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Housing Prices, Unemployment Rates, Disadvantage, and Progress toward a Degree

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ABSTRACT

Housing Prices, Unemployment Rates, Disadvantage, and Progress toward a Degree

Rising unemployment and housing price appreciation are associated with increased college enrollment. Enrollment does not, however, guarantee completion. We use a discrete time, competing hazard function that accommodates individual-specific heterogeneity to assess the impact changing unemployment and housing prices have on progress toward a college degree in the United States for students interviewed for the 1996-2001 Beginning Post-Secondary Survey. The results indicate that rising unemployment rates have at best a modest effect on six year graduation rates. Both boys and girls are, however, more likely to not be enrolled and less likely to have graduated at the six-year mark when housing prices appreciate, and this effect is more pronounced for more disadvantaged youth.

JEL Classification: I21, I24

Keywords: higher education, graduation, housing prices, unemployment, disadvantage

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Housing Prices, Unemployment Rates, Disadvantage, and Progress toward a Degree

1. Introduction

For the average American, the economic meltdown of 2007 was particularly notable for the substantial decline in housing values and the doubling of the unemployment rate.[1] US housing values fell on average 18% between June 2007 and June 2009, and bottomed out in early 2012 over 25% below June 2007 values.[2] Meanwhile the unemployment rate rose from 4.4% in May 2007 to 10.0% in October 2009. The impact of these changes reverberated throughout the economy, but likely hit disadvantaged households especially hard. Of particular interest here is the impact changing housing prices and unemployment have on progress towards a bachelor's degree for youth as a whole and for more disadvantaged youth. Evidence suggests that enrollment is positively related to both housing wealth and the unemployment rate, but enrollment does not guarantee completion. On average only about 66% of those who enroll in a four-year college in the US complete within six years. There are multiple mechanisms by which unemployment generally and the housing market in particular might influence attendance and graduation; theory does not provide a clear prediction. Data from the 1996-2001 Beginning Post-Secondary Survey are used to estimate a discrete time, competing hazard function of post-matriculation enrollment behavior as a function of the unemployment rate and housing prices to determine the empirical relation. These factors are

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[1] Stock prices also fell significantly, but as 80% of stocks are held by the wealthiest 10% of the population (von Hoffman 2013) the decline in stock prices is unlikely to have had a substantial effect on college enrollment or graduation. Homeownership is more widespread, with rates hovering around 69% in 2007 and exceeding 50% even for those with less than median household income (Callis and Kresin 2015).

[2] Calculated using the December 2013 release of the Freddie Mac House Price Index. http://www.freddiemac.com/finance/fmhpi/

further interacted with measures of household income (or parental background) in order to determine whether youth from more disadvantaged backgrounds are more sensitive to such macroeconomic fluctuations.

2. Literature

Theoretically, the unemployment rate has both a 'substitution' and an 'income' effect on college enrollment. Human capital theory predicts that individuals will enroll in college and persist provided the expected future benefits from doing so exceed the expected future costs. The chief cost associated with enrollment is the opportunity cost of foregone employment. Higher unemployment rates make employment today less advantageous and cause substitution into higher education. However, higher education is also expensive in the US and higher unemployment rates can inhibit the ability to pay for college – causing an 'income' effect.[3] Thus, the theoretical impact of the unemployment rate on enrollment and progress toward a degree is uncertain.

Empirical estimates generally support a positive relation between unemployment and college enrollment, suggesting the substitution effect dominates (Clark 2011, Dellas and Koubi 2003, Dellas and Sakellaris 2003, Barrow and Davis 2012, Dynarski 2002). Evidence indicates the effect is not uniform across institutions or populations. Stratton, O'Toole, and Wetzel (2004) find that the fraction enrolling part-time rises with the unemployment rate, suggesting enrollment may change on the intensive as well as extensive margin. Bozick (2009) reports the association is stronger for students from low income households, and that

[3] Several authors (Johnson 2013, Card and Lemieux 2000, Clark 2011) have further pointed out that higher unemployment may increase the direct costs associated with college by reducing public funding.

enrollment rises at four year institutions but can fall at community colleges – suggesting students may substitute towards four year institutions in the face of higher unemployment. Gustman and Steinmeier (1981) find a positive relation for men, no significant relation for white women, and a significant negative relation for non-white women, for whom they argue the constraint on ability to pay (i.e. income concerns) may outweigh the substitution effect.

Theoretically, the impact of home appreciation on enrollment also has opposing 'income' and 'substitution' effects. Home owners experiencing substantial housing price appreciation may be able to tap into their equity in order to fund higher education – an income effect. Alternatively, one could argue that a booming housing market provides substantial job opportunities for less educated youth and opportunities, at least in the construction sector, that pay well. Thus, youth may be enticed to substitute toward the labor market when housing prices rise. Note that the income effect of housing prices is concentrated amongst home owners, while the substitution effect would be felt more generally, suggesting a difference that can be tested empirically. In addition, the housing market provides an alternative investment to human capital, and rising returns in that market may also trigger a substitution effect.

Evidence regarding the impact of housing price appreciation on college enrollment is rather limited. Analyzing the behavior of high school graduates from home owning families, Lovenheim (2011) estimates that a $10,000 increase in home equity increases the probability of college enrollment by about 0.7 percentage points. This effect is particularly large for youth from lower income households (5.7 percentage points), perhaps because lower income households are more likely to spend accrued equity than higher income households (Mian and

Sufi 2014). This evidence supports the 'income' effect of housing values on enrollment, particularly for youth from disadvantaged, but home owning, households.

There is also evidence of a substitution effect. Charles, Hurst, and Notowidigdo (2016) report that the housing boom reduced college enrollment. That these reductions were particularly marked at two-year institutions suggests enrollment intensity was also affected. Although this effect was observed for both men and women, Charles et al. (2016) attribute the result to improved labor market opportunities.

The extant literature focuses primarily on total enrollment or on the decision to enroll, but the theoretical arguments linking housing prices and the unemployment rate to enrollment apply as well to post-matriculation decisions, with a couple modifications. First, changing values are likely to be more important than absolute levels as individuals have already made the decision to enroll.[4] Second, rising unemployment may differentially impact graduation rates. Facing poor labor market opportunities, individuals may be more inclined to continue investing in skills rather than risk having those skills depreciate waiting for a job offer. In addition, there is a substantial literature (Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012; Liu, Salvanes, and Sørensen 2016) documenting that graduating from college when the unemployment rate is high can have substantial and persistent negative effects on earnings. Facing such prospects, students may try to delay their entry into the labor market either by dragging out their undergraduate experience or by transitioning directly into graduate school.

[4] The level of unemployment may still be important for its impact on the selection of youth into higher education. Controlling for region, however, we find the level of the unemployment rate has no significant association with progress toward a degree or enrollment intensity.

Kahn (2010) and Johnson (2013) both report a positive relation between graduate school enrollment and the unemployment rate.

Evidence linking unemployment and housing prices to progress toward a degree is limited. Stratton, O'Toole, and Wetzel (2007) find that those initially enrolling full-time are less likely to drop out when the unemployment rate is high, while the unemployment rate is not significantly associated with drop out for those initially enrolled part-time. Light (1996) finds that men who have stopped out are more likely to reenroll when the unemployment rate increases. Lovenheim and Reynolds (2013) report that youth from low income, home owning households who experience substantial increases in housing value are more likely to receive a bachelor's degree, suggesting that they may be more likely to progress towards a degree. These results could, however, be driven by the impact housing values have on the institution attended rather than the progress post matriculation. Those from low income, home owning households are more likely to enroll in four year flagship institutions with higher graduation rates and less likely to enroll in community colleges when housing prices rise. Charles et al. (2016), by contrast, observe a negative relation between housing market conditions and college attainment, particularly at two-year institutions. The goal of this analysis is to provide further micro-level evidence of the impact conditions in the labor and the housing market have on progress towards a degree and graduation, particularly for less advantaged populations.

3. Methodology

3.1 A Binary Choice Model of Initial Enrollment Status

The estimation sample consists only of individuals who enroll in college, thus the decision to enroll has already been made.[5] However, individuals may matriculate as full-time or part-time students. The intensive margin of the initial enrollment status is modeled as a binary choice,

(1) $$I = X\delta + \Theta + \varepsilon$$

where I represents the utility derived from initially matriculating part-time as compared to full-time. I itself is not observed. Instead we observe $I^* = 1$ if $I > 0$ and the individual matriculates as a part-time student, and $I^* = 0$ if $I < 0$ and the individual matriculates as a full-time student. X is a vector of time-invariant characteristics observed prior to enrollment. The error term consists of two parts, one that is (Θ) and another that is not (ε) related to subsequent transition probabilities. That part which is related to subsequent transition probabilities reflects unobserved heterogeneity and is assumed to be normally distributed. This binary choice is estimated using a logit specification. Results using a probit are similar.

3.2 A Discrete Time Competing Hazards Model of Transition

To model the subsequent enrollment path and bachelor's degree receipt, we utilize a discrete time, competing hazards function. A discrete time analysis is appropriate because higher education is organized into discrete periods known as terms. A discrete choice model

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[5] That the decision to enroll cannot also be modeled with these data is a weakness of this analysis, but the rich background information and substantial sample size available from this data source allows estimation of a more detailed model of progress than would be possible using data from other data sets such as the NLSY.

is appropriate because only a discrete number of transition possibilities exist. Individuals who are enrolled full-time or part-time in term T can subsequently not be enrolled, be enrolled part-time, be enrolled full-time, or graduate in term T+1. Individuals who are not enrolled in term T can remain unenrolled, enroll part-time, or enroll full-time in term T+1; they are not permitted to transition directly to graduation.[6] Graduation is treated as an absorbing state. This specification naturally controls for right censoring as individuals who have not graduated in the last term they are observed are still 'at-risk' for graduation. In all, there are eleven possible transitions.

Let the hazard of transitioning from state j to state k be h_{jk}. We proceed by estimating the transition hazards using a multinomial logit specification that controls for time invariant (X) and time varying covariates (W) as well as past enrollment behavior (Z) and unobserved heterogeneity (Θ). If S_j represents the set of states to which one can transition from state j, then,

$$h_{jk}(t) = \frac{\exp\left(\alpha_{jk} X + \beta_{jk} W_t + \gamma_{jk} Z_t + \lambda_{jk} \Theta\right)}{\sum_{s \in S_j} \exp\left(\alpha_{js} X + \beta_{js} W_t + \gamma_{js} Z_t + \lambda_{js} \Theta\right)} \quad (2)$$

represents the hazard associated with movement from state j to state k at time t, and α, β, and γ are coefficient vectors to be estimated. These parameters are normalized to zero in the case that individuals continue in the same state (k = j) and estimated robustly to control for heteroscedasticity. As described above, Θ captures unobserved heterogeneity. This term is

[6] The twenty-two individuals who do appear to make a transition from not enrolled to graduated are recoded as moving from part-time enrollment to graduation. These individuals appear to have completed their required class work in the summer.

moderated in this framework by the coefficient vector λ.[7] Positive values of λ_{jk} indicate that individuals who are more likely to matriculate part-time are also more likely to make transitions from state j to k.

4. Data

The data used for this analysis are drawn from the restricted access 1996-2001 Beginning Postsecondary Survey (BPS) collected by the National Center for Education Statistics (NCES) of the Department of Education. These data follow a nationally representative sample of students for six years following their matriculation to a postsecondary institution. The sample is restricted to those initially attending a public or not-for-profit four-year institution, so as to focus on students clearly interested in an academic bachelor's degree, and reporting enrollment data for the full period. After excluding those persons assigned a zero weight and those graduating in less than two years, the sample includes about 6,330 individuals.

In order to control for academic ability/performance, the sample is further restricted to individuals who are no older than age 20 upon matriculation and who report a permanent address within the United States. Those living abroad and those over the age of 20 are substantially less likely to report either SAT/ACT test scores or high school grades. A handful of other individuals are excluded for missing covariates such as age or household income, or because they are observed simultaneously enrolling in both semester and quarter

[7] This specification mimics that employed by Kalenkoski, Ribar, and Stratton (2011) to model adolescent time use.

based programs.[8] The final sample consists of about 5,800 individuals.[9] All estimates are presented using longitudinal weights.

These data include detailed term-by-term enrollment information as well as standard demographic, academic background, and household information. Table 1 provides information on the dependent variables in this analysis. The first row indicates that 4.3% of the sample initially enroll part-time. The remainder of the table summarizes the transition behavior. Overall, 76% of all the transitions begin from a state of full-time enrollment, 6% begin from part-time enrollment, and the remainder transition from non-enrollment. The most common outcome is to remain in the same state: 85% of those enrolled full-time and 86% of those not enrolled do not change states. Those enrolled part-time have more diverse transition probabilities, but still have a 67% probability of remaining enrolled part-time.

Table 1 here

Figure 1 illustrates the observed time path of enrollment. The fraction not enrolled rises, but at a diminishing rate. Part-time enrollment is quite steady for the first three years, then increases a bit before falling off. Full-time enrollment constitutes the most likely state until it is eclipsed by graduation which jumps at the end of year four, rises to 50% at the end of year five, and reaches 65% at the end of year six.[10]

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[8] Individuals may be enrolled in either a semester or a quarter based system, may be simultaneously enrolled in multiple institutions with the same calendar system, and may transition between these systems. Dummy variables are used to identify the type of system and the term from which the individual is transitioning. Spells of non-enrollment are assumed to be of the same type as the last term of enrollment.

[9] Security concerns require that sample sizes be rounded to the nearest ten.

[10] The National Center for Education Statistics reports six year graduation rates for the cohort of students entering all four year institutions in 1996 as 55.4%, but these figures include for profit institutions whose graduation rates were on the order of 28% and fail to count those who transfer and subsequently graduate.

Figure 1 here

The matrix X of time invariant covariates incorporates demographic, familial, and academic background variables, all of which have been linked to progress towards a degree (see Bound and Turner 2011 for a review). The demographic controls capture gender, race (black and other), ethnicity, and region of residence (eight census regions). As the sample is already restricted to individuals no older than twenty, no age measure is included. Familial variables include household income and dummy variables identifying independent students (2.2% of the sample),[11] those whose most-educated parent does not have a college degree (42.5% - henceforth called first generation college students), and those for whom parental education is missing (5.6%). Particularly pertinent to this study is a dummy variable identifying those students whose parents own their own home. Fully 78% are home owners and over half of the others (12%) may be, but are missing this information. Information on SAT scores, the curriculum followed in high school, and high school GPA comprises the academic background data. ACT scores are converted to their SAT equivalent using a 1999 concordance table. A dummy variable is included to identify those scores that were converted (30.6%) and to identify individuals for whom no test scores were available (2.4%). Adelman (2006) emphasizes the importance of controlling for high school curriculum. To this end, information on the highest level of math each respondent expects to complete in high school is included. The base and modal case is pre-calculus/trig (39.9%), with algebra and calculus the alternatives. High school GPA is self-reported and captured using dummy variables. The base case (and the sample norm) is a GPA of greater than 3.25 or A (38.8%). High school GPA is missing more often than any other data (10.6%) but all these ability/background

[11] The overwhelming majority of independent students are also low income.

measures are missing far less frequently than is the case in other data commonly used to examine college enrollment. Weighted sample means for these individual-specific, time invariant measures are reported in Table 2 both for the initial sample and for the transition sample.

Two types of time varying, individual level covariates (W) are incorporated: marital/parental status and college grades. Both beginning of term marital and parental status as well as changes are likely to influence enrollment behavior and do so differently for men and women. This information is not always reported, but as the vast majority of individuals were single (99.5%) and childless (98.9%) upon entering college and observed changes were rare, those missing data were pooled with those who were or became married/parents to create indicators. These variables thus indicate a possible not a certain change in status. Even using this broad measure, 80% were definitely unmarried and 90% were definitely childless in the spring of 2001 when last observed. As status changes were not likely to be complete surprises, these are calculated as with perfect foresight over the course of the semester in the case of marriage and over the course of the semester plus three months in the case of childbirth. Marriages and births that occur around graduation are ignored as they are likely timed in anticipation.

Cumulative college grades were reported at three points in time: the end of the first year, the end of the third year, and the end of the sixth year. Grades are frozen for individuals who cease enrollment. Grades from the first year are used to model enrollment through year two. Grades from year three are used to model enrollment through year four. Grades from year six are used to model enrollment in years five and six. Grades are missing for only 2% of the observed transitions and always missing for fewer than thirty respondents.

Finally, there are controls for past enrollment behavior (Z). Time invariant dummy variables identify individuals who initially enrolled part-time and who did not initially enroll in fall 1995. Also included are dummy variables identifying the term from which individuals are transitioning (spring semester, fall quarter, winter quarter, and spring quarter – fall semester being the base case). These are necessary to capture the fact that individuals are more likely to withdraw between academic years than within an academic year. As graduation spikes in year four, a dummy to identify the spring 1999 term is incorporated. Finally, quadratic measures of the number of years individuals have spent not enrolled, enrolled part-time, and enrolled full-time since matriculation but prior to term j are constructed. Incorporating these measures of past enrollment allows us to test whether previous behavior is a significant predictor of future behavior, and graduation is certainly contingent upon having completed a certain number of credits. Sample means for both the time varying covariates (W) and the past enrollment behavior measures (Z) are reported in Appendix A.

These are all important control variables, but none capture the key variables of interest: the unemployment rate and housing price. The quarterly unemployment rate is drawn from Bureau of Labor Statistics Local Area Unemployment data while monthly home price values are taken from Freddie Mac Housing Price Index, adjusted for overall inflation using the Consumer Price Index. These data are available at the state level and are matched to the analysis sample based on the state of the institution where individuals initially matriculated. The change in the unemployment rate between two quarters and one quarter prior to the beginning of a term is used to model subsequent behavior ($UR_{t-1} – UR_{t-2}$ where t reflects the quarter of initial enrollment or the quarter to which an individual is transitioning).[12] While it is recent changes in the unemployment rate that logically have a salient impact on behavior by changing opportunity costs and income today, changes in real housing values have to be more persistent to alter behavior. Home owners must have accumulated enough equity to warrant pulling some out to pay for higher education (the income effect) and/or the job market must have had time to create alternative opportunities (the substitution effect). Measures of change over a 30 month period were incorporated in the estimates reported here.[13] We discuss sensitivity testing of these unemployment rate and housing price change measures in a separate section of the paper.

As the sample covers only a single cohort's behavior, it is vital to demonstrate that there is sufficient variation in these variables to affect decision making. Given the unemployment rate change measure employed (a one quarter lag), the relevant analysis period is January 1995 to January 2001. The sample average values for (UR_{t-1} – UR_{t-2}) are reported in Table 2. The unemployment rate at the time these individuals initially enrolled averaged 5.5%, having risen on average almost half a percentage point in the previous year. Unemployment rates on average declined over the next six years at a rate of about a quarter of a percent a year (4 x -0.070). Figure 2 illustrates the difference between the maximum and minimum unemployment rates during the analysis period for each state. The average state difference is 1.8 percentage points, which given the initial average state unemployment rate constitutes a substantial 33% differential. In order to test whether the unemployment rate

[12] Thus, the change in the unemployment rate between the third and second quarters of the year is used to model matriculation in the fall term and the change in the unemployment rate between the fourth and third quarters of the year is used to model the transition from fall to spring.

[13] Thus, the change in housing prices between January 1993 and July 1995 is used to model matriculation status in Fall 1995 and the change in housing prices between June 1993 and December 1995 is used to model the transition from Fall 1995 to Spring 1996.

disproportionately affects the disadvantaged, an interaction term between the unemployment rate change measure and household income is also incorporated in the model.

Table 2 here

Figure 2 here

Figure 3 illustrates how nominal housing prices and the overall price index evolved between 1975 and 2013 at the national level. Real housing prices began their historic rise only in the late 1990s, toward the end of the observed enrollment period. However, the variation in real housing prices by state in the relevant analysis period (July 1993 through January 2001 – allowing for the 30 month window) is substantial (see Figure 4). By state this differential ranged from -28% in Hawaii and -4% in Pennsylvania to 35% in Massachusetts and 46% in Colorado.

Figure 3 here

Figure 4 here

As discussed, the impact of housing price appreciation may differ by home ownership status and income level. The expectation is that rising home equity may provide a source of funds for students whose families are home owners and may increase their progress towards a degree, but a robust housing market may also offer alternative opportunities that make enrollment less attractive and so negatively impact persistence and graduation. Again, disadvantaged youth may be more responsive to these price changes so a full complement of interaction terms between home ownership, housing price appreciation, and income is included. In some cases this involves simply a dummy identifying households in the lowest 25% of the income distribution – households with annual earnings of no more than $30,000 1995$. Sample means for the home price appreciation measure itself are reported in Table 2.

As unemployment rates and housing prices are state specific they may be interrelated and/or they may capture unobserved state-specific effects rather than the intended time varying effects. The data confirm there is a moderately strong negative correlation between the unemployment rate and housing prices ($\rho = -0.47$), indicating that higher unemployment rates are associated with lower housing prices. However, the correlation between changes in the unemployment rate and housing prices is both smaller and positive ($\rho = 0.25$). That several different state linked measures are included should act to mitigate concerns about state-specific effects. Further, while it is not possible to include state fixed effects with only a single cohort, dummy variables for eight Census regions are incorporated so that effects are actually calculated off within region changes in the unemployment rate and housing prices.

5. Results

Robust parameter estimates for the key variables of interest are reported in Table 3. The first row contains results related to initial enrollment status. Subsequent rows provide results for each of the possible transitions. Other coefficient estimates are reported in Appendix B.

Table 3 here

Evaluated at sample means, rising unemployment is associated with a lower probability of matriculating as a part-time student. This result is consistent with the notion that rising unemployment reduces the opportunity cost associated with more intensive enrollment patterns. However, youth from households in the lowest decile of the income distribution (below $14,000) are predicted to be equally or more likely to enroll part-time in the face of rising unemployment. This may be because youth from lower income, more disadvantaged, households are choosing to enroll part-time rather than not enroll at all. As our sample consists only of those who decide to enroll, we cannot control for such selection.

Most students whose parents are home owners are less likely to enroll part-time. The exception is students from low income households whose enrollment at the intensive margin does not vary with home ownership (p-value 0.63). Rising housing prices are also associated with less part-time enrollment, and this association does not differ significantly by household income. Unlike the data used by Lovenheim (2011) and Lovenheim and Reynolds (2013), these data contain no information, self-reported or otherwise, on housing prices or equity, so it is not possible to estimate how much appreciation each homeowner has experienced. We can only identify the average effect of housing price appreciation for youth from home owning households, but do so separately for low versus other income households. Consistent with results reported by both Lovenheim (2011) and Lovenheim and Reynolds (2013), we find that housing price appreciation is associated with more intense, full-time matriculation only for youth from low income, home owning households.

Subsequent transitions also appear sensitive to local economic conditions. Changing unemployment rates are significantly associated with transition probabilities, though the effect differs somewhat by household income. Home ownership is associated with less movement between full-time and non-enrollment, though not for students from low income, home owning households (p-value 0.41). Housing price appreciation is associated with significant churn and churn that differs somewhat by household income level, but the effect is not significantly different for students from home owning households in general (p-value 0.12) or for those from low income, home owning households (p-value 0.18).

The transition results in particular, however, are difficult to interpret. The goal is to examine how changes in the unemployment rate and housing prices relate to progress toward a degree, particularly for students from disadvantaged households. However, the precise direction of these effects and their marginal impact on graduation rates is not clear. For example, a positive coefficient in the logit modeling the transition from full-time to part-time enrollment means the variable increases the probability of these transitions relative to remaining enrolled full-time and likely increases the observed time spent enrolled part-time, but the impact on graduation depends also on the effect this variable has upon transitions from part-time enrollment and on how past enrollment behavior influences subsequent transitions.

In order to better assess the marginal effect each variable has on progress toward a degree and to demonstrate the degree to which our model is able to reproduce observed enrollment paths and outcomes, we use our parameter estimates to simulate enrollment paths and final outcomes for the estimation sample. For the base case simulation, the time invariant factors are encoded as reported by the individual. Unemployment rate and housing price variables also take their observed values. Marital and parental status and college grades are fixed at their starting values. About 20% of respondents are coded as possibly changing marital status over the course of the panel survey; about 9% may become parents. While married persons are somewhat more likely to transition to graduation, parents are somewhat less likely to do so. Simulations reveal that the net effect of fixing these variables at their initial values as compared to their final values is small. College grades, on the other hand, have a consistent and significant positive impact on progress towards a degree and are reported to increase over time. About 30% report a cumulative college GPA of 3.25 or better in the first year. This fraction rises to almost 43%, despite the fact that those failing out of school and not returning retain their record of failing grades throughout. Freezing grades at their initial rather than final values increases the simulated probability of non-enrollment and decreases the simulated graduation rate by about eight percentage points. Freezing grades at their initial values also reduces the fraction of youth still enrolled full-time six years following matriculation relative to observed values, suggesting that rising grades may increase time to graduation. The measures of Z or past enrollment are allowed to evolve as predicted by the simulation. To capture the heterogeneity component Θ, each individual is replicated fifty times with Θs generated as random draws from a normal distribution with the variance as estimated. Transitions are simulated by comparing the estimated hazard, including the heterogeneity component, to a random draw.

Table 4 presents simulated marginal effects for the income, unemployment, and housing related variables. The first two columns show results for initial enrollment status. The remainder of the columns show predicted status in Spring 2001, the final term for which actual enrollment is observed. The first row shows actual outcomes in Spring 2001. The second row shows predicted outcomes for the base case. The predicted probability of initially being enrolled part-time is a bit lower than the actual probability (3.6% versus 4.3%). The predicted outcome in Spring 2001 is, as suggested above, skewed towards more non-enrollment (29.4% versus 23.4%); less persistence, particularly of full-time enrollment (4.2% versus 8.6%); and less graduation (62.8% versus 63.6%). Nevertheless, the time pattern of predicted enrollment generated by this simulation (shown in Figure 5) is very similar to the actual path (shown in Figure 1). This model fits the data remarkably well.

Table 4 here

Figure 5 here

The remainder of Table 4 shows simulated marginal effects. These effects are calculated by fixing the sample values for one or more variables and comparing these predicted outcomes with other predicted outcomes (e.g. increasing the change in the unemployment rate by a fixed amount for every observation and comparing the predicted outcome from this simulation with the predicted outcome from the baseline simulation). What follows includes only a limited discussion of initial enrollment status as these probabilities change relatively little. Furthermore, as the predicted probability of still being enrolled either part-time or full-time in Spring 2001 is small, the discussion below focuses primarily on the predicted probability of no longer being enrolled in college and the predicted probability of having graduated by Spring 2001. When one of these measures rises, the other almost always falls by approximately the same magnitude.

Given the importance of interactions between our key variables of interest (changing unemployment and housing prices) and household income, we begin by simulating outcomes for household incomes at approximately the 25th, 50th, and 75th percentile levels and comparing them to the baseline predictions in row two. Income has very little impact on the predicted probability of initially enrolling part-time – with no difference larger than 0.2 percentage points (5%). Household income is, however, associated with substantial differences in the probability of having graduated versus not being enrolled in Spring 2001. Raising household income to the 75th percentile raises the probability of having graduated and lowers the probability of no longer being enrolled in Spring 2001 by just over one percentage point. Given the much lower probability of not being enrolled as compared to having graduated, this one percentage point change reduces the probability of not being enrolled by 4% but increases the probability of having graduated by only 2%. Lowering household income to the 25th percentile has an even larger marginal impact. The probability of not being enrolled in Spring 2001 is about 1.5 percentage points (8%) higher and the probability of having graduated commensurately lower. Disadvantage, as captured by household income, is associated with significantly less progress toward a degree. The majority of the results that follow in Table 4 use either the simulated base case or these simulated income results for comparison purposes. The final column of the table indicates to which results each simulation is compared.

We look first at the association between changes in the unemployment rate and the outcomes of interest. The simulation reported in row 6 takes the base case and increases the change in the observed unemployment rate by one standard deviation (about two-thirds of a percentage point per year) above that actually observed. Thus, if the unemployment rate fell by 0.5 percentage points during a given six month period, in the simulation the unemployment rate falls by 0.17 (-0.5+0.67/2) percentage points. Increasing unemployment rate changes in this way lowers the probability of matriculating part-time by 0.5 percentage points (13%), a result that is consistent with a substitution toward more intense enrollment and away from the less rewarding labor market. Looking at predicted outcomes in Spring 2001, we find the simulated marginal effect of rising unemployment rates yields an increased probability of not being enrolled (about 0.3 percentage points or 1%) and a corresponding decrease in the probability of having graduated, perhaps because the marginal students attracted to college during poor labor markets are less likely to complete. These results do not provide much evidence that students generally delay graduation when the job market is weak.

The simulation results reported in rows 7 through 9 identify the marginal impact of changes in the unemployment rate by household income. These results indicate that the marginal effect of changing unemployment rates is greatest for students from high income households. It is those from high income households who are particularly less likely to matriculate as part-time students when the unemployment rate is rising (0.7 percentage points or 19%) and who are less likely to have graduated by Spring 2001 (0.5 percentage points or about 1%). Interestingly, for those from higher income households 40% of the reduction in the predicted probability of having graduated is accounted for by a higher probability of still being enrolled part-time. By comparison, students from low income households are actually slightly less likely to not be enrolled and more likely to have graduated. These results suggest that students from higher income households may be more likely to attempt to time their graduation to avoid entering the labor market when their prospects are poor.[14] Students from more disadvantaged households may not have the financial resources to prolong their enrollment.

The remainder of Table 4 focuses on the effects of home ownership and housing price appreciation. The association with home ownership is substantial. Owning a home is associated with a 29% lower probability of initially enrolling part-time (calculated by comparing simulated outcomes assuming all versus no students are from home owning households). The simulated marginal effect of home ownership on Spring 2001 outcomes is also substantial. Family home ownership is associated with a 7% (2.3 percentage point) lower probability of not being enrolled and a 4% (2.5 percentage point) higher probability of having

[14] Further evidence that students from higher income households may be delaying their graduation in the face of poor labor market conditions is visible in the time sequence of part-time enrollment. The probability of being enrolled part-time is projected to be 1.0 percentage point higher for students from high as compared to low income households at the 4 and 5 year points, but 1.4 percentage points higher in year 4 and 1.25 percentage points higher in year 5 when the unemployment rate is rising faster.

graduated. As noted earlier, this effect is limited to higher income households: the marginal effect of home ownership on college outcomes for students from low income households is both negligible and in the opposite direction.

The effect of housing price appreciation is calculated by taking the observed price changes as the point of comparison and adding a per 30 month period, 1 standard deviation change (+6.7%) to the observed change. We first examine the association between housing price appreciation and outcomes for the entire population. The probability of initially enrolling part-time is lower by 1.0 percentage points or about 28% when housing prices appreciate. The probability of not being enrolled in Spring 2001 rises by 7.6% (2.2 percentage points) while the probability of graduating by Spring 2001 falls by 3.0% (1.9 percentage points), accounting for over 80% of the increased probability of not being enrolled. A decline in the fraction enrolled part-time in Spring 2001 explains the rest. These constitute substantial effects.

The next three rows of Table 4 demonstrate that while the direction of the effect is similar for all income groups, the magnitude of the effect on progress toward a degree differs substantially by income. It is students from low income households who are more sensitive to prices in the housing market. Both the relative and the absolute magnitude of the effect is greater for these more disadvantaged students. These results support those of Charles et al. (2015) who found that enrollment was lower (and employment higher) during housing booms especially for individuals at the margin. They found that the enrollment effect was greater at two-year than at four-year colleges. Our model suggests that part-time matriculation (enrollment at the intensive margin) and progress toward a degree at four-year colleges is also affected.

Previous research focused on students whose parents were home owners to estimate the impact of home price appreciation (Lovenheim and Reynolds 2013). We find the effect of a one standard deviation higher housing price appreciation on Spring 2001 outcomes is roughly the same for home owners as for the population as a whole (results available upon request). In no case is the difference more than 0.6 percentage points. We do find, however, as shown in the final row of Table 4, that as compared with students from low income households facing rising housing prices, those from low income, home owning households facing rising housing prices have a 13.5% lower probability of matriculating part-time, a finding that complements Lovenheim and Reynolds's (2013), though the absolute magnitude of this differential is small (0.26 percentage points).

Simulated marginal effects for other covariates are reported in Appendix C. Many of these effects are substantial. Women, for example, are predicted to be substantially less likely to initially enroll part-time than men (2.8% versus 4.5%) and substantially more likely to have graduated (64% versus 62%). Graduation rates are similar for whites and African Americans, but African Americans are more likely to still be enrolled and so could have higher eventual graduation rates. Ethnic differences are larger. As compared to non-Hispanics, Hispanics are estimated to be 5% (3 percentage points) less likely to have graduated, with the difference primarily offset by higher probabilities of not being enrolled and being enrolled part-time, suggesting that final graduation rates are likely to be smaller for Hispanics. The marginal effect of ethnicity on the predicted probability of initially being enrolled part-time is also notable as Hispanics are predicted to be 0.6 percentage points (or 18%) less likely to matriculate part-time. Family characteristics play a role, too. First generation college students are predicted to be about 12% (8 percentage points) less likely to have graduated than students with one or more college educated parent. This lower probability is primarily offset by higher predicted non-enrollment, indicating they are not just taking longer to earn the degree.

The marginal effect of academic preparation on matriculation intensity and college success is even larger. Almost 40% of the sample self-reports having a high school GPA of A: some of these values may be overstated. Still, having a high school GPA of B or lower is estimated to almost double the probability of matriculating part-time as compared to having a high school GPA of A – perhaps because such students are 'testing the waters'. Students with such low high school GPA are also substantially less likely to be predicted to have graduated (18% or 12 percentage points) and more likely to not be enrolled six years later. Somewhat surprisingly, there is only a one percentage point swing in the difference between the simulated effect of taking calculus (the high) rather than pre-calculus (the medium) curriculum, but stopping below the pre-calculus level is associated with substantially worse outcomes – namely about a 6 percentage point lower graduation rate and a 6 percentage point higher rate of non-enrollment as compared to the simulated outcomes for those taking calculus. Higher SAT scores have a similar but substantially more muted association with progress towards a degree than high school grades, with simulated marginal effects only in the 2 to 3 percentage point range.

The controls for heterogeneity (Θ) in this estimation are found to be highly statistically significant (p-value 0.0000). The bottom rows of Appendix C demonstrate the impact Θ has upon the estimates. As compared with the baseline model from Table 4, setting Θ equal to zero reduces the probability of initially enrolling part-time by almost one percentage point and increases the probability of having graduated by 2.5 percentage points. Drawing values of Θ

that are one standard deviation away from the mean of zero has large effects on all the outcomes, with positive values not surprisingly increasing the probability of initially enrolling part-time. Positive values also increase the probability of being enrolled part-time or having a degree in Spring 2001, and reduce the probability of not being enrolled or being enrolled full-time.

6. Sensitivity Testing

We tested several alternative unemployment rate and housing price change measures. The results reported above are for a one period lagged change in the quarterly unemployment rate ($UR_{t-1} - UR_{t-2}$). Estimates obtained using a two period lagged change ($UR_{t-1} - UR_{t-3}$) and a double lag ($U_{t-2} - UR_{t-3}$) did not fit the data as well. Likewise, estimates using an 18, 24, and 36 rather than 30 month window for housing price changes were obtained. The likelihood value is higher with longer windows, but flattens out considerably after 24 months. The log likelihood value differed only in the sixth digit using a 36 month window. Results are reported for data matching the unemployment rate and housing price data to the state in which each individual first attended college. Alternative specifications matching unemployment rate and housing price data to each individual's state of residence (or the state of the high school he/she attended) yielded similar results, but with a lower likelihood value. The likelihood value was slightly higher when modeling the initial enrollment decision as a function of economic conditions in the state of residence (where presumably the family home is located) and the subsequent transitions as a function of economic conditions in the state where the respondent attended college. Controls for the unemployment rate itself (in addition to the regional dummies and the change in the unemployment rate) were not statistically significant (p-value 0.66).

We explored in alternative specifications explanations for the housing market effects. As we control for unemployment rate changes in our baseline specification, it is not economic conditions so broadly measured that explain the housing market effects we observe. Specifications including measures of 24 or 36 month changes in the number of housing permits issued in lieu of housing price changes did not fit the data very well. This finding could arise because building permits are a noisy measure of construction activity[15]. If rising housing prices influence progress towards a degree by providing job opportunities in the construction sector, then one would expect to observe men being more responsive than women since the construction sector is clearly male-dominated. Just as Charles et al. (2016) find results are similar for men and women, however, we find that housing price appreciation does not have a differential impact by gender (p-value 0.42). Housing price data may capture more than simply the construction sector. To test this, we used Current Population Survey data from the Bureau of Labor Statistics to construct measures of the employment rate and the labor force participation rate by quarter and state for young persons (age 17-26) with a high school but not a college degree. These measures should capture labor market opportunities for young high school graduates. Neither 1, 2, or 3 year differences in these measures whether included alone or also interacted with family income (using either a continuous measure or a dummy for low family income) was found to be statistically significant. These results are not surprising given the limited correlation between these labor force measures and

[15] Building permits are obtained before construction begins and in fact construction may not occur at all. Also worth noting is the low correlation between housing price appreciation and housing permits: 0.16.

housing prices (never higher than 0.07 in absolute value). Perhaps rising housing prices attract investment away from higher education, particularly in disadvantaged households that may be less familiar with the returns to higher education.[16]

Finally, the main results use household income as a measure of disadvantage. Other measures of disadvantage in higher education exist. In particular, first generation college students often have difficulty making progress toward a degree and are generally identified as disadvantaged in the education literature. We reestimated our model interacting both the unemployment rate and the housing price change measures with a dummy variable for first generation status rather than family income to see how robust our estimates are to use of this alternative measure of disadvantage. It is worth noting that the overlap between low income and first generation college students is limited. While 61% of first generation college students are low income, only 36% of low income students are first generation. The simulated marginal effect of unemployment rate changes on progress is larger but not substantially different by parental education. The simulated marginal effect of housing prices is virtually identical and larger for students with less versus more educated parents (who are predicted to be 12% more likely to not be enrolled and 5.6% less likely to have graduated at the six year mark), indicating that disadvantaged students whether measured by household income or parental education are both less likely to progress toward a degree during housing booms than are more advantaged students. Home ownership status has little incremental effect for first

[16] We also explored the possibility that housing market conditions might influence progress toward a degree via their influence on enrollment. While we find that full-time equivalent enrollment growth is positively related to housing prices, the correlation is below 0.08 and housing prices are still significant determinants of enrollment, particularly for disadvantaged youth, when controls for enrollment growth are included in the hazard function.

generation college students. Thus again, we find that the substitution effect of housing prices is greater than the income effect and particularly so for less advantaged students.

7. Conclusion

Prior research suggests that higher unemployment rates increase college enrollment as youth substitute toward higher education when labor market conditions are not so favorable, while rising housing prices increase enrollment for youth from low income, home owning households perhaps because they are able to tap into their rising household wealth to fund higher education. Increased enrollment does not, however, guarantee graduation. Given the substantial increases in unemployment and decreases in housing prices experienced in the US during the Great Recession, it is of some interest to examine the impact these factors have on progress towards a degree, rather than simply enrollment. Evidence from a cohort of students entering college in the 1995-96 academic year and followed through Spring 2001 is examined here using a discrete time hazard model that allows for individual-specific heterogeneity. During this period, the national unemployment rate fell almost 25% (about 1.4 percentage points) while real housing prices increased on average about 21%.

Our data do not enable us to study the enrollment decision itself, however we do find evidence that the intensive margin of the initial enrollment spell is sensitive to changing unemployment and housing prices. Rising unemployment rates are associated with more full-time versus part-time enrollment, consistent with substitution towards higher education and away from the labor market in the face of lower opportunity costs. Greater housing price appreciation is also found to be associated with a higher probability of full-time enrollment, particularly for low income home owners. This finding is consistent with the hypothesis that housing price appreciation brings about a positive income effect for low income home owners who might otherwise be financially constrained.

Other simulation results indicate that rising unemployment rates are associated with slightly lower six year graduation rates, offset to a significant degree by higher part-time enrollment at the six year point, particularly for youth from higher income households. It may be that these students are attempting to delay or time their graduation in the hope that labor market conditions will improve. That this behavior is more prevalent amongst students from higher income households may reflect the fact that these students have the financial resources to drag out their enrollment. If graduating during a period of high unemployment causes long run scarring, this means that it is students from low income backgrounds who may be more likely to suffer. However, it may also be the case that the long term consequences that have been attributed to graduating during periods of high unemployment are due to selection. If graduates during economic downturns are more likely to be from more disadvantaged backgrounds and consequently have fewer labor market contacts than those from more advantaged backgrounds, they may make worse initial job matches. Research has found that these first jobs can have substantial long term consequences (Oreopoulos et al. 2012).

The association between home ownership and progress toward a degree is much stronger. Individuals from home owning households are substantially more likely to have graduated six years later. Such households have already demonstrated their willingness to invest in the real estate market; they may also be more willing to invest in higher education. This effect is, however, not observed for youth from low income, home owning households, perhaps because these households are strapped for cash.

The effect of housing prices on progress toward a degree is more complex. We find that housing price appreciation increases the predicted probability of not being enrolled and reduces the predicted probability of having graduated six years following matriculation, particularly for students from disadvantaged households. This effect holds whether disadvantage is measured by household income or parental education and does not differ significantly by home ownership status. We find no differential effect by student gender and no evidence that building permits are a better measure than housing prices, suggesting that the construction sector alone is not responsible. These results provide corroborating evidence for findings by Charles et al. (2015) that booming housing markets boost employment and reduce enrollment, particularly for youth on the margin for enrollment in higher education. We do not, however, find evidence that rising home prices are associated with substantially different employment rates or labor force participation rates for youth with high school degrees. Nor is there evidence that these labor market conditions are significantly associated with progress toward a degree. Further research into the mechanisms underlying the relation between housing prices and college enrollment is necessary. One possibility is that rising housing prices make real estate an attractive investment alternative as compared to higher education.

Overall, these results imply that the rising unemployment rates of the Great Recession may have caused youth from more advantaged households to drag out their undergraduate enrollment, while the falling housing prices may have increased progress toward a degree, particularly for youth from less advantaged households. Simulated results leaving initial conditions and housing prices at baseline levels but allowing subsequent unemployment rates to evolve as they did for those entering college in the 2005-6 academic year show a significant increase in part-time enrollment in 2009-10 but little effect on six year graduation rates. The simulated effect of the housing market meltdown (holding initial conditions and unemployment rates at their baseline values) is to increase six year graduation rates by 2 percentage points, almost double the fraction enrolled part-time at the six year point, and reduce non-enrollment at the six year point by 4.5 percentage points – substantial shifts. While actual six year graduation rates did rise for the cohorts entering college during the Great Recession, they did not rise this much. Any housing market effects were likely moderated as so many households lost their homes during the crisis. While household income and parental education have long been known to be closely associated with college enrollment and progress toward a degree, this paper demonstrates that these measures of household disadvantage play an important role as well in mediating the relation between college outcomes and economic conditions, as measured both by the unemployment rate and especially by housing prices.

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Figure 1
Enrollment Status over Time

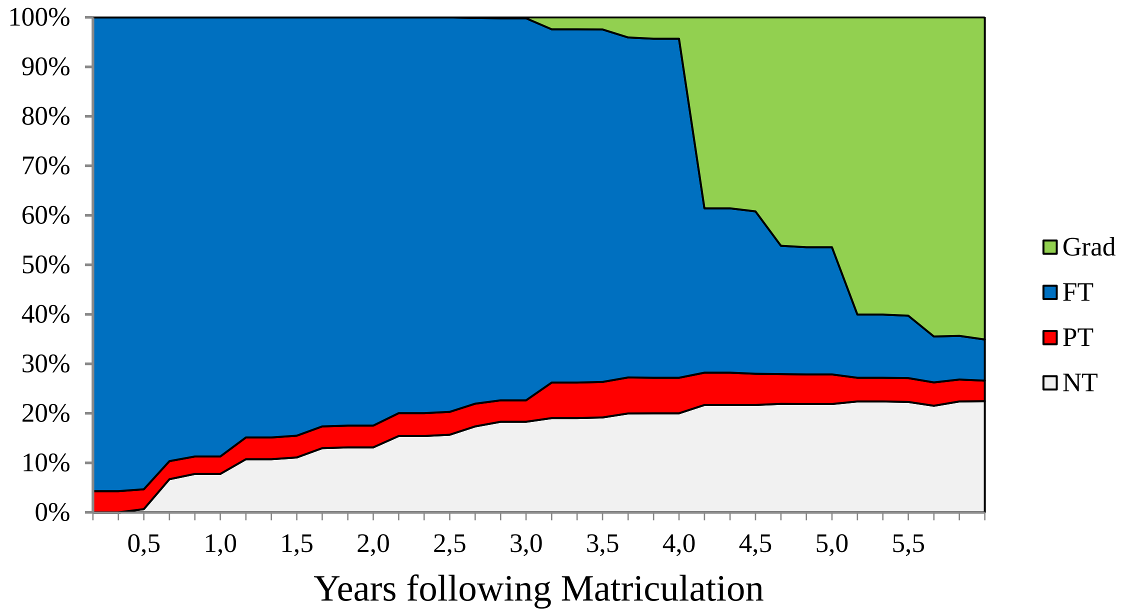
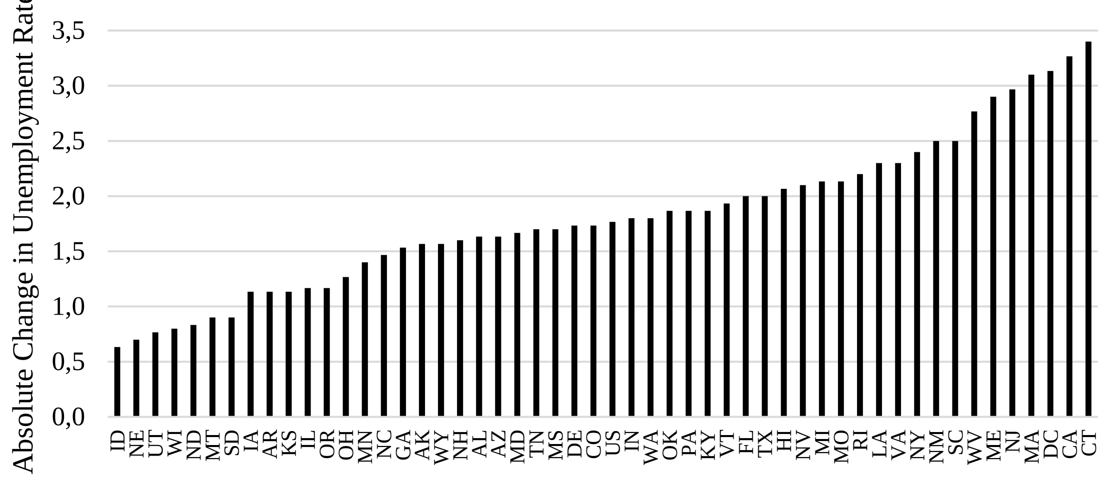


Figure 2
Magnitude of Unemployment Rate Changes:
Jan. 1995-Jan. 2001



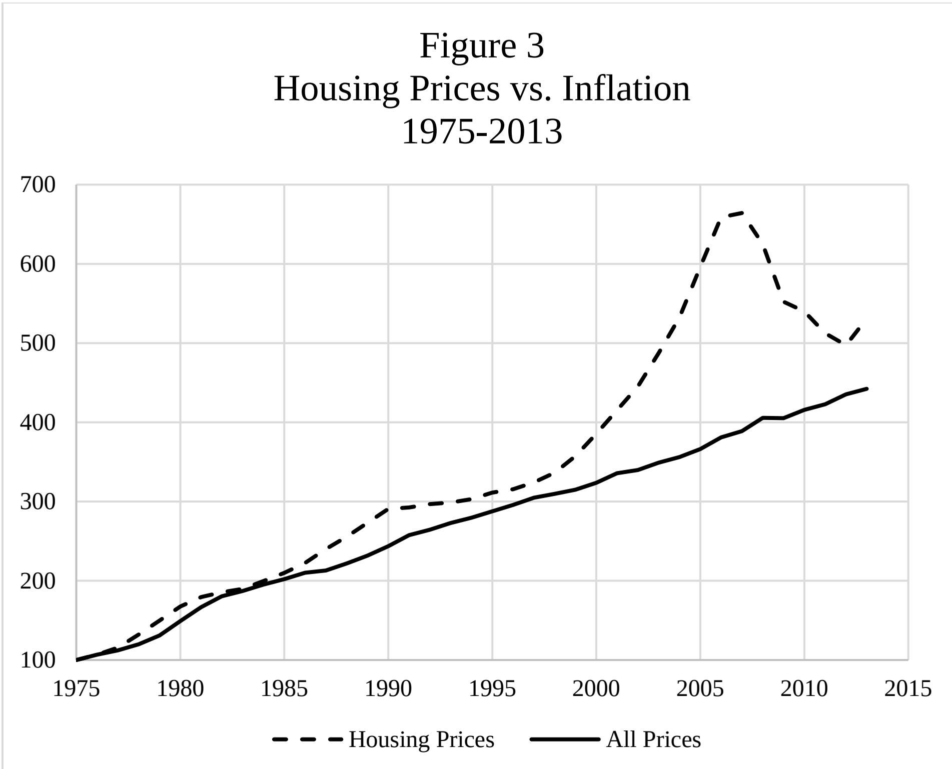


Figure 3
Housing Prices vs. Inflation
1975-2013
700
600
500
400
300
200
100
1975
1980
1985
1990
1995
2000
2005
2010
2015
Housing Prices
All Prices

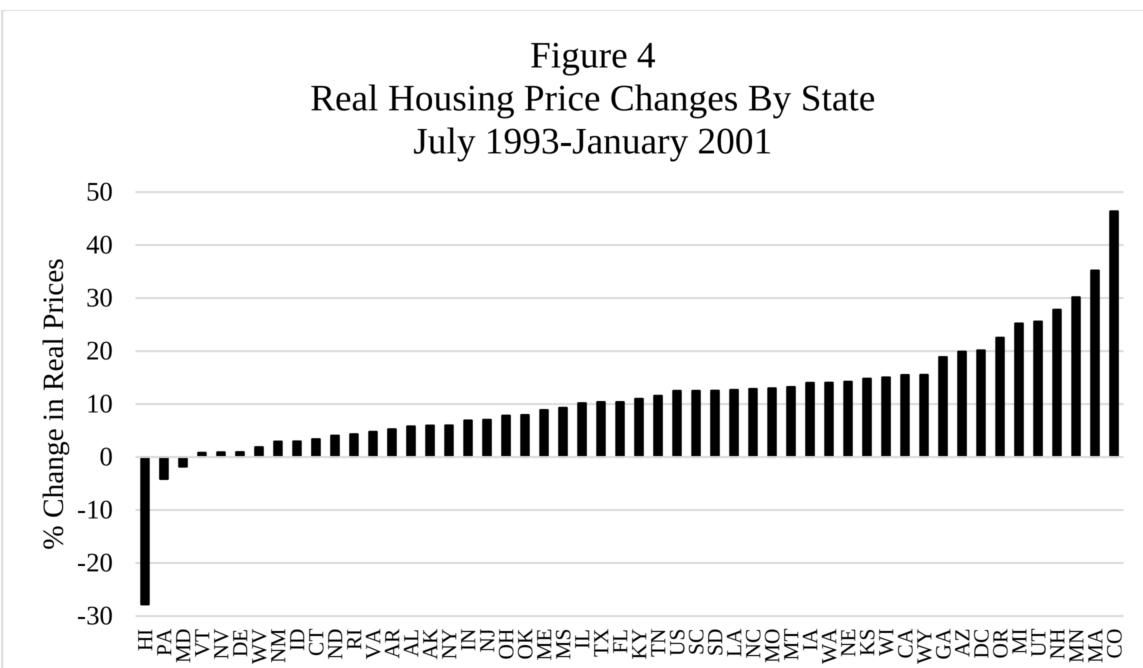


Figure 4
Real Housing Price Changes By State
July 1993-January 2001
% Change in Real Prices
50
40
30
20
10
0
-10
-20
-30
HI PA MD VT NV DE WV NM ID CT ND RI VA AR AL AK NY IN NJ OH OK ME MS IL TX FL KY TN US SC SD LA NC MO MT IA WA NE KS WI CA WY GA AZ DC OR MI UT NH MN MA CO

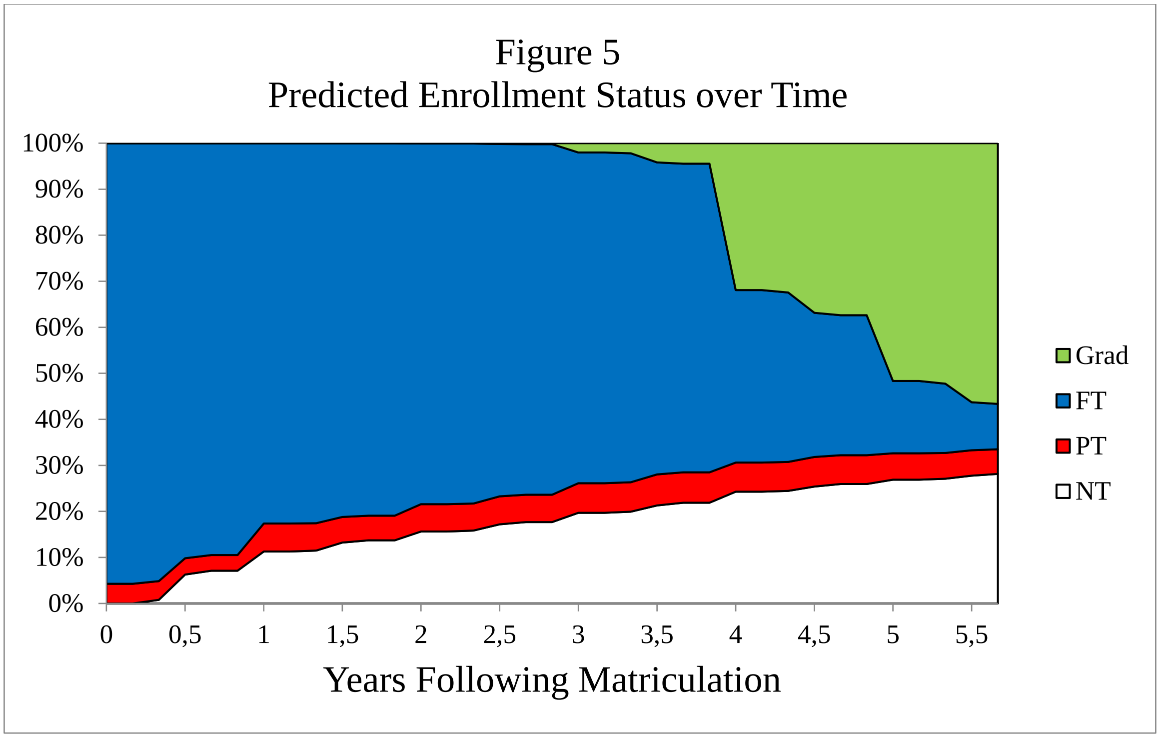


Figure 5
Predicted Enrollment Status over Time

Table 1: Enrollment Behavior

	Enrollment Status				
	Full-Time	Part-Time	Not Enrolled	Graduate	Overall
First Term	95.71%	4.29%			100%
Transitional Analysis: Initial Enrollment					
Full-Time	85.24%	1.66%	5.22%	7.87%	76.00%
Part-Time	12.69%	67.01%	15.47%	4.84%	6.09%
Not Enrolled	10.32%	4.00%	85.67%	0.00%	17.90%

Table 2: Weighted Sample Characteristics

	Initial Enrollment	Transition Equations
Change in Unemployment Rate	0.069	-0.070
Real Housing Price Appreciation	1.158	3.977
Female	0.548	0.539
Black	0.110	0.115
Other Race	0.108	0.114
Hispanic	0.081	0.084
Income (/1000)	61.293	59.893
Independent	0.022	0.023
First Generation	0.425	0.440
Parent's Education Unknown	0.056	0.058
Own a House	0.781	0.772
Home Ownership Missing	0.119	0.123
SAT Test Score (/100)	9.692	9.589
ACT Dummy	0.306	0.316
Missing Test	0.024	0.026
Math Prep: Algebra	0.235	0.246
Math Prep: Trig	0.399	0.397
Math Prep: Calculus	0.261	0.249
Missing Math Prep	0.106	0.108
High School GPA A	0.388	0.370
High School GPA B	0.274	0.275
High School GPA C-	0.232	0.248
Missing High School GPA	0.106	0.107
~ Number of Observations	5,800	58,830
Weighted Number of Observations	1,152,277	11,674,510

Eight dummies for region of the country and interaction terms between the unemployment rate and income and between housing prices, income, and home ownership are also included.

Table 3: Key Parameter Estimates

	Change in Unemp. Rate	Change in Unemp. Rate * Income	Home Owner, Not Low Income	Home Owner, Low Income	Housing Price Appreciation	Housing Price Apprec. * Income	Price * Not Low Income Owner	Price * Low Income Owner
<u>Initial Enrollment Status:</u>								
Part-Time	0.3354	-0.0246 ***	-0.4573 **	-0.1636	-0.0645 **	0.0001	0.0080	-0.0548 **
	(0.9547)	(0.0082)	(0.2227)	(0.2528)	(0.0259)	(0.0001)	(0.0227)	(0.0271)
<u>Transition Equations:</u>								
Full-Time to	-0.1157	0.0064 **	-0.1794 **	-0.0496	0.0356 ***	-0.0001 **	-0.0102	-0.0038
Not Enrolled	(0.2092)	(0.0032)	(0.0839)	(0.0885)	(0.0081)	(0.0001)	(0.0077)	(0.0094)
Full-Time to	1.6076 ***	0.0074 *	0.1424	-0.1363	-0.0291 *	-0.0002 **	0.0252 *	-0.0089
Part-Time	(0.3735)	(0.0041)	(0.1531)	(0.1730)	(0.0170)	(0.0001)	(0.0138)	(0.0176)
Part-Time to	0.9936 **	-0.0076	0.0655	0.0081	0.0598 **	-0.0003	-0.0426	-0.0438
Not Enrolled	(0.4914)	(0.0062)	(0.2971)	(0.2953)	(0.0279)	(0.0003)	(0.0274)	(0.0315)
Part-Time to	2.5968 ***	-0.0092	0.2519	-0.2914	0.0322	-0.0004	0.0019	-0.0392
Full-Time	(0.8476)	(0.0125)	(0.3361)	(0.3480)	(0.0331)	(0.0003)	(0.0300)	(0.0372)
Not Enrolled to	0.3924	-0.0070	0.1194	0.0763	-0.0586 ***	0.0005 **	0.0209	0.0169
Part-Time	(0.5454)	(0.0073)	(0.2179)	(0.2338)	(0.0207)	(0.0002)	(0.0173)	(0.0228)
Not Enrolled to	0.1052	-0.0035	-0.3443 ***	-0.1752	-0.0218 *	0.0004 ***	-0.0041	0.0112
Full-Time	(0.3660)	(0.0044)	(0.1266)	(0.1392)	(0.0131)	(0.0001)	(0.0119)	(0.0143)
Full-Time to	-0.4008	0.0141 ***	0.1720	0.0852	-0.0095	-0.0001	-0.0091	-0.0240 *
Graduate	(0.3017)	(0.0034)	(0.1137)	(0.1308)	(0.0114)	(0.0001)	(0.0100)	(0.0129)

Part-Time to	-0.0999	-0.0010	0.5992	0.9072	0.1357 ***	-0.0003	-0.0230	0.0278
Graduate	(0.9812)	(0.0099)	(0.5228)	(0.5531)	(0.0508)	(0.0003)	(0.0366)	(0.0488)
Chi-Squared P-Value	0.0000 (a)	0.0004	0.0011 (b)	0.2248 (c)	0.0000 (d)	0.0003 (e)	0.0476 (f)	0.0549 (g)

(a) Tests for exclusion of all unemployment information.
(b) Tests for exclusion of all home ownership information.
(c) Tests for exclusion of all low income home owner information.
(d) Tests for exclusion of all housing price information.
(e) Tests for exclusion of interaction between income and housing price information (with and without home ownership).
(f) Tests whether home owners act differently when housing prices appreciate as compared to non-home owners.
(g) Tests whether persons from low income, home owning households act differently when housing prices appreciate as compared to all other home owners.
Huber-corrected standard error reported in parentheses.
Specification also includes controls for gender, race (2), and Hispanic ethnicity; combined SAT score, dummy indicators for those taking the ACT and for those missing test scores; a dummy to identify independent students, household income; a dummy to identify students whose parents did not complete college and a dummy to identify students with missing parental education; high school math curriculum (2) or missing indicators; high school GPA (2) or missing indicators; dummy variables to identify married persons and parents separately by gender. All the transition equation also include: dummy variables to identify those who become parents separately by gender; dummy variables to identify those who initially enrolled part-time or in a non-fall term; college GPA measures (4); dummy variables to identify term from which are transitioning (4); dummy variables to identify Spring 1999; a dummy to identify those missing home ownership info; and quadratic measures of time not enrolled, time enrolled part-time, and time enrolled full-time. The transition equations not leading to graduation also include gender specific dummies to identify those who marry.

Table 4: Simulated Marginal Effects

	Initial Enrollment		Status as of Spring 2001								
	Part-Time	% Δ	Not Enrolled	% Δ	Part-Time	% Δ	Full-Time	% Δ	Grad.	% Δ	
Actual	4.29		23.43		4.31		8.63		63.63		
Predicted	3.56		29.41		3.60		4.18		62.81		
Simulated Marginal Effect of Income											
Low Income ($30K = ~25th percentile)	3.40	-4.6%	31.85	8.3%	3.01	-16.4%	4.72	12.9%	60.42	-3.8%	(a)
Middle Income ($50K = ~ 50th percentile)	3.53	-0.9%	29.54	0.4%	3.63	0.8%	4.12	-1.4%	62.70	-0.2%	(a)
High Income ($75K = ~ 75th percentile)	3.69	3.6%	28.12	-4.4%	3.72	3.3%	4.18	0.0%	63.98	1.9%	(a)
Simulated Marginal Effect of Unemployment Rate											
Unemp Rate Increases by 1 sd/6 months	3.08	-13.5%	29.72	1.1%	3.76	4.4%	3.99	-4.5%	62.53	-0.4%	(a)
Low Income & Rising Unemp Rate	3.22	-5.4%	31.52	-1.0%	3.15	4.7%	4.67	-1.1%	60.65	0.4%	(b)
Middle Income & Rising Unemp Rate	3.10	-12.1%	29.81	0.9%	3.75	3.3%	3.95	-4.1%	62.50	-0.3%	(b)
High Income & Rising Unemp Rate	2.98	-19.2%	28.78	2.3%	3.93	5.6%	3.82	-8.6%	63.48	-0.8%	(b)
Simulated Marginal Effect of Housing Market											
Do Not Own a Home	4.81		31.61		3.26		4.67		60.46		
Own a Home	3.42	-29.0%	29.29	-7.3%	3.60	10.4%	4.15	-11.1%	62.96	4.1%	(c)
Low Income Home Owner	3.26	-4.3%	31.89	0.1%	2.93	-2.7%	4.80	1.7%	60.38	-0.1%	(b)
Middle Income Home Owner	3.39	-3.9%	29.21	-1.1%	3.79	4.4%	3.99	-3.2%	63.00	0.5%	(b)

High Income Home Owner	3.56	-3.6%	27.82	-1.1%	3.9	4.8%	4.04	-3.3%	64.25	0.4%	(b)
Housing Prices Increase 1 sd/30 months	2.55	-28.4%	31.65	7.6%	2.99	-16.9%	4.42	5.7%	60.94	-3.0%	(a)
Low Income & Housing Prices Increase 1 sd/30 months	1.97	-42.1%	35.27	10.7%	2.27	-24.6%	5.13	8.7%	57.33	-5.1%	(b)
Middle Income & Housing Prices Increase 1 sd/30 months	2.60	-26.4%	31.89	8.0%	3.11	-14.3%	4.25	3.2%	60.75	-3.1%	(b)
High Income & Housing Prices Increase 1 sd/30 months	2.79	-24.4%	29.56	5.1%	3.23	-13.2%	4.47	6.9%	62.74	-1.9%	(b)
Low Income Home Owner & Housing Prices Increase 1 sd/30 months	1.70	-13.5%	35.05	-0.6%	2.26	-0.4%	5.31	3.5%	57.38	0.1%	(d)

(a) compares with Predicted, (b) compares with Income, (c) compares with Own a Home, (d) compares with Low Income & Housing Prices Increase.

Results based on simulation with 50 draws.

Appendix A
Sample Means for Additional Covariates

Variables	Means
Married (or missing marital status)	0.127
Parent (or missing parental status)	0.054
Marry (or may have)	0.085
Became a Parent (or may have)	0.026
College GPA 3.25+	0.326
College GPA 2.75-3.25	0.312
College GPA 2.25-2.75	0.189
College GPA < 2.25	0.154
College Grades Missing	0.020
Began Part-Time	0.048
Did Not Begin in the Fall	0.041
Fall Semester	0.422
Spring Semester	0.383
Fall Quarter	0.067
Winter Quarter	0.066
Spring Quarter	0.062
Spring of 1999	0.095
Time Spent Not Enrolled	0.326
Time Spent Enrolled Part-Time	0.125
Time Spent Enrolled Full-Time	1.730
~Number of Observations	58,830
Weighted Number of Observations	11,674,510

Appendix B: Other Parameter Estimates

	Initial Enrollment Status	Transition Equations: Full-Time to …		
Parameter	Part-Time	Not Enrolled	Part-Time	Graduate
Constant	-3.1375 ***	-3.5623 ***	-4.5487 ***	-14.6519 ***
	(0.8497)	(0.2882)	(0.6204)	(0.7035)
Female	-0.5477 ***	0.0063	-0.2510 **	0.1706 ***
	(0.1497)	(0.0513)	(0.0993)	(0.0656)
Black	-0.0792	-0.1019	-0.0861	-0.4312 ***
	(0.2333)	(0.0788)	(0.1591)	(0.1149)
Other Race	0.1855	-0.1043	0.2774 *	-0.0688
	(0.2646)	(0.0919)	(0.1481)	(0.1132)
Hispanic	-0.2465	0.0204	0.0000	-0.2031
	(0.2724)	(0.0989)	(0.1651)	(0.1240)
Test Score (/100)	-0.1785 ***	-0.0022	-0.0507 *	0.0719 ***
	(0.0565)	(0.0170)	(0.0303)	(0.0205)
ACT Test	0.6764 ***	0.2057 ***	0.3277 **	-0.1842 **
	(0.2271)	(0.0706)	(0.1383)	(0.0936)
Missing Test Score	-1.0390 *	0.5724 ***	-0.3935	0.5519
	(0.5933)	(0.2111)	(0.4343)	(0.3660)
Calculus	0.0431	-0.0934	0.0247	0.0623
	(0.2282)	(0.0730)	(0.1169)	(0.0778)
Algebra	0.0819	0.1697 ***	0.0235	-0.2570 ***
	(0.1928)	(0.0614)	(0.1125)	(0.0893)
Missing Math Preparation	1.3529 ***	0.5125 ***	-0.0307	0.0069
	(0.4183)	(0.1488)	(0.2696)	(0.1971)
High School GPA: B to A-	0.4956 **	0.2435 ***	0.3549 ***	-0.1449 *
	(0.2223)	(0.0705)	(0.1342)	(0.0814)
High School GPA: B or lower	0.7950 ***	0.4762 ***	0.4716 ***	-0.3903 ***
	(0.2502)	(0.0854)	(0.1689)	(0.1243)
Missing High School GPA	-0.1138	-0.0735	0.4043	-0.1991
	(0.4277)	(0.1608)	(0.2645)	(0.1935)
Independent	1.3895 ***	-0.0616	0.4872	0.7311 **
	(0.5115)	(0.1896)	(0.3446)	(0.3145)
Income/1000	2.8904 **	-1.4329 **	0.2943	1.1164 **
	(1.2074)	(0.6839)	(0.8628)	(0.5617)

Appendix B: Other Parameter Estimates (cont.)

	Initial Enrollment Status		Transition Equations:					
			Full-Time to …					
Parameter	Part-Time		Not Enrolled		Part-Time		Graduate	
First Generation	0.1274		0.2437	***	0.1802	*	-0.3676	***
	(0.1564)		(0.0530)		(0.0951)		(0.0720)	
Parental Education Missing	-0.5840		0.0099		0.6787	***	-0.2772	*
	(0.3920)		(0.1222)		(0.2228)		(0.1667)	
Married	-4.0000	(a)	-0.4438	*	0.1289		0.4325	***
			(0.2459)		(0.3908)		(0.1460)	
Female * Married	3.6449	***	0.5776	*	0.4480		0.0687	
	(1.0668)		(0.2964)		(0.4587)		(0.1729)	
Parent	-0.8975		0.9259	***	0.8653	**	-0.0369	
	(1.3063)		(0.1912)		(0.3987)		(0.3393)	
Female * Parent	1.2676		-0.5425	**	-0.0681		-0.4884	
	(1.2977)		(0.2635)		(0.4813)		(0.3971)	
Marry (b)			0.5239	*	0.2973			
			(0.2697)		(0.4473)			
Female * Marry (b)			-0.3588		0.1446			
			(0.3330)		(0.5216)			
Became a Parent			0.3072		0.1994		0.0153	
			(0.3047)		(0.4566)		(0.5858)	
Female * Became a Parent			0.6902	**	-0.0355		0.2424	
			(0.3482)		(0.6012)		(0.6561)	
Home Ownership Missing	-0.4321		-0.1672		-0.2365		0.0000	
	(0.3122)		(0.1147)		(0.2237)		(0.1596)	
Began Part-Time			0.0974		0.0290		-0.1932	
			(0.2587)		(0.5430)		(0.4941)	
Did Not Begin in Fall Term			0.5414	***	-0.3359		0.3757	
			(0.1056)		(0.2336)		(0.2483)	
College GPA: 2.75-3.25			0.0901		0.0215		-0.4596	***
			(0.0707)		(0.1185)		(0.0691)	
College GPA: 2.25-2.75			0.4178	***	0.2042		-1.0760	***
			(0.0834)		(0.1320)		(0.1057)	
College GPA: < 2.25			1.3445	***	0.8877	***	-2.8316	***
			(0.0812)		(0.1464)		(0.3235)	

Appendix B: Other Parameter Estimates (cont.)

	Initial Enrollment Status	Transition Equations: Full-Time to …		
Parameter	Part-Time	Not Enrolled	Part-Time	Graduate
Missing College Grades		1.3603 ***	0.3741	-0.9292 ***
		(0.1770)	(0.3084)	(0.2617)
Spring Semester		0.6506 ***	1.4627***	1.3526 ***
		(0.0538)	(0.1048)	(0.0812)
Fall Quarter		-0.2129 *	-0.0978	-0.6217 ***
		(0.1191)	(0.2245)	(0.2089)
Winter Quarter		0.6849 ***	-0.5784 *	-0.6636 **
		(0.1343)	(0.3323)	(0.2739)
Spring Quarter		0.7290 ***	1.9397***	1.4446 ***
		(0.1440)	(0.2276)	(0.2089)
Spring 1999		0.1279 ***	-0.9898***	1.2579 ***
		(0.0952)	(0.2266)	(0.0789)
Years Not Enrolled		1.2210 ***	0.5217	0.1008
		(0.1844)	(0.4165)	(0.4936)
Years Not Enrolled Squared		-0.2977 ***	-0.1026	0.3172 *
		(0.0791)	(0.1683)	(0.1773)
Years Enrolled Part-Time		1.0649 **	-0.5169	0.4755
		(0.3991)	(1.0158)	(0.6079)
Years Enrolled PT Squared		-0.3167 ***	-0.1460	0.5344 ***
		(0.1283)	(0.3029)	(0.2006)
Years Enrolled Full-Time		-0.4107 ***	-0.8712***	4.3099 ***
		(0.0945)	(0.1058)	(0.3568)
Years Enrolled FT Squared		0.0987	0.1815***	-0.2273 ***
		(0.0247)	(0.0399)	(0.0568)

Appendix B: Other Parameter Estimates (cont.)

Transition Equations:

Parameter	Part-Time to … Not-Enrolled		Part-Time to … Full-Time		Part-Time to … Graduate		Not Enrolled to … Part-Time		Not Enrolled to … Full-Time	
Constant	-0.9135		2.3312	**	-12.4106	***	-3.0386	***	-0.4857	
	(1.0745)		(1.0984)		(2.4819)		(0.6730)		(0.4240)	
Female	-0.2076		-0.1419		0.7935	***	0.4228	***	-0.1217	
	(0.1776)		(0.1964)		(0.2991)		(0.1436)		(0.0898)	
Black	0.0928		0.5232	*	-0.1942		0.1874		-0.0015	
	(0.2567)		(0.3055)		(0.4436)		(0.1904)		(0.1380)	
Other Race	-0.2481		0.6144	**	0.6430		0.4373	*	-0.0952	
	(0.2532)		(0.2707)		(0.4150)		(0.2399)		(0.1537)	
Hispanic	-0.1660		-1.2085	***	-0.4966		-0.1159		-0.2185	
	(0.2924)		(0.3154)		(0.5828)		(0.2504)		(0.1598)	
Test Score (/100)	0.0960	*	0.0249		0.2821	***	0.1212	***	0.0641	**
	(0.0515)		(0.0610)		(0.0885)		(0.0395)		(0.0263)	
ACT Test	-0.0228		-0.4577		-0.6043		-0.0543		-0.5439	***
	(0.2848)		(0.3352)		(0.3720)		(0.1766)		(0.1124)	
Missing Test Score	0.6578		-0.4561		4.0411	***	0.9635	**	-0.2261	
	(0.6774)		(0.8014)		(1.1658)		(0.4785)		(0.3197)	
Calculus	0.0184		-0.2050		0.0261		0.1287		-0.0097	
	(0.2540)		(0.2565)		(0.3288)		(0.1842)		(0.1166)	
Algebra	0.4899	**	0.2636		0.2184		0.0101		-0.1499	
	(0.1965)		(0.2228)		(0.3520)		(0.1548)		(0.1045)	
Missing Math Preparation	-0.0359		-0.3473		-0.8252		-0.6062	*	-0.1176	
	(0.4593)		(0.5162)		(0.6553)		(0.3579)		(0.2194)	

Appendix B: Other Parameter Estimates (cont.)

Transition Equations:

Parameter	Part-Time to … Not-Enrolled		Full-Time		Graduate		Not Enrolled to … Part-Time		Full-Time	
High School GPA: B to A-	0.0426		-0.5324	**	-0.4995		0.1255		-0.1248	
	(0.2746)		(0.2672)		(0.3719)		(0.1865)		(0.1167)	
High School GPA: B or lower	0.1852		-0.7998	**	-0.6300		0.3779	*	-0.1275	
	(0.3556)		(0.3674)		(0.4965)		(0.2105)		(0.1310)	
Missing High School GPA	0.7807		-0.7704		-0.0821		0.3557		0.0519	
	(0.4958)		(0.5510)		(0.6734)		(0.3678)		(0.2331)	
Independent	-0.9770	*	-2.2791	***	-2.0657		-0.2131		-0.4030	
	(0.5428)		(0.7791)		(1.4712)		(0.4059)		(0.2984)	
Income/1000	0.8487		-4.5062		-3.3658		-2.0370		1.1813	
	(2.1036)		(2.7511)		(2.5235)		(1.8993)		(1.0064)	
First Generation	0.1203		-0.4732	**	-0.5880	*	-0.1860		-0.2564	***
	(0.1815)		(0.1954)		(0.3402)		(0.1358)		(0.0873)	
Parental Education Missing	0.2152		0.4090		0.0201		-0.3089		-0.7217	***
	(0.3951)		(0.3739)		(0.5750)		(0.3146)		(0.2410)	
Married	-0.2251		-0.8371		1.1674	**	-0.3345		-0.5637	*
	(0.3465)		(0.6367)		(0.5443)		(0.3889)		(0.2994)	
Female * Married	0.8621	*	1.4172	*	-0.2078		-0.0920		-0.6340	
	(0.4694)		(0.7528)		(0.6333)		(0.4800)		(0.3862)	
Parent	0.9528	***	0.4308		-0.0453		0.3493		-0.6874	**
	(0.3600)		(0.7527)		(0.7801)		(0.3626)		(0.2888)	
Female * Parent	-1.0673	**	-1.4870		-0.9784		-0.8022	*	0.7189	**
	(0.4984)		(0.9273)		(1.0049)		(0.4389)		(0.3322)	

Appendix B: Other Parameter Estimates (cont.)

Transition Equations:

Parameter	Part-Time to … Not-Enrolled		Part-Time to … Full-Time		Part-Time to … Graduate		Not Enrolled to … Part-Time		Not Enrolled to … Full-Time	
Marry (b)	0.1746		0.1389				-0.1714		-0.5080	
	(0.3851)		(0.7221)				(0.4113)		(0.3719)	
Female * Marry (b)	-0.4902		0.2686				-0.1417		1.0847	**
	(0.5287)		(0.8325)				(0.5209)		(0.4533)	
Became a Parent	-0.1862		0.0419		1.5569		-0.8533		0.5434	*
	(0.7455)		(1.1312)		(1.0219)		(0.5393)		(0.3193)	
Female * Became a Parent	0.6383		-0.2213		-2.6592	*	-0.4696		-1.0941	***
	(0.8765)		(1.3425)		(1.4470)		(0.7341)		(0.4098)	
Home Ownership Missing	0.1115		0.0118		0.7824		0.4794	*	-0.0634	
	(0.3891)		(0.4652)		(0.6500)		(0.2809)		(0.1898)	
Began Part-Time	-0.0122		0.5033		0.9095		-0.3924		0.3582	
	(0.7383)		(0.7727)		(1.0526)		(0.5088)		(0.2972)	
Did Not Begin in Fall Term	-0.1716		-1.1320	***	0.7016		0.0122		-0.1361	
	(0.3375)		(0.4065)		(0.8961)		(0.2424)		(0.1723)	
College GPA: 2.75-3.25	0.1516		-0.1028		-0.1511		-0.4269	**	-0.5864	***
	(0.1904)		(0.2105)		(0.2990)		(0.1726)		(0.1162)	
College GPA: 2.25-2.75	-0.0738		0.0001		-0.5695		-0.9290	***	-0.8582	***
	(0.2224)		(0.2386)		(0.3694)		(0.2157)		(0.1406)	
College GPA: < 2.25	0.7635	***	-0.2519		-3.5694	**	-1.0385	***	-1.4320	***
	(0.2279)		(0.2591)		(1.5825)		(0.2239)		(0.1448)	
Missing College Grades	1.6037	***	0.7369		0.2540		-0.6937	**	-1.0674	***
	(0.4300)		(0.6406)		(1.2248)		(0.3060)		(0.2363)	

Appendix B: Other Parameter Estimates (cont.)

Transition Equations:

	Part-Time to …						Not Enrolled to …			
Parameter	Not-Enrolled		Full-Time		Graduate		Part-Time		Full-Time	
Spring Semester	0.8688	***	2.3109	***	2.1821	***	0.2130	*	1.0975	***
	(0.1390)		(0.1797)		(0.3015)		(0.1284)		(0.0922)	
Fall Quarter	-0.3929		-0.0526		0.5303		-0.5018	*	-0.2055	
	(0.2766)		(0.3425)		(0.6658)		(0.2578)		(0.1943)	
Winter Quarter	0.3649		0.6669	*	-0.3802		-1.1976	***	-0.6792	**
	(0.3040)		(0.3889)		(0.6797)		(0.4246)		(0.2750)	
Spring Quarter	0.7014	**	0.7268	*	0.7898		0.9535	***	1.7726	***
	(0.3184)		(0.3974)		(0.6838)		(0.2850)		(0.1935)	
Spring 1999	-0.2877		-1.6041	***	-0.0330		-0.0552		-0.3274	**
	(0.1902)		(0.3823)		(0.2920)		(0.1810)		(0.1299)	
Years Not Enrolled	0.3663		-1.1949	**	-0.7100		-0.8338	***	-1.2763	***
	(0.3790)		(0.4737)		(0.8419)		(0.1970)		(0.1245)	
Years Not Enrolled Squared	-0.1749	*	0.0600		0.3018		0.1369	***	0.1456	***
	(0.0993)		(0.1514)		(0.2541)		(0.0479)		(0.0370)	
Years Enrolled Part-Time	0.6508	**	-0.2197		1.7485	**	-0.0575		-1.0975	***
	(0.3217)		(0.4072)		(0.7979)		(0.5990)		(0.3159)	
Years Enrolled PT Squared	-0.0383		0.0549		0.1217		-0.0449		0.1258	
	(0.0706)		(0.0869)		(0.1531)		(0.1342)		(0.1186)	
Years Enrolled Full-Time	-1.9934	***	-3.1525	***	2.6781	***	-0.1036		0.0603	
	(0.3923)		(0.4721)		(1.0070)		(0.2250)		(0.1380)	
Years Enrolled FT Squared	0.3353	***	0.4331	***	-0.1141		0.0363		-0.0620	*
	(0.0889)		(0.1024)		(0.1557)		(0.0480)		(0.0321)	

Appendix B: Other Parameter Estimates (cont.)

<u>Heterogeneity Parameters</u>		
Lambda FT to Not Enrolled	-0.2850	
	(0.4634)	
Lambda FT to PT	1.0163	
	(0.7156)	
Lambda FT to Graduate	0.9202	*
	(0.5186)	
Lambda PT to Not Enrolled	-1.4977	*
	(0.7921)	
Lambda PT to Not Enrolled	-1.4977	*
	(0.7921)	
Lambda PT to FT	-1.5767	**
	(0.7831)	
Lambda PT to Graduate	-1.2414	
	(1.2144)	
Lambda Not Enrolled to PT	0.9464	
	(0.7930)	
Lambda Not Enrolled to FT	0.4523	
	(0.3666)	
Sigma	0.9671	*
	(0.5658)	
Log Likelihood	-24428.9	

(a) All the men who were married at the outset were enrolled full-time.

(b) As there is a distinct spike in marriages around the time of graduation, these variables are excluded from the analysis on account of endogeneity.

Asterisks indicate statistical significance at the *** 1% level, ** 5% level, and * 10% level.

Also included in the analysis are the variables listed in Table 3 of the text and 8 region dummies.

Appendix C: Additional Simulated Marginal Effects

	Initial Enrollment		Status as of Spring 2001							
	Part-Time	% Δ	Not Enrolled	% Δ	Part-Time	% Δ	Full-Time	% Δ	Grad-uate	% Δ
Men	4.46		30.20		3.55		4.61		61.64	
Women	2.84	-36.4%	28.68	-5.0%	3.66	3.1%	3.82	-17.1%	63.85	3.6%
White	3.54		29.86		3.49		3.99		62.66	
African American	3.31	-6.4%	28.78	-3.6%	3.80	8.9%	5.34	33.8%	62.08	-0.9%
Other Race	4.12	16.4%	27.58	-7.6%	4.00	14.6%	4.15	4.0%	64.26	2.6%
Non-Hispanic	3.63		29.20		3.57		4.19		63.05	
Hispanic	2.96	-18.4%	31.74	8.7%	4.09	14.6%	4.21	0.5%	59.96	-4.9%
Not First Generation	3.47		25.87		3.32		4.14		66.67	
First Generation	3.84	10.8%	32.80	26.8%	3.90	17.5%	4.45	7.5%	58.85	-11.7%
HS GPA: A	2.68		24.81		2.72		4.29		68.18	
HS GPA: B to A-	4.03	50.5%	30.33	22.2%	3.74	37.5%	4.25	-0.9%	61.67	-9.5%
HS GPA: B or lower	5.11	91.1%	34.89	40.6%	4.60	69.1%	4.64	8.2%	55.88	-18.0%
Math Prep: Calculus	3.07		25.90		3.83		4.17		66.10	
Math Prep: Pre-Calculus	2.95	-3.7%	27.21	5.1%	3.73	-2.6%	4.31	3.4%	64.75	-2.0%
Math Prep: Algebra	3.18	3.5%	31.75	22.6%	3.54	-7.6%	4.57	9.6%	60.14	-9.0%
SAT: 1200	1.93		25.18		3.01		4.35		67.46	
SAT: 1000	2.48	28.6%	26.23	4.2%	3.19	6.0%	4.53	4.1%	66.05	-2.1%
SAT: 800	3.13	62.1%	27.38	8.7%	3.39	12.6%	4.72	8.5%	64.50	-4.4%
0 se	2.63		28.43		2.25		4.02		65.30	
+1 se	5.99	127.93	20.39	-28.28	6.51	189.33	2.72	-32.34	70.38	7.78
-1 se	1.04	-60.51	38.59	35.74	0.73	-67.56	5.68	41.29	55.00	-15.77

HS stands for High School
Results based on simulation with 50 draws.
Comparison groups are those missing entries for the %Δ.

Footnotes