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Does the availability of parental health insurance affect the college enrollment decision of young Americans?☆

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ABSTRACT

The present study examines whether the college enrollment decision of young individuals (student full-time, student part-time, and non-student) depends on health insurance coverage via a parent's family health plan. Our findings indicate that the availability of parental health insurance can have significant effects on the probability that a young individual enrolls as a full-time student. A young individual who has access to health insurance via a parent can be up to 22% more likely to enroll as a full-time student than an individual without parental health insurance. After controlling for unobserved heterogeneity this probability drops to 5.5% but is still highly significant. We also find that the marginal effect of the availability of parental health insurance has a larger effect on older students between ages 21 and 23. We provide a brief discussion about possible implications of the Affordable Care Act of 2010 in this context.

1. Introduction

In 2009, 50.7 million (16.7%) Americans did not have health insurance (DeNavas-Walt, Proctor, & Smith, 2010). Of those uninsured the largest groups are young adults ages 18–24 (30.4%), Hispanics (32.4%), and households with annual incomes below $25,000 (26.6%). A striking pattern found in the data is that health insurance coverage rates of young adults drop significantly at the age of 19 except for those who attend college full-time (Kriss, Collins, Mahato, Gould, & Schoen, 2008). According to the Government Accountability Office (2008), 80% of college students have health insurance coverage. Those most likely to be uninsured include minority students, part-time students, and students from low-income families. Being uninsured has also been linked to restricted access to health care, delays in needed health care, and less frequent contact with health care providers (compare Callahan & Cooper, 2005; Callahan, Hickson, & Cooper, 2006).

To alleviate the situation of the young, various reform proposals to help cover young adults have been proposed. Some of these ideas included the extension of Medicaid, the extension of the age limit for dependent children from 19 to 22 and older in private insurance contracts, and some type of university provided low cost health insurance to cover the college student population (compare Holahan & Kenney, 2008; Kriss et al., 2008). Recently policy makers have reacted and included a provision that allows young adults to stay on their parents' health insurance plans until

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they turn 26 in the Patient Protection and Affordable Care Act that passed in spring of 2010. However, in evaluating these reforms and reform proposals it is important to understand the incentives that are present.

In this project we therefore investigate if the availability of parental health insurance has an effect on the college enrollment decision of the young. In particular we are interested in whether or not students are more likely to enroll as full-time students when their parents have health insurance that covers them. At the time of data collection, many private group insurances allowed insuring a dependent child up to age 24 if the child is a full-time student, which explains the higher coverage rates among the college population compared to members of the same age cohort (Holahan & Kenney, 2008).

Starting with Phelps (1973) and later Manning et al. (1987), demand estimation for health care provides strong evidence that people tend to be responsive to the price of health care and by extension to the price of health insurance. Because employer-provided health insurance is not taxed, price responsiveness is generally determined by examining the effects of taxes on coverage. Studies that isolate variations of tax rates across time (Long & Scott, 1982; Vroman & Anderson, 1984) and across tax brackets (Holmer, 1984; Sloan & Adamache, 1986; Woodbury, 1983) suggest that people are responsive to the price of health insurance. Other studies have found that unique changes in the tax code can increase health insurance coverage among targeted populations (Baughman, 2005; Gruber & Poterba, 1994). Taken together, these results identify a downward sloping health insurance demand curve and suggest that workers are rational in their choices regarding the amount of health insurance coverage to purchase.

Recently, there has been a push beyond estimating price elasticity of demand for health insurance towards examining the effect of the presence of health insurance on labor supply (Gruber & Madrian, 2002). Not surprisingly, workers respond in predictable ways when public policy is crafted to provide health insurance under certain conditions for certain populations. Specifically, studies have focused on the effect of the presence of health insurance on retirement decisions. In the US and in Taiwan, access to post-retirement health insurance leads to earlier retirement as documented in Gruber and Madrian (1995), Madrian (1994), Rogowski and Karoly (2000), and Hsieh (2008). Labor supply decisions later in life thus appear to be influenced by the availability of health insurance.

But these effects of health insurance on labor supply do not appear to be restricted to end-of-career labor decisions. Similar to the retirement decision, schooling decisions for young adults may also be influenced by the availability of health insurance. First, the presence of parental health insurance has been shown to improve educational outcomes in Levine and Schanzenbach (2009). This suggests that health insurance leading to better health may make college enrollment possible for some marginal students. Second, health insurance for young people often depends on parental income and employment (Collins, Schoen, Kriss, Doty, & Mahato, 2006; GAO, 2008; Kriss et al., 2008), but for college students the presence of health insurance can be completely dependent on whether or not the student is enrolled in school full-time. Collins et al. (2006) provide ample descriptive statistics highlighting this situation. Additionally, because financial aid and fellowships have already been found to impact the college enrollment and retention decisions of young adults (see Cornwell, Mustard, & Sridhar, 2006; Linsenmeier, Rosen, & Rouse, 2006; Singell, 2004; Van der Klaauw, 2002), the availability of parental health insurance coverage may serve as a tuition subsidy for a young adult desiring to be a full time student. At this point we are not aware of any analysis that examines the possibly causal relationship between parental health insurance and the college enrollment decision of young adults.

Because full-time students are much more likely to complete their college degree than part-time students (Chen, 2007), parental health insurance provides full-time students with a significant tax break and with a better chance to complete their college degree and earn more income over their lifetime. Thus, it is important to model this decision process to better understand the extent to which the presence of parental health insurance impacts college enrollment decisions and future income streams.

Using data from a national database, the Survey of Income and Program Participation (SIPP) in years 2001, 2004 and 2008, our results suggest that a student who is insured via her parent's health insurance plan is 5.5% more likely to enroll as a full-time student than a student without parental coverage. According to the analysis, if considering the decision of going to college at all, individuals with parental health insurance are 22.0% more likely to enroll in college as a full-time student. At the same time, a student with parental health insurance is 2.6% less likely to enroll as a part-time student. Note that while careful attention was given to trying to eliminate reverse causality in our model, the nature of the setting we model here suggests it is still potentially present. Even so, we can carefully conclude that it is possible that the introduction of the Affordable Care Act of 2010 could introduce new incentives for young adults with, possibly, unintended consequences.

The paper is structured as follows. The next section will introduce the empirical model. Section 3 describes the survey data. Section 4 presents the results. We conclude in Section 5. Appendix A contains all tables and figures.

2. The empirical model

The underlying decision process of an individual can be described as a two stage decision process as in Fig. 1. In the first stage the individual decides whether to become a student or whether to start working. In the second stage, the individual decides whether to enroll as a full-time student or as a part-time student. We use three separate approaches to estimate how the availability of parental health insurance will affect the probability of being a full-time student, a part-time student, or a non-student. While it is one of our fundamental assumptions used throughout this paper, it may not be initially obvious when we observe a full-time student with parental health insurance that the presence of parental health insurance was what lead to the student's full-time status. Thus, even though we proceed cautiously in modeling this decision process throughout the rest of the paper, we note that for many young Americans parental health insurance during the time when data was collected was attainable only if the young person was a full-time student.

2.1. Multinomial Logit model on full-data set

In the first step we try to put minimum restrictions on the decision process and let the individual decide between all three options, full-time, part-time, or non-student. Since our model is invariant across alternatives (i.e. we only have case specific variables to work with), we use a multinomial Logit model of the following form:

$$p_{ij} = Pr[Primary - occupation_i = j|X_i| = \frac{\exp(\alpha_j + \beta_j X_i)}{\sum_{k=1}^{3} \exp(\alpha_k + \beta_k X_i)}, \quad j = 1, \ldots, 3, \tag{1}$$

where p_{ij} is the probability that individual i chooses primary-occupation j = {*Full-Time-Student*, *Part-time-student*, *Non-student*} and X denotes the regressor matrix. This model is easy to implement but carries the strong assumption of independence of irrelevant alternatives, or *IIA*. We discuss tests of *IIA* and the problems with misspecification in the results section.

2.2. Probit model on limited data set

Since the choice between the three occupational choices can be driven by unobserved factors like innate ability that are very difficult to measure with the data from SIPP, we next attempt to control for these unobservables. Unobserved omitted variables like innate cognitive abilities could impact college enrollment decisions, but researchers have trouble separating these factors from learned skills that are more easily observed (Anger & Heineck, 2010a, 2010b; Cunha & Heckman, 2007). Innate cognitive abilities appear to be related to earnings (see Anger & Heineck, 2010a) but are not transmitted from parent to child as readily as learned skills (see Anger & Heineck, 2010b) so it's unclear what the impact, if any, of innate cognitive abilities will be on college enrollment decisions. We partly control for unobserved heterogeneity by estimating a simpler Probit model on a more homogenous group of individuals, namely students only.

We first construct a dummy variable indicating whether an individual is enrolled as full-time student or not. We then estimate a simple Probit model that does not require the IIA assumption of the multinomial Logit model and regress this dummy variable on a list of regressors X_i for individual i. This vector includes a variable indicating whether the student has health insurance via her parents, as well as many other individual and parental characteristics. The probability for being enrolled full-time can be written as

$$p_i = Pr[EnrolledFullTime_i = 1|X_i] = \Phi(\alpha + \beta X_i), \tag{2}$$

where α is an intercept term, β is a slope vector, and X_i the regressor list of individual i, and Φ is the cumulative distribution function of the standard normal distribution. We use this model on the full data set consisting of full-time students, part-time students, as well as non-students.

Second, in order to partly control for unobserved heterogeneity that is biasing the results in models (1) and (2), we next limit our analysis to individuals who have already decided to go to college and now choose between full vs. part time enrollment. These individuals are likely to be more homogenous than the overall group of 17–23 year olds as can easily be seen from the summary statistics presented in the next section. This model is therefore less likely affected by endogeneity issues of parental health insurance. The Probit model for this version can be written as

$$p_i = Pr[EnrolledFullTime_i = 1|X_i, student] = \Phi(\alpha + \beta X_i). \tag{3}$$

2.3. Heckman selection model

In order to estimate the two-step decision process that is laid out in Fig. 1, we finally employ a selection model a la Heckman. A bivariate sample selection model is defined by a *selection equation* (sometimes called a participation equation) and an *outcome equation*. The selection equation defines a latent variable that measures the difference between a person's reservation value for enrolling as a student and the net price of enrolling as student. Whenever the reservation value exceeds the price, the individual enrolls as student, so that the observed indicator variable is *d_Student* = 1 and zero otherwise. The outcome equation is a linear probability model and defines the probability of enrolling full-time. Naturally it can only be observed if *d_Student* = 1. The error terms of both selection- and outcome equations are possibly correlated. Separate estimations of the two equations would assume independence and therefore lead to inconsistent estimates of the slope parameters of the explanatory variables if the errors are in fact correlated.

Estimation of the bivariate sample selection model by ML is straightforward given the additional assumption that the errors are jointly normally distributed and homoskedastic. If there is no correlation between the two error terms after controlling for observed individual characteristics, then the two equations can be modeled separately, and a two-part model is appropriate. However, if the errors of the selection equation and the outcome equation are correlated, some unobserved factors are affecting both processes. In this case the selection is on unobservables and selection models are more appropriate (see Cameron & Trivedi, 2005, for discussion of the properties of this estimator).[1]

3. Data

3.1. The Survey of Income and Program Participation (SIPP)

The Survey of Income and Program Participation (SIPP) is a longitudinal survey where each household is re-interviewed every four months. We use a total of 2 waves per year for the most recent years 2001, 2004 and 2008: Wave 1 and wave 4 of year 2001, wave 1 and wave 4 of year 2004 as well as wave 1 and wave 4 of year 2008. The panel structure is only given for waves that are from the same year so that wave 4 individuals in year 2001 are the same individuals as wave 1 individuals in 2001, just one year older. The data between wave 1 and 4 shows little variation for all years other than an increase in the age of individuals and their parents. We therefore pool the data and control for time and family effects in our main estimates. However, in order to check the robustness of our estimates we also control for individual fixed effects using the full panel structure in the results section of this paper.[2]

Information collected in SIPP falls into two categories: core and topical. The core content includes questions asked at every interview and covers demographic characteristics, labor force participation, program participation, earned and unearned income, transfer payments, non-cash benefits from various programs, asset ownership, and private health insurance. Most core data are measured on a monthly basis, although a few core items are measured only as of the interview date, once every four months. The topical questions produce more detailed information about certain aspects (e.g. assets and liabilities, school enrollment, marital history, fertility, migration, disability, and work history) and are asked less frequently.

We also merge parental information into the young persons' data files. This was done by using information about the head of the household and merging the father's information into the young persons' data file. If the father was missing, we used the mother's information. We indicate these variables with the prefix Parent.[3] Summary statistics of the sample with parental information are presented in Table 1.

After merging and cleaning the data, 33,470 individual observations between age 17 and 23 remain. See Table 1 for a summary of all used variables. We first use a pooled data set where roughly 14.4% (4825 individuals) of all observations are from wave 1 of year 2001, 13.2% (4414 individuals – almost all repeated from wave 1) are from wave 4 of year 2001, 18.7% (6262 individuals) are from wave 1 of year 2004, 18.8% (6277 individuals – almost all repeated from wave 1) are from wave 4 of year 2004, 17.5% (5854) are from wave 1 of year 2008, and 17.4% (5838 individuals – almost all repeated from wave 1) are from wave 4 of year 2008. Summary statistics per wave are available in a separate appendix upon request from the authors.

3.2. Dependent variable

In order to study a more general process of occupational choice, we create a three state multinomial variable called *Primary-occupation* = {*Student full-time*, *Student part-time*, *Non-student*} using information from the variables *EnrolledFullTime* and *EnrolledPartTime* provided by the data. If a person is neither enrolled full-time nor part-time, we assume the person is not a student. The pooled sample consists of 20,843 full-time students, 1996 part-time students, and 10,631 individuals that are not enrolled in college. We present summary statistics of the pooled sample by occupational choice in Table 2. Full-time students are overrepresented in our sample which has partly to do with the composition of SIPP itself but also with the merging of parental information into the core data of 17–23 year olds which is more readily available for full-time students than for non-students. However, we conduct robustness checks of our results and find that even after randomly dropping various groups of full-time students our results still hold and are highly significant.[4]

3.3. Explanatory variables

We use the following independent variables in the regressions explaining occupational choice in model 1 and full vs. part-time enrollment of students in models 2 and 3.[5]

3.3.1. Health insurance

The indicator variable *Third-party-health-insurance* measures whether individuals are covered by someone

[1] An additional procedure, Heckman's two-step procedure, augments the OLS regression by an estimate of the omitted regressor using a Probit estimator on the selection equation. This omitted regressor, the inverse Mills ratio, is then introduced into the outcome equation as an additional explanatory variable. The correlation between the two errors can then be estimated. The Heckman two-step estimator only requires a linear relationship between the two error terms and not joint normality as with the ML estimator. It is therefore less restrictive and more robust to possible misspecification of the error characteristics. Another procedure is Heckman's two-step estimator with exclusion restrictions. This estimator does not exclusively rely on the non-linearity of the model for parameter identification which could lead to weak identification and hence biases. Since it is difficult to find an explanatory variable that affects the probability of enrolling as a student at all but not the probability to enroll as full-time student, we use the ML specification with the joint normal assumption on the errors and rely on non-linearity for identification.

[2] Year 2001 data has 9 waves available. Years 2004 has 12 waves and year 2008 currently has 7 waves available. We therefore concentrate on wave 1 and wave 4 of each year respectively.

[3] Controlling for father and mother separately would have reduced the sample size significantly.

[4] See Section 4.4 on sensitivity analysis.

[5] Some omitted variables like educational quality, ability, and discount rate are not included in the SIPP data but could affect both enrollment and health insurance. Altonji, Elder, and Taber (2005) offer a technique to assess the potential importance of these unobservables in the enrollment decision, but we leave that exercise for future research as it is beyond the scope of this study.

else's plan. The survey asks whether an individual is covered by her own plan, someone else's plan, both or neither. If the individual responds that her coverage is via someone else's plan only then *Third-party-health-insurance* is set equal to one.

The variable *Third-party-health-insurance* is not restricted to measure only the availability of parental health insurance but also includes unsubsidized health insurance from other private health care plans. In order to measure whether the health insurance of an individual is from her parents, we create a binary variable *ParentHealthIns* which is set equal to one whenever the variable *Third-party-health-insurance* indicates that the individual has health insurance through a third party. Also, we only assign a value of one to this variable if the young individual is not on Medicaid and is unmarried in order to exclude cases where young individuals get insurance from their spouses. The variable *ParentHealthIns* is a better proxy for the kind of government subsidized health insurance that full-time students get via their parents than the original variable *Third-party-health-insurance*.

The indicator variable *PrivateHealthIns* measures whether the person has health insurance other than Medicare or Medicaid. The indicator variable *LostParentIns* asks for the reasons why the individual is not covered by any health insurance. If the individual answers that she has no health insurance because she is no longer covered by parents, then *LostParentIns* is set equal to one.

3.3.2. Demographic variables

We measure an individual's age, health, race, and gender. As expected for this age group with average age of 19.3 we find that only a very small share of 5.4% reported a physical or mental health problem. The sample includes 15.0% black individuals and 10.2% Hispanic individuals. There are 46.7% females in the sample and 2.0% report that they are currently married. If we compare the subset of full-time students in Table 3 we find that the full-time student population is on average younger (18.7 years), healthier (3.8% report a physical or mental health problem), less diverse (13.7% black and 8.4% Hispanic), and more gender balanced (49.7% is female).

3.3.3. Income

Income is reported in thousands of dollars per month. The majority of individuals between 17 and 23 report that they had income in the reference period (60.9%). Only two individuals report a monthly income larger than $10,000. We drop these two observations from the sample. We also drop seven individuals with negative income. We also measure whether an individual is supported by low income (Pell) grants, receives college assistance, is supported by other Federal grants, lives on student loans, or is the recipient of scholarships.

3.3.4. Parent information

The parental characteristics that we control for include a set of dummy variables for no-high school, highest degree high school, and highest degree college. We use high school as reference category and do not include it in the regression analysis. We control for parent health and age. The average age of a parent is 48 years and 12.5% report that they have a physical or mental health problem. Roughly 14.3% of the parents have not finished high school compared to 25.6% who have a college degree (the dummy variable that measures high school degree only is again the base category that is dropped from the analysis). Since we use household heads as parent proxy we only have 27.1% female parents in the sample. The parents' household earnings distribution is between $0 and $59,728 per month and highly right skewed so that we use log(household income +1) as regressor. In addition we add a dummy variable that measures whether a parent is employed. Finally we control for industry type and type of occupation of parents using the same categories as Abowd and Stinson (2011). The categories for the industry codes are listed in Table 1. All variables describing parental characteristics are denoted with the prefix *Parent_* in all tables presented in Appendix A.

4. Results

4.1. A multinomial Logit model of occupational choice of young individuals

In this section we present results for the multinomial Logit model of occupational choice, between (1) full-time student, (2) part-time student, and (3) non-student. The model is formally described by expression (1) in the model section. This model assumes independence of irrelevant alternatives (*IIA* assumption). We will test for this assumption is this section.

Table 3 presents the marginal effects of the exogenous regressors. All standard errors are robust and clustered by family. Since the model is non-linear, all marginal effects are presented for a base category individual defined as an 18-year old unmarried white female with median income, no mental health problems, no parental health insurance, no private health insurance, and no public or private scholarships or grants whose parent is a 50 year old male, has a high school degree, does have private health insurance, and does not have a physical or mental health problem.

We find that the marginal effects for the base category individual indicate that the availability of parental health insurance increases the probability of being a full-time student by 22.0%. At the same time the availability of parental health insurance decreases the probability of enrolling as a part-time student by about 2.6% and it decreases the probability of not enrolling in college by 19.4%. These are all highly significant coefficient estimates.[6]

Age decreases the probability of being enrolled as a full-time student and therefore increases the probability of

[6] Except for rounding errors, the marginal effects in the table will add up to zero.

being a part-time or non-student (by definition). We cannot find a significant relationship between race and the college enrollment decision except for Hispanic individuals who seem more likely to choose being part-time students. Females have a higher probability of being enrolled full-time at college; they also face a lower probability of not going to college at all than males. Being married decreases the likelihood that an individual enrolls full-time and increases the chance that an individual does not attend college. As expected, the level of income is negatively correlated with being enrolled full-time in college whereas the availability of grants and scholarships increase the probability of enrolling full-time. On the other hand, individuals with income are more likely to be enrolled as full-time students as opposed to individuals without any income at all (measured by variable *d_income*).

All parental characteristics that we control for are significantly related to the decision to enroll as full-time student. A parent's years of education, age, and income significantly increase the probability of an individual to enroll full-time at a university or college. Furthermore, children of parents that are employed or business owners also have a higher probability to be enrolled as full time students. Children of parents with private health insurance and health problems are less likely to be enrolled full-time as are children without a father in the household.[7] The multinomial Logit model carries the *IIA* assumption (independence of irrelevant alternatives) which assumes that the relative probability of choosing to be a full-time student over being a non-student is independent of the option of being a part-time student. This is potentially a very strong assumption. A Hausman test of *IIA* is inconclusive as it rejects the null hypothesis of *IIA* when non-student is the omitted category but fails to reject when full-time or part-time student are the omitted categories. A very similar result holds when we run the Small-Hsiao test as it also fails to reject *IIA* when part-time student is the omitted category but does reject *IIA* when non-student is the omitted.[8] We therefore do not have conclusive evidence for IIA and run the risk of estimating a misspecified Logit model.

Since we are limited to case specific variables – for example, individuals who chose to be workers do not report the cost of college, or the availability of student loans – we cannot specify a conditional or nested Logit model, a model that would not assume *IIA*. We therefore proceed with a Probit specification that does not assume *IIA*.

4.2. Probit model of choosing full-time student status

In order to relax the *IIA* assumption we use a Probit model and estimate the model using a binary choice variable *EnrolledFullTime* that is set equal to unity whenever an individual between 17 and 23 is enrolled full-time at a college or university. This leaves a residual group of part-time students and non-students. The estimation results of the simple Probit model are presented in Table 4.

We again report marginal effects for a base category individual defined as an 18-year old unmarried white female with median income, no physical or mental health problems, no parental health insurance, no private health insurance, and no financial assistance from either the college or from public sources whose parent is a 50 year old male, has a high school degree and private health insurance, and does not have a physical or mental health problem.

In the most general analysis where the entire population of students and non-students is examined, the representative student (as defined above) is 21.3% more likely to enroll full-time if parental health insurance is available (compare the first column in Table 4). The standard errors are calculated by clustering to a parent identification number so that information provided by siblings is correctly accounted for. This regressor (i.e. *ParentHealthIns*) is highly significant. If the health insurance is from a private insurance company, then the individual is more likely to be enrolled full-time.

We also find that individuals with physical or mental problems are on average 7.3% less likely to be enrolled full-time (i.e. *PhysMentalProblem*). In addition, the older the individual is, the less likely the individual is to be enrolled full-time. Further, females are 5.2% more likely to have full-time status. Perhaps somewhat surprisingly, there are no significant correlations with race indicator variables. As before, the level of income is negatively related with full-time enrollment status whereas the variable measuring whether an individual has income at all is positively related. As expected we also find that grants, scholarships, and student loans all increase the probability of being a full-time student. Finally, family background is a good predictor for a young individual's college enrollment decision. Students whose parents have a college degree are 12.2% more likely to be enrolled full-time (i.e. *Parent_College*). Children with high-income parents are 1.0% more likely to enroll full-time. As before in the multinomial Logit model, children whose parents are employed or business owners have a higher probability to enroll as full-time students.

4.2.1. Controlling for unobserved heterogeneity

This first approach falls short in two important dimensions. The first is that the choice set is overly simplistic as the individual chooses only whether or not to become a full-time student. This choice is too simple because a choice to not become a full-time student includes being either a part-time student or a non-student. The coefficient estimates of the explanatory variables therefore do not distinguish between important effects that can be caused by the potential choice of being either a part-time student or a non-student. In addition, the results might be driven by some unobserved heterogeneity that distinguishes the pool of students from the pool of non-students and that drives both the college enrollment

[7] Note that when we constructed the parental variables we first used information from the father and if that was not available we used information from the mother.

[8] All tests are implemented in Stata using the mlogtest command by Long and Freese (2006) and test statistics are reported in Table 3.

decision and the availability of parental health insurance (e.g. endogeneity problem).

Therefore we repeat the analysis and concentrate only on the subgroup of students. This effectively controls for unobserved heterogeneity that our model can otherwise not capture explicitly. In the second column in Table 4 we run the same Probit regression model on the student population only, so that individuals who are not enrolled full-time, are enrolled part-time by definition. When concentrating on the student population only, we can automatically control for unobserved heterogeneity that distinguishes the student population from the non-student population that we cannot explicitly control for with our data in the first model (e.g. unobserved higher innate learning ability of students vs. non-student, etc.).

We find that our earlier result still holds, but that some regressors lose their explanatory power. First, the availability of parental health insurance only causes an increase in the probability of being a full-time student of 6.5% as opposed to 21.3% in the previous model. We would of course anticipate such a drop since we now look at the pool of students, who effectively have decided to attend college already and the only decision left is whether to enroll full-time or part-time. However, parental health insurance is still significant in affecting this choice. Note that Dynarski (2003) finds that an additional $1000 of student aid increases the share of high school graduates attending college by almost 4%, so our result appears plausible once we control for unobserved heterogeneity.

Once students have decided to go to college the coefficient estimates for private health insurance, health problem, female, being married and other federal grants become insignificant. The most interesting drop in significance is probably the one for the gender dummy. Earlier being female increased the probability of full-time enrollment by 5.2%, however, once we reduce the choice to full vs. part-time enrollment, gender becomes insignificant. It appears that gender only plays a role in the initial decision whether to go to college at all, but once that decision has been made, student decisions about enrollment status between men and women are indistinguishable. Interestingly, the race dummy variable for Hispanic is now significant and reduces the probability to enroll as full-time student by 2.4%.

In addition, it is confirmed that the full-time or part-time enrollment decision for students whose parents have no high school degree are not distinguishable from students whose parents have a high school degree. This is partly due to attrition in the sample of students with parents who have no high school degree. In addition, we find that whether parents have a college degree is still highly significant and increases the probability that the student is enrolled full-time by 3.4% (down from 12.2% in the full sample). Parental income, measured as household income, is not significant anymore.

4.2.2. Baseline probabilities and marginal effects by age and income

We next investigate potential non-linearities in the model that controls for heterogeneity (the student only sample) by calculating the probability of the baseline individual (i.e. 18-year old female, etc.) enrolling as full-time student over age. We report these results in panel 1 of Fig. 2. As Stratton, O'Toole, and Wetzel (2004) find, younger students have a higher probability to enroll as full-time students (about 95% for 17 year olds). This probability then starts to drop non-linearly as the individual gets older. A 23-year old has only a 70% probability to enroll full time. In panel 2 of Fig. 2 we calculate the marginal effect of the availability of parental health insurance on the probability to enroll as full-time student for the baseline individual. We see that for a young individual the marginal effect of parental health insurance is smaller (about 4%) than for an older student (about 14% for a 23 year old). The older the student gets the larger the marginal effect of parental health insurance on the probability of enrolling as full-time student.

The developmental period of emerging adulthood, experienced from 18 to 23 years old, marks a time where young people experience a more transient lifestyle (see Arnett, 2000). Typically, during this time, stability in choices such as living arrangements and school attendance change at an elevated rate. The data reflect these changes where older students are less likely to enroll as full-time students (see panel 1 in Fig. 2) as they become more at risk to either drop out of college or scale back their college activities (i.e. become part time students) due to events accompanying maturing into adulthood (i.e. need for independence from parents, jobs, acceptance of responsibilities, etc.). Having access to parental health insurance under the condition of being enrolled full-time at college therefore presents a stronger factor in being enrolled full-time for a 23 year old than for a 17 or 18 year old individual who may not yet acknowledge needs such as having health insurance.

We next present a similar graph over household income in Fig. 3. Both panels in this figure indicate that changes in levels of income do not have strong effects on the baseline probability to enroll full-time and the marginal effect of parental health insurance. This is not surprising as parental income was not a significant regressor in column 2 of Table 4.

4.2.3. Average marginal effects

Due to the non-linearity of our econometric model we have so far presented marginal effects of a baseline individual. In Table 4 we also present the marginal effects of the two Probit models evaluated at the average of the explanatory variable (columns 3 and 4). The marginal effects at the average of our sample are qualitatively the same as the ones reported for the 18-year old female baseline individual. Quantitatively though it turns out that the average marginal effects of the regressors tend to be smaller than the marginal effects reported for the baseline individual (compare column 2 to column 4 in Table 4).

4.3. Heckman selection model

The results of the estimated selection model are reported in Table 5. This model closely mimics the suggested decision process introduced in Fig. 1. We again present marginal effects of all covariates evaluated at the sample average and provide three marginal effects estimates that are customary in the literature on sample selection models.

The first column contains the marginal effects for the probability of the variable *EnrolledFullTime* being observed or $\partial \Pr(EnrolledFullTime \text{ observed})/\partial x_i$. The second column presents the marginal effects for the expected value of *EnrolledFullTime* conditional on being observed: $\partial E[EnrolledFullTime|EnrolledFullTime \text{ observed}]/\partial x_i$. Finally, column three shows the marginal effects for the expected value of Enrolled full-time, $\partial E[EnrolledFullTime]/\partial x_i$. The three sets of marginal effects in case the covariate x_i is an indicator variable are calculated as follows (here we define $y = EnrolledFullTime$): (i) $\Pr(y_i \text{ observed}|x_i = 1) - \Pr(y_i \text{ observed}|x_I = 0)$, (ii) $E[y_i| \; y_i \text{ observed}, \; x_i = 1] - E[y_i|y_i \text{ observed}, x_i = 0]$, and (iii) $E[y_i|x_i = 1] - E[y_i \; |x_i = 0]$.

From Table 5 we can again see that the effect of parental health insurance on being enrolled as full-time student is highly significant and slightly larger than the marginal effects of our earlier Probit estimates.

4.4. Sensitivity analysis

We next test the robustness of our results with respect to alternative specifications of the econometric model as well as alternative sample weights. All results of this sensitivity analysis are available in a separate appendix upon request from the authors.

We first use the panel structure of wave 1 and wave 4 from the three available years 2001, 2004 and 2008 and estimate a linear probability model of being enrolled full-time with individual fixed and random effects to control for unobserved individual heterogeneity like innate ability. We do the same on the student-only subsample. Including an indicator variable for lagged parent health insurance supports the direction of our suggested causal chain from parental health insurance to the enrollment decision of the young. Lagged parental health insurance is a highly significant predictor for student enrollment choice and positively affects full time enrollment.[9] Finally, we add lagged enrollment as an additional regressor and measure the effect of parental health insurance on current enrollment. A Hausman test confirms that fixed effects are present in all three specifications and that the random effects model is likely to be inconsistent (Hausman & McFadden, 1984). We next use a within-family estimator, where we differentiate the dependent and independent variables with its lagged values. This allows us to regress changes in full-time enrollment status on changes of covariates over the same period like for a fixed effects estimator. Finally we create sibling pairs where we regress the enrollment decision of the younger sibling on changes of covariates from its older sibling. This allows us to control for unobserved family fixed effects.[10] Either way, all six panel estimator models as well as the within family estimator models confirm our earlier results and show that parental health insurance increases the probability to enroll as full time student significantly.

We next use alternative sets of explanatory variables, interaction terms that indicate whether parents are business owners, alternative data weights, and alternative sample sizes that correct for the slight overrepresentation of the student population in the SIPP dataset and re-estimate the effect of parental health insurance on full-time enrollment using the student only subsample. We again find that our results are robust with respect to these changes and that parental health insurance has a significant positive effect on the probability of being enrolled full-time.

4.5. Implications

We briefly summarize the incentive structure concerning parental health insurance and full-time student status. We first describe the incentive structure before the Affordable Care Act (ACA, a.k.a. the Obama health reform) passed in early 2010 in the first row of Table 6. The pre-ACA policy stipulated that students be enrolled full-time in order to stay on their parents' health insurance. This was generally possible until age 24. That is, this policy provided an incentive to be enrolled full-time for 17–24 year olds because it came with the additional benefit of "free" health insurance from parents. Consequently this age group had reduced incentives to enroll part-time (because they would then lose the insurance) or work full-time (because they would also lose free parental health insurance and not be likely to have acceptable health insurance coverage in their first job). To some extent students who were enrolled full-time had an incentive to postpone entering the labor force because they would lose their free health insurance from their parents. Students therefore had an incentive to postpone graduation. Parental health insurance was lost for young adults in the 24–26 age group under the pre-ACA policy, so those individuals were exposed to high risk in becoming uninsured and faced strong incentives to find full-time work with employer provided health insurance.

Under the ACA 2010 (second row in Table 6) the incentive structure changes. Individuals of group 1 now have an incentive to enroll part-time only or work while keeping their parental health insurance. At the same time, it will be easier for low-income students, who before could not be enrolled full-time due to financial constraints, to study part-time while keeping parental health insurance. Group 2 now has a lower risk of being uninsured, but they also have a greater incentive (compared to pre-ACA days) to postpone graduation and a reduced incentive to find full-time work.

4.5.1. Back-of-the-envelope calculation

We next provide a brief back-of-the-envelope calculation to highlight the impact of the results from our empirical study. In fall 2007, there were approximately 10.6 million undergraduate students 18–24 years old in the US. Of these undergraduates, approximately 8.3 million were full-time and 2.3 million were part-time (Snyder, Dillow, & Hoffman, 2008). Additionally, almost 19 million

[9] Future research could provide a more rigorous examination of this relationship.

[10] We would like to thank an anonymous referee for suggesting this estimator type. Other research designs are possible. For example, Cutler and Gruber (1996) use simulated instruments for Medicaid expansion as an instrumental variable for insurance coverage. This kind of design could be used in future research.

individuals between the age of 18 and 24 were not enrolled in a degree-granting institution.[11] Using these 2007 numbers, we can assume that under a policy world where parental health insurance is tied to full-time student status (pre-ACA), any incoming cohort of 17–18 year-olds would have roughly 28.34% enroll as full-time students, 7.76% would enroll as part-time students, and 63.90% would not enroll at all.

For the sake of the following discussion we assume that the coefficient estimates on parental health insurance in columns 3 and 4 of Table 4 (i.e. 20.0% and 5.5% respectively) measure the increase in the probability due to the law specifically tying full-time status and eligibility for parental health insurance together. In this case our estimates in Table 4 suggest that under the Affordable Care Act, available health insurance for all 17–23 year-olds would decrease the probability to enroll as a full-time student to 8.3% as parental health insurance is no longer tied to full-time status. When looking only at the student population, the probability to enroll as a full-time student decreases to 73.0%. For all individuals age 17–23 in an ACA policy world, our results suggest that 980,242 fewer individuals could choose to become full-time students.

Chen (2007) finds that 43.7% of full-time students earn their bachelor's degree within six years of first enrolling, while between 6.9% and 25% of part-time students earn their degree in the same time. The almost one million individuals that are no longer full-time students in the ACA policy world (compared to a pre-ACA world) will either switch to being a part-time student or else not enroll in school at all. We can set a lower bound on our estimate of the impact of the ACA on US income if we assume that all the switches are to part-time students. In this case, after six years there could be 272,017 fewer college graduates annually on the market. In setting an upper bound on the impact of the ACA on US income, we assume that all the switches are to individuals not enrolling in school at all, suggesting there could be 428,366 fewer college graduates on the market. If we restrict our attention to just the student population, we expect 97,313 full-time students to switch to part-time status, which would result in 27,004 fewer college graduates on the market.

Recent estimates indicate that college graduates earn almost $20,000 more annually than high school graduates. If we look at all young adults age 18–24, we estimate that the ACA could decrease US income by between $5.4 billion and $8.6 billion annually after a 6-year period has passed and fewer individuals maintain full-time student status. Restricting our focus to just the student population suggests US income could drop by about $540 million. This figure is lower since we assume that all the switches are from full-time to part-time status and that all individuals are students. It must be noted that this example provides only a very rough calculation about one possible unintended consequence of the ACA which does not factor in the many additional effects of the ACA that may actually increase the number of total students, such as pricing restrictions on insurance companies, reduction of life-time limits and subsidies to buy health insurance.

5. Conclusion

While our analysis does not present a dynamic view of the college enrollment decision process, it does present evidence suggesting that access to parental health insurance can be a predictor of full-time college enrollment. A full-time schedule allows students to complete degrees in shorter amounts of time and to access benefits of college degrees in less time than it takes students who are not enrolled full-time. This may contribute to students from higher income levels being better able to attain socioeconomic status similar to that of their families of origin or higher, while students from lower income families are less able to bridge to higher income levels in adulthood.

Bozick (2007) suggested that more support is needed, in addition to grants and aid, to provide better security for low-income students in their transition to adulthood.[12] Due to the growing concern that low-income students are not completing college (McNeil & Klein, 2009), the need for accessible health insurance should be one support that is considered. As policy related to health care access is debated, the discussion should include access to resources that may be impacted by health insurance coverage. Clearly issues related to health are at stake, but other factors that are affected by access to health insurance and support enriching opportunities should be considered. Low-income youth transitioning to adulthood face a number of challenges including the daunting task of determining if college is a viable option. In making this decision, more support should be offered to meet student needs and increase the likelihood that students will attend college full-time. But access to health insurance for young adults without a tie to full-time student status would potentially provide an unintended consequence that stands in the way of college enrollment and completion.

Our results carry policy implications for reforming the health insurance environment for young Americans. Since the majority of health insurance contracts from parents are employer provided and thus tax free, there seems to be a reverse subsidy to higher income young people who are

[11] We calculated this number using data from Table 2 in the Annual Estimates of the Resident Population by Sex and Selected Age Groups for the United States: April 1, 2000 to July 1, 2008 (NC-EST2008-02), Population Division, U.S. Census Bureau, Release Date: May 14, 2009.

[12] The DREAM Act of 2010, which was not passed, is another attempt along these lines. It is intended to grant conditional nonimmigrant status to certain unauthorized residents which would make them eligible for federal student loans. Congressional Budget Office (CBO) cost estimates of the proposed bill include the effect of higher tax revenues from increased reporting of employment income by parents, but do not include the effect of higher tax revenue from higher incomes due to an increased number of college graduates. This is puzzling since a major provision of the bill requires unauthorized residents addressed by this bill to be admitted to a college or university and despite CBO's prediction that college and university enrollments will increase as a result of the bill. Note that our back-of-the-envelope calculations focus exclusively on estimating the change in incomes from changing college and university enrollments as a result of the ACA.

now more likely to enroll as full-time students in order to benefit from this subsidy. The Patient Protection and Affordable Care Act that passed in 2010 now includes a provision that allows young adults to stay on their parents' health insurance plans until they turn 26 regardless of student status. It is expected that about 1.2 million young adults could eventually take advantage of the new rule after becoming active in the fall of 2010 (Collins & Nicholson, 2010). We cautiously note that this reform, to some extent, removes some of the incentive to be enrolled full-time. We plan to explore the effects of this reform on student enrollment and how it addresses the reverse subsidy issue in future research.

Appendix A

See Tables 1–6 and Figs. 1–3.

Table 1
Summary statistics of 17–23 year olds: SIPP of 2001, 2004, and 2008 including parent information.

Variable	Mean	Std. err.
ParentHealthIns	.5039737	.002733
EnrolledFullTime	.6227368	.0026494
EnrolledPartTime	.0596355	.0012944
WorkFullTime	.1777114	.0020895
WorkPartTime	.3047206	.002516
PrivateHealthIns	.6742157	.0025618
LostParentIns	.0175082	.0007169
PhysMentalProblem	.0542874	.0012385
Age	19.26923	.0103339
AgeSquared	374.8772	.4077437
Race_Black	.1498058	.0019508
Race_Hispanic	.101942	.0016539
Female	.4665671	.0027269
Married	.0196295	.0007583
LogIncome	3.47584	.0175722
d_Income	.6091425	.0026671
PellGrant	.0703316	.0013977
CollegeAssistance	.0152973	.0006709
OtherFedGrant	.0098895	.0005409
StudentLoan	.0872124	.0015422
Scholarship	.0595757	.0012938
StateScholarship	.0304153	.0009387
Parent_PrivateHealthIns	.7472662	.0023755

Table 1 (*Continued*)

Variable	Mean	Std. err.
Parent_NoHighSchool	.142695	.0019118
Parent_College	.2550045	.0023825
Parent_PhysMentalProblem	.1253361	.0018098
Parent_Age	47.98279	.0368033
Parent_Female	.2713774	.0024306
Parent_HHLogIncome	8.243586	.0069317
Parent_Employed	.8334927	.0020363
Parent_Business	.1446669	.0019228
Categories for parents industry codes		
1. Agriculture	.0197789	.0007611
2. Mining	.0057664	.0004139
3. Construction	.0883179	.001551
4. Manufacturing non-durable	.0557215	.0012538
5. Manufacturing durable	.0979086	.0016245
6. Transportation, comm., public utility	.0818046	.0014981
7. Wholesale trade: durables	.0200777	.0007667
8. Wholesale trade: non-durables	.0157156	.0006798
9. Retail	.0927696	.0015858
10. Finance/insurance	.0526442	.0012207
11. Business and repair	.0247386	.000849
12. Personal services	.0208545	.0007811
13. Entertainment and recreation	.0344488	.0009969
14. Professional services	.1884972	.0021378
15. Public administration	.0587989	.0012859
Categories for parents occupation codes		
1. Executive, administrative, managerial	.2689573	.0024238
2. Professional specialties – math/science	.0752316	.0014418
3. Health – doctor/dentist	.041231	.0010868
4. Teachers	.031939	.0009611
5. Professional specialties – social science	.0065432	.0004407
6. Social workers/clergy	.0132656	.0006254
7. Lawyers/judges	.007798	.0004808
8. Writers, artists, entertainment, athletes	.0085151	.0005022
9. Technicians, related support	.0527039	.0012214
10. Sales	.0526143	.0012204
11. Administrative support	.1308336	.0018433
12. Service	.0112937	.0005776
13. Farm, forestry, fishing	.0578428	.001276
14. Precision production, craft, repair	.0957275	.0016082
15. Operators, fabricators, laborers	.0033463	.0003157
16. Military	.1421572	.0019088
2001: 1	.1441589	.00192
2001: 4	.1318793	.0018495
2004: 1	.1870929	.0021317
2004: 4	.1875411	.0021337
2008: 1	.1749029	.0020765
2008: 4	.1744249	.0020743
Observations	33,470	

Table 2
Summary statistics of 17–23 year olds by occupational choice: SIPP of 2001, 2004, and 2008 including parent information.

Variable	Mean full-time students	Std. err.	Mean part-time students	Std. err.	Mean non-students	Std. err.
ParentHealthIns	.6600297	.0032812	.3712425	.0108168	.2229329	.0040369
EnrolledFullTime	1	0	0	0	0	0
EnrolledPartTime	0	0	1	0	0	0
WorkFullTime	.05599	.0015925	.2985972	.010246	.3936601	.0047386
WorkPartTime	.3518687	.0033079	.3491984	.0106731	.2039319	.003908
PrivateHealthIns	.780214	.0028684	.6292585	.0108138	.4748377	.0048434
LostParentIns	.0100273	.0006901	.0305611	.0038537	.0297244	.0016472
PhysMentalProblem	.0376625	.0013187	.0591182	.0052803	.085975	.0027189
Age	18.66838	.0116678	19.95391	.0404946	20.31869	.0172914
AgeSquared	351.3457	.4529613	401.4299	1.625753	416.0275	.70165

Table 2 (*Continued*)

Variable	Mean full-time students	Std. err.	Mean part-time students	Std. err.	Mean non-students	Std. err.
Race_Black	.1371204	.0023826	.1457916	.0079009	.1754303	.0036889
Race_Hispanic	.0835292	.0019165	.1618236	.0082455	.126799	.0032274
Female	.4964736	.0034633	.493988	.0111935	.4027843	.004757
Married	.0072926	.0005894	.0210421	.0032133	.0435519	.0019796
LogIncome	2.864266	.0207854	4.613037	.070593	4.461371	.0322692
d_Income	.564698	.0034343	.7229459	.0100199	.674913	.0045431
PellGrant	.103488	.0021099	.0986974	.0066775	0	0
CollegeAssistance	.023797	.0010558	.008016	.0019965	0	0
OtherFedGrant	.0143933	.000825	.0155311	.0027684	0	0
StudentLoan	.133522	.0023561	.0681363	.0056415	0	0
Scholarship	.0923571	.0020055	.0345691	.0040901	0	0
StateScholarship	.0469222	.0014648	.0200401	.0031375	0	0
Parent_PrivateHealthIns	.8014681	.002763	.7269539	.0099747	.6448123	.0046417
Parent_NoHighSchool	.0996018	.0020743	.1588176	.0081832	.2241558	.0040448
Parent_College	.321019	.0032339	.1948898	.0088685	.1368639	.0033336
Parent_PhysMentalProblem	.1041117	.0021155	.1412826	.0077983	.1639545	.003591
Parent_Age	47.86509	.0460774	48.55361	.1488503	48.10639	.0668927
Parent_Female	.2418078	.0029659	.2965932	.0102262	.3246167	.0045414
Parent_HHLogIncome	8.315555	.0086333	8.276173	.0246573	8.096366	.0128581
Parent_Employed	.8617282	.002391	.8146293	.0087002	.7816762	.0040068
Parent_Business	.1563594	.0025158	.1287575	.0074987	.1247296	.0032047
Observations	20,843		1,996		10,631	

Table 3
Multinomial Logit model.

Variables: marginal effects	Full-time (0/1)	Part-time (0/1)	Non-student (0/1)
ParentHealthIns	0.220***	−0.0260***	−0.194***
	(0.00959)	(0.00369)	(0.00923)
PrivateHealthIns	0.116***	0.00552	−0.122***
	(0.0118)	(0.00477)	(0.0109)
LostParentIns	−0.000645	0.0326**	−0.0320
	(0.0275)	(0.0135)	(0.0249)
PhysMentalProblem	−0.0773***	0.00390	0.0734***
	(0.0186)	(0.00715)	(0.0179)
Age	−1.385***	0.110***	1.275***
	(0.0486)	(0.0205)	(0.0494)
AgeSquared	0.0315***	−0.00255***	−0.0289***
	(0.00122)	(0.000508)	(0.00123)
Race_Black	0.00774	−0.000704	−0.00703
	(0.0130)	(0.00509)	(0.0125)
Race_Hispanic	−0.00343	0.0174***	−0.0139
	(0.0156)	(0.00645)	(0.0152)
Female	0.0640***	0.00720**	−0.0712***
	(0.00848)	(0.00301)	(0.00840)
Married	−0.167***	−0.0143*	0.181***
	(0.0293)	(0.00842)	(0.0287)
LogIncome	−0.0716***	0.00751***	0.0641***
	(0.00349)	(0.00143)	(0.00363)
d_Income	0.307***	−0.0112	−0.296***
	(0.0213)	(0.00888)	(0.0227)
PellGrant	0.363***	0.00565	−0.368***
	(0.0134)	(0.00635)	(0.0134)
CollegeAssistance	0.387***	−0.0182	−0.368***
	(0.0176)	(0.0127)	(0.0134)
OtherFedGrant	0.340***	0.0281	−0.368***
	(0.0226)	(0.0196)	(0.0134)
StudentLoan	0.389***	−0.0206***	−0.368***
	(0.0131)	(0.00474)	(0.0134)
Scholarship	0.388***	−0.0194***	−0.368***
	(0.0138)	(0.00629)	(0.0134)
StateScholarship	0.393***	−0.0243***	−0.368***
	(0.0146)	(0.00773)	(0.0134)
Parent_PrivateHealthIns	−0.0662***	0.0114**	0.0548***
	(0.0125)	(0.00449)	(0.0119)

Table 3 (*Continued*)

Variables: marginal effects	Full-time (0/1)	Part-time (0/1)	Non-student (0/1)
Parent_NoHighSchool	−0.0863***	−0.00603	0.0923***
	(0.0134)	(0.00458)	(0.0134)
Parent_College	0.137***	−0.0127***	−0.125***
	(0.0116)	(0.00416)	(0.0112)
Parent_PhysMentalProblem	−0.0272*	0.00496	0.0222
	(0.0147)	(0.00581)	(0.0142)
Parent_Age	0.00255***	0.000206	−0.00275***
	(0.000708)	(0.000250)	(0.000690)
Parent_Female	−0.0378***	0.00307	0.0348***
	(0.0114)	(0.00425)	(0.0113)
Parent_HHLogIncome	0.0124***	0.000810	−0.0132***
	(0.00385)	(0.00156)	(0.00376)
Parent_Employed	0.0528**	−0.00287	−0.0499**
	(0.0254)	(0.00987)	(0.0249)
Parent_Business	0.0422***	−0.00442	−0.0378***
	(0.0133)	(0.00479)	(0.0129)
Observations: 33,470			

Note: Standard errors in parentheses. Dependent variable is occupational choice: (1) full time student; (2) part time student and (3) non-student. We report marginal effects for an 18-year old, unmarried white female with median income, no health problems, no parental health insurance, and no private health insurance whose parent is a 50 year old male, with median income, no health problems, private insurance and a high school degree. Data is from SIPP 2001, 2004, and 2008 including parental information. Observational units are individuals age 17–23. Covariates controlling for time, geographical location, parents' industry, and parents' occupational codes are omitted due to space constraints. The test results for IIA from mlogtest can be summarized as follows:

Hausman tests of IIA assumption H_0: IIA					Small-Hsiao tests of IIA assumption H_0: IIA						
Omitted	chi2	df	$P \geq$ chi2	Evidence	Omitted	ln L(full)	ln L(omit)	chi2	df	$P \geq$ chi2	Evidence
2	−0.000	6	1.000	For H_0	2	−5414.08	−5365.74	96.67	112	0.849	For H_0
3	816.252	109	0.000	Against H_0	3	−2878.97	−2701.15	112	355.64	0.000	Against H_0

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Probit model marginal effects.

Variables	(1) All individuals	(2) Students only	(3) All individuals average marginal effects	(4) Students only average marginal effects
	Full-time (0/1)	Full-time (0/1)	Full-time (0/1)	Full-time (0/1)
ParentHealthIns	0.213***	0.0645***	0.200***	0.0552***
	(0.00918)	(0.00657)	(0.00897)	(0.00495)
PrivateHealthIns	0.104***	0.00934	0.0954***	0.00548
	(0.0109)	(0.00825)	(0.0102)	(0.00490)
LostParentIns	−0.00342	−0.0324	−0.00297	−0.0186
	(0.0247)	(0.0215)	(0.0215)	(0.0129)
PhysMentalProblem	−0.0726***	−0.0158	−0.0651***	−0.00885
	(0.0163)	(0.0136)	(0.0151)	(0.00778)
Age	−1.233***	−0.348***	−1.068***	−0.193***
	(0.0420)	(0.0404)	(0.0359)	(0.0170)
AgeSquared	0.0280***	0.00785***	0.0243***	0.00436***
	(0.00106)	(0.000987)	(0.000904)	(0.000430)
Race_Black	0.00634	0.00310	0.00548	0.00172
	(0.0117)	(0.00845)	(0.0101)	(0.00468)
Race_Hispanic	−0.00669	−0.0238**	−0.00581	−0.0133**
	(0.0140)	(0.0103)	(0.0122)	(0.00587)
Female	0.0517***	0.00489	0.0444***	0.00267
	(0.00749)	(0.00525)	(0.00643)	(0.00287)
Married	−0.141***	−0.0119	−0.131***	−0.00668
	(0.0251)	(0.0224)	(0.0252)	(0.0128)
LogIncome	−0.0620***	−0.0244***	−0.0537***	−0.0135***
	(0.00295)	(0.00262)	(0.00253)	(0.00117)
d_Income	0.253***	0.0836***	0.226***	0.0475***
	(0.0188)	(0.0163)	(0.0174)	(0.00900)

Table 4 (*Continued*)

Variables	(1) All individuals Full-time (0/1)	(2) Students only Full-time (0/1)	(3) All individuals average marginal effects Full-time (0/1)	(4) Students only average marginal effects Full-time (0/1)
PellGrant	0.352***	0.0345***	0.269***	0.0191***
	(0.0126)	(0.00731)	(0.00667)	(0.00377)
CollegeAssistance	0.281***	0.0559***	0.210***	0.0294***
	(0.0488)	(0.0148)	(0.0303)	(0.00703)
OtherFedGrant	0.279***	0.00528	0.209***	0.00292
	(0.0432)	(0.0216)	(0.0264)	(0.0118)
StudentLoan	0.377***	0.0638***	0.294***	0.0363***
	(0.0120)	(0.00681)	(0.00600)	(0.00290)
Scholarship	0.360***	0.0614***	0.272***	0.0338***
	(0.0155)	(0.00792)	(0.00829)	(0.00358)
StateScholarship	0.369***	0.0650***	0.267***	0.0345***
	(0.0191)	(0.00968)	(0.00953)	(0.00414)
Parent_PrivateHealthIns	−0.0637***	−0.0270***	−0.0547***	−0.0154***
	(0.0114)	(0.00790)	(0.00956)	(0.00408)
Parent_NoHighSchool	−0.0755***	−0.00553	−0.0672***	−0.00307
	(0.0118)	(0.00866)	(0.0108)	(0.00484)
Parent_College	0.122***	0.0335***	0.105***	0.0199***
	(0.0109)	(0.00664)	(0.00908)	(0.00369)
Parent_PhysMentalProblem	−0.0234*	−0.0166	−0.0204*	−0.00925
	(0.0131)	(0.0102)	(0.0115)	(0.00576)
Parent_Age	0.00215***	0.000131	0.00186***	7.28e−05
	(0.000634)	(0.000427)	(0.000549)	(0.000238)
Parent_Female	−0.0355***	−0.0148**	−0.0309***	−0.00808*
	(0.0102)	(0.00749)	(0.00895)	(0.00413)
Parent_HHIncome	0.0104***	−0.000488	0.00899***	−0.000271
	(0.00344)	(0.00247)	(0.00298)	(0.00137)
Parent_Employed	0.0502**	0.0201	0.0442**	0.0111
	(0.0226)	(0.0184)	(0.0203)	(0.0103)
Parent_Business	0.0353***	0.0130*	0.0303***	0.00723*
	(0.0121)	(0.00760)	(0.0102)	(0.00416)
Observations	33,470	22,839	33,470	22,839

Note: Standard errors in parentheses. The dependent variable is enrolled full-time a 0/1 dummy variable taking on value one if a student is enrolled full time. In column (1) and (2) we report marginal effects for an 18-year old, unmarried white female with median income, no health problems, no parental health insurance, and no private health insurance whose parent is a 50 year old male, with median income, no health problems, private insurance and a high school degree. In columns (3) and (4) we report average marginal effects. Data is from SIPP 2001, 2004, and 2008. Observational units are individuals age 17–23 in the first and third columns, and students only in the second and fourth columns. Covariates controlling for time, geographical location, parents' industry, and parents' occupational codes are omitted due to space constraints.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Heckman selection model estimated by maximum likelihood (Y = enrolled full-time).

Variables	Pr[Y observed]	$E[Y\|Y$ observed]	$E[Y]$
ParentHealthIns	0.00753***	0.0776***	0.0838***
	(0.000524)	(0.00692)	(0.00688)
PrivateHealthIns	0.00537***	−0.00267	0.00212
	(0.000581)	(0.00949)	(0.00939)
LostParentIns	0.00116*	−0.0514**	−0.0502**
	(0.000666)	(0.0255)	(0.0254)
PhysMentalProblem	−0.00271***	−0.00817	−0.0105
	(0.000812)	(0.0119)	(0.0119)
Age	−0.0419***	−0.113***	−0.150***
	(0.00226)	(0.0289)	(0.0287)
AgeSquared	0.000954***	0.00212***	0.00296***
	(5.41e−05)	(0.000750)	(0.000746)
Race_Black	0.000245	0.00175	0.00197
	(0.000398)	(0.00657)	(0.00654)
Race_Hispanic	0.000667	−0.0309***	−0.0302***
	(0.000451)	(0.00907)	(0.00901)

Table 5 (*Continued*)

Variables	Pr[Y observed]	$E[Y\|Y$ observed]	$E[Y]$
Female	0.00218***	0.00244	0.00437
	(0.000271)	(0.00372)	(0.00371)
Married	−0.00929***	−0.0211	−0.0291
	(0.00222)	(0.0284)	(0.0280)
LogIncome	−0.00193***	−0.0156***	−0.0173***
	(0.000123)	(0.00106)	(0.00105)
d_Income	0.0119***	0.0359***	0.0461***
	(0.00133)	(0.00570)	(0.00573)
PellGrant	0.0208***	0.0185***	0.0369***
	(0.000705)	(0.00679)	(0.00681)
CollegeAssistance	0.00639***	0.0306***	0.0362***
	(0.000290)	(0.00908)	(0.00908)
OtherFedGrant	0.00570***	−0.0119	−0.00687
	(0.000265)	(0.0165)	(0.0165)
StudentLoan	0.0279***	0.0516***	0.0763***
	(0.00100)	(0.00528)	(0.00533)
Scholarship	0.0163***	0.0358***	0.0502***
	(0.000586)	(0.00536)	(0.00538)
StateScholarship	0.00899***	0.0442***	0.0522***
	(0.000390)	(0.00741)	(0.00742)
Parent_PrivateHealthIns	−0.00150***	−0.0325***	−0.0337***
	(0.000357)	(0.00863)	(0.00857)
Parent_NoHighSchool	−0.00365***	−0.00270	−0.00592
	(0.000643)	(0.00799)	(0.00790)
Parent_College	0.00354***	0.0238***	0.0269***
	(0.000321)	(0.00476)	(0.00475)
Parent_PhysMentalProblem	−0.000716	−0.0101	−0.0107
	(0.000502)	(0.00797)	(0.00792)
Parent_Age	8.82e−05***	−3.28e−05	4.58e−05
	(2.29e−05)	(0.000321)	(0.000320)
Parent_Female	−0.00117***	−0.00799	−0.00899
	(0.000400)	(0.00552)	(0.00549)
Parent_HHLogIncome	0.000448***	−0.00258	−0.00217
	(0.000120)	(0.00168)	(0.00168)
Parent_Employed	0.00174*	0.00994	0.0114
	(0.000969)	(0.0140)	(0.0139)
Parent_Business	0.00114***	0.00733	0.00831
	(0.000369)	(0.00536)	(0.00535)
Observations	33,470	33,470	33,470

Standard errors in parentheses. Dependent variable is enrolled full-time a 0/1 dummy variable taking on value one if student is enrolled full time. The selection is on whether an individual is a student. We report three sets of marginal effects that are all evaluated at the average of all independent variables: (i) the marginal effects for the probability of enrolled full-time being observed: Pr(EnrolledFull observed), (ii) the marginal effects for the expected value of enrolled full-time conditional on being observed: E(EnrolledFull|EnrolledFull observed), (iii) the marginal effects for the expected value of enrolled full-time, E(EnrolledFull). Data is from SIPP 2001, 2004, and 2008. Observational units are individuals age 17–23. Covariates controlling for time, geographical location, parents' industry, and parents' occupational codes are omitted due to space constraints.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 6
Incentive structure under pre- and post ACA reform.

Policy	Group 1: 17–24		Group 2: 24–26	
Pre-ACA	Reverse subsidy for high income students Incentive to postpone graduation ⇑ Full-time ↓ Part-time ↓ Work-full time	Parent health insurance stops	High risk of losing insurance ↓ Full-time ↓ Part-time ⇑ Work-full	
Post-ACA	Incentive to enroll as part-time student Easier for low income students to study part-time ↓ Full-time ⇑ Part-time ⇓ Work work-full		Low risk of losing insurance Incentive to postpone graduation ↓ Full-time ⇑ Part-time ↑ Work-full	Parent health insurance slops

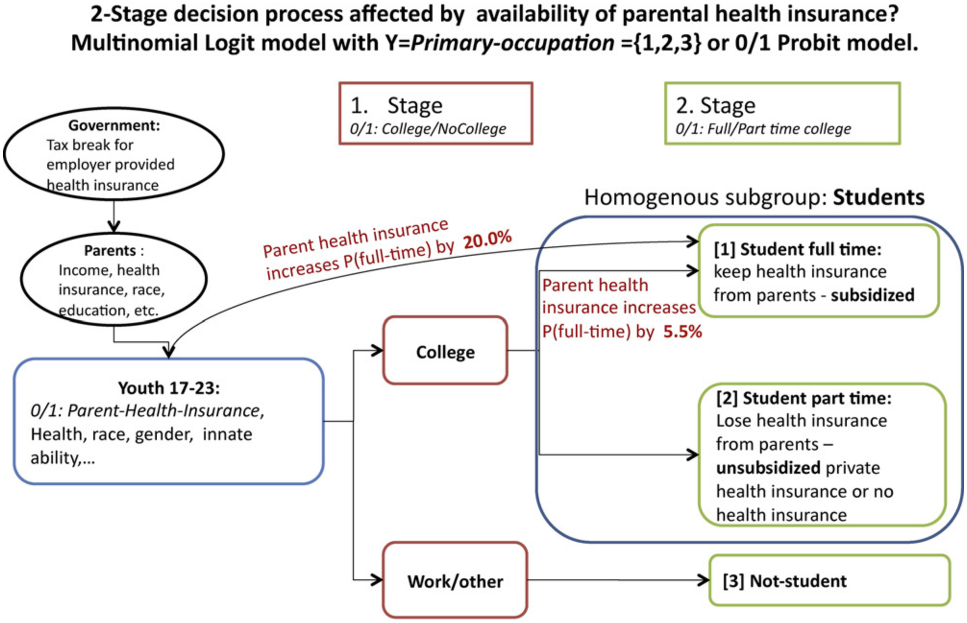

Fig. 1. Two stage decision process of a young individual deciding to go to college or not.

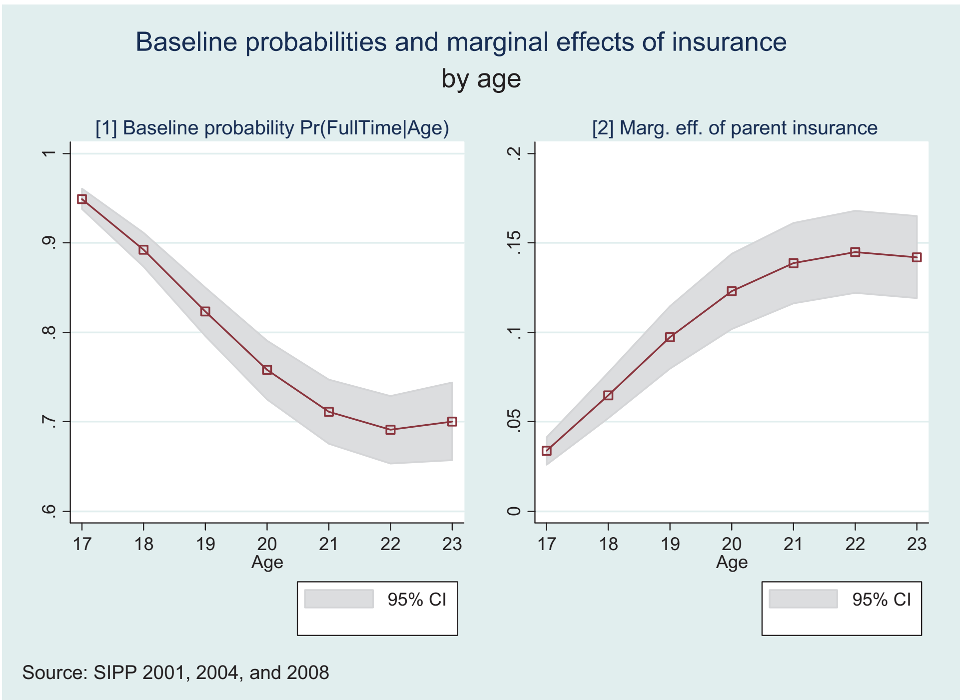

Fig. 2. Probit model. *Note*: Baseline probability of choosing the status of full-time student and marginal effects of the availability of parental health insurance on choosing to be a full-time student by age. We report marginal effects for an 18-year old, unmarried white female with median income, no health problems, no parental health insurance, and no private health insurance whose parent is a 50-year old male, with median income, no health problems, private insurance and a high school degree.

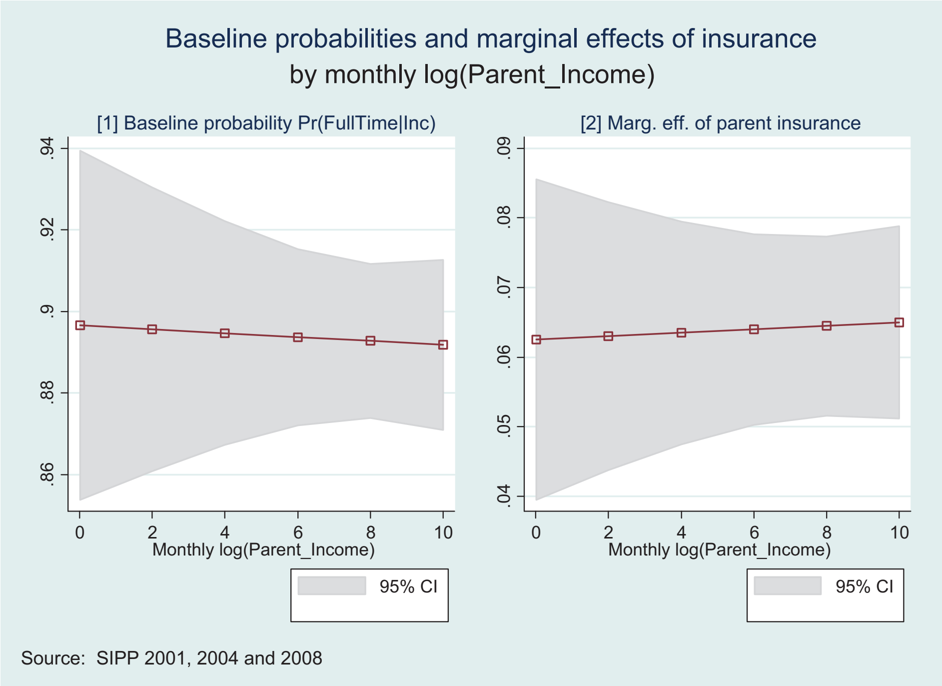

Fig. 3. Probit model. *Note*: Baseline probability of choosing the status of full-time student and marginal effects of the availability of parental health insurance on choosing to be a full-time student per monthly income in 1000 dollar units. We report marginal effects for an 18-year old, unmarried white female with median income, no health problems, no parental health insurance, and no private health insurance whose parent is a 50-year old male, with median income, no health problems, private insurance and a high school degree.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.econedurev.2012.09.010.

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