw from school, do not file FAFSA's in both years makes it difficult to estimate the effect of financial aid. When we impute data for these people, we find estimates suggesting that increases in financial aid reduce the likelihood that students withdraw from college.

C. Cross Sectional Identification

One might also identify the effects of need-based financial aid by comparing the need-based awards of different students at a single moment in time. There are a number of reasons that students may have different need-based awards. Students may differ from each other in terms of personal income and assets, family income and assets, family size, parental age, college of attendance, and enrollment status (full versus part time). All of these differences will lead to differences in students' need-based financial aid. Much of this variation will not be helpful in identifying the effects of Pell grants. These sources of variation will also likely affect students' drop-out behavior independent of need-based awards.

college; however, their predictive power is limited. When I model changes in sibling attendance on these variables, I get a very low R-squared. After rounding the predicted values to the nearest integer, the specification predicts that 0.05% of students who filed FAFSA's in both periods would have had a change in the number of siblings attending college. In reality, 20.5% of students had a change in the number of siblings attending college.

However, there is some variation across individuals that might be useful. In particular, differences in family size and the number of children in college may facilitate identification in a cross-section. The Pell grant formula contains a number of discontinuities, the largest of which is based on family size and the number of students attending college. Even these sources of variation may not be exogenous. For example, if a family can only afford to send one child to school, they may choose the student who has the most potential to benefit from college. This student's Pell grant would likely be smaller than it would be for a comparable family that sent multiple children to school. However, in this example, comparing this solitary student to other families with multiple children attending would lead to a bias since the family with fewer children in college sent a child to college with a greater chance of succeeding. As a result of this potential bias, I will primarily focus on results that take advantage of discontinuities in family size. I will also briefly show estimates based on discontinuities in both family size and the number of children in college.

Table 4 shows the changes in Pell Grants that accompany changes in family size. The table shows three different schedules linking family size and the number of children attending college.¹⁰ Each schedule corresponds to a different income level (\$40,000, \$50,000, or \$60,000). For example, among the families with \$50,000 in income, a family of 2 with one in college would receive a Pell grant of \$975. If the family was actually a 3-person family with one in college, then the Pell grant would be \$1575 per person. Figure 1 shows similar comparisons for different family sizes. There are three lines corresponding to family sizes of three, four, and five. The Pell grants shown in the figure

¹⁰ The computations assume that the family has no assets and that the students do not contribute to the family's estimated family contribution.

assume that only one child is attending college. As seen, the differences in family size can lead to systematic differences in students' Pell grants. These systematic differences create discontinuities that can be exploited to estimate the effect of Pell grants on students.

Assuming that the differences between family size are unrelated to a student's success in college, comparisons can be made between families of different sizes who have the same number of children in college. However, as Table 4 shows, there is heterogeneity in income (and thus Pell grant) within a given family size. For discontinuity analysis to work, the families on either side of the discontinuity should be similar except for the discontinuity. As a result, when making comparisons across family sizes, we need to stratify the groups so that comparisons are made across relatively homogeneous groups (e.g. people with similar income and assets).

Intuitively, the easiest way to estimate the effect of the Pell grant while taking advantage of this discontinuity is to use a Wald estimator (Wald 1940). To find the Wald estimator, one must first isolate two groups that are fairly homogeneous. Across the groups, the Wald estimator is found by taking the ratio of the differences across groups of the dependent variable (stop-out behavior) and the independent variable (size of the Pell grant). For example, suppose we could identify all people who have low income and few assets and have one child in college. Some of these families are 2-person families and some are 3-person families. Assuming that family size is uncorrelated with an individual's success in college, we could estimate a Wald estimator across these groups. Let y_i be the average withdrawal rate for group i . Group i takes on a value of 1 for the group of students in 2-person families with one in college and 2 for the group of students

in 3-person families with one in college. Let x_i be the average Pell grant for group i . The Wald estimator between these groups would then be

$$\mathbf{b}_{wald} = \frac{y_2 - y_1}{x_2 - x_1}.$$

The denominator should be the expected change in the Pell grant as a result of this discontinuity within this income-asset group. The numerator would be the difference in stop-out rates between these groups.

After computing the first Wald statistic, we could then create a Wald estimator between each income-asset grouping within the sets of 2- and 3-person families. If we had 10 income-asset groupings, we would have 10 Wald estimators. These Wald estimators can be combined by taking a weighted-average of the estimators (weighted by the number of observations in each group 2). We could similarly create Wald estimators across adjacent groupings of family size. For example, we could compare 3- and 4- person families. Of course, in the estimation of each Wald statistic we would actually have multiple Wald statistics comparing income-asset groupings across each discontinuity.

While this approach seems straightforward, other discontinuities in the Pell formula complicate the estimation of Wald statistics. For example, there are some income ranges where students would receive the maximum Pell grant regardless of their family size or the number of children attending college. The Wald statistic would not be defined (or would be greatly inflated) over these ranges. Similarly, the Wald statistic will not be defined for families that would have received no Pell grant regardless of their family size or the number of children in college. Since these groups will likely create additional noise in the estimation, we may want to exclude these groups at times.

Before estimating the Wald statistics, we need to create the income-asset groupings needed to create comparisons between homogeneous groups. To create groupings, I re-estimate each student's Pell grant assuming that he or she belonged to a 2-person family with only 1 person attending college. I then divide this group into 6 parts based on the revised Pell grant:

1. People whose Pell grant in a 2-person family with 1-in college would have been at the maximum of \$3125.
2. People with revised Pell grants between \$3124 and \$2001.
3. People with revised Pell grants between \$2000 and \$1001.
4. People with revised Pell grants between \$1000 and \$401.
5. People with revised Pell grants at the Pell grant minimum of \$400.
6. People with revised Pell grants equal to zero.

Having uniform groupings across cells makes it much easier to estimate the Wald statistics and their standard errors. Creating groupings around Pell grant values also avoids the problem that wealthier families are more likely to apply if they have more children. These families are identified in group 6. Also, I separate people who would have had the Pell grant minimum (\$400) since in the Pell grant formula there is a discontinuity that allows families across a wider range of income to have this value of Pell grant. I use these revised Pell grants only for the purpose of creating homogeneous groups (i.e. identifying families with similar assets and incomes). When actually computing the Wald statistics, I use the actual Pell grants.

Figure 2 shows an example of how the discontinuity works. The sample of students is from group 3 above. These students would have had similar Pell grants had

their family size not been different. The left axis of Figure 2 plots these students' actual Pell grants across family size. The Pell grant increases with the number of children. The right-side axis of Figure 2 plots the stop-out rates for these students. The stop-out rate declines for students with larger families. Assuming that family size affects stop-out rates only through its effect on Pell grant size, then stop-out rates are negatively related to Pell grant size for these students. We could produce similar figures for each homogeneous group of students.

Table 5 shows the regression-based Wald estimates for the whole sample. Following Angrist (1991), the efficient combination of Wald estimators is just the instrumental variables estimate of y (stop-out behavior) on x (size of Pell grant) where dummy variables for each homogeneous group and family size combination are used as instruments for x . For example, if all families were 2, 3, or 4 people in size, then I would include 18 dummy variables as instruments (i.e. for each of the 6 homogenous income/asset groupings defined above, I would include 3 dummy variables for the possible family sizes).

Column 1 of Table 5 shows the instrumental variable estimate when I estimate the regression excluding those for whom there is no variation in Pell grants.¹¹ The estimated effect is negative and significant. A \$1000 increase in Pell grants stemming from differences in family size corresponds to a 4 percentage point decrease in likelihood that a student drops out. The result suggests that systematic differences in Pell grants lead to differences in stop-out rates for students. Larger Pell grants reduce students' probabilities of withdrawing.

¹¹ The maximum income in this group is \$25,000.

In Column 2 of Table 5, I include only the students who took the ACT exam. The estimated effect suggests that a \$1000 increase in students' Pell grants leads to a 1.2 percentage point reduction in the probability that a student withdraws although the result is not statistically significant. In Column 3, I provide a small specification test. Rather than use stop-out behavior as the dependent variable, I use the ACT score. If the specification is correctly identified, there should be no significant differences between ACT scores between groups. Indeed, the estimated relationship is indistinguishable from zero.

Another way to estimate the effects of Pell is to use an instrumental variable approach where the "delinearized" Pell grant is used as an instrument for the actual Pell grant. To do this, I run a regression of the actual Pell grant on a quartic in the key variables that determine the Pell grant (family income, family assets, family size, and number of children in the family attending college). The residuals from this regression should be primarily made up of discontinuities in the Pell formula along these dimensions. I then use the residual as an instrument for the actual Pell grant in a simple regression of stop-out behavior on students' Pell grants.¹² I restrict the sample to students whose families have less than \$150,000 in assets or less than \$115,000 in annual income. The results appear in Columns 4 and 5 of Table 5. Similar to Column 3, I find that a \$1000 increase in Pell grants is associated with a 3 percentage point reduction in the likelihood that a student drops out.

¹² This is identical to running a regression of stop-out behavior on the Pell grant value and a quartic in the variables that determine the Pell grant. These strategies estimate the same estimator with only a negligible change in standard errors. I report the standard errors from the "instrument" approach since it may be intuitively easier to identify what source of variation is behind the estimated effect.

In Column 5, I use a similar procedure except that I put campus fixed effects in the regression that predicts students' Pell grants. This is important since different campus costs can lead to differences in the size of students' Pell grants. Again, I use the residuals from this 1st stage as an instrument in the next. The results drop in magnitude and are statistically indistinguishable from zero.

The final column of Table 5 estimates the effects of Pell grants using both the discontinuities from family size and the number of children in college. I use the same methodology except now I compare differences in Pell grants resulting from differences in the number of children going to college as well. The results are similar to those in Column 1. I find that a \$1,000 increase in Pell corresponds to a 4 percent reduction in the likelihood that students withdraw.

What conclusions should be drawn? First, while the estimates reinforce a negative relationship between the size of one's Pell grant and stop-out behavior, they are not completely robust to specification. When I focus on the sample taking the ACT (Column 2) and when I include additional campus level controls (Column 5), the results are indistinguishable from zero. Additionally, there is substantial heterogeneity around the discontinuity and efforts to create comparisons among homogeneous groups may not fully account for the heterogeneity. Overall the results seem supportive of those in the panel identification although the results are not robust to different subsamples.

IV. Conclusion and Policy Implications

This paper set out to estimate the effects of Pell grants on student retention. Using panel and cross-sectional variation as sources of identification, this paper attempts

to estimate the relationship. The panel identification results suggest strongly that Pell reduces drop-out rates. The regression-discontinuity results show similar results although they are more fragile. The regression-discontinuity results, however, are less likely to be biased by other factors than the specifications which use cross-sectional variation.

The finding that Pell grants affect student persistence has several policy implications. Most importantly, it implies that federal and state needs-based policies and aid matter and that they influence the likelihood that students continue from year to year in college. Even if these aid programs have no effect on enrollment (as Kane 1999 and Leslie and Brinkman 1987 show), need-based programs may impact educational attainment. The finding that aid increases persistence may suggest that front-loaded financial aid programs may improve student retention in the first years of college.¹³

The results in this paper may also support conclusions in Dynarski (2002) and Turner and Bound (2002). These papers focused on beneficiaries of the Social Security Student Benefit Program and the G. I. Bill respectively. The papers found that need-based aid affected both enrollment and completion.

While many policymakers may view this finding that need-based aid improves retention as being "good" for society, it is not clear that this is so. As Jonathan Guryan points out in the comments that follow this chapter, more education may not be optimal for all students in society. There may be a number of students who do not have the skills and for whom a college degree may not improve earnings. If these students are the marginal students for whom the Pell grant program influences college persistence, then the measured effect in this paper may reflect an inefficient use of societal resources.

¹³ DesJardins, Ahlburg, and McCall (2002) finds that frontloaded aid programs have a "modest impact" on student retention.

In order to fully resolve the question of whether increased persistence is "good" for society, we would need to know how an additional year of education affects the earnings for these marginal students. In estimates of the returns of education for the entire population, Jaeger and Page (1996) argue that the returns to a second year of college have significant effects on earnings, particularly if students finish an Associate's Degree. These estimates suggest that persistence into the second year of college is a positive outcome; however, the estimated return in Jaeger and Page (1996) is for the whole population. It is not clear that this estimated return would be the same for the marginal students affected by Pell grants. Evidence from Tobias (2000) suggests that the returns to education are concentrated at the highest ability students and remain small for lower ability students. Moreover, as Sarah Turner points out elsewhere in this volume, the marginal students are likely less prepared for college and more likely to hold a GED than a high school diploma.¹⁴ There is little empirical evidence on the returns to an additional year of college for these students.

Finally, there are two empirical points that should be considered in interpreting the results in this paper. First, the paper focuses solely on student persistence between the first and second year of college in adjacent years. Researchers have documented the growing trend of students to take breaks at various times during college (e.g. Turner's chapter in this volume). DesJardins, Ahlburg, and McCall (2002) examine enrollment probabilities over a longer stretch of time. They find that need-based aid has no long-run effect on enrollment probabilities. They are using a sample in which students repeatedly enter and exit higher education. While the sample they use focuses on students who

¹⁴ Many of these students enroll in college remediation. Ongoing research by Bettinger and Long (2003) examines the effect college remediation on college outcomes and student earnings.

initially enrolled at a four-year campus, their finding suggests that examining the effect of financial aid on retention over a longer stretch of time may be important.

Second, as states continue to gather more complete and expansive data on their students, economists and others researchers will be able to employ methods that exploit variation in Pell grant formulae. However, even if better data are available, researchers should take care in how they deal with changes in Pell grant eligibility and missing data. Students who leave school after their first year are less likely to file additional FAFSA's making it difficult for researchers to measure their financial status. Research that fails to control for these missing data may be biased.

Table 1. Average Student Characteristics

	4-year College	2-year College
Out of State Student	.103	.032
Lives on Campus	.557	.024
Age	18.8 (2.5)	21.0 (6.2)
Non-White	.134	.173
Hours Completed by Fall 1999	13.4 (4.7)	11.2 (6.3)
Left Institution After 1 year	.278	.491
Left Higher Education After 1 Year	.201	.431
Took ACT exam	.750	.446
ACT Composite Score (36=max)	21.8 (4.3)	18.9
Filed FAFSA for Fall 1999	.653	.628
Uncovered Financial Need (\$)	423.0 (716.1)	24.1 (172.4)
Uncovered Financial Need Cond'l on Being >0	1081.8 (773.7)	82.0 (310.5)
Filed FAFSA for Fall 2000	.490	.399
Uncovered Financial Need (\$)	1261.5 (951.4)	21.3 (93.1)
Uncovered Financial Need Cond'l on Being >0	1400.2 (900.2)	41.3 (126.5)
Change in Pell Grant (Cond'l on Pell eligibility in 99 or 00)	1691 (994)	881 (762)

Source: Author's calculations from unpublished data from the Ohio Board of Regents

Notes: Standard deviations appear for non-binary variables. Data are for full-time students who first entered Ohio public colleges and/or universities in Fall 1999. Uncovered financial need equals tuition less the estimated family contribution from the FAFSA less any Pell Grant for which the student was eligible.

Table 2. Association Between Financial Aid and Stop-out Behavior

	Dependent Variable = Student "Stopped-out"					
	All Students				Students Taking ACT Exam	
	(1)	(2)	(3)	(4)	(5)	(6)
Level of Financial Aid (000's)	.033 (.002)	.006 (.003)	.0002 (.003)	-.005 (.003)	.005 (.003)	.002 (.003)
Log of Parents' Income		-.036 (.005)	-.030 (.005)	-.042 (.005)	-.030 (.006)	-.024 (.005)
Out of State Student		.072 (.077)	.055 (.073)	.041 (.073)	.365 (.152)	.165 (.172)
Age		.022 (.004)	.018 (.004)	.020 (.004)	.018 (.005)	.016 (.005)
Male		.029 (.005)	.003 (.004)	.003 (.004)	.017 (.005)	-.002 (.005)
Lives on Campus		-.082 (.007)	-.057 (.007)	-.112 (.004)	-.079 (.007)	-.062 (.007)
Took the ACT		-.113 (.007)	-.063 (.007)	-.088 (.007)		
ACT Score					-.0003 (.0007)	.004 (.001)
Freshman Grade Point Average			-.138 (.003)	-.136 (.003)		-.132 (.003)
Includes HS GPA controls	No	No	No	No	Yes	Yes
Includes Race Fixed Effects	No	Yes	Yes	No	Yes	Yes
Includes Campus Fixed Effects	Yes	Yes	Yes	No	Yes	Yes
R-squared	.108	.112	.204	.192	.091	.169
N	37028	30851	29778	29778	24627	24012

Source: Author's calculations from unpublished data from the Ohio Board of Regents

Notes: White standard errors are in parentheses. Data are for full-time students who first entered Ohio public colleges and/or universities in Fall 1999. The sample varies across columns due to missing data on student characteristics or first-year GPA data.

Table 3. OLS Regressions of Stop-out Behavior on Changes in Pell Grants:
Results with Panel Data

Dep Var = Student Stopped-out	Full Sample: Students Filing FAFSA in 1999-00			4-yr students	Students Filing FAFSA both years
	(1)	(2)	(3)	(4)	(5)
Imputed Increase in Financial Aid (000's)	-.086 (.002)	-.092 (.002)	-.092 (.002)	-.064 (.003)	.018 (.008)
Level of Financial Aid in 1999-2000 (000's)		.025 (.002)	.026 (.002)	.020 (.002)	.006 (.002)
Includes Covariates	No	Yes	Yes	Yes	Yes
Includes Campus Fixed Effects	Yes	No	Yes	Yes	Yes
N	35233	35233	35233	21506	24116

Source: Author's calculations from unpublished data from the Ohio Board of Regents

Notes: Standard errors are reported in parentheses. Samples in Columns 1-3 include all students who FAFSA's in 1999-2000. Column 4 focuses only on students who attended a 4-yr college in 1999-2000. Column 5 includes only those students who applied for financial aid in both years. Covariates include an indicator for whether the student was from out of state, age, gender, whether the student lives on campus, whether the student took the ACT exam, students' freshman GPA, and controls for race.

Table 4. Pell Grant by Family Size and the Number of Children in College

Income=\$40,000		Number of Children in College			
		1	2	3	4
Number in	2	\$2175	\$2475	--	--
Family	3	\$2875	\$2775	\$2775	--
	4	\$3125	\$3125	\$2975	\$2875
	5	\$3125	\$3125	\$3125	\$3075
	6	\$3125	\$3125	\$3125	\$3125
Income=\$50,000		Number of Children in College			
		1	2	3	4
Number in	2	\$975	\$1775	--	--
Family	3	\$1575	\$2175	\$2275	--
	4	\$2325	\$2425	\$2575	\$2575
	5	\$3125	\$2825	\$2775	\$2775
	6	\$3125	\$3125	\$3075	\$2975
Income=\$60,000		Number of Children in College			
		1	2	3	4
Number in	2	\$0	\$975	--	--
Family	3	\$400	\$1475	\$1775	--
	4	\$1075	\$1825	\$2175	\$2275
	5	\$1875	\$2275	\$2375	\$2475
	6	\$2675	\$2675	\$2675	\$2675

Source: Author's calculations.

Notes: Calculations assume that the families have zero assets and no student contribution in the computation of the estimated family contribution. Calculations also assume that students attend high-cost institutions.

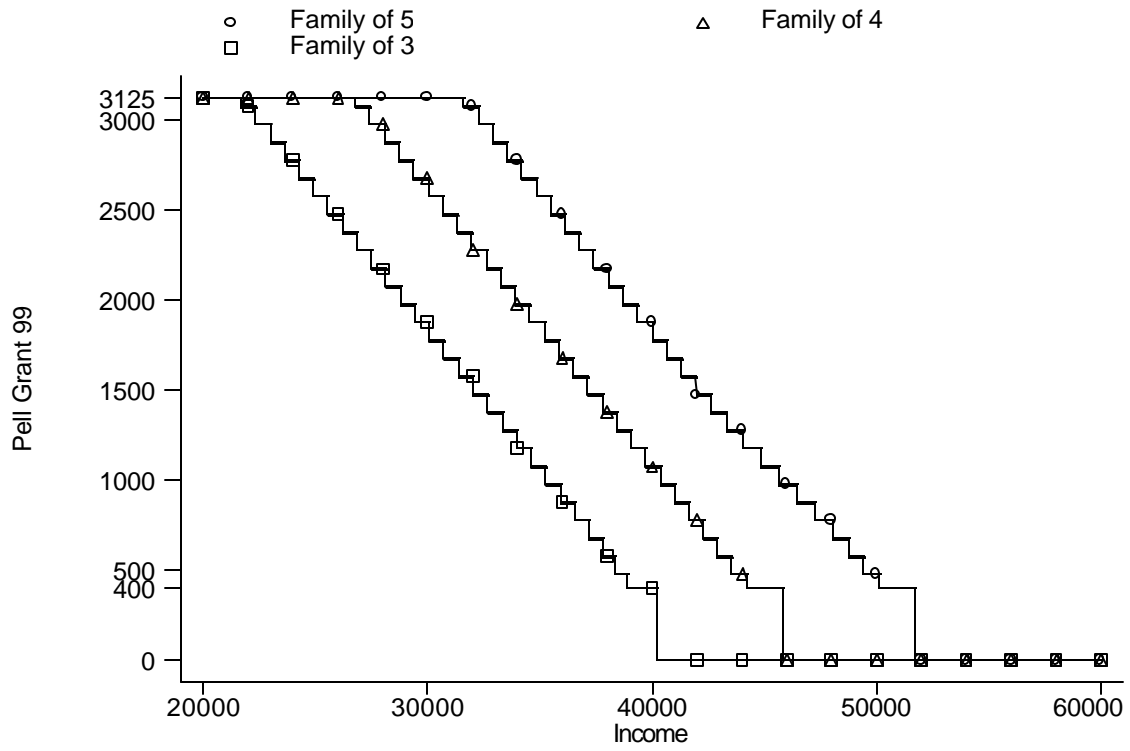
Table 5. Wald/IV Estimates of Effect of Financial Aid on Stop-out Behavior

Dependent Variable= Stop-out Behavior	Wald	Wald ACT Sample	Wald Dep Var= ACT Score	IV	IV W/ Campus Fixed Effects	Wald Family &Child Discont
	(1)	(2)	(3)	(4)	(5)	(6)
Level of Pell Grant in 1999-2000 (in 000's)	-.037 (.009)	-.012 (.010)	.100 (.099)	-.029 (.004)	.0004 (.004)	-.036 (.009)
N	6114	4470	4470	29936	29936	6398

Source: Author's calculations from unpublished data from the Ohio Board of Regents

Notes: White standard errors are reported in parentheses. Columns 1-3 and 6 include only students with positive Pell grants less than the maximum. In Columns 4-5, the instrument for "Level of Pell Grant" is the residual from a regression of Pell grant on a quartic of the key variables determining Pell grants (family income, assets, family size, number of children in college). The IV columns exclude families with income greater than \$115,000 or assets greater than \$150,000. Campus fixed effects are included in the 1st stage of the specification in Column 5 to control for the fact that different school costs will lead to different size Pell grants.

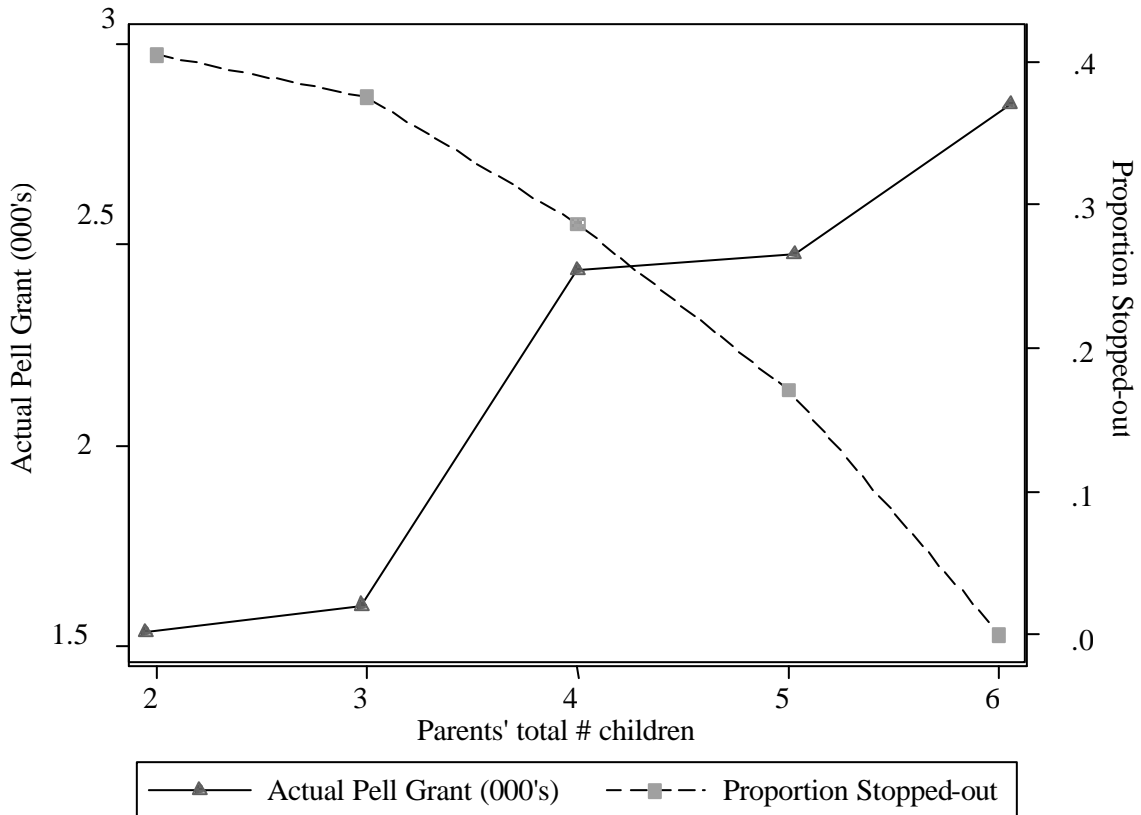
Figure 1. Pell Grants by Family Size



Source: Author's Calculations

Notes: The estimated Pell grants are formulated assuming no assets or student contribution. The Pell grants further assume that only one person from the family is attending a high cost institution.

Figure 2. Average Pell Grants and Stop-out Rates Across Family Size Discontinuity



Source: Author's calculations from unpublished data from the Ohio Board of Regents

Notes: Sample is restricted to families whose assets and income are such that their college-age children would have had a Pell grant between one and two thousand dollars if they had only had one child.

Works Cited

- Angrist, Joshua. 1991. Grouped-Data Estimation and Testing in Simple Labor-Supply Models. *Journal of Econometrics*. 47 (2-3): 243-66.
- Bettinger, Eric and Bridget Long. 2003. The Effect of Remediation on Student Outcomes: the Plight of Underprepared Students in Higher Education. Working Paper, Case Western University, Cleveland, Ohio.
- Bound, John and Sarah Turner. 2002. Going to War and Going to College: Did WorldWar II and the G.I. Bill Increase Educational Attainment for Returning Veterans? *Journal of Labor Economics*. 20 (4): 784-815.
- College Board. "Trends in Student Aid 2001." 2001.
<<http://www.collegeboard.com/press/cost01/html/TrendsSA01.pdf>> (27 August 2003).
- DesJardins, S.L., D.A. Ahlburg, and B.P. McCall. 2002. Simulating the Longitudinal Effects of Changes in Financial Aid on Student Departure from College. *The Journal of Human Resources*. 37 (3): 653-679.
- DesJardins, S.L., D.A. Ahlburg, and B.P. McCall. 1999. An Event History Model of Student Departure. *Economics of Education Review*. 18: 375-390.
- Dixit, Avinash and Robert Pindyck. 1994. *Investment Under Uncertainty*. Princeton, New Jersey: Princeton University Press.
- Dynarski, Susan. 1999. Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion. Working Paper, National Bureau of Economic Research, Cambridge, MA.
- Ehrenberg, Ron and D. Sherman. 1984. Optimal Financial Aid Policies for a Selective University. *Journal of Human Resources*. 19 (2): 202-30.
- Jaeger, David A. and Marianne Page. 1996. Degrees Matter: New Evidence on Sheepskin Effects in the Returns to Education. *Review of Economics and Statistics*. 78 (4): 733-741.
- Kane, Thomas J. 1996. Rising Public College Tuition and College Entry: How Well Do Public Subsidies Promote Access to College? Working Paper, National Bureau of Economic Research, Cambridge, MA.
- Kane, Thomas J. 1999. *The Price of Admission: Rethinking How Americans Pay for College*. Washington, D.C.: Brookings Institution Press.
- Leslie, Larry L. and Paul T. Brinkman. 1987. *The Economic Value of Higher Education*. New Hampshire: MacMillian.
- Manski, Charles F. 1993. Adolescent Econometricians: How Do Youth Infer the Returns to Schooling? In *Studies of Supply and Demand in Higher*. ed. Charles Clotfelter and Michael Rothschild. Cambridge, MA: National Bureau of Economic Research.
- Mortenson, Thomas. 1988. Pell Grant Program Changes and Their Effects on Applicant Eligibility 1973-74 to 1988-89. American College Testing Program Research Series Report. Iowa City, Iowa.
- Myers, S.C. and S. Majd. 1990. Abandonment Value and Project Life. *Advances in Futures and Options Research*. 4: 1-21.

- Ohio Board of Regents. State-Supported Ohio College and University Performance Report: Student Outcomes and Experiences. 2001. <<http://www.regents.state.oh.us/perfrpt/2001index.html>> (29 August 2003).
- Seftor, Neil and Sarah Turner. 2002. Back to School: Federal Student Aid Policy and Adult College Age Enrollment. *Journal of Human Resources*. 37 (2): 336-352.
- Singell, Larry. 2001. Come and Stay a While: Does Financial Aid Affect Enrollment and Retention at a Large Public University? Working Paper, University of Oregon, Eugene, Oregon.
- St. John, Edward P., Glenda D. Musoba, and Ada B. Simmons. Keeping the Promise: The Impact of Indiana's 21st Century Scholars Program. Policy Research Report, Indiana Education Policy Center. <<http://www.indiana.edu/~iepc/hepolicy.html>>(4 September 2003).
- St. John, E.P., S. Hu and T. Tuttle. 2000. Persistence by Undergraduates in an Urban Public University: Understanding the Effects of Financial Aid. *Journal of Student Financial Aid*. 30 (2): 23-37.
- St. John, E.P., S. Hu and J. Weber. 2000. Keeping Public Colleges Affordable: A Study of Persistence in Indiana's Public Colleges and Universities. *Journal of Student Financial Aid*. 30 (1): 21-32.
- Tobias, Justin. 2003. Are Returns to Schooling Concentrated among the Most Able? A Semiparametric Analysis of the Ability-Earnings Relationships. *Oxford Bulletin of Economics and Statistics*. 65 (1): 1-29.
- U.S. Department of Education. "Paige Hails House for Not Leaving Pell Grant Recipients Behind." 22 May 2002. <<http://www.ed.gov/PressReleases/05-2002/15222002.html>> (27 August 2003).
- Wald, Abraham. 1940. The Fitting of Straight Lines if Both Variables are Subject to Error. *The Annals of Mathematical Statistics*. 11 (3): 284-300.
- Wei, Christina and C. Dennis Carroll. 2002. Persistence and Attainment of Beginning Students with Pell Grants. Working Paper, National Center for Education Statistics, Washington, D.C.
- Wetzel, James, Dennis O'Toole and Steven Peterson. 1999. Factors Affecting Student Retention Probabilities: A Cast Study. *Economics of Education Review*. 23 (1): 45-55.