Two Essays on Students' Homework Time in High School

Steven McMullen

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Approved By:

Thomas Mroz

David Blau

Donna Gilleskie

David Guilkey

Helen Tauchen

Abstract

Steven McMullen: Two Essays on Students' Homework Time in High School
(Under the direction of Thomas Mroz)

In the first essay I use nationally representative panel data on student behavior and academic performance to test two possible policy reforms. First, I examine a policy that increases the amount of homework that students complete. Second, I examine the impact of increasing the amount of homework assigned. Previous studies have not been able to consistently estimate the impact of homework because of important omitted variables and measurement error, which strongly bias the estimated impact of homework time. This paper, however, uses an instrumental variables approach with student fixed effects to account for both time-varying and time-invariant unobserved characteristics and inputs. This approach produces estimates of the impact of homework time on academic achievement that are much larger than those of previous studies. Also, when compared to popular policy changes such as decreasing class size or increasing teachers' wages, a policy of assigning more homework is found to be the most cost effective policy tool. Finally, these findings suggest that assigning additional homework primarily improves the achievement of low performing students and students in low performing schools. Thus, assigning more homework could help close the gap in achievement between high and low performing students.

The second essay examines the extent to which high school students respond to education and labor market incentives when making decisions about homework, and whether or not to drop out of high school. Student and state fixed effects estimators as well as a discrete time hazard model are used to estimate these effects. I find that students' choices about homework and enrollment both respond to labor market incentives in similar ways. Students are less likely to drop out of high school and complete more homework when more education-intensive industries are present in their state. Higher unemployment rates are associated with lower dropout probabilities and a decrease in the amount of homework completed. Finally, young women, low income students, and low achieving students increase their enrollment and homework time in response to a higher minimum wage.

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Chapter 1: Introduction

There has been considerable attention paid to the quality of secondary education in the United States since the Coleman report was published in 1966, highlighting the inequality of education achievement, especially between schools. This attention has taken the form of political action and reform at the federal level, via the Elementary and Secondary Education Act of 1965, Goals 2000 legislation (1994), and most recently, the No Child Left Behind Act (2002). Each of these policies has attempted to address what has become the most important education policy challenge of this century: the stark gap in achievement that exists between the high and low achieving students in the US. Much attention has been paid to the racial and socio-economic dimension of these achievement disparities. African American and Hispanic students tend to perform well below comparable white and Asian students. Moreover, low income students perform well below their high income peers.

Education reform has also been motivated by international achievement comparisons. The Third International Math and Science Study which compared math and science performance by students across a number of countries found that US high school students ranked 28th and 17th in mathematics and science, respectively, out of 41 countries (Aksoy and Link 2000). This comparison also highlighted the gap in homework time between students in the US and elsewhere. Among the 20 countries surveyed, in a ranking of average time spent on homework, the US tied for 18th place. Additionally, despite media reports to the contrary, the number of students spending less than an hour of homework per day has been increasing since 1984 (Brookings Institution 2003) and currently more than two thirds of high school students are in this category.

The policy response to these achievement problems has been varied. Many aspects of the education system have been the target of reforms over the last 40 years including curriculum, class and school structure, teacher training and compensation, school financing, and school governance. At the school level, with the advent of magnet and charter schools, experimentation has become commonplace. While the evidence on charter schools overall is mixed, a few specific charter schools may have discovered a set of reforms that allow them increase student achievement where traditional public schools have not been able to.

One such school model is worth highlighting. The KIPP (Knowledge is Power Program) schools, and others such as Roxbury Prep (Massachusetts) have made increasing homework demands on their students a central element of their reforms. Each school assigns around two hours of homework to each student per night, and each school has some disciplinary policy in place to motivate students to complete all of their homework. At risk students in these schools have shown much higher improvement in standardized exams than have their peers in neighboring public schools.

There is however, still debate about the source of these schools' successes (EPI 2005). Because these schools may have a favorably selected sample of students, their success is not necessarily evidence that this schooling model is superior, and without data from the schools, that question can not be answered directly. What can be investigated, and is in the second chapter of this dissertation, is whether a policy of increasing the amount of homework that students complete would significantly increase their academic achievement.

This study falls within a strong body of work by many scholars who have attempted to evaluate school reforms, and have greatly advanced our knowledge regarding school effectiveness. Unfortunately, the largest determinants of student success are often the characteristics that are difficult, expensive, or impossible to manipulate. For example, there is now a consensus that reducing class size has a positive effect on student achievement, especially in early grades. Unfortunately, the impact is often too small and the change too expensive for this to be a main component of a solution to the achievement problem (Hanushek 1998).

As a contribution to this field, this dissertation presents evidence, in the second chapter, that the amount of time that students spend doing mathematics homework is a very strong determinant of their achievement on a standardized mathematics test. An additional hour of mathematics homework per week over the course of a school year is estimated to increase their achievement, relative to their peers, by 8 to 9 percentile points. Thus it is likely that policies which increase the amount of homework that students complete will be quite successful at improving achievement. While other researchers have found that homework time has a positive effect on student achievement, this uses an approach which is better able to take into account the differences, often unobservable, between students that can make comparisons difficult. This method, which uses individual fixed effect models with instrumental variables to control for individual and school level heterogeneity, produces estimates of the impact of homework time that are much larger than other studies have produced.

One obvious policy to increase homework time is simply to have teachers assign additional homework. Even though assigning homework only results in a fraction of students actually completing much additional homework, the impact is fairly strong. When compared from a cost-effectiveness standpoint with other reforms – increasing teachers' salaries and decreasing class size – assigning additional homework is found to increase achievement far more than these other policies for the resources invested.

Moreover, the students whose mathematics test scores improve the most as a result of either completing more homework or being assigned more homework are those students who are low-performing in 8^{th} grade, or those who attend relatively low-performing schools. In fact, assigning additional homework is more likely to induce these at-risk students to complete more homework than the high-performing students or those in high-performing schools. This suggests that schooling policies which increase the homework demands on students may be one way to improve the performance of at-risk students, and decrease the achievement gap.

While the second chapter documents that the amount of homework students complete is a strong determinant of academic success, it leaves relatively unexplored students' reasons for spending time on homework. The third chapter aims to help build a successful homework policy reform by exploring the factors that motivate students to invest their time on schoolwork. As a starting point for this analysis, this chapter proposes a model of student behavior in high school that takes into account student's expectations about future college and employment choices and opportunities. The main contribution of this section is the prediction that students' will respond to current and future expected labor market opportunities by completing more or less homework.

In the empirical section of this chapter, the impact of various labor market conditions on the amount of homework students complete is compared to the impact of these conditions on the probability of dropping out of school. Unlike the determinants of homework time, factors which contribute to a higher dropout rate are well-documented in the literature, and therefore make a good point of comparison. Overall, there are some similarities between students' responses in terms of homework and dropout probabilities. Young women, low income students and low achieving students complete more homework and are less likely to drop out of school in response to a higher minimum wage. Similarly, all students, though women especially, are more likely to complete high school and do more homework in response to growth in education-intensive industries. Finally, higher unemployment rates are associated with fewer students dropping out and decreases in homework time, with the strongest effects among young men.

While these effects are not large enough to predict large changes in academic achievement over the course of the business cycle, they do provide some framework for understanding the documented correlation between SAT test scores and education wage premium (Bishop 1991). These results also establish that students respond to labor market incentives when they are making choices about homework, which is consistent with forward looking rational behavior. If this is the case, a homework policy that establishes stronger incentives to complete homework, in conjunction with increased homework assignments, could be very effective.

Being limited to the questions available in the National Education Longitudinal Study of 1988, this work can not address some of the obvious questions that arise concerning the type of homework assigned, the way in which the homework is completed, or the attention paid to the homework by the instructors. Nevertheless, these findings indicate that current homework practices are highly effective, and successful innovations regarding the type of homework assigned would likely only improve these strong results.

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Chapter 2: Impact of Homework Time on Academic Achievement

I. Introduction

The amount of homework that students should complete has been an issue of debate and scholarship for decades. Some schools, such as the KIPP (Knowledge Is Power Program) schools have demonstrated much higher than normal achievement growth, often among at-risk populations (AEI 2005), by assigning more homework than other public schools[1] and implementing strict homework completion policies.[2] Scholars disagree however, about whether their success is due primarily to a superior schooling model or to favorable student selection (Rothstein et al. 2005). The academic literature pertaining to these reforms, despite much research on the topic, is not conclusive. Previous studies have done little to correct for the biases caused by omitted variables that likely influence students' choices regarding study time.[3]

In this paper, I examine two related issues. The first is the effect of students' time spent *doing* homework on achievement test scores. The second is the impact of *assigning*

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[1] Assigning homework seems to be less and less popular. The Brookings Institution press release (2003) writes that "Since 2001, feature stories about onerous homework loads and parents fighting back have appeared in *Time*, *Newsweek*, and *People* magazines; the *New York Times*, *Washington Post*, *Los Angeles Times*, *Raleigh News and Observer*, and the *Tampa Tribune*; and the *CBS Evening News* and other media outlets." Their research indicates that the homework load for most US students is actually quite low.

[2] Other successful charter schools have implemented similar reforms, such as Roxbury Prep School in Boston, MA.

[3] Recent work done by economists such as Aksoy and Link (2000), and Stinebrickner and Stinebrickner (2007) have made progress, but their approaches can only address a subset of the endogeneity problems involved with measuring this effect. The difference between their results and those of previous scholars (Cooper et al 1998) indicates that the endogeneity problems result in large biases.

additional homework on achievement. By testing the impact of these policies using nationally representative data, this study avoids the sample selection problems that accompany comparisons of charter school students' test scores with those of their peers. The primary econometric challenge that this study overcomes is that there are likely a host of unobserved variables, such as student ability, that influence both how much time a student spends on homework and the students' achievement test scores. By combining instrumental variables estimation with an individual-fixed-effects specification, I control for both unobserved heterogeneity that is constant over time and time-varying heterogeneity that might influence the amount of time students spend on homework. This approach yields estimates of the impact of homework that are much larger than those of previous studies. The presence of time-varying unobserved factors is especially important to consider when estimating the impact of education inputs that are under the students' control, since students can respond in each period to changing incentives.

I find that one extra hour of mathematics homework per week improves mathematics achievement by 0.243 standard deviations[4]. This change is large enough to move a student from the 50th percentile of math achievement to the 59th percentile[5] over the course of a school year. Additionally, this effect varies based on student characteristics and institutional factors. I find evidence that low achieving students and those in lower-performing schools realize much higher returns to their homework time than other students. Likewise, a policy of *assigning* more homework disproportionately

[4] The impact is reported here in terms of the standard deviation of the mathematics achievement test score used as the measure of academic achievement in this study. The sample used for this study is nationally representative, and thus the impacts can be interpreted as increases in achievement relative to the performance of similar students in the US.

[5] The impacts are relative to students who do not increase their homework time.

benefits these students. These findings lead to two important conclusions. First, it is possible for students to overcome past poor performance or a low quality school by spending more time doing homework. Second, a policy that increases the amount of homework assigned is likely to reduce the gap between low and high achieving students.

Finally, in order to compare policy instruments, I estimate the cost-effectiveness of increasing student achievement for each of the following changes: assigning more homework, decreasing class size, and increasing teachers' salaries. For a given monetary investment, increasing the amount of assigned homework improves achievement 3.5 times as much as increasing teachers' wages, and 11 times as much as decreasing class size.

II. Background

Previous studies within the education production function literature have documented a number of inputs that have an impact on students' academic achievement. These include school funding (Altonji and Dunn 1996), class size,[6] teacher characteristics and training (Hanushek, et al 1998; Hanushek and Rivkin 2007), the amount of time spent in class or in school (Aksoy and Link 2000), and the performance of a student's peers (Sacerdote 2001; Zimmerman 2003; Hanushek and Rivkin 2006). Certain characteristics of the student and their family also are important, including parents' permanent income (Blau 1999; Dahl and Lochner 2005) as well as the student's race and sex.

[6] Decreasing class size has a small impact, with the most benefit in early grades. For a review of the class size literature, see Hanushek (1998).

The focus of this study is on another input: student time spent on homework. The theoretic literature predicts a positive impact of homework time on academic achievement (Betts 1996; Neilson 2005). Almost all of the empirical studies on this topic find evidence that homework time has a positive impact on academic achievement, although there is no consensus on the magnitude of the impact. The literature pertaining to this topic will be presented in two sections: first, a review of literature from outside the economics discipline and second, a review of recent work done by applied economists.

Within the fields of education, psychology, and sociology there has been much research on the impact of homework. Cooper et al. (2006) provides a good review of recent work in these fields. All of the published studies that Cooper et al. review that use multivariate regression analysis find similar results: increased homework causes a small increase in academic achievement. These studies, however, are limited to cross section analysis and do not try to take into account omitted inputs or characteristics. Shuman et al. (1985), Hill (1991), and Rau and Durand (2000) all find similar results when trying to document the impact of homework time on the performance of college students. Each study either finds the relationship hard to document or finds a small effect of homework time on college grades.

Applied economists have only recently started to pay attention to the impact of homework time on achievement, starting with Julian Betts' 1996 analysis of the Longitudinal Study of American Youth. Since then Aksoy and Link (2000), Eren and Henderson (2007), and Stinebrickner and Stinebrickner (2007) have all examined this question. Each of these studies makes a serious attempt to address unobserved inputs. Eren and Henderson, in the parametric portion of their paper, use a value added specification,[7] both Betts and Aksoy and Link use a specification with student fixed effects, and Stinebrickner and Stinebrickner use the students' roommate's videogame ownership as an instrument, estimating the effect with two stage least squares.

This study improves the estimation of the effect of homework on academic achievement in three ways. First, the primary shortcoming in this literature is that previous work fails to adequately account for unobserved inputs that influence both academic achievement and the amount of time spent on homework. None of these studies, with the exception of Stinebrickner and Stinebrickner[8] can account for unobserved influences that vary over time. To address this potential problem I use the amount of assigned homework and the student's locus of control[9] as instruments for student homework time, as well as a student fixed effects. Dealing with the endogeneity of students' homework time in this manner greatly influences the estimated effects. Second, previous research has documented that the return to homework time varies based on a student's ability (Eren and Henderson 2007). In this study, I document that the return to homework also varies with school quality. Finally, this paper documents that a policy of increasing the amount of homework assigned to students is a cost-effective alternative to traditional policy interventions, and that this policy would disproportionately aid low-performing students and those in low-performing schools.

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[7] The value added specification is a cross section regression with a lagged test score (or other dependent variable) included on the right hand side of the equation to control for past achievement, inputs, and student characteristics. For more detail and a specification comparison, see appendix D.

[8] Stinebrickner and Stinebrickner (2007) does a good job documenting the relationship between homework and achievement, but does so within a selected non-representative college age population. Their instrumental variable strategy, however, is not reproducible on a large scale.

[9] The locus of control measures the extent to which a student believes that she can influence her own future outcomes. For a detailed description, see appendix A.

III. A Model of Homework Time Allocation and Academic Achievement

This section presents a standard model of homework demand in the context of an education production function. This framework will be used in the next section to motivate an econometric strategy. The utility of student *i* at time *t* depends on leisure time (D_i-H_{it}), future expected wages (W_i), grades (G_{it}), and individual preferences (X_{it}^{P}), where D_i is the disposable time available to the student to allocate between homework time (H_{it}) and leisure. Students choose the amount of homework to complete that maximizes their utility.

(1) $$U_{it} = u(D_i - H_{it}, W_i, G_{it,} X_{it}^{P})$$

The students' human capital (E_{it}) is also a function human capital investments prior to 8th grade (P_i), innate ability (A_i), school and district inputs (S_{it}), teacher inputs (T_{it}), individual characteristics (X_{it}^{C}), work experience (Ex_{it}), and a shock (υ_{it}) that might include an external event (illness, divorce) or the chance of getting placed in a class which proves exceptionally difficult or easy for other reasons.

(2) $$E_{it} = f\left(H_{it}, A_i, P_i, S_{it}, T_{it}, X_{it}^{C}, Ex_{it}, \upsilon_{it}\right)$$

This education production function will dictate the return (in terms of academic achievement) of an hour of homework, which can vary by student ability, school quality, and other characteristics. Grades are a function of student's human capital, the amount of homework assigned (Ha_{it}), and the amount of homework completed (H_{it}).

(3) $$G_{it} = g\left(E_{it}, H_{it}, Ha_{it}\right)$$

Education, and thus homework, pays off by increasing expected future wages, which are rewarded at rate *p* which is the market price of human capital.

(4) $$W_i = pE_{it}$$

A student's demand for homework will depend on the elements of her utility function, the determinants of her future expected income, and the inputs into the education production function.

(4) $$H_{it}^{*} = h(A_i, P_i, S_{it}, T_{it}, p, Ha_{it}, X_{it}^{P}, X_{it}^{C}, Ex_{it}, \upsilon_{it})$$

Even within a class students will vary in the amount of homework that they do because they differ in levels of ability, levels of past achievement, preferences, and because they realize different shocks to their education which may induce them to study more or less often.

IV. Empirical Approach

Using a framework based on the theoretical model, this section explains the challenge of identifying the parameters of the education production function (equation 2), and presents an econometric approach for overcoming these challenges.[10] The simplest approach would be to estimate the following linear econometric model:

(5) $$AT_{it} = \alpha_0 + \alpha_1 H_{it} + \alpha_2 S_{it} + \alpha_3 T_{it} + \alpha_4 X_{it} + \lambda_i + \varepsilon_{it}$$

where AT_{it} is an achievement test score, which serves as a measure of human capital, the alpha parameters represent the impact of the inputs on academic achievement, λ_i is an error term that is constant over time, and ε_{it} is a time-varying error term. The error term λ_i will include two unobserved determinants of a student's human capital: student ability (A_i) and education inputs up until the start of grade 8 (P_i). The time varying error term

[10] For a more general discussion of the identification of education production function parameters see Todd and Wolpin 2003.

(ε_{it}) will include the unobserved education shock (υ_{it}). Estimating this model may produce biased estimates of the impact of homework (the parameter α_1) for three reasons:

1. The input H_{it} is partially determined by the student ability (A_i) and previous human capital investments (P_i), which also impact the students' achievement. These inputs are unobserved, however, and their impact on student study time is uncertain.
2. The unobserved human capital shock υ_{it} likely biases the parameter estimate downward, since a negative shock to a students' education would likely both decrease the amount the student learns in the year and increase the amount of time spent on homework (Stinebrickner and Stinebrickner 2007).[11]
3. The amount of homework that students complete is measured with some error. This variable is recorded categorically, and the questions and categories change slightly across waves. Measurement error of this type is likely to bias the estimates downward.[12]

Because the magnitude of these impacts is unknown, and there are possible biases in each direction, it is unclear whether the OLS cross section estimates will be biased upward or downward.

[11] For example, if a student became seriously ill for one semester, their test scores would likely suffer, but at the same time, they might increase the amount of time spent on homework in an attempt to make up for missed school. This would create a spurious negative correlation between homework time and test scores. A similar process may be likely for other types of shocks to a students' education, such as an poor teacher-student match. For a larger discussion of this effect, see Stinebrickner and Stinebrickner 2007.

[12] If the effect of the coding is to, on average, under-report the amount of homework done, then it is possible that the homework parameter would be biased upward as a result of this measurement error. In the more likely case that the reporting error is symmetric or close to symmetric around the true value, then the bias will be downward.

One method for addressing these identification problems is the use of instrumental variables estimation. The required instruments must affect student homework and be uncorrelated with the omitted variables. Using these variables to instrument for homework time isolates variation in the homework variable that is not correlated with the omitted variables. Estimating the effect of this exogenous variation in homework on achievement gives a consistent estimate of the impact of homework.

Using the two stage least squares estimation method, the first stage equation is estimated as in equation (6):

$$H_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 S_{it} + \beta_3 T_{it} + \beta_4 X_{it} + \beta_5 L_{it} + \phi_i + \varphi_{it} \tag{6}$$

In this specification Z_{it} is the set of instruments. Also the school inputs, teacher inputs and observed student characteristics are assumed to be exogenously determined. The second stage equation is the education production function as shown in equation (7), which includes the amount of homework predicted by the estimation of equation (6) ($\hat{H}_{it}$) instead of the observed homework amount (H_{it}).

$$AT_{it} = \alpha_0 + \alpha_1 \hat{H}_{it} + \alpha_2 S_{it} + \alpha_3 T_{it} + \alpha_4 X_{it} + \lambda_i + \varepsilon_{it} \tag{7}$$

The omitted ability, past inputs, and education shock variables (A_i, P_i, υ_{it}) are still present in the error terms in equation (7), but they will not be correlated with the predicted homework variable ($\hat{H}_{it}$).

The instrumental variables approach may not produce a consistent estimate of the impact of homework if there are endogenous variables other than the homework variable. If the omitted variables are also correlated with the other inputs in the education production function, then including these other inputs can bias the estimate of the effect of homework (α_1). A fixed effects estimator (or within estimator) can be useful for eliminating certain types of omitted variables problems. If an individual fixed effect is included, this will absorb the time-invariant individual specific error term λ_i.

This will eliminate bias caused by omitted variables under certain conditions. First, the omitted variables must not change over time. Second, the relationship between the omitted variables and achievement must be linear. Third, inputs in the education production function may be correlated with the time invariant error term (λ_i) but not with the time varying error. Thus even if there are multiple endogenous inputs in the education production function, the bias from time-invariant omitted variables, such as student ability (A_i) and education investments from before 8th grade (P_i), will be eliminated. Moreover, if the other inputs, such as teacher experience, certification, wages, or class size, are selected by students and parents, this selection is likely based on permanent student characteristics. As such, any bias caused by self selection is likely eliminated by using student fixed effects.

The fixed effects estimation will likely produce estimates of the impact of homework (α_1) that are biased downward, for two reasons. First, the time varying omitted shock υ_{it} may be correlated with the transitory portion of the homework and test score variables. If this is the case, the fixed effects will magnify the impact of transitory changes in homework due to this shock. Second, the measurement error will now account for an even larger portion of the variation left in the observed amount of homework. This means that the bias caused by measurement error will be more serious in a fixed-effects specification than in the first specification (equation 5).

In order to address these problems, I use instrumental variables to estimate a specification that includes student fixed effects. To do so, a student fixed effect is included in both the first and second stage equations. This somewhat eases the task of finding valid instruments, since instruments need to be uncorrelated with the time-varying error term, but may be correlated with the time-invariant error term.

Instruments

The two variables used in this study as instruments are the amount of homework assigned by the student's teacher and the student's measured locus of control. The amount of homework assigned by the student's instructor is unlikely to have any direct causal impact on test scores, apart from the effect on the amount of homework completed. This variable may reflect the ability and motivation of the students, however, if teachers assign more homework to classes with gifted or more motivated students, such as advanced placement or honors courses. Thus this variable may not be a valid instrument, except when student fixed effects are included in the first stage regression. The fixed effects will control for any selection based on time-invariant characteristics, such as student ability. The exogeneity of the instruments is tested in section six.

The second variable that is used to predict students' homework is the locus of control. This variable measures the degree to which a student believes that she can impact her own future, and varies greatly within students over time. A student with an internal locus is more likely to believe that her future depends on choices that she makes, while a student with an external locus is more likely to believe that external forces will dictate the events of her life.[13] Previous studies have found that a strong internal locus of control is associated with positive outcomes in situations that require independent decision-making, such as positive health behaviors (Steptoe and Wardle 2001), lower dropout rates in distance education (Parker 1999) and success in web-based coursework (Wang and Newlin 2000). Students with an internal locus, on average, spend more time doing homework, since they are more likely to expect the time investment today to pay off in the future. It may not be immediately obvious that the student's locus of control will be unrelated to their academic performance except through homework. It is reasonable to assume, however that variations in this variable do not impact a student's ability to answer mathematical questions correctly. I will show that the students' locus of control does predict the amount of time spent on homework, and does not, in a fixed effects specification, separately predict achievement test scores.

V. Data

The primary data used for the empirical work come from the National Education Longitudinal Study of 1988, a nationally representative longitudinal survey of students who were in the 8th grade in 1988. Follow up surveys were given in 1990 and 1992, with teacher and school counselor surveys in each wave, and parent surveys in the first and third waves. With each survey the students were given achievement exams in mathematics, science, English, and history. The exams are designed to allow comparison across waves, and to accurately test students at different achievement levels, and are reported as a standardized variable with a t-distribution, with mean 5 and a standard

[13] The locus of control used here is a combination of students' answers to three standard questions which ask the student things which might influence their future. For a detailed description of the construction of the locus of control variable, see appendix A.

Table 1: Summary Statistics

	Wave 1		Wave 2		Wave 3	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hours of Mathematics Homework per Week	1.46	1.68	5.31	4.74	5.76	4.27
Hours of Assigned Homework per Week[14]	2.23	0.95	3.21	1.79	2.88	1.41
Mathematics Test Score	4.68	0.83	5.21	0.95	5.87	0.96
Class Size (in units of 10 students)	2.41	0.51	2.35	0.55	2.78	1.66
Teachers are Certified in Subject Matter	0.82	0.37	0.99	0.08	0.99	0.10
Inexperienced Teachers	0.10	0.22	0.11	0.22	0.07	0.25
Minimum Annual Teacher Wage	28.48	5.18	29.40	5.60	30.92	6.64
Locus of Control	0.09	0.58	0.06	0.61	0.14	0.62
Average Peers' Test Score	5.34	0.52	5.49	0.68	5.65	0.73
Average Peers' HW Time on all subjects	5.43	1.72	7.46	2.29	13.14	3.37
State Unemployment Rate	5.70	1.54	5.60	0.98	7.22	1.41
Minimum Wage	3.37	0.07	3.50	0.29	4.27	0.08
Industry Mix	8.05	0.16	8.08	0.17	8.09	0.16
State Public four year tuition	1.61	0.53	1.92	0.67	2.43	0.82
State Financial Aid Per Student	0.33	0.27	0.36	0.28	0.46	0.39
State Higher Ed. Appropriations Per Student	6.39	1.88	6.90	2.05	6.74	1.64
Number of Students	7450		6402		3758	

This Data is from the National Education Longitudinal Study of 1988. Wave 1 corresponds to students in the 8th grade, wave 2 to the 10th grade, and wave 3 to the 12th grade. The summary statistics for this sample do not differ substantially from the complete sample of collected data. All monetary variables are measured in thousands of dollars, and inflation adjusted to 2005 dollars.

deviation of 1. Of the 17,580 students who have at least two recorded mathematics exam scores, 2295 students were not included in the sample used here because they did not respond to the questions about homework time or locus of control. Moreover, 5928 students were not included because the students' teachers did not respond to questions about their class size, experience or assigned homework, and 1455 were not included because of missing data on teachers' wages or the student's peers' behavior. The resulting sample includes 17610 observations on 7902 students. The characteristics of these students do seem to differ from the general sample on many key variables, both

[14] The amount of homework assigned per week is a classroom level variable, not student. It is computed as an average of the observed teachers' responses.

Table 2: Education Production Function Estimation Results

	1	2	3	4	5	6	7
Estimation Method	OLS	2SLS	OLS	2SLS	2SLS	2SLS	2SLS
Hours of Math Homework per Week	0.036	0.839	0.006	0.221	0.222	0.244	0.243
	(0.002)	(0.084)	(0.001)	(0.072)	(0.074)	(0.087)	(0.086)
Class Size (in units of 10 students)	-0.028	-0.015	-0.010	0.002	0.002	0.004	0.004
	(0.008)	(0.029)	(0.004)	(0.010)	(0.011)	(0.012)	(0.012)
Certified Teacher	0.126	-0.070	-0.011	-0.014	-0.014	-0.002	-0.001
	(0.026)	(0.057)	(0.014)	(0.034)	(0.034)	(0.037)	(0.037)
Inexperienced Teacher	-0.237	0.091	-0.016	0.090	0.099	0.108	0.106
	(0.029)	(0.102)	(0.015)	(0.051)	(0.052)	(0.059)	(0.058)
Minimum Annual Teacher Pay (in thousands)	0.006	0.025	0.003	0.009	0.007	0.005	0.004
	(0.002)	(0.005)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Student Fixed Effects	no	no	yes	yes	yes	yes	Yes
Peer Characteristics	no	no	no	no	yes	yes	Yes
Labor Market Characteristics	no	no	no	no	no	yes	Yes
Higher Edu. Market Characteristics	no	no	no	no	no	no	Yes

Standard errors are shown in parentheses. The dependent variable for each regression is the mathematics achievement test score. All regressions include wave indicators. The sample includes 17610 observations on 7902 students. Columns one and two are pooled regressions with the standard errors clustered at the level of the individual. The first stage regressions are shown in Table 3.

because of non-random attrition and non-random survey non-response.[15] Summary statistics of the variables used in this paper are shown in Table 1. In addition to the NELS data, data on state minimum wage laws from the Department of Labor are added, as are industry mix data from the 1988, 1990, and 1992 IPUMS Current Population Survey March supplement (King et al. 2008). The state level unemployment rate data came from Bureau of Labor Statistics. These data sets are used to create the labor market variables, which are merged with the NELS by the students' state of residence. Finally, the higher education variables come from the Almanac of Higher Education (Chronicle of Higher Education 1989, 1991, 1993). For variable definitions, see appendix A.

[15] See appendix F for an analysis of the attrition problem and sample comparisons.

VI. Results

This section first summarizes the estimates of the education production function. Second, it examines the validity of the instrumental variables, and finally it compares the impact of various education policies.

The Impact of Mathematics Homework on Mathematics Achievement

Table 2 displays estimates from each of estimation techniques and specifications described in the previous section.[16] Each specification includes wave indicator variables, the average observed class size and three indicators of teacher quality: whether the student's teachers are certified in their subject, an indicator that the teacher has less than 4 years of experience, and the minimum teacher pay in the student's school.[17]

The ordinary least squares estimate of the impact of an hour of mathematics homework per week, shown in column one, is a 0.036 standard deviation increase in the student's mathematics test score, which corresponds to an improvement of about 1.5 percentile points.[18] This estimate may be biased if the students' unobserved prior education inputs or innate abilities influence the amount of time spent on homework. Column two shows the two stage least squares estimates of the same specification. The amount of homework assigned and the student's locus of control are used as instruments excluded from the second stage to identify the amount of homework that students complete. The instrumental variables estimate is twenty-three times higher that the

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[16] For the full results for the main specifications, see appendix B.

[17] For a comparison to the "value added" specification, see appendix D. For an discussion of the problem of the left-censored independent variable, see appendix F.

[18] Starting from the 50^{th} percentile in Mathematics test scores within the sample.

estimate from column one, at 0.839 achievement test standard deviations, or an improvement of 29 percentile points for each hour of homework. This estimate is likely much higher for three reasons. First, it corrects for the downward bias due to measurement error. Second, it corrects for the downward bias documented by Stinebrickner and Stinebrickner (2007) that results from students responding to education shocks. Third, the two stage least squares estimate could be biased upward if students with greater motivation or intelligence select more difficult courses that include more assigned homework, since the amount of homework assigned is being used as an instrument. I test the validity of the instruments later, and find that in this specification, the estimate of the impact of homework is likely biased upward due to selection of this type.

The instrumental variables estimate may also be biased if students select other inputs based on unobservable characteristics. For example, parents of more able children may select better school districts with smaller class sizes and more qualified teachers. If this is the case, the other endogenous inputs can bias the estimate of the impact of an extra hour of homework.

In order to control for these selection issues, a fixed effects specification is employed. If the selection is based on student characteristics that do not change over time, then the student-fixed effects estimate will eliminate the bias not only in the impact of hours of homework, but also in the other inputs. This estimator will also control for the linear effects of any differences in past inputs that are not included in these specifications. The third column in Table 2 shows the estimates of the same specification as the one shown in the first column, but with student fixed effects included.

These estimates are much smaller. The impact of an hour of homework with student fixed effects is 1/6th the size of the OLS estimates presented in the first column.

The problems with the fixed effects estimates can be addressed by using instrumental variables in addition to the student fixed effects. The fourth column in Table 2 shows the results of the student fixed effects specification estimated using two-stage least squares, where the excluded instruments are again the amount of homework assigned by the student's teachers and the student's locus of control. This estimate, while less precisely estimated than the fixed-effects estimate, is much higher, and gives a quantitatively and qualitatively different result. A student who completes an extra hour of homework each week is estimated to improve her mathematics test score by 0.22 standard deviations, an improvement of 8 percentile points for each hour studied. A standard deviation increase in mathematics homework time, roughly 4 hours per week, would increase the student's mathematics test score by 30 percentile points. Even if we accept the lower bound of the 95% confidence interval for this estimate, which is 0.079 standard deviations, the return to homework is still 13 times higher than the fixed effects estimate. This lower bound estimate indicates that an hour of homework per week would move a student from the 50th percentile to the 53rd percentile in mathematics achievement.

If the instruments provide exogenous variation in student homework time, the estimates in the fourth column should not change substantially when other inputs are included in the specification. Columns five through seven test this by adding a series of other factors which might influence homework time. In each case the estimate of the return to homework changes only a small amount.

First, in order to control for other school-wide inputs and peer group influences, the specification shown in column five includes the average amount of homework done by the students' peers,[19] and the average mathematics test score of the student's peers.[20] The estimate of the impact of homework remains almost exactly the same.

Second, in column six, four state level labor market variables are added to the specification: the unemployment rate, the unemployment rate squared, the minimum wage, and an industry mix index that categorizes industries based on the average education level of their workers. These variables have been shown to be important predictors of student homework time (McMullen 2007). Moreover, column seven adds three higher education characteristics: the average tuition in four-year public institutions by state, the financial aid per college student by state, and state-level higher education appropriations per student. The combined impact of the labor market and college market variables is a small increase in the estimated impact of homework, indicating that controlling for external economic influences does not substantially impact the estimate of the return to homework.

In the final specification, shown in the seventh column, one hour of homework is estimated to increase as student's mathematics test score by 0.241 standard deviations, or nine percentile points. Four additional hours of math homework per week, a little over a standard deviation change, could move a student from the 50th percentile in mathematics to the 82nd percentile.

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[19] The students peers, in this case, are any students with observed test scores from the same school in the same year.

[20] Manski (1993) and Hanushek et. al. (2003) argue that peer effects of this type can introduce a bias due to the reintroduction of a student's ability through the student's influence on her peers. The estimated impact of homework does not change when these variables are included, indicating that if these variables are problematic, they do not bias the estimate of the impact of homework.

Other recent studies that have estimated the impact of homework time on student achievement have not been able to account for both time-varying and invariant unobserved characteristics. These studies found much smaller impacts.[21] The results reported here indicate that the use of student fixed effects to control for omitted inputs and characteristics has consistently produced estimates that are too low. This is likely the case because of a downward bias that results from measurement error, as well as downward bias caused by students responding to negative or positive education shocks. It is also likely that the impact of unobserved past inputs and characteristics biased the result downward, although the direction of bias from this source is uncertain. In light of this, the correction provided by the instrumental variables estimate is especially valuable.

First Stage Results and Instrument Validity

It is important to demonstrate that the excluded instruments strongly predict students' homework time without an independent effect on test scores. Table 3 shows the first stage equations for each of the regressions from Table 2 that were estimated with two-stage least squares. These results show that both hours of assigned homework and locus of control are important determinants of student homework time in each specification. Additionally, the last row in Table 3 shows the p-value for an F-test on the joint significance of the excluded instruments. The null hypothesis, that both variables

[21] The estimates presented in this paper are larger in magnitude than any in Cooper et al.'s 2006 review. Aksoy and Link also used the NELS data, and employed student fixed effects. See Aksoy and Link (2000) table three specification 1. Their estimate is divided by 13, which is the approximate standard deviation reported in table 1. They found results similar to those in table two column three: an hour of homework increases mathematics achievement by 0.051 standard deviations. The results of this study indicate that the true effect is much larger.

Table 3: First Stage Equation Estimation Results: Determinants of Student Homework Time

Corresponding Column in Table 2:	2	4	5	6	7
Hours of Homework Assigned per Week*[22]	0.113	0.071	0.071	0.064	0.065
	(0.023)	(0.026)	(0.026)	(0.026)	(0.026)
Locus of Control*	0.448	0.142	0.132	0.128	0.127
	(0.053)	(0.076)	(0.075)	(0.075)	(0.075)
Class Size (in units of 10 students)	-0.016	-0.055	-0.060	-0.062	-0.062
	(0.034)	(0.041)	(0.040)	(0.040)	(0.040)
Certified Teacher	0.244	0.025	0.013	-0.028	-0.032
	(0.061)	(0.144)	(0.144)	(0.144)	(0.144)
Inexperienced Teacher	-0.361	-0.495	-0.507	-0.500	-0.496
	(0.113)	(0.155)	(0.154)	(0.154)	(0.154)
Minimum Teacher pay	-0.023	-0.027	-0.020	-0.013	-0.011
	(0.005)	(0.009)	(0.009)	(0.009)	(0.010)
Student Fixed Effects	no	yes	yes	yes	Yes
Peer Characteristics	no	no	yes	yes	Yes
Labor Market Characteristics	no	no	no	yes	Yes
Higher Edu. Market Characteristics	no	no	no	no	Yes
Sargan Statistic (Chi-Sq p-value)	0.253	0.655	0.608	0.694	0.679
P-value for F-test of the joint impact of excluded instruments	0.000	0.006	0.006	0.012	0.011

The asterisk denotes instruments excluded from the second stage regression. Standard errors are shown in parentheses. The dependent variable for each regression is the total hours of math homework reported by the student. All regressions include wave indicators. The sample includes 17396 observations on 7808 students. Column two is a pooled regression with the standard errors clustered at the level of the individual. The second stage regressions are shown in Table 2.

have no impact on student's homework, would be rejected at less than a 2% confidence level for every specification.

For these instruments to be valid, however, it is also necessary that they do not have an independent impact on test scores, once the impact of homework is taken into account. The Sargan test for the over-identification of all instruments is reported for each specification in the last row of Table 2. This test checks for a relationship between the

[22] Because the assigned homework variable is an average of the observed teachers, who may or may not be the student's mathematics instructor, parameter estimates can not be interpreted as the additional homework that students complete in response to an assignment.

Table 4: Testing Instrument Validity

Dependent Variable	Independent Variable	Without Student Fixed Effects	With student Fixed Effects
Assigned HW	Lagged Test Score	0.359	0.139
		(0.021)	(0.118)
Locus of Control	Lagged Test Score	0.180	-0.035
		(0.009)	(0.037)
Assigned HW	Locus of Control	0.136	-0.001
		(0.018)	(0.029)

Standard errors are shown in parentheses. Each regression includes a wave indicator, and the specifications in row 2 include teacher pay, teacher experience and teacher certification variables.

instrumental variables residual and all of the exogenous variables in the model.[23] The null hypothesis for this test is that the instruments are uncorrelated with the error term, and thus that they are correctly excluded from the second stage equation. The null hypothesis can not be rejected for any of the fixed effects specifications at any conventional confidence level. This test indicates that both the student's locus of control and the amount of homework assigned are valid instruments in a fixed effects specification.

Despite this evidence, it is possible that the amount of assigned homework or the locus of control is correlated with past achievement. To test this, I estimate the impact of a lagged test score on the amount of homework students were assigned, including some current teacher-related covariates on the right hand side. The results are shown in Table 4. The estimates in the first column show that lagged test scores are strong predictors of each instrument when student fixed effects are not included. When the specification includes student fixed effects, however, the coefficient associated with the lagged test

[23] The Sargan statistic is obtained by regressing the IV residual on all exogenous variables, obtaining the R^2 term, and multiplying it by the number of observations. This resulting test statistic has a Chi-squared distribution with degrees of freedom equal to the number of instruments minus the number of endogenous variables.

scores can not be distinguished from zero. This indicates that past academic achievement is not correlated with the instruments when fixed effects are included.

It is also possible that both of the instruments are correlated with the same unobserved student or school characteristics and contain the same bias. In the last row and last column of Table 4 the locus of control is regressed on the amount of assigned homework in specification with student fixed effects and period intercepts. In this specification the student's locus of control has no effect on the amount of homework that the student is assigned. These variables, therefore, likely do not capture any common unobserved variables and do provide exogenous variation in homework time.

Diminishing Returns To Homework Time

So far the econometric model estimated has restricted the impact of homework to a linear effect, not allowing the possibility of diminishing returns to studying. This restriction is easily relaxed by estimating a second order polynomial in homework, which is done in Table 5. The first two columns show the first stage equations predicting student

homework time and student homework time squared. The instruments excluded from the second stage equation were the amount of assigned homework, the locus of control, and each of these instruments squared.

For students currently not spending any time doing mathematics homework, the return on completing one hour of homework per week would be about a 10 percentile point improvement in mathematics test scores. This return decreases as students spend more time studying. The marginal effect of studying an additional hour if the student is

Table 5: Decreasing Returns to Hours of Homework

	1	2	3
Dependent Variable	Hours of Math HW	Hours of Math HW Squared	Math Test Score
Hours of Math Homework per Week			0.295
			(0.059)
Hours of Math Homework Squared			-0.012
			(0.003)
Hours of HW Assigned per Week	0.091	0.707	
	(0.051)	(1.080)	
Hours of Homework Assigned Squared	-0.003	-0.011	
	(0.004)	(0.084)	
Locus of Control	-0.046	-4.518	
	(0.128)	(2.687)	
Locus of Control Squared	0.173	4.089	
	(0.069)	(1.459)	
Locus of Control Times Hours of Assigned Homework	0.065	1.398	
	(0.038)	(0.793)	
Class Size (in units of 10 students)	-0.062	-1.790	-0.015
	(0.040)	(0.849)	(0.007)
Teacher Certified in Subject	-0.029	-1.686	-0.020
	(0.144)	(3.025)	(0.023)
Inexperienced Teacher	-0.503	-10.490	-0.005
	(0.154)	(3.232)	(0.031)
Minimum Teacher pay	-0.010	-0.263	0.002
	(0.010)	(0.203)	(0.002)
Marginal Effect of HW Evaluated at the mean			0.206
			(0.041)

Standard errors are in parentheses. The first two columns are the first stage equations; the third column is the second stage equation. Each regression includes student fixed effects, peer characteristics, labor market and higher education market characteristics, and wave indicators.

currently studying the average amount (about 3.7 hours) is a 7.5 percentile point increase in test scores. These results also indicate that mathematics homework ceases to improve test scores if a student does more than about 11 hours per week. By this standard, the majority of students could increase their test scores if they spent more time on their mathematics homework.

Table 6: Impact of Homework Time by Student Achievement and School Quality

Group		8th Grd. Sci. Exam	School Quality
Bottom Half	Hours of Math Homework	0.324	0.485
		(0.088)	(0.246)
	Math HW Squared	-0.017	-0.027
		(0.005)	(0.017)
	Marginal Effect	0.198	0.279
		(0.057)	(0.157)
Top Half	Hours of Math Homework	0.142	0.234
		(0.072)	(0.063)
	Math HW Squared	-0.004	-0.010
		(0.004)	(0.004)
	Marginal Effect	0.109	0.161
		(0.047)	(0.041)

The impact is measured by the coefficients associated with an hour of homework per week in an instrumental variables regression with student fixed effects, where the dependent variable is the Mathematics achievement test score. Student achievement is measured by the student's 8th grade science test scores. School quality is measured by the average mathematics test score of all other observed students in the same school.

Impact of Homework Time by Achievement Level and School Quality

In this section, I will try to relax the restriction that students at different levels of achievement or in different types of schools receive the same return on homework time. To do this I estimate the specification from Table 5 separately for high achieving and low achieving students, as well as high and low performing schools.[24] Each specification includes a squared term,[25] and thus marginal effects are reported, evaluated at the mean reported homework time for the entire sample.

First, students are separated into two groups of equal size based on their 8th grade science test scores. The students in the lower achieving group experience much higher returns to studying than those in the high achievement group. The impact of an hour of homework for the low-achievement group is large enough to improve a student's

[24] I also tested to see if the effect differed by class size, teacher experience, race, and parents' income. None of these divisions yielded interesting differences.

[25] The effect is similar if the squared term is not included. The second order polynomial is used in this section because this specification results in more precise estimates.

mathematics achievement by 7.6 percentile points. An additional hour of homework by a high achieving student, however, only improves her achievement by 4 percentile points.

This indicates that students who fall behind do have some ability to catch up to their peers simply by doing the same amount of homework. For example, consider a student in the low achievement group, who is currently spending one hour on homework each week. By studying three hours more per week, this student could move from the 25th percentile to the 50th percentile in a single year. A student in the high achievement group, who is currently studying one hour a week, would have to study seven additional hours each week to make a similar move from the 50th to the 75th percentile. This evidence does not support the common assumption that more able students receive a higher return to homework time because their time is more productive (Neilson, 2005; Eren and Henderson, 2007).

Second, students were split into groups of equal size based on the test score performance of their peers, as a general measure of school quality. Students in the lower performing schools experienced a return to homework time that was twice as strong as those in high performing schools. A student in a low performing school, who currently studies one hour each week that wanted to move from the 50th percentile to the 75th percentile, would have to study 1.8 additional hours per week, whereas a student in a high performing school would have to study four additional hours to improve the same amount. This may indicate that at low performing schools homework is a stronger determinant of success. Bishop (2007) reports that less material is presented in class time in low performing schools, which may partially explain why studying at home would be more beneficial for these students. Overall, this investigation provides evidence that students' achievement in mathematics can be dramatically improved by effort, even if the student finds herself at the bottom end of the achievement distribution in a low performing school.

Impact of Assigned Homework on Academic Achievement

While students are able to adjust the amount of time they spend on homework directly, the more realistic policy instrument is the amount of homework that teachers assign. Teachers' assignments, even if only completed a fraction of the time, have a strong influence on the amount of homework students complete. For comparison, the regression below shows the impact of a series of policy instruments, including the amount of mathematics homework assigned by teachers per week (h_{it}), on a mathematics test score (TS_{it}):[26]

(12)

$$\underset{}{TS_{it}} = \underset{(0.005)}{0.020h_{it}} - \underset{(0.0002)}{0.0007h_{it}^2} - \underset{(0.006)}{0.012s_{it}} - \underset{(0.021)}{0.018c_{it}} - \underset{(0.024)}{0.018x_{it}} + \underset{(0.001)}{0.002p_{it}} + \alpha_7 pc_{it} + w_t + \mu_i + \varepsilon_{it}$$

Where s_{it} is the school class size (in units of 10 students), c_{it} indicates that the teacher is certified in mathematics, x_{it} is the fraction of the students' observed teachers that have less than three years of teaching experience, p_{it} is the minimum teacher pay in the students' school, pc_{it} is a pair of peer characteristics variables including an average of peers' test scores and the average amount of homework completed by the student's peers. Additionally w_t is a set of wave-specific dummy variables, μ_i is a student specific

[26] This regression is on a smaller sample of 9776 observations on 4990 students. This is the sample of students who have multiple responses by a mathematics instructor. The larger sample consists of students who study math but may or may not have had a mathematics instructor interviewed.

Table 7: Impact of a $10,000 per classroom investment:

Policy	Impact: SD	Impact: Percentile Points
Increasing Assigned Homework	0.071	2.67
	(0.023)	
Increasing Teachers' Wages	0.020	0.80
	(0.012)	
Decreasing Class Size	0.006	0.24
	(0.003)	

Results are calculated using the coefficients reported in equation 12, an average class size of 25, average yearly teachers' wage of $47,602, an hourly wage of $29.75 for teachers, and an opportunity cost of $10.37 for students. Standard errors are shown in parentheses. See appendix C for calculations.

intercept or fixed effect, and ε_{it} is the error term.[27] The effects of teacher certification and teacher experience are not precisely estimated; neither effect is statistically different from zero at any conventional confidence level. These two policies are excluded from the following analysis. The marginal effect of assigning an additional hour of homework for students currently being assigned the average amount (2.9 hours per week) is 0.016 (standard error 0.004) test score standard deviations.

To compare the size of these effects, it is useful to do a comparison of the cost of implementing each policy, and the resulting academic achievement gains. Table 7 shows the impact on mathematics achievement of a $10,000 investment in three possible policies. To approximate the social cost of assigning more homework, I assume that teachers are paid almost $30 an hour for their time. The time of the students is valued at the average wage in 1990 for teenagers between the ages of 16 and 18 converted to 2005 dollars, plus the present discounted value of the return that students receive from an additional hour of work experience. The total opportunity cost in 2005 dollars is estimated to be $10.37.[28] The cost of decreasing class size is limited here to the cost of

[27] For the full results from the regression shown in equation 12, see appendix B.

[28] For a complete description of all of the cost calculations that went into table 7, see appendix C.

Table 8: Impact of Assigned Homework on Mathematics Achievement by Achievement and School Quality

	8th Grade Sci. Exams	School Quality
Bottom Half	0.012	0.013
	(0.005)	(0.005)
Top Half	0.004	0.002
	(0.004)	(0.004)

Standard errors are shown in parentheses. For each result, assigned homework is used to predict mathematics achievement in a student fixed effect regression specification. Teacher experience, certification, salary, class size, peer effects, and wave indicators were also included in each specification. Prior Achievement is measured using the students' 8th grade science achievement test. School quality is measured using the average test score of other observed students in the same school.

hiring additional teachers. The cost of building new classrooms and the impact of decreasing teacher quality are not considered here. Using these values and the parameter estimates from equation 12, I can calculate the approximate number of new hours of homework, that can be completed for a $10,000 investment, and the impact of that homework increase. The calculations that went into Table 7 are shown in appendix C.

The first column shows the impact in on mathematics achievement in standard deviations, the second shows the impact in percentile point improvements. Assigning additional homework is estimated to have 3.5 times the impact of increasing teachers' wages for a given monetary investment. Similarly, assigning additional homework has over 11 times the impact per dollar of decreasing class size.

Finally, it is worth exploring whether this policy will have a differential impact based on school quality and prior student achievement. Table 8 shows the impact of assigning additional mathematics homework for the top and bottom halves of the achievement and school quality distributions. The impact is estimated with similar precision for each subgroup, but the effect is much smaller for high performing students and students in high performing schools. Assigning an additional hour of homework per week to a student whose peers are, on average, below the 50th percentile in mathematics achievement is estimated to improve their achievement by 1/2 of a percentile point. Comparing this effect to the impacts in Table 7, a $10,000 investment put into increasing homework for a classroom of students in this low-performing group would increase each student's achievement by .084 standard deviations, or 3.36 percentile points. This effect is larger than the impacts of similar investments in homework, teachers' wages, or class sizes shown in Table 7.[29]

VII. Conclusions

The results in this paper strongly support the argument that policies that increase the time that students spend on their homework, and policies that increase the amount of assigned homework are likely to increase the performance of low-performing students and those in low-performing schools. Specifically, students who do an extra hour of mathematics homework per week achieved 8 to 9 percentile points better than their peers on standardized exams. Because the sample used is nationally representative, the results should be applicable to a number of school settings. As a caveat however, there is some evidence that the sample used for this analysis suffers from non-random attrition due to dropouts and/or incomplete survey response.

As a tool of policy, increasing the amount of homework that students complete shows some promise. Assigning additional homework is estimated to have a much larger

[29] It is difficult to measure the difference in impact of teacher salaries and class size between these groups, because of the imprecise estimates. The impact of decreasing class size and increasing teachers' wages by school quality and student performance is as follows (standard errors in parentheses): decreasing class size by 10 students is estimated to increase performance by 0.017 (0.012) standard deviations among low performing students, 0.015 (0.012) standard deviations among high performing students, 0.03 (0.03) standard deviations among students in low performing schools, and 0.013 (0.008) standard deviations among students in high performing schools. Increasing teachers wages by $1000 is estimated to increase achievement by 0.0008 (0.002) standard deviations among low performing students, 0.002 (0.002) standard deviations among high performing students, -0.007 (0.006) standard deviations among students in low performing schools, and 0.004 (0.002) standard deviations among students in high performing schools.

impact per dollar invested than either increasing teachers' wages or decreasing class sizes. Additionally, because much of the benefit of assigning additional homework goes to low-achieving students and students in low-performing schools, this policy could be useful for lowering the achievement gap between high achieving and low achieving students.

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Chapter 3: Do High School Students Respond to Labor Market and Education Incentives? An Analysis of Homework Time and Dropout Rates

Introduction

In the labor economics and education literature, there is some evidence that student achievement is correlated with economic conditions (Bishop 1991). While it is often assumed that students consider labor market incentives when choosing how long to remain in school, choices students make in school have largely been ignored. This paper presents evidence that students respond to labor market opportunities when making choices about both school enrollment and study time. Moreover, the evidence suggests that students are not merely trading off school work for labor market participation, but are instead considering future labor market opportunities when deciding how much time to spend on homework.

In order to understand the relationship between students' education choices and external incentives, I present a model of forward looking students with incomplete information about future labor market conditions. Within such a framework, students choose to either stay in school or drop out based on both present and expected future labor market opportunities. Similarly, students choose how much time to spend on homework based primarily on expected future returns in higher education and the labor market.

Informed by this model, I estimate the impact of labor market variables on both the probability that a student will drop out of high school and the amount of time students devote to homework. In order to address possible biases due to geographic selection and unobserved individual heterogeneity, I estimate specifications that include state and individual fixed effects, and control for important individual and family demographic characteristics.

I find that the probability of dropping out of school and the amount of homework that students complete are both influenced by education and labor market conditions. Shifts in the state industry mix toward higher-education jobs are associated with lower dropout rates and increases in student homework. Additionally, a higher minimum wage decreases dropout rates and increases the amount of homework that students do. Finally, a higher unemployment rate increases the amount of homework that students complete.

Background literature on the relationship between students' education choices and their opportunities:

The current research dealing with student decision making while in high school has focused primarily on enrollment choices. This focus has left students' other decisions, such as how much homework to do, relatively unexamined. There is strong evidence for example, that students' decisions to drop out of high school are dependent on immediate labor market incentives, such as changes in low-skill wages (Black, McKinnish, and Sanders 2005; Gustman and Steinmeier 1981). Ribar (1993, 2001) found mixed evidence that young people who have completed high school respond to returns to education and changes in average wages when making enrollment decisions.

Others have looked at the impact of unemployment trends and found that their effect on enrollment is small, (Ihlanfeldt 1992) and that it varies substantially between men and women (Card and Lemieux 1997). Finally, there is evidence that students' college enrollment decisions are dependent on their current labor market opportunities (Fredriksson 1997) as well as changes in the return to education (Card and Lemieux 2001).

In a closely related issue, there has been considerable research regarding the impact of the minimum wage on school enrollment. Using the Leighton and Mincer (1981) framework, the theoretical predictions about this relationship are ambiguous. An increase in the minimum wage can have multiple effects: the anticipated wage if employed can increase, the probability of employment can decrease, and the return to skill can increase. If a student's wage prospects[30] fall, because the increased unemployment probability outweighs the increase in wages, then students will demand more schooling. If wage prospects increase, students may still demand more schooling if the returns to schooling increase faster than wage prospects. This could occur as a result of firms substituting more skilled workers for less skilled workers in response to the wage regulation. If, however, wage prospects increase faster than the return to schooling, students at the margin will choose to substitute labor market activity for continued schooling, and drop out of school.[31]

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[30] Leighton and Mincer define "wage prospects" as the minimum wage times the perceived probability of finding employment in the covered sector. In the case of risk neutrality, this is equal to the expected wage, in the case of risk aversion, wage prospects will be lower than the expected wage.

[31] Agell and Lommerud (1997) propose a model in which the effect of a minimum wage is to increase investment in education among those of moderate skill, and decrease education among those with low skill. I find that the opposite seems to occur: students with low academic performance have the stronger positive enrollment and homework responses to a higher minimum wage.

The empirical research on the topic has produced mixed results. Neumark and Wascher (1995a, 1995b, 2003) have found that students are more likely to drop out of school when the minimum wage increases. Chaplin, Turner and Pape (2003), found similar results, but only among younger students in states that did not have school attendance requirements after age 16. Matilla (1978), however found a positive enrollment response, and Cunningham (1981) found a positive enrollment response for some groups and a negative response for others.

Students may also make decisions about the amount of time to spend on homework based on expected future labor market conditions. Bishop (1991), documents a relationship between high school student achievement test scores and the return to education. His framework attributes this relationship to students choosing to exert additional effort when returns to education are higher; however he is not able to document this claim with data on study time. Similarly, Georgia's Hope scholarship program has been the subject of a series of studies, one of which shows that student achievement has increased among students near the margin of qualification for the program (Henry and Rubenstein 2002). Again, without data on student effort, this achievement gain is attributed to increased time on homework. Thus, while the literature has not directly addressed the possible relationship between homework time and education or labor market incentives, these studies suggest two possible determinants of student homework time: the labor market return to education and the price of college education.

If doing homework is rewarded in the form of higher wages, it is likely that this return is not realized immediately upon entering the labor market. Farber and Gibbons

(1996) propose a dynamic model of learning about worker ability in the labor market which predicts that time invariant abilities, such as the cognitive human capital not reflected in years of schooling, will be increasingly correlated with wages as the worker's experience in the labor market increases. As time passes employers learn about workers' true productivity, and workers wages will thus more accurately reflect human capital as their years of experience increase. This prediction is supported by their empirical work as well as that of others (Murnane, Willett, and Levy 1995, Bishop 1992). The implication of these findings is that students' effort in school to build up human capital will likely pay off later in their working careers, while their years of schooling will pay off immediately after leaving school.

A model of students' education and homework choices:

The following three-period model illustrates the possible influences that labor market conditions and education incentives can have on students' choices. Students face a standard tradeoff between consumption and leisure, choosing how many hours to work in each period, how much time to spend doing homework in the first period, whether to drop out of high school, and whether to attend college. In the first period, students can choose to complete high school, in which case their first period utility U_1 depends on their choice of the number of hours to work (h_1) and the amount of time to spend on homework (HW). In each period, there is some probability, determined by the period specific unemployment rate μ_t, that work will not materialize, and the student will be constrained to zero hours of work for that period, yielding a utility in which consumption is determined by y, the student's consumption endowment.

(1) $$U_1 = u\left(y + w_L h_1, T - HW - h_1 - t_{hs}\right)$$

Here T is the student's endowment of time, w_L is the wage earned by workers without a high school degree, and t_{hs} is the amount of time devoted to attending high school.

Students observe employment opportunities before deciding whether to drop out of high school, still a student could drop out of high school even if employment in period one is not an option. If the student chooses to drop out of high school, their first period utility is determined by the following:

(2) $$U_1 = u\left(y + w_L h_1, T - h_1\right)$$

Students discount future utility at a rate β. In the second period, if the student chose to complete high school, the student can now choose either to attend college, or to enter the labor market full time. If college is chosen the student's second period utility is as follows:

(3) $$U_2 = u\left(y + w_{hs}\left(HW\right)h_2 - C\left(HW\right), T - h_2 - t_{college}\right)$$

Where with probability μ_2 the student's hours of work are constrained to zero. Consumption in college is dependent on the cost of college, C, which is a function of how much homework the student completed in high school. Additionally, the wage of students who finish high school is also a function of their high school homework time. If instead the student chooses to enter the labor market, their utility is:

(4) $$U_2 = u\left(y + w_{hs}\left(HW\right)h_2, T - h_2\right)$$

As before, with probability μ_2 the student's hours of work are constrained to zero.

In the third period students enter the labor market full time. Those who finish college now earn a wage equal to w_c, also a function of the amount of homework the student completed, whereas students who did not attend college still earn a the wage w_{hs}. Their third period utility functions differ only by the wage and their chosen hours of work. In each case, the probability that h_3 is constrained to equal zero is μ_3.

(5)
$$U_3 = u\left(y + w_c\left(HW\right)h_3, T - h_3\right)$$
$$U_3 = u\left(y + w_{hs}\left(HW\right)h_3, T - h_3\right)$$

In this framework, students have two complementary ways to invest in human capital, one is to stay in school and the other is to complete more homework in the first period. Homework pays off both in terms of higher wages and lower college costs. Optimal investments in human capital will depend on the exogenous inputs into the model, including the cost of college, the unemployment rate, and the return on human capital.[32] If a student has a high discount rate, a future positive return on homework time may not he large enough to compensate students for the lost leisure or disutility from doing homework in the first period. If this is the case, they may spend little or no time doing homework.

Also, students observe the future cost of higher education and future labor market conditions with uncertainty. If their expectations of future conditions are functions of the current state, then the optimal schooling, homework, and hours of work choices will depend on current period wages, college tuition costs, and unemployment.

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[32] The wage gain in the third period that a student will receive for completing college is: $w_c(HW) - w_{hs}(HW)$, empirically this will likely be positive. The return that a student receives for doing an additional hour of homework while in high school will be different depending on the student's choice of education attainment. For high school dropouts, there is no return on homework, for high school and college graduates, the return in future wages is $\frac{dw_i}{dHW}$, where i is the education level of the student.

This model also provides some conditions under which the labor market parameters will certain effects on student's human capital investments.[33] In the simple case in which the student does not choose the hours worked, an increase in the unemployment rate will decrease the amount homework students complete because of the decreased probability of a future wage or tuition reward. If hours of work are chosen, then the result is mixed. If we assume a non-backward bending labor supply curve, then the result will be the same. But absent this assumption, a increase in unemployment could cause a decrease in expected future income, if this income effect is strong enough to overwhelm the substitution effect (substituting leisure for homework because the reward for homework has fallen) then students could increase their homework time in response to a lower unemployment rate.

An increase in the unemployment rate, in this framework, will always cause students to be more likely to drop out of school. This arises because students know their employment opportunities for period 1 (either they have a job available or not), so the unemployment rate only changes the probability of employment in future periods.

Estimating the impact of labor market conditions on the probability of dropping out of high school:

For the estimation of the impact of labor market conditions on the probability of dropping out of school, I employ a discrete time hazard framework as shown below:

$$(Y^*_{ijt} \mid Y^*_{ijt-1} = 0) = \alpha_0 + \alpha_1 U_{jt-1} + \alpha_2 I_{jt-1} + \alpha_3 M_{jt-1} + \alpha_4 C_{jt-1} + \alpha_5 X_{ijt-1} + \xi_{ijt}$$

(6) $Y^*_{ijt} = 1$ if student is not enrolled in school at time t.

$Y^*_{ijt} = 0$ if student is enrolled in school at time t.

[33] For a derivation of these results, see appendix G.

Where U_j is the state specific unemployment rate, I_j is a variable that captures how education-intensive the industries are in state j. M_j is the state specific minimum wage rate, and C_j is the cost of public college education. Additionally, X_{ij} is a vector of student and family characteristics, and can be included to capture important differences between demographic groups. I estimate equation (6) using a probit estimator. The parameter estimates, when transformed into marginal effects, can be interpreted as the impact of a given labor market variable on the probability that a student will drop out of school.

Student's dropout decision can occur anytime between the survey periods. In the NELS data, that means the student could have dropped out of high school up to 1.5 to 2 years prior to it showing up in the next survey. For this reason lagged labor market conditions are used to predict dropout behavior. When the same specifications are estimated using current labor market conditions, the econometric model's explanatory power falls dramatically.

Estimating the impact of labor market conditions on students' homework time:

A simple way to estimate the impact of education and labor market incentives on homework choices would be to use ordinary least squares to estimate the following specification:

(7) $$H_{ij} = \beta_0 + \beta_1 U_j + \beta_2 I_j + \beta_3 M_j + \beta_4 C_j + \beta_5 X_{ij} + \varepsilon_{ij}$$

Where H_{ij} is the hours of homework that student i in state j reports completing per week. In this reduced form specification, the impact of these education and labor market variables can be interpreted as the response of students to these incentives when choosing how much homework to complete.[34]

In the specification described above, the parameters of interest will only be estimated without bias if there is no unobserved component that influences both the labor market conditions and the amount of homework that students complete. For example, it is possible that there is some characteristic of a household that makes parents more likely to select a certain labor market, and also causes them to encourage their child to study more in high school. If this characteristic is not fully accounted for with variables about parents' labor force status, education, income and other family characteristics in the data set, then this selection into a particular labor market could bias the estimates of each parameter. This problem could also occur, as the labor market changes, if people move to areas with lower unemployment or higher wages. It is likely, however, that some portion of this selection happens within states, and since I am using state-wide measures of labor market characteristics, this should be less of a problem. The problem remains, however, if people select their home state based on some unobservable characteristic.

If the problematic omitted variables are state-level characteristics that correlate with both the labor market variables and student effort, then unbiased estimates can be obtained by including state fixed effects. This requires significant variation over time in the labor market conditions however, since the cross-state variation will be absorbed by the fixed effects.

It is also possible that the unobserved family or student characteristics are correlated with the labor market characteristics. If these variables do not change over

[34] Because homework time is conditional on a student not dropping out of school, all of the results for this section are valid for the sample of students who remain in school at least through the 10^{th} grade.

time or the migration is sufficiently slower than the observed changes in the labor market, unbiased estimates can be obtained by estimating a specification that includes student fixed effects. Student fixed effects will also fix problems associated with selection at other levels, such as selection at the school or class level, if the selection is based on individual characteristics. This approach also requires variation in the labor market variables of interest over time.

Data

The primary data I am exploring on students' behavior and characteristics will come from the National Education Longitudinal Study of 1988 (NELS). The labor market data comes from the 1988, 1990, and 1992 Current Population Survey (CPS) March supplement, and the Department of Labor. The higher education variables come from the Almanac of Higher Education (Chronicle of Higher Education 1989, 1991, 1993).

The NELS was designed to be a nationally representative sample of students in the 8^{th} grade in 1988. Surveys were given to the student, one of the student's parents, two of the student's teachers, and one school representative three times: in 8^{th}, 10^{th}, and 12^{th} grade. The students were also given exams in four subjects. Due to low response to some parts of the survey many of the original observations were dropped from the sample used in this analysis. The remaining sample has similar characteristics to the broader sample; for an explanation of the drops and a comparison of the sample statistics, see appendix F. In the final sample, 36698 observations over three periods are used to analyze student's homework completion.

Table 1: Selected Summary Statistics

Variable	Wave 1 (1988) Mean	Wave 1 (1988) SD	Wave 2 (1990) Mean	Wave 2 (1990) SD	Wave 3 (1992) Mean	Wave 3 (1992) SD
Hours of Homework Completed per Week	6.061	5.095	7.926	6.539	14.129	9.663
Unemployment Rate (2-year ave.)	6.054	1.787	5.476	1.207	6.879	1.621
Minimum Wage (2007 dollars)	5.901	0.163	5.600	0.489	6.311	0.115
Industry Education Score	8.067	0.168	8.091	0.173	8.094	0.165
Public 4-year tuition (in 1000's of 2007 dollars)	2.787	0.901	3.025	1.059	3.584	1.203
Observations	18294		11785		6619	
Dropped Out of School			0.030	0.169	0.040	0.197
Unemployment Rate (2-year ave.)			6.051	1.781	5.490	1.155
Minimum Wage (1990 dollars)			5.903	0.174	5.637	0.527
Industry Education Score			8.068	0.167	8.097	0.178
Public 4-year tuition (in 1000's of 2007 dollars)			2.776	0.895	2.995	1.056
Observations			20870		19573	

The sample used to examine dropout rates is less restricted because a different set of covariates is used for this analysis, but is limited to the 2nd and 3rd waves in order to perform the hazard analysis. This sub sample includes 40595 observations over two periods. In this group, 3 percent of students who were in the survey in 8th grade had dropped out by 10th grade, and 4 percent of those in the survey in 10th grade had dropped out of school by 12th grade. Table 1 shows selected summary statistics for the two samples. For variable definitions, see appendix A.

The primary measure of effort will be the number of hours the student spends on homework per week. This measure includes homework on all subjects, and is student reported. A student is determined to have dropped out of school only if the survey can confirm that the student is not attending school. This results in slightly lower dropout rates[35], since it is likely that some of the students who do not show up in later waves have dropped out of school but the survey organization was unable to confirm their status.

[35] The cumulative dropout rate for this sample is 3% for students between 8th and 10th grade and 4% for students between 10th and 12th grade, producing a 7% cumulative dropout rate in this sample. In the

This restricted sample of dropouts is preferable to using a graduation rate, since many students who do not remain in the study may have lost contact for another reason.

To create the education-industry mix variable I utilize the 1988, 1990 and 1992 Current Population Survey March supplement data, all from the IPUMS data archive (King et al. 2008). I restricted this sample to those between ages 16 and 65 who are not residing in group quarters. This variable is created by first assigning a value to each industry that equaled the average education level of its observed workers. Second, each state is assigned a value created using a weighted average of these education scores, where the weights are the number of employees in that particular industry in the state in a given year.[36] Changes in this variable over time reflect changes in the education-intensity of the jobs available in the state.

The minimum wage variable is defined as the highest applicable legal wage minimum, either the state or federal minimum wage for the given year, adjusted for inflation using the consumer price index. There were 16 states that had state minimum wage laws that exceeded the federal legal minimum at some point over the four year period, and all states experienced a change in the legal minimum at some point over this four year window.

The unemployment information comes from the local area unemployment statistics data available from the Bureau of Labor Statistics. The variable is constructed

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sample not restricted by the covariate set, the cumulative dropout rate is 9.7%. The National Center For Education Statistics (2002) found that in 1992, about 11% of 16 to 24 year olds were currently high school dropouts, indicating that about 12% of dropouts were not confirmed as such by the survey. For a discussion of the differences between the sub-sample and full NELS sample, see appendix F.

[36] The CPS person weights were used to ensure that these averages were representative of the state population.

by averaging the monthly state level unemployment rate for the current and previous year. Changing the construction of this variable to a one month or one year average does not noticeably change the results.

Results – The impact of labor market conditions on students' dropout choices

The probit estimates of the impact of labor market variables on the probability that students will drop out of school are shown in Table 2. Marginal effects are reported, evaluated at the sample mean of each variable.[37] In the first specification, the cost of higher education, measured here as the average (tuition) cost of a 4-year public college education, has a small negative impact on the probability of dropping out of school, though the parameter estimate is not statistically different from zero. The industry education score, which measures how education-intensive the industries in the state are, is a strong predictor of student dropout behavior. The standard deviation of this variable is about 0.17 in this data;[38] a change of this magnitude is estimated to decrease the probability of dropping out of high school by 0.65 percentage points. A higher unemployment rate is estimated to decrease the probability of dropping out of school, with the biggest impact for increases in the range below 5%. Finally, a $1 increase the

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[37] The marginal effects are computed for continuous variables as $\phi(\beta' x)\beta$ where $\phi(\cdot)$ is the standard normal density function, x is vector of covariates, and β is the vector of estimated coefficients. Marginal effects for the dichotomous variables are calculated for a discrete change in the dependent variable from 0 to 1.

[38] The average 2-year change in the industry education score is about 0.1, so a one standard deviation change is reasonable.

Table 2: The Impact of Labor Market Conditions on the Probability of Dropping Out of High School.

	2	3
Public four year college tuition (in thousands)	-0.0003	-0.0009
	(0.0014)	(0.0010)
Industry Education Score	-0.0327	-0.0121
	(0.0068)	(0.0044)
Unemployment rate: 4.8 to 5.5 percent	-0.0040	-0.0018
	(0.0058)	(0.0042)
Unemployment rate: 5.5 to 6.3 percent	-0.0042	-0.0030
	(0.0033)	(0.0023)
Unemployment rate: 6.3 to 7.5 percent	-0.0044	-0.0013
	0.0038	(0.0027)
Unemployment rate: above 7.5 percent	-0.0070	-0.0026
	(0.0042)	(0.0033)
Minimum Wage	-0.0063	-0.0047
	(0.0030)	(0.0023)
Individual Characteristics	X	X
Family Characteristics		X

Discrete time hazard model, estimated as a probit, with standard errors (in parentheses) clustered at the state level. A time period is two years. The unemployment rate is the two year monthly average over the current and previous year, the excluded unemployment rate category is from 2.4 to 4.8 percent. Other variables are lagged one period. The total number of observations is 40443. Marginal effects are reported. All specifications include a wave three intercept. Individual characteristics include sex, race, and locus of control. Family characteristics include parents education, income, and whether the family owns more than 50 books. All monetary values are in 2007 dollars.

minimum wage, contrary to the findings of some of the literature,[39] is estimated to decrease the probability of dropping out by 0.74 percentage points.

The second specification includes parent's characteristics. Controlling for these observable demographic characteristics decreases the magnitude of all of the parameter estimates except the impact of increasing the cost of public higher education. Students are estimated to somewhat decrease their probability of dropping out of school in

[39] Neumark and Wascher (1995a, 1995b, 2003) and Chaplin, Turner and Pape (2003) both find that increases in the minimum wage increase dropout rates, Evans and Turner (1995) challenged this result. Matilla (1978) and Cunningham (1981) both found decreased dropout rates as a result of higher minimum wages.

Table 3: The Impact of labor market conditions on the probability of dropping out by sex, achievement, and income.

Group	Female	Male	High Income	Low Income	High Achievement	Low Achievement
Public four year college tuition (in thousands)	-0.0010	-0.0009	-0.0017	-0.0007	-0.0018	0.0002
	(0.0011)	(0.0012)	(0.0011)	(0.0011)	(0.0008)	(0.0015)
Industry Education Score	-0.0153	-0.0085	-0.0046	-0.0154	-0.0071	-0.0147
	(0.0060)	(0.0052)	(0.0073)	(0.0061)	(0.0037)	(0.0066)
Unemployment rate: 4.8 to 5.5 percent	0.0017	-0.0056	0.0037	-0.0046	0.0007	-0.0049
	(0.0039)	(0.0052)	(0.0032)	(0.0053)	(0.0024)	(0.0072)
Unemployment rate: 5.5 to 6.3 percent	-0.0010	-0.0052	0.0036	-0.0065	-0.0006	-0.0067
	(0.0024)	(0.0032)	(0.0025)	(0.0030)	(0.0023)	(0.0039)
Unemployment rate: 6.3 to 7.5 percent	-0.0005	-0.0021	0.0045	-0.0042	0.0024	-0.0067
	(0.0031)	(0.0037)	(0.0032)	(0.0036)	(0.0022)	(0.0041)
Unemployment rate: above 7.5 percent	-0.0022	-0.0027	0.0042	-0.0056	0.0045	-0.0111
	(0.0032)	(0.0046)	(0.0031)	(0.0042)	(0.0027)	(0.0050)
Minimum Wage	-0.0057	-0.0036	-0.0019	-0.0071	-0.0006	-0.0093
	(0.0025)	(0.0028)	(0.0031)	(0.0031)	(0.0019)	(0.0043)
Observations	20460	19983	18452	21991	21001	19442

Discrete time hazard model, estimated as a probit, with standard errors (in parentheses) clustered at the state level. A time period is two years. The unemployment rate is the two year monthly average over the current and previous year, the excluded unemployment rate category is from 2.4 to 4.8 percent. Other variables are lagged one period. Marginal effects are reported. All specifications include a wave three intercept. Individual characteristics include sex, race, and locus of control. Family characteristics include parents education, income, and whether the family owns more than 50 books. All monetary values are in 2007 dollars. The income specifications are split based on annual family income in 8th grade. The achievement specifications are split based on 8th grade achievement exams in four core subjects.

response to an increase in college tuition. The degree to which industries in the state are education intensive does have an impact that is significant at the 5% confidence level: the estimates indicate that a standard deviation increase in this measure decreases the probability of dropping out of high school by 0.26 percentage points. The effect of the minimum wage is also somewhat diminished, but these estimates still indicate that a $1 increase in the minimum wage decreases the probability of dropping out by 0.59 percentage points.[40]

[40] For full results from specification 2, see appendix B. These results are robust to changes in the specification. Neither adding interaction terms or relaxing linear specification for the variables of interest changes the qualitative results.

There is some evidence that that young men and young women respond differently to labor market incentives (Ribar 2001, Card and Lemieux 2001).[41] Using the same specification used in column 3 of Table 2, Table 3 shows estimates the effects separately by sex, parents' income, and achievement in 8th grade. In general, women, low-income students, and those with low achievement are more responsive than their counterparts. Specifically, women are almost twice as responsive to changes in the degree of education-intensity in industry, and their response to changes in the minimum wage is 77% larger than the response of men. Conversely, men seem more responsive to changes in the unemployment rate than women, though the estimates are very imprecise.

Increased college tuition is associated with a decreased probability of dropping out of school for almost all students, with the largest impact among high achieving students. Even with this group the impact is not large: a $1000 increase in public tuition decreases the probability of dropping out by 0.18 percentage points. It is young women, low income students and low achieving students, however, that respond to changes in the industry mix. A one standard deviation increase in the industry-education variable corresponds with a 0.42 percentage point and 0.32 percentage point decrease in the probability that low income and low achieving students respectively, will drop out of high school. Similarly, while high income and high achieving students have little or no response to a change in the minimum wage, low income and low achieving students respond to a dollar increase in the minimum wage by increasing their enrollment in high

[41] There are a number of reasons that women and men might respond to labor market signals differently, at the time that this data was collected, women had lower high school graduation rates, lower college attendance rates (conditional on high school completion), and lower labor force attachment (Card and Lemieux 2001). For this reason it makes sense that more women might be on the margin between entering the labor market or not, and are more likely to be swayed by changes in the minimum wage or returns to education. Similarly, with lower labor force attachment, they may be less influenced by unemployment rate changes.

school. The size of the impact for low income students is about 1.3 percentage points for both groups. The impact of changes in the unemployment rates for these groups is less clear. Both low achieving and low income students in general have a stronger response than their counterparts, though the direction of the impact is not consistent, and the magnitudes of many of the effects are not statistically different from zero.

Results – The impact of education and labor market incentives on students' homework time

In addition to choosing whether or not to finish high school, students also choose how much effort to exert while in school. The amount of time spent on homework is one avenue for students to exert effort and invest in human capital. Table 4 shows the results of four regression specifications, each predicting student homework time using state level college tuition prices and a series of labor market variables. The estimates in column one indicate that a one thousand dollar increase in four year public university tuition decreases students' homework time by about 13 minutes per week. A standard deviation increase in the industry-education score corresponds to an increase in homework time of about 23 minutes per week. The estimate for the impact of the minimum wage indicates that a $1 increase in the minimum wage in a state will increase the amount of homework that students do by about 21 minutes per week. The impact of the unemployment rate has high standard errors, and in this specification, is estimated to have a generally positive impact on the amount of homework that students complete. [42]

[42] Because I use a homework measure which combines all subjects, very few students report doing zero hours of homework per week. For this reason, tobit estimates of the impact of labor market conditions on homework time are extremely similar to OLS estimates.

Table 4: The response of students' homework time to labor market conditions

	1	2	3	4
Public four year college tuition (in thousands)	-0.222	-0.240	-0.011	-0.086
	(0.113)	(0.092)	(0.182)	(0.189)
Industry Education Score	2.242	0.670	0.973	1.096
	(0.605)	(0.508)	(0.694)	(0.728)
Unemployment rate: 4.8 to 5.5 percent	0.056	-0.110	-0.757	-0.892
	(0.274)	(0.228)	(0.168)	(0.182)
Unemployment rate: 5.5 to 6.3 percent	-0.042	0.068	-1.072	-1.089
	(0.254)	(0.209)	(0.162)	(0.176)
Unemployment rate: 6.3 to 7.5 percent	0.095	0.071	-1.373	-1.334
	(0.283)	(0.214)	(0.204)	(0.223)
Unemployment rate: above 7.5 percent	0.147	0.091	-1.482	-1.512
	(0.347)	(0.271)	(0.241)	(0.264)
Minimum Wage	0.353	0.381	0.411	0.405
	(0.258)	(0.247)	(0.160)	(0.173)
Student, Family, and Peer Achievement		X	X	X
State Fixed Effects			X	
Student Fixed Effects				X

The dependent variable in each specification is the number of hours of homework completed per week. Each regression has a sample of 36698 observations. Standard errors are clustered at the state level. The excluded unemployment rate category is from 2.4 to 4.8 percent. The student, family, and peer characteristics include the amount of homework assigned, the students' locus of control, an average of the peers' test scores in the student fixed effects specifications, and these variables plus parents' education, income and whether the family owns more than 50 books in the specificiatons without student fixed effects. Each specification includes wave indicators. All monetary values are in 2007 dollars.

There is some reason to believe that these cross section estimates may be biased. If there are differences in populations across states that influence how much homework students do, these characteristics could end up being correlated with the parameters of interest. To address geographic selection that is based on student and family characteristics, I include a series of covariates that are important determinants of student homework time, including the amount of homework that was assigned by the students teachers, the student’s locus of control, the average of the student’s peers’ test scores, parent’s education, parent’s income, and whether the household owns more than 50 books. The inclusion of these variables has some impact on the estimates, most notably the impact of the education-intensity of industry and the unemployment rate.

It is also possible that the parameters of interest are correlated with other unobserved permanent state-wide characteristics of the population. One way to control for this unobserved state heterogeneity is to include state level fixed effects in the specification. This is done in column 3.[43] In this specification the impact of college tuition becomes trivial. The impact of the having more education intensive industry growth increases by about a third, and the impact of increasing the minimum wage increases by about 8%. The impact of the unemployment rate changes dramatically. These estimates indicate that students consistently decrease the amount of homework that they complete as the unemployment rate increases, with diminishing effect at higher unemployment rates. A change in the unemployment rate from 5 to 6 percent is estimated to decrease the amount of homework students do by about 19 minutes per week.[44]

It is also possible, however that some sort of geographic selection based on unobserved individual or family characteristics is driving these results. The student and family covariates may not capture this selection sufficiently, but any permanent heterogeneity should be captured by individual fixed effects. Column 4 shows a specification with student fixed effects, but no state fixed effects.[45] These results are very similar to the specification with state fixed effects. The only exception is the impact

[43] In specification 3, the state effects are jointly statistically different from zero at the 1% confidence level.

[44] These results are similar when compared to a specification that uses the natural log of homework as a dependent variable. See appendix D for a comparison.

[45] The family characteristics are not time-variant in this data, and thus it is not possible to include them in the individual fixed effects specifications.

Table 5: The response of students' homework time to labor market conditions by sex, income and achievement.

Population	Women	Men	High Income	Low Income	High Achievement	Low Achievement
Public four year college tuition (in thousands)	-0.109	-0.078	-0.086	-0.090	-0.251	0.055
	(0.276)	(0.259)	(0.258)	(0.279)	(0.266)	(0.268)
Industry Education Score	2.373	-0.017	1.757	0.396	0.753	1.034
	(1.029)	(1.031)	(1.038)	(1.024)	(1.053)	(1.001)
Unemployment rate: 4.8 to 5.5 percent	-0.752	-1.001	-0.842	-1.011	-1.059	-0.919
	(0.258)	(0.257)	(0.254)	(0.264)	(0.261)	(0.254)
Unemployment rate: 5.5 to 6.3 percent	-1.011	-1.149	-1.094	-1.115	-1.331	-1.022
	(0.248)	(0.251)	(0.251)	(0.250)	(0.262)	(0.237)
Unemployment rate: 6.3 to 7.5 percent	-1.122	-1.534	-1.197	-1.508	-1.206	-1.616
	(0.315)	(0.315)	(0.310)	(0.324)	(0.318)	(0.311)
Unemployment rate: above 7.5 percent	-1.567	-1.438	-1.452	-1.615	-1.605	-1.695
	(0.371)	(0.375)	(0.368)	(0.382)	(0.381)	(0.364)
Minimum Wage	0.578	0.229	0.281	0.527	0.104	0.629
	(0.240)	(0.248)	(0.243)	(0.246)	(0.248)	(0.239)
Observations	18696	18002	17697	19001	17119	19579

The dependent variable in each specification is the number of hours of homework completed per week. The full sample, split approximately in half for each pair of specifications includes 31334 observations. Each specification also includes the amount of homework assigned, the student's locus of control, an average of peers' test scores, and wave indicator variables. The excluded unemployment rate category is from 2.4 to 4.8 percent. All monetary values are in 2007 dollars. The income specifications are split based on annual family income in 8th grade. The achievement specifications are split based on 8th grade achievement exams in four core subjects.

of college tuition, which has a larger impact, but is still not significantly different from zero.[46]

As with student's dropout decisions, it is likely that students' responses vary by sex, family income, and achievement. In Table 5 the student fixed-effects specification is estimated separately by these variables. The differences between the responses of men and women are similar to those shown in Table 3. Women respond more strongly to changes in the education-intensity of industry and changes in the minimum wage. In fact,

[46] For full results for specification 4, see appendix B. These results are robust to changes in the specification. Neither adding interaction terms or relaxing the linear specification changes the qualitative results. Also, in a specification that includes both state and individual fixed effects, the state fixed effects are not jointly statistically different from zero.

men respond half as strongly to changes in the minimum wage, and show no response to changes in the education intensity of industry. Conversely, young men have a slightly stronger response to changes in the unemployment rate.

Contrary to the results in Table 3, it is high income students who show a stronger response to changes in the education intensity of industries. In keeping with earlier results however, low income students have a much stronger response to changes in the unemployment rate and the minimum wage. Low achieving students have a stronger response to changes in the education-intensity of industries than high achieving students, and a response to the minimum wage that is six times greater in magnitude. Their responses to changes in the unemployment rate however, are similar.

The direction of the impacts for homework time is consistent with the impacts of the same variables on the probability of dropping out of school. A more education intensive industry mix encourages more investment in human capital both in terms of enrollment and homework, especially among women. A higher unemployment rate, where it is estimated to have an effect, consistently induces young people to invest less in human capital. The industry education score is a likely indicator of higher returns to education, and should signal to young people that investments in education will be rewarded in the labor market. Conversely, a higher unemployment rate diminishes expected labor market returns at all levels, thus diminishing the value of human capital investment.

According to Leighton and Mincer's (1981) framework, the minimum wage has effects both on labor supply and labor demand. The positive correlations found here between the minimum wage and students' human capital investments is consistent with a higher youth unemployment rate, and with firms substituting high-skill workers for low-skill workers in response to a minimum wage increase. Or, in similar fashion, firms my decrease the amount of training that they provide, inducing workers to pursue more training through schooling and homework.

As stated earlier, there is evidence that investment in homework pays off in the long run, compared to years of schooling, which are rewarded in the labor market more immediately.[47] This payoff timeframe is consistent with the observed impacts of the unemployment rate. If students take the unemployment rate to be a signal of future employment prospects, and this effect dominates the short-run trade-off between labor market participation and human capital investment, then there will be, as observed, an inverse relationship between the unemployment rate and human capital investment.

Conclusions

Given concerns about academic achievement in U.S. secondary education, there are obvious reasons to increase time spent on homework (McMullen 2008) and lower dropout rates among high school students. These estimates provide evidence that a wider range of determinants may be important for understanding student achievement. In particular, students' human capital investment while in high school is influenced by education and labor market incentives.

An implication of these findings is that shifts in the labor market toward more education-intensive jobs seem to increase students' investment in human capital, through both enrollment and homework time. Conversely, high unemployment rates decrease the amount of homework students do. These relationships hold up both in cross sectional

[47] See Farber and Gibbons (1996), Murnane, Willett, and Levy (1995), and Bishop (1992).

and panel data analysis, indicating that they are not driven by geographic selection or unobserved state characteristics. These indicate that some of the geographic variation in achievement outcomes are likely due to these labor market factors, and not directly attributable to school or teacher characteristics.

Finally, students have real responses to the supply-side impacts of changes in the minimum wage. Women, low income students, and low achieving students especially increase their human capital investment when faced with a higher minimum wage. This finding runs counter to some of the literature on the minimum wage and dropout rates. The effect is appears both in student's enrollment and homework choices, and occurs most strongly in the groups that are more likely to be impacted by the minimum wage.

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Appendix A: Variable Definitions

Mathematics Test Scores: The cognitive tests were given to students with each survey, and varied according to students' past performance. For this reason, raw scores are not used, but instead the scores are normalized across waves, and I divided the variables by 10 within each year so that the standard deviation is approximately equal to 1. The tests were created to allow comparison across grades, and to accurately measure student achievement even if students do not complete the entire exam.

Hours of Mathematics Homework: This variable measures the number of hours that the student spends per week on mathematics homework. The NELS data records the hours of homework completed in a series of categories. Each student is assigned the mean value for their category.

Hours of Homework: This variable measures the number of hours that the student spends per week on homework in all subjects. The NELS data records the hours of homework completed in a series of categories. Each student is assigned the mean value for their category.

Class Size: This is defined as the average size of the observed classes taken by the student in each wave.

Teacher Has Certification in Field: This variable equals 1 if all of the teachers surveyed for this student have the certification to teach the class that the student is taking. It equals 0.5 if one teacher is certified and the other is not, and it equals 0 if all of the teachers surveyed are not certified.

Inexperienced Teacher: This indicator variable is equal to one if the teacher interviewed has three or less years of experience. The source variables did not allow for separate indicators for one, two, and three years of experience.

Minimum Teachers' Wage: This variable comes from the school counselors' survey, and records the minimum annual wage for a teacher in the school that the student is attending. This variable is adjusted so that it is measured in units of $1000 inflation-adjusted 2005 dollars.

Assigned Homework: This is a continuous variable recording the average hours per week that the students' interviewed teachers assigned. The source variables were all continuous, though the base year was a weekly variable and the second and third waves asked for daily amounts. I multiplied the daily homework amounts by 5 to get the weekly amount.

Locus of Control: This is a composite of three questions, which measures the degree to which the student has an "internal" locus of control. Students with an internal locus believe that their actions and choices can shape their future, where students with an external locus believe external events will be the primary determinants of what their future is like. A higher number indicates that the students' locus is more internal. The questions ask the student to agree or disagree (five point scale) with the following statements:

> "In my life, good luck is more important than hard work for success."
> "Every time I try to get ahead, something or somebody stops me."
> "My plans hardly ever work out, so planning only makes me unhappy."

Minimum Wage: The highest legally binding minimum wage for the student's state of residence, either the statewide or federal minimum. This variable is adjusted for inflation to 2005 dollars.

Unemployment Rate: The 2 year average of the monthly unemployment rate for the students' state of residence.

Industry Mix: An industry-education index. This variable takes the nation-wide average education level for employees in a given industry based on the 1990 IPUMS CPS march supplement. The index is a sum of this statistic for each industry in the state, weighted by the number of people in the state that are employed in that industry.

Parents' Income: Annual family income recorded in 1988. The variable is recorded in 14 categories. The value of this variable is the average of the category range, those in the top category were assigned 1.5 times the top value.

Parents' Education: The average years of schooling of the student's parents.

Family owns more than 50 books: A dichotomous variable indicating whether or not the student's family owns more than 50 books.

Appendix B: Selected Full Regression Results

Table B1: Full Regression Output for the Main Results – Chapter 2

	1	2	3
Dependent Variable:	Hours of Homework	Math Test Scores	Math Test Scores
Hours of Mathematics Homework per Week		0.243	
		(0.086)	
Hours of Assigned Homework per Week	0.065		0.009
	(0.026)		(0.003)
Locus of Control	0.127		
	(0.075)		
Class Size (in units of 10 students)	-0.062	0.004	-0.012
	(0.040)	(0.012)	(0.006)
Teachers are Certified in Subject Matter	-0.032	-0.001	-0.020
	(0.144)	(0.037)	(0.021)
Inexperienced Teachers	-0.496	0.106	-0.015
	(0.154)	(0.058)	(0.023)
Minimum Annual Teacher Wage	-0.011	0.004	0.002
	(0.010)	(0.003)	(0.001)
Average Peers' Test Score	0.001	0.001	0.001
	(0.001)	(0.000)	(0.000)
Average Peers' HW Time	0.117	-0.029	-0.002
	(0.018)	(0.011)	(0.002)
State Unemployment Rate	-0.996	0.262	
	(0.197)	(0.100)	
State Unemployment Rate Squared	0.063	-0.017	
	(0.014)	(0.007)	
Minimum Wage	0.285	-0.104	
	(0.234)	(0.065)	
Industry Mix	0.229	-0.089	
	(0.525)	(0.136)	
State Public four year tuition	0.091	-0.022	
	(0.210)	(0.210)	
State Financial Aid Per Student	-0.499	0.206	
	(0.508)	(0.137)	
State Higher Ed. Appropriations Per Student	-0.082	0.016	
	(0.078)	(0.021)	
Wave 2 Indicator	3.599	-0.351	0.521
	(0.114)	(0.316)	(0.011)
Wave 3 Indicator	3.325	0.165	0.972
	(0.299)	(0.300)	(0.023)
Constant			3.997
			(0.085)
No. of Observations	17610	17610	9776
No. of Students	7902	7902	4990

Standard errors are reported in parentheses. Column 1 shows the full first stage results from Table 3 column 7. The column 2 shows the second stage results from Table 2 column 7, and the last column shows the results from equation 12. All equations include student fixed effects. The homework used in column two is the value of homework time predicted by the specification in column one.

Table B2: Full results for selected specifications – Chapter 3

Specification	Table 2: Col. 3	Table 4: Col. 5
Public four year college tuition (in thousands)	-0.0009	-0.0782
	(0.0010)	(0.2016)
Industry Education Score	-0.0121	1.0984
	(0.0044)	(0.7431)
Unemployment rate: 4.8 to 5.5 percent	-0.0018	-0.8846
	(0.0042)	(0.1832)
Unemployment rate: 5.5 to 6.3 percent	-0.0030	-1.0799
	(0.0023)	(0.1783)
Unemployment rate: 6.3 to 7.5 percent	-0.0013	-1.3164
	(0.0027)	(0.2256)
Unemployment rate: above 7.5 percent	-0.0026	-1.4926
	(0.0033)	(0.2692)
Minimum Wage	-0.0047	0.4248
	(0.0023)	(0.1734)
Female	-0.0020	
	(0.0011)	
Black	-0.0052	
	(0.0017)	
Hispanic	-0.0002	
	(0.0022)	
Asian/Pacific Island	-0.0097	
	(0.0019)	
American Indian	0.0166	
	(0.0044)	
Other Race	0.0099	
	(0.0083)	
Parents' Education	-0.0098	
	(0.0011)	
Parents' Log Income	-0.0085	
	(0.0008)	
Family Owns >50 Books	-0.0068	
	(0.0019)	
Hours of Homework Assigned		0.1736
		(0.0333)
Average of Peers' Test Scores		0.0368
		(0.0126)
Locus of Control		0.3635
		(0.1003)
Wave 2 Indicator		1.5591
		(0.1275)
Wave 3 Indicator	0.0089	7.3914
	(0.0024)	(0.1921)

Column one is estimated as a probit, and has a sample size of 40443. Column two is estimated using OLS, includes student and state fixed effects, and has a sample size of 31334 observations.

Appendix C: Policy Comparison

Results shown in Table 7.

Assigning Additional Homework:

Average Annual Teacher Salary for 2005: $47,602 (American Federation of Teachers 2007) Hourly wage: $47,602 a year / 40 weeks per year / 40 hours per week = $29.75 per hour.

I assume that 1 hour of assigned homework takes the teacher 1 hour to prepare and record. So a one hour increase in homework per week would cost the teacher $29.75 per week for 40 weeks, totaling $1190.

Among students for whom a mathematics instructor is surveyed, when the first stage equation from Table 3 column 5 is estimated, the coefficient on the hours of homework assigned variable is 0.103. This indicates that students complete an additional 0.103 hours of homework per hour assigned. The value of students' time has two components, first, the wages they could earn, for which I use the 1990 average hourly wage for 16 to 18 year olds, which in 2005 dollars is $5.63 per hour[48]. Additionally, the opportunity cost for the students includes the value of work experience. To estimate the present discounted value over the student's lifetime of an hour of work experience, I estimated the following wage equation using the 1990 5% census sample:

$$\text{Log}\, W_i = \alpha_1 + \alpha_2 Educ_i + \alpha_3 Exp_i + \alpha_4 X_i + \varepsilon_i$$

Where W_i is the hourly wage, $Educ_i$ is a vector of education attainment indicator variables, Exp_i is a vector of 25 experience indicators variables, defined as age - years of

[48] This is very close to the federally mandated minimum wage for 1990, which in 2005 dollars is $5.68 per hour. Teenagers could be lawfully paid less than the minimum wage in some circumstances.

school – 6, and X_i is a vector of sex and race indicator variables. The α_3 coefficients are used to create a wage profile for a person with a high school education over a 50 year working career, assuming that they start with the average wage cited above, $5.63 per hour. The profile of a similar person with one less experience step is subtracted from this profile, to find the wage profile difference due to an additional year of experience at the beginning of their career. Finally, this schedule of wage differences is discounted using a 5% interest rate, and divided by a 50 week year, 40 hour a week working schedule to find the value of an hour of experience. This amount, in 2005 dollars is $4.74. The total hourly opportunity cost for a student is therefore $10.37. Assuming the class includes 25 students, the student cost of an additional hour of assigned homework for one week is $26.70. Over 40 weeks, the total cost to students is $1068.11.

Thus the total social cost of assigning one additional hour of homework per year is $2258. A $10,000 investment in additional assigned homework could "buy" 4.43 hours of homework per year. This homework investment, multiplied by the homework coefficient from equation 12 is 4.43*.016 which is a 0.07 standard deviation increase. This would result in a class wide increase in math achievement of 2.7 percentile points.

Increasing Class Size

The average class size observed in the NELS data is 25 students. The cost of decreasing a class by one student is therefore roughly 1/25th of the cost of a teacher's annual salary. So $47,602/25 = $1904 is the relevant cost. This understates the cost if there are space constraints, and the schools need to find additional classroom space or build new schools.

A \$10,000 investment in class size reduction per classroom would thus be enough to reduce classes by 5.25 students. This reduction, according to the impact estimated in equation 12, would increase students' mathematics achievement by 0.006 standard deviations. This corresponds to a change of 0.24 percentile points. This impact is overestimated, however, if lower quality teachers are hired in order to reduce class size.

Increasing Teachers' Wages

The only teachers' pay measure available in the NELS data across all three waves is the minimum full time teacher's wage. Since most teachers get paid according to a district-wide scale that depends on education and experience, the minimum wage is probably a good measure of the impact of wages, since it will not be confounded with the impact of teachers' education or years of experience.

The impact associated with increasing a teachers' wage by \$10,000 is ten times the impact shown in equation 12, which amounts to 0.02 standard deviations. This effect would increase the mathematics achievement by 0.8 percentile points.

Table D1: Comparison with Value-Added Specification

Estimation Method	OLS	OLS	OLS	2SLS
Hours of Math Homework per Week	0.009	0.007	0.006	0.244
	(0.001)	(0.001)	(0.001)	(0.087)
Class Size (in units of 10 students)	-0.010	-0.008	-0.011	0.004
	(0.004)	(0.004)	(0.004)	(0.012)
Certified Teacher	0.035	0.020	-0.012	-0.002
	(0.057)	(0.058)	(0.014)	(0.037)
Inexperienced Teacher	-0.041	-0.027	-0.011	0.108
	(0.021)	(0.021)	(0.015)	(0.059)
Minimum Annual Teacher Pay (in thousands)	0.002	0.002	0.002	0.005
	(0.001)	(0.001)	(0.001)	(0.003)
Lagged Mathematics Test Score	0.903			
	(0.006)			
Student Fixed Effects	No	No	Yes	Yes

The total number of observations for each specification is 17610. Each specification also includes peers' test scores, peers' homework time, labor market conditions, and wave indicators. The dependent variable for columns 1,3, and 4 is the student's mathematics test score, for column 2 it is the difference between the current test score and that of the previous period.

Appendix D: Alternate Specifications

The "value added specification" has become a standard in the education production function literature, due largely to the prevalence of data which does not allow more detailed specifications of the production function. In the context of this paper, a value added specification would be the following:

$$AT_{it} = \alpha_0 + \alpha_1 H_{it} + \alpha_2 S_{it} + \alpha_3 T_{it} + \alpha_4 X_{it} + \alpha_5 AT_{it-1} + \lambda_i + \varepsilon_{it}$$

The only difference between this specification and the one in equation 7 is the addition of the achievement test score from the previous period to the right hand side of the equation. This lagged test score is meant to control for all time-invariant unobserved student characteristics (λ_i), and thus produce a less-biased estimate of the parameters of interest. Another common method for estimating a value added specification is to use the difference in test scores between two periods as the dependent variable, while using nondifferenced independent variables. For a broader discussion of the merits of this approach see Todd and Wolpin (2003).

It is likely that the value added specification will produce estimates that suffer from the same biases as the fixed effects specifications, which also control for time-invariant student characteristics, but do nothing to eliminate bias due to measurement error or time varying education shocks. Moreover, since the lagged test score on the right hand side is an endogenous variable, the presence of this control may bias the estimates of the other parameters.

Table D1 shows the results of three specifications similar to that of Table 2 column 6. The first column is a valued-added specification, estimated with OLS, the second column shows the same specification, only instead of a lagged test score, this specification includes student fixed effects. Finally, column three includes student fixed effects and is estimated using two stage least squares. The value-added specifications in the first and second columns produce results that are of similar magnitude to the fixed effects specification, and with similar precision. The results are much smaller than those produced with the fixed effects-IV estimation strategy used in this study. Using the value added approach to investigate the impact of homework on academic achievement would result in estimates that are much lower than the true value.

Somewhat in the spirit of the value added specification, it is also worth considering specifications which include inputs from previous periods, but not the lagged test score. The justification for this specification is that the current test score is a product of multiple years of inputs, and the fixed effects will eliminate the influence of inputs prior to the first period, but inputs from the previous period might still be relevant.

Table D2: Alternate Specifications

	1	2
Hours of Math Homework per Week	0.192	-0.038
	(0.124)	(0.043)
Hours of Math Homework Per Week in Previous Period	0.136	
	(0.089)	
Hours of Math Homework per Week Squared	-0.010	
	(0.006)	
Hours of Math Homework Per Week in Previous Period Squared	-0.005	
	(0.005)	
Hours of Math Homework per Week in Wave 2		0.148
		(0.031)
Hours of Math Homework per Week in Wave 3		0.181
		(0.035)
Class Size (in units of 10 students)	-0.001	0.000
	(0.001)	(0.001)
Class Size in Previous Period	0.002	
	(0.003)	
Certified Teacher	0.099	0.021
	(0.151)	(0.022)
Certified Teacher in Previous Period	-0.032	
	(0.043)	
Inexperienced Teacher	0.055	0.038
	(0.050)	(0.027)
Inexperienced Teacher in Previous Period	0.121	
	(0.107)	
Minimum Annual Teacher Pay (in thousands)	0.005	0.003
	(0.003)	(0.001)
Minimum Annual Teacher Pay in Previous Period	0.004	
	(0.004)	
Observations	3612	17610

Standard errors are shown in parentheses. The dependent variable for each regression is the mathematics achievement test score. All regressions include wave indicators, peer characteristics, student fixed effects, labor market conditions and higher education conditions. In column one, the excluded instruments are the amount of homework assigned, the locus of control, each of these squared, and lagged values of these four instruments. In the second column, the excluded instruments are the locus of control and the amount of homework assigned interacted with wave indicators.

Column 1 in Table D2 shows the results of a specification in which the contemporaneous and lagged values of each input into the education production function are included. The value of inputs two periods back can not be included in a specification that includes fixed effects. The cost of adding in these other inputs is that the sample is limited to only 3612 students, since this specification requires three observations on each student. Because of the smaller sample, the estimates are somewhat less precise.

This specification does show that past inputs do affect current performance. The lagged homework variable, which is estimated using two stage least squares, is estimated to have 7/10ths the effect of contemporaneous homework. None of the estimates in this specification, however, are statistically different from zero.

It is also worth considering different effects by grade. The specification estimated in column 2 of Table D2 estimates three homework effects, one for each year in the sample. This specification produces similar results to those in column 1. This specification indicates that in high school homework has a much stronger effect than in 8^{th} grade. This specification has some advantages over the one used in the Table 2, except that the instruments are not as powerful in 8^{th} grade as they are in 10^{th} and 12^{th} grades, so the 8^{th} grade estimate is less trustworthy.

Chapter 3

As an additional specification test, Table D3 compares two sets of results for the homework model. Column 1 shows the results from Table 4 column 4, which uses weekly homework as the dependent variable and column 2 uses the natural log of weekly homework as a dependent variable. Column 3 displays the marginal effects from the specification in column two, using homework hours as the units, so that they can be compared to the results from column 1. The marginal effects were calculated using the smearing factor as outlined in Naihua Duan (1983) and Norton (2006): assuming non-

Table D3: Specification Comparison For Homework Model

	1	2	3
Public four year college tuition (in thousands)	-0.086	0.017	0.115
	(0.189)	(0.021)	
Industry Education Score	1.096	0.040	0.268
	(0.728)	(0.083)	
Unemployment rate: 4.8 to 5.5 percent	-0.892	-0.130	-0.884
	(0.182)	(0.021)	
Unemployment rate: 5.5 to 6.3 percent	-1.089	-0.136	-0.924
	(0.176)	(0.020)	
Unemployment rate: 6.3 to 7.5 percent	-1.334	-0.159	-1.083
	(0.223)	(0.025)	
Unemployment rate: above 7.5 percent	-1.512	-0.181	-1.231
	(0.264)	(0.030)	
Minimum Wage	0.405	0.074	0.504
	(0.173)	(0.004)	

Column 1 shows the results using hours of homework per week as the dependent variable. Column 2 shows results when the log of homework hours is used as the dependent variable, column three displays the estimates from column 2 shown as marginal effects in homework hours, comparable to column 1.

normal homoskedastic errors, the estimated marginal impact of a change in an independent variable x is equal to $\frac{\partial \mathrm{E}[H]}{\partial x} = \hat{\beta}_x \mathrm{E}\left[\hat{H}\right]$ where $\mathrm{E}\left[\hat{H}\right] = e^{X\hat{\beta}}\left(\frac{1}{N}\sum_{i=1}^{N} e^{\hat{\varepsilon}_i}\right)$.

The effects of industry score and public college tuition differ between specifications, though the differences are not statistically significant. The impact of the unemployment rate, while slightly smaller with the log specification, is similar. The impact of the minimum wage is close between the two specifications, with slightly higher results in the log specification.

Table D4 shows the results for a specification that includes another potentially important dependent variable in the dropout model: the high skill-low skill log wage differential.[49] If this wave difference is large, students would be expected to drop

[49] This variable was created using the 1988, 1990 and 1992 March CPS data. The average log wage is calculated for high and low skill groups, based on education, where high skilled

Table D4: Dropout Model Extensions

	1	2
Public four year college tuition (in thousands)	-0.0002	0.0030
	(0.0013)	(0.0055)
Industry Education Score	-0.0310	-0.0003
	(0.0070)	(0.0163)
Unemployment rate: 4.8 to 5.5 percent	-0.0043	-0.0028
	(0.0057)	(0.0047)
Unemployment rate: 5.5 to 6.3 percent	-0.0046	-0.0101
	(0.0035)	(0.0034)
Unemployment rate: 6.3 to 7.5 percent	-0.0048	-0.0104
	(0.0040)	(0.0042)
Unemployment rate: above 7.5 percent	-0.0066	-0.0045
	(0.0041)	(0.0049)
Minimum Wage	-0.0068	0.0037
	(0.0030)	(0.0032)
High skill - Low skill Log Wage Difference	-0.0159	
	(0.0137)	
State Fixed Effects		X
Observations	40433	40433

Discrete time hazard model, estimated as a probit, with standard errors (in parentheses) clustered at the state level. A time period is two years. The unemployment rate is the two year monthly average over the current and previous year, the excluded unemployment rate category is from 2.4 to 4.8 percent. Other variables are lagged one period. The total number of observations is 40443. Marginal effects are reported. All specifications include a wave three intercept. Individual characteristics include sex, race, and locus of control. Family characteristics include parents education, income, and whether the family owns more than 50 books. All monetary values are in 2007 dollars.

out of high school less often. Column one shows the primary dropout specification with this variable included, and the parameter estimate indicates that this effect is negative, as hypothesized, but the parameter estimate can not be distinguished from zero.

The second column in Table D4 includes state fixed effects into the main dropout specification. There is some danger in this method since some states have less than 100 observations, and with small cell sizes, the probit estimates are inconsistent with fixed effects. Even with the lost degrees of freedom, the unemployment rate still has a negative effect in the low to middle ranges. The other labor market variables' estimates can not be distinguished either from zero or the estimates presented in Table 2.

Appendix E: Sensitivity of Results

In order to further test the sensitivity of the results reported in chapter 2, Table E1 shows, in columns 1 and 2, two specifications that test the validity of the instruments. Each specification includes one of the two instruments in the second stage equation, using the other instrument to identify the impact of homework. In each case, the included instrument does not have a statistically significant impact on students' achievement. This provides additional evidence that the two instruments are correctly excluded from the second stage equation, and provide exogenous variation in homework time.

Table E1: Education Production Function Estimation Results

	1	2	3
Hours of Math Homework per Week	0.299	0.221	0.240
	(0.182)	(0.096)	(0.107)
Class Size (in units of 10 students)	0.001	0.000	0.000
	(0.002)	(0.001)	(0.001)
Certified Teacher	0.005	0.002	0.005
	(0.045)	(0.034)	(0.041)
Inexperienced Teacher	0.129	0.089	0.101
	(0.102)	(0.061)	(0.064)
Minimum Annual Teacher Pay (in thousands)	0.005	0.005	0.006
	(0.004)	(0.002)	(0.003)
Locus of Control		0.010	
		(0.022)	
Hours of Homework Assigned	-0.005		
	(0.014)		
Obs	17610	17610	14610

Standard errors are shown in parentheses. The dependent variable for each regression is the mathematics achievement test score. All regressions include wave indicators, peer characteristics, student fixed effects, labor market conditions and higher education conditions. Column 3 does not include the students only observed in waves 1 and 3.

The third column tests an alternate sample of the NELS data. There 3000 students who are only included in the main sample in waves 1 and 3. Because the gap between observations is longer for these students, it is worth testing to make sure that excluding them from the sample does not change the results. The results are very similar to those displayed in Table 2, indicating that this sample change is not an important one.

Though almost all studies of homework effectiveness focus on mathematics homework and achievement, it is worth considering whether these results are applicable to other subjects. Table E2 shows the results of the primary specification (Table 2 column 7) reported homework amounts and test scores from four different subjects for comparison. Unfortunately, the instrumental variable strategy is not effective for these other subjects. The two instruments, while strong predictors of the amount of

Table E2: Impact of homework by subject

	Impact of an hour of homework (SE)	F-Statistic for Test of instruments (P-Value)
Mathematics	0.243	4.460
	(0.086)	(0.012)
English	0.757	0.600
	(0.697)	(0.547)
History	0.000	0.900
	(0.121)	(0.408)
Science	0.117	2.240
	(0.092)	(0.106)

Each cell in column one is from a separate regression, with specifications that differ only by the subject matter in the test (dependent variable) and homework completed (independent variable). Each was estimated using instrumental variables, where the excluded instruments were the locus of control and the amount of homework assigned. The second column shows the f-statistic and p-value for a joint test of the significance of the excluded instruments in the first stage equation.

mathematics homework that students complete, are much less powerful predictors of homework completed in other subjects. To show this, I display in column two the F-statistic and p-value on the f-test of the joint significance of the excluded instruments. Only for mathematics homework can null hypothesis (that the instruments are not jointly equal to zero) be rejected at a 5% confidence level. For this reason, a different estimation approach will have to be used to do a good comparison of the impact of different types of homework.

Because there are a number of students in the data that report doing zero hours of homework, there is some worry that the linear specifications presented in this paper will not be able to account for the behavior of students in this group. This is the case especially if there is a much higher return to doing the first hour of homework than subsequent hours, a problem which is partially addressed by the quadratic specification employed in table 5. The problems associated with left-censored data are not likely to apply to this study however, since only 4.3% of the students in the sample reported doing zero hours of homework. Nevertheless, Table E shows the results from four specifications which test the importance of this feature of the data. The first two specifications include student fixed effects, and are estimated using OLS.

Table E3: Left Censored Data Tests

Estimation Method	OLS	OLS	2SLS	2SLS
Hours of Math Homework per Week	0.006	0.005	0.244	0.212
	(0.001)	(0.001)	(0.087)	(0.104)
Homework indicator (zero if homework=0, 1 if homework>0)		0.078		1.270
		(0.018)		(1.897)
Class Size (in units of 10 students)	-0.011	-0.011	0.004	0.002
	(0.004)	(0.004)	(0.012)	(0.012)
Certified Teacher	-0.012	-0.012	-0.002	0.000
	(0.014)	(0.014)	(0.037)	(0.036)
Inexperienced Teacher	-0.011	-0.010	0.108	0.104
	(0.015)	(0.015)	(0.059)	(0.061)
Minimum Annual Teacher Pay (in thousands)	0.002	0.002	0.005	0.005
	(0.001)	(0.001)	(0.003)	(0.003)

The total number of observations for each specification is 17610. Each specification also includes student fixed effects, peers' test scores, peers' homework time, labor market conditions, and wave indicators.

The only difference between the specifications is that the second specification includes a homework indicator variable, which equals 1 if a student does any mathematics homework, and zero otherwise. The third and fourth specifications are estimated using two stage least squares, and the fourth specification also includes the homework indicator variable. In both pairs of regressions, the specification that includes the indicator variable has a slightly lower marginal impact of an additional hour of homework. The difference, however, is slight. So while the indicator variable does have a large estimated impact, the marginal effects of doing an hour of homework seem robust to these other specifications.

Appendix F: Sample Attrition

The full sample of students surveyed in the NELS is much larger than the sample used in this study. Because of the estimation strategy used in this paper, a student can only be included if there are at least two periods in which all of the necessary variables are observed. Students are dropped for many reasons: the NELS sampled out 6000 students after the first wave, some students dropped out of school, and most importantly, many students or teachers did not provide answers for all of the questions. To expore whether or not sample attrition is a problem, Table F1 compares the summary statistics of students in the first wave for four samples: the full NELS sample, the sample of students who were not sampled out after the first wave, the sample of students who are questioned in the second wave, and the sample used in this study. While many of the differences are not striking, for most of the variables the difference between the variable means from the full sample and the study sample are statistically different at the 5% level. Most notably, the locus of control and achievement test scores show large differences between samples. The difference between the second and third samples indicate that non-random attrition

Table F1: Summary Statistics - Sample Comparison

	Full NELS Sample		Sample w/o students randomly dropped		Continuing Sample		Study Sample	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Hours of Math Homework per Week	1.419	1.700	1.436	1.720	1.503	1.755	1.463	1.676
Assigned Homework per Week	2.267	1.057	2.234	1.029	2.257	1.014	2.235	0.952
Mathematics Test Score	4.462	0.887	4.507	0.887	4.628	0.862	4.676	0.832
Class Size (in units of 10 students)	23.659	5.874	23.797	5.570	23.830	5.535	24.058	5.120
Teachers are Certified in Subject	0.809	0.372	0.816	0.366	0.817	0.365	0.817	0.366
Inexperienced Teachers	0.107	0.238	0.105	0.233	0.102	0.229	0.098	0.216
Minimum Annual Teacher Wage	28.953	6.273	29.205	5.919	29.055	5.979	28.484	5.178
Locus of Control	0.003	0.620	0.015	0.615	0.065	0.596	0.094	0.579
Average Peers' Test Score	52.753	6.033	52.924	5.862	53.486	5.840	53.373	5.175
Average Peers' HW Time	5.410	1.943	5.350	1.902	5.464	1.948	5.433	1.718
State Unemployment Rate	5.595	1.556	5.626	1.544	5.580	1.519	5.701	1.539
Minimum Wage	3.373	0.099	3.371	0.090	3.372	0.089	3.366	0.071
Industry Mix	8.070	0.163	8.065	0.162	8.069	0.162	8.051	0.163
State Public four year tuition	1.567	0.502	1.569	0.510	1.582	0.512	1.614	0.533
State Financial Aid Per Student	0.368	0.315	0.360	0.305	0.365	0.307	0.330	0.268
State Higher Ed. Appropriations Per Student	6.919	2.074	6.854	2.044	6.851	2.045	6.395	1.877
Number of Students	20660 to 26820		15696 to 20764		13150 to 17135		7450	

This Data is from the National Education Longitudinal Study of 1988. All four samples examine only the statistics of students in the 8th grade (wave 1). All monetary variables are measured in thousands of dollars, and inflation adjusted to 2005 dollars. The continueing sample includes only students who are surveyed in the second wave. The second sample eliminates only those that were randomly dropped by the NELS study after the first wave.

due to dropouts and students leaving the sample seems to cause some of the difference, while the difference between columns 3 and 4 indicate that non-random survey non-response causes some large differences as well. Overall the sample used for the study does seem to be different than the original NELS sample, which raises the possibility that the results are biased and/or not representative. That said, the inclusion of student fixed effects in the mains specifications may ameliorate this problem somewhat.

Tables F2 and F3 compare the summary statistics from the samples used in the third chapter to comparable summary statistics from the unrestricted NELS sample. In

Table F2: Summary statistics for hazard model sub sample and full NELS sample.

	Sub Sample		Full NELS Sample	
	Mean	SD	Mean	SD
Dropped Out of School[50]	0.035	0.183	0.049	0.216
Unemployment Rate (2-year ave.)	6.231	1.588	6.244	1.583
Minimum Wage (1990 dollars)	5.774	0.409	5.771	0.419
Industry Education Score	8.082	0.173	8.082	0.169
Public 4-year tuition (in 1000's of 2007 dollars)	2.882	0.983	2.842	0.970
Female	0.506	0.500	0.498	0.500
Black	0.115	0.318	0.132	0.338
Hispanic	0.115	0.320	0.143	0.350
Asian/Pacific Islander	0.061	0.239	0.071	0.256
American Indian	0.029	0.168	0.033	0.179
Race Missing	0.009	0.096	0.012	0.107
Parents' Education	3.156	1.259	3.110	1.292
Parents' Income	10.865	0.951	10.832	0.969
Family has more than 50 books	0.900	0.300	0.891	0.311

Table F2 the second and third waves of data are included, for Table F3, all three waves. Again, the differences between the full sample and the sample used in this study are significant for some important variables, such as the dropout rate and locus of control.

Finally, to illustrate where observations were lost, Table F4 shows the cumulative drops for different categories of variables for both samples used in the third chapter. The largest number of dropped variables is the results of students who did not answer many or most of the questions in the main survey. There were also many observations for which the teacher or parent surveys were not completed.

[50] The mean of this variable is not the same as the dropout rate for this sample, since this sample combines students from multiple waves. The cumulative dropout rate for the restricted sample is 7%, compared to about 9.7% in the unrestricted sample.

Table F3: Summary statistics for homework sub sample and full NELS sample

	Sub Sample		Full NELS sample	
	Mean	SD	Mean	SD
Hours spent on homework per week	8.115	7.221	8.260	7.499
Unemployment Rate (2-year ave.)	6.017	1.662	6.076	1.658
Minimum Wage (1990 dollars)	5.878	0.389	5.913	0.409
Industry Education Score	8.079	0.170	8.080	0.167
Public 4-year tuition (in 1000's of 2007 dollars)	3.007	1.054	3.015	1.059
Parents' Education	3.230	1.258	3.139	1.286
Parents' Income	10.926	0.918	10.864	0.947
Family has more than 50 books	0.911	0.284	0.899	0.302
Average of peers' test scores	54.334	6.946	53.891	7.295
Average hours of homework assigned	2.675	1.492	2.674	1.505
Locus of Control	0.051	0.618	0.017	0.632

Table F4: Observations Dropped from Full NELS Sample

	Dropout Sample	Homework Sample
Full NELS hazard model sample	52832	82182
Race and Sex	48133	55349
Parents Characteristics	40443	46027
Peer characteristics		42826
Teacher Survey		36698

Cell entries represent number of observations left when the different groups of variables are added to the analysis. The final sample for each part of the analysis is the bottom number in each column.

Appendix G: Model Implications

As described in the paper, in the following three-period model students face a standard tradeoff between consumption and leisure, choosing how many hours to work in each period, how much time to spend doing homework in the first period, whether to drop out of high school, and whether to attend college. In the first period, students' utility U_1 depends on their choice of the number of hours to work (h_1) and the amount of time to spend on homework (HW).

$$U_1 = u\left(y + w_L h_1, T - HW - h_1 - t_{hs}\right)$$

Here T is the student's endowment of time, w_L is the wage earned by workers without a high school degree, and t_{hs} is the amount of time devoted to attending high school. In each period, there is some probability, determined by the period specific unemployment rate μ_t, that work will not materialize, and the student will be constrained to zero hours of work for that period, yielding a utility in which consumption is determined by y, the student's consumption endowment.

Students observe employment opportunities before deciding whether to drop out of high school, still a student could drop out of high school even if employment in period one is not an option. If the student chooses to drop out of high school, their first period utility is as follows:

$$U_1 = u\left(y + w_L h_1, T - h_1\right)$$

Students discount future utility at a rate β. In the second period, if the student chose to complete high school, the student can now choose either to attend college, or to enter the labor market full time. If college is chosen the student's second period utility is as follows:

$$U_2 = u\left(y + w_{hs}\left(HW\right)h_2 - C\left(HW\right), T - h_2 - t_{college}\right)$$

Where with probability μ_2 the student's hours of work are constrained to zero. Consumption in college is dependent on the cost of college, *C*, which is a function of how much homework the student completed in high school. Additionally, the wage of students who finish high school is also a function of their high school homework time. If instead the student chooses to enter the labor market, their utility is:

$$U_2 = u\left(y + w_{hs}\left(HW\right)h_2, T - h_2\right)$$

As before, with probability μ_2 the student's hours of work are constrained to zero.

In the third period students enter the labor market full time. Those who finish college now earn a wage equal to w_c, also a function of the amount of homework the student completed, whereas students who did not attend college still earn a the wage w_{hs}. Their third period utility functions differ only by the wage and their chosen hours of work. In each case, the probability that h_3 is constrained to equal zero is μ_3.

$$U_3 = u\left(y + w_c\left(HW\right)h_3, T - h_3\right)$$
$$U_3 = u\left(y + w_{hs}\left(HW\right)h_3, T - h_3\right)$$

Because a student's employment status in period one is known before they choose whether or not to drop out of school, if the student is unemployed in the first period, h_1 will equal zero. This yields the following objective function:

- If the student chooses not to drop out of school, and to go to college:

$$\begin{aligned}U = {} & u\left(y + w_L h_1, T - HW - h_1 - t_{hs}\right) + \\ & \beta(1-\mu_2)u\left(y + w_{hs}\left(HW\right)h_2 - C\left(HW\right), T - h_2 - t_{college}\right) + \beta\mu_2 u\left(y - C\left(HW\right), T - t_{college}\right) + \\ & \beta^2(1-\mu_3)u\left(y + w_c\left(HW\right)h_3, T - h_3\right) + \beta^2\mu_3 u\left(y, T\right)\end{aligned}$$

- If the student finishes high school and does not finish college:

$$\begin{aligned} U = u\left(y + w_L h_1, T - HW - h_1 - t_{hs}\right) + \\ \beta(1-\mu_2)u\left(y + w_{hs}\left(HW\right)h_2, T - h_2\right) + \beta\mu_2 u\left(y, T\right) + \\ \beta^2(1-\mu_3)u\left(y + w_{hs}\left(HW\right)h_3, T - h_3\right) + \beta^2\mu_3 u\left(y, T\right) \end{aligned}$$

- If the student drops out of high school:

$$\begin{aligned} U = u\left(y + w_L h_1, T - h_1\right) + \\ \beta(1-\mu_2)u\left(y + w_L h_2, T - h_2\right) + \beta\mu_2 u\left(y, T\right) + \\ \beta^2(1-\mu_3)u\left(y + w_L h_3, T - h_3\right) + \beta^2\mu_3 u\left(y, T\right) \end{aligned}$$

The impact of an increase in the unemployment rate on the probability of dropping out of school:

First, I assume that future unemployment rates are strictly increasing functions of the current unemployment rate, to capture the effect that changes in the current unemployment rate has on student's expectations of future unemployment rates. Second, let the functions V_{do} and V_{hs} be value functions, defined as:

(1) $$V_e = U(h_1^*, h_2^*, h_3^*, HW^*, \psi)$$

where U is the objective function of the student, h_1^*, h_2^*, h_3^*, and HW^* are the values of the choice variables that maximize the students expected discounted utility U, and ψ is the set of exogenous parameters, including w_L, w_{hs}, and μ_t. Here, e is the student's chosen education track, either drop out (do) or high school (hs), and the value functions represent the total utility that the student will receive in each education track. Using the envelope theorem to simplify the comparison, if $\frac{dV_{do}}{d\mu_1} > \frac{dV_{hs}}{d\mu_1}$ then an increase in the unemployment rate will increase the probability of dropping out, since the total utility expected if the student drops out will be decrease less than their expected utility if in high school. The comparison is thus between:

$$\frac{dV_{do}}{d\mu_1} = \beta\mu'_2(\mu_1)\left[-u\left(y+w_L h_2, T-h_2\right)+u\left(y,T\right)\right]+ \\ \beta^2\mu'_3(\mu_1)\left[-u\left(y+w_L h_3, T-h_3\right)+u\left(y,T\right)\right]$$

and:

$$\frac{dV_{hs}}{d\mu_1} = \beta\mu'_2(\mu_1)\left[-u\left(y+w_{hs}\left(HW\right)h_2, T-h_2\right)+u\left(y,T\right)\right]+ \\ \beta^2\mu'_3(\mu_1)\left[-u\left(y+w_{hs}\left(HW\right)h_3, T-h_3\right)+u\left(y,T\right)\right]$$

$\frac{dV_{do}}{d\mu_1}$ will always be larger than $\frac{dV_{hs}}{d\mu_1}$ because high school graduates' wages are assumed to be strictly greater than the wages of dropouts.

The impact of an increase in the unemployment rate on the optimal amount of homework completed:

To examine this effect, I start by looking at the case of the student who is not pursuing college. I assume all first derivatives are positive, second derivatives are negative, and cross partials are positive. Using the implicit function theorem and Cramer's rule,

$$\frac{dHW}{d\mu_1} = \frac{U_{h_1h_1} \bullet U_{h_2h_2} \bullet U_{h_3h_3} \bullet U_{HWHW}}{|H|}$$

where H is the four by four matrix of second derivatives of the function U. This quantity can only be signed if we make the assumption that the labor supply curve is non-backward bending, or that the income effect that results from a decrease in the unemployment rate (increased future expected income) is not larger than the substitution effect (more homework today and less leisure because of the higher payoff for homework due to lower unemployment probability). Under this condition, the second derivatives U_{h2HW} and U_{h3HW} are strictly positive, and then $\frac{dHW}{d\mu_1}$ is negative.

This result also holds for students who choose to attend college. The only difference in this case is that homework also affects the price of college, but if doing more homework has decreases the price of a college education (because of merit aid, scholarships, or simply because the work is easier) then this only increases the delayed payoff for homework, leaving the effect of the unemployment rate on the optimal amount of homework time negative.

The impact of an increase in the cost of college education on human capital investment:

In an argument virtually identical to the one above, an increase in the cost of college education is a negative future income shock, similar to an increase in unemployment. Thus, under the condition stipulated above, this will cause students to complete less homework. An increase in the cost of college also has an unambiguous positive effect on the probability of dropping out of school in this model.

A note on the unemployment rates:

A more realistic model would include multiple unemployment rates in each period, which would depend on the person's level of education. This simpler model is used in the paper because the use of multiple unemployment rates created a significant colinearity problem in the empirical work, and thus only a single unemployment rate was used. Thus in order to create predictions from the model that were applicable to the empirical work, a single unemployment rate is preferable.

It is worth noting, however, that since the second and third period unemployment rates are considered to be functions of the first period unemployment rate, it is easy to consider the case in which these future unemployment rates are functions of both the first period unemployment rate and the chosen education level. The predictions derived above would remain unchanged in that case that the second and third period unemployment rate functions $\left(\mu_2\left(\mu_1, e\right)\right)$ are separable in μ_1 and *e*. Then the first derivatives of these unemployment functions respect to μ_1 would be equal, and the derivations above would remain unchanged.