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Predicting Higher Education Enrollment in the United States: An Evaluation of Different Modeling Approaches

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ABSTRACT The purpose of this paper is to assess the state of the art in model-based enrollment prediction for U.S. higher education. We review available studies, consider methodological and data-availability issues raised by the approaches reflected in the literature, and report on a study comparing the forecast performance of several alternative models. We conclude that combining the results from disaggregated forecasting models and trying alternative approaches is a much better option for predicting higher education enrollments than searching for a universal model that works for all groups at all times.

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Running Head: Predicting Higher Education Enrollment

While there is a sizable literature on college enrollment, far more of the work has been concerned with hypothesis testing than with forecasting. That is, the literature has tended to concentrate more on determining variables that are statistically significantly related to college enrollment than in constructing models that forecast enrollment well. It is commonly thought that the model that best fits the sample data is the best forecasting model. This, however, is often not the case (see Pant and Starbuck (1990)). R-squared and t-statistics are not necessarily criteria that one should use to choose a forecasting model. Forecast performance is a more appropriate criterion. Thus, our analysis of the enrollment literature differs significantly in emphasis from many other reviews (such as McPherson (1978) and Leslie and Brinkman (1988)) because of our central concern with forecasting.

The purpose of this paper is to assess the state of the art in model-based enrollment prediction for U.S. higher education. Section (1) discusses structural econometric models of enrollment while section (2) deals with econometric forecasting models. Raving surveyed the specific findings in these literatures, in section (3) we consider the basic methodological differences between these approaches and the different types of data demands these approaches impose. In section (4) we compare the forecasting performance of several different enrollment models. Conclusions are reported in section (5).

(1) STRUCTURAL ECONOMETRIC MODELS OF ENROLLMENT DETERMINATION

As we have noted, the hypothesis testing approach to analyzing enrollment behavior is not generally the best for forecasting purposes, but the literature based on this approach is a fruitful source of information about which variables influence the probability of people deciding to attend college. We therefore begin our discussion of enrollment determinants by reviewing evidence from this literature. Following this, we examine the forecasting literature for evidence on the significance of these factors in forecasting future enrollment levels.

Findings from the literature on structural determinants of enrollment are based on three types of studies:

(1) ***Studies of Aggregate Enrollment Data for the United States*** Several studies employ time series data, most at a high level of aggregation across both student and institutional types (see, for example, Campbell and Siegel (1967) and Hight (1975). Hight's study distinguishes public and private enrollment). McPherson and Schapiro (1991) use a more disaggregated approach, analyzing time series data for subsets of the population classified by race, gender and income, and for public and private institutions separately. Another group of aggregate studies use cross-section data for states. These include Peltzman (1972) McPherson (1974) and Hopkins (1974). Most studies using these methodologies are fairly old, although recent studies suggest that the main findings from earlier work probably hold up over time. Although the studies just mentioned are not oriented to forecasting, they are similar in approach to the time series forecasting models discussed in more detail below.

(2) ***Studies of Enrollment Demand at Individual Institutions*** Several large state systems and some private institutions have undertaken studies of demand for their enrollment. Among the most prominent of these studies have been Hoenack (1967) for the University of California, Hoenack and Weiler (1975, 1979) for the University of Minnesota, and Ehrenberg and Sherman (1984) for Cornell University. Obviously estimates of enrollment behavior for particular universities do not necessarily translate directly into implications for aggregate enrollment behavior, but they may provide useful guidance on identifying variables that influence enrollment.

(3) ***Studies of the Enrollment and College Choices of Individual Students*** These studies, relying on large longitudinal survey data bases of individual high school graduates, have become the most prominent and influential types of study in recent years. An early example of the genre is Radner and Miller (1975), undertaken for the Carnegie Commission on Higher Education. Another

very influential study, relying on the National Longitudinal Survey of the High School Class of 1972, is Manski and Wise (1983). Other studies of the college enrollment decision using this data set include Blakemore and Low (1983) and Behrman, Kletzer, McPherson, and Schapiro (1994). Relatively little work on enrollment demand has so far been undertaken with the High School and Beyond survey of the High School Classes of 1980 and 1982.

Each of these types of analysis has strengths and weaknesses, and the balance of advantages depends on the purpose to which the data are put. Most analysts would agree that for the purpose of studying the underlying determinants of the enrollment choices of students, the individual choice models relying on large longitudinal data bases are probably best. However, because these models are almost invariably confined to studying the choices of a group of individuals from a given cohort, they are severely limited in studying certain kinds of effects that may operate over time. These include systematic effects that may be related to the size of the cohort (see further discussion below) as well as changes in the overall institutional setting that may systematically affect behavioral responses. It might be, for example, that the introduction of generally available federal student aid would have important effects on the whole college choice process, affecting students' course-taking patterns in high school and their orientation to whether they would consider college in the first place. If people behave differently in these two kinds of environments, a study of the behavior of a single cohort, either before or after the change, would fail to detect these important effects.

Time series models may have more ability to capture such effects, as well as cohort size effects, and other systematic variations over time (for example in rates of return). At the same time, it tends to be difficult in time series work to sort out the influence of different variables whose movements are correlated over time, and time series data are not available for long periods and tend to be thin on some of the variables of interest.

Finally, for obvious reasons, it is generally not possible to aggregate up from behavioral coefficients observed for a particular school to make generalizations at the national level.

Despite these differences and limitations, there is in fact a fairly high degree of agreement in the literature on which variables are reliably observed to influence enrollment behavior. (For a more detailed comparative analysis of studies see McPherson (1978), Leslie and Brinkman (1988) and Becker (1990)). Across a wide range of studies, the following variables consistently turn up as having statistically significant effects on enrollment (sign of effect shown in parentheses): family income (positive), parents' educational attainment (positive), tuition levels (negative), student aid levels (positive), and student's academic aptitude (positive). It has also been found in several studies that the size of the tuition effect declines as family income rises. Various attempts have been made to include rate of return measures in enrollment studies; while there are serious measurement problems, the effect of rate of return (as measured generally by the relationship between the wages of high school graduates and expected wages of college graduates) is generally found to be positive. Finally, there has been a scattering of investigations of the influence of variation in unemployment rates on enrollment behavior. One would expect some positive and some negative influence of unemployment on enrollment rates: higher unemployment reduces the opportunity cost of attending college but increases the difficulties of financing. The most reliable studies seem to indicate that community college enrollments, but not other enrollments, increase when the unemployment rate rises (see Betts and McFarland (1992)).

Unfortunately, there are several reasons why it is not easy to translate even the more reliable of these findings into forms that are useful for improving short run enrollment forecasts. First, some of the most reliably estimated effects pertain to variables that are inherently long run in their impact. This is most obviously true of student's academic ability and parental educational background. Neither of these variables is subject to sharp short run fluctuations. Family income variables may be more variable in the short run, but the best evidence is that it is the family's longer-run expected income (their permanent income) which is important in influencing decisions to enroll, although short-term fluctuations in income may well influence the timing of enrollment. Second, some variables which may be subject to shorter run fluctuations are themselves difficult to forecast. This is true of short run variations in tuition. It may also be true of expected earnings of college educated workers. Expectations formations processes for college wages are not well understood (see Manski (1993)), and conceivably may fluctuate significantly in response to varying perceptions of the economic future. Yet our ability to forecast such rapid shifts in expectations is quite limited.

Even though one cannot go directly from these structural models to improved forecasts, these models have guided the choice of variables and modeling strategies in developing the forecasting models to which we turn next.

(2) *ECONOMETRIC FORECASTING MODELS*

Forecasting models naturally highlight variables that have significant variation over the forecasting period and can themselves be forecast well. Certain of these variables, like costs of college and unemployment rates, are similar to those employed in the studies just surveyed. Others, like cohort size and marriage rates, are employed because they may influence the underlying structural forces affecting enrollment determination and because they are themselves relatively easy to observe and forecast.

The models surveyed in this section are time-series enrollment models for the United States. Although more suitable for forecasting purposes than a number of the models discussed in the preceding section, it is important to note that most of these models too have been developed more with an eye to shedding light on enrollment determinants than on producing accurate forecasts. Some key variables treated in these models, and summaries of what is known about their impact, follow.

Cohort Size

Other things equal, it seems reasonable to anticipate that the number of persons enrolling from a given population group will be proportional to the size of that group. The Department of Education's methodology for estimating the cost of federal aid, for example, takes such population size variation into account by applying fixed enrollment rates to data on expected changes in the size of populations.

However, work in economics and demography has emphasized the further notion that changes in the size of population groups may influence the rate at which members engage in various activities, including enrolling in college. Easterlin (1968, 1980) puts forth a cohort size model in which birth rates have important economic and behavioral effects. Ahlburg, Crimmins and Easterlin (1981) applied a cohort size analysis to college enrollment, arguing that swings in cohort size affect enrollment rates. Specifically, they argue that large cohorts depress the returns from college (relative to the return to high school), and that lower returns imply lower enrollment. In addition, they argue that large cohorts raise the proportion of families with two or more children of college age and that this increase in financial stress leads to lower enrollment rates. Thus, large cohorts have lower enrollment rates while small cohorts have higher rates. Note that this suggests less variation over time in the number of college going students than is usually supposed: when there is a large base, the enrollment rate falls; when there is a small base, the enrollment rate rises.

A good number of studies include a cohort size variable (the ratio of the number of people in a particular birth cohort to the number of people in another birth cohort) or a relative income variable (the ratio of the earnings of people in a particular birth cohort to the earnings of people in another birth cohort).[1] The advantage of using a relative cohort size variable (whether using lagged birth rates or the ratio of the size of a cohort relative to the size of the previous cohort) are, first, that you do not have to specify the exact mechanism by which cohort size affects relative income (as does Macunovich (1993)) and second, that the values of this variable (relative cohort size) are known with a fair degree of accuracy for 10 to 20 years into the future.

Recent developments in modeling college enrollment from the cohort perspective have looked at more complicated conceptions of the role of cohort size, namely that the size of the cohort may be less important to individual decisions than the position of the individual relative to the peaks and troughs of the demographic cycle. This approach was first used by Wachter and Wascher (1984) and has subsequently been investigated both empirically and theoretically by Falaris and Peters (1992), Connelly (1986), and Stapleton and Young (1988). Wachter and Wascher's basic claim is that individuals born earlier in the baby boom will have a higher enrollment rate while those born later have a lower enrollment rate. Individuals early in the baby boom will speed up their education (be more likely to enroll) to move away from the peak of the cohort where wages are depressed the most. Individuals late in the baby boom will delay college, attempting to move away from the peak of the baby boom. While Wachter and Wascher argue that this "differential tracking" effect results from the depressing impact of cohort size on wages, it is also possible that it reflects parents' ability to help with the costs of financing education. The first child (more likely to be born early in the boom) may have an advantage over following children in terms of parents' income.

1 In cohort size studies, it is assumed that the major effect of a change in relative cohort size is a change in relative income. A relatively large cohort, for example, leads to relatively low earnings for that group of people, primarily due to crowding in the labor market.

Children born later may have to delay college for funding reasons.[2]

Wachter and Wascher (1984) operationalize their relative cohort conception through two measures. The first, which they call the relative younger cohort variable, is the ratio of the size of neighboring younger cohorts to the size of own cohort. They use the ten years after own cohort to define the numerator. Similarly, they use the ten years prior to own cohort as the numerator in defining their relative older cohort variable. Their bands, then, are twenty years, centered on own cohort.[3]

The other variables in their model are those used by Ahlburg, Crimmins, and Easterlin (1981). They find empirical support for their cohort-lead and cohort-lag effects and find that the differential tracking model fits the enrollment data better than a model with relative cohort size. Unfortunately, they did not compare the accuracy of forecasts from the differential tracking model versus the conventional relative cohort model.

Wachter and Wascher make a further point that is of relevance to modeling the college enrollment decision. They argue that structural models -- those that use income or relative income measures instead of the underlying demographic measures -- are using biased measures of the expected return to education since they only capture the lead-cohort effect, that is, the effect of somewhat older workers on an individual's rate of return to education. These measures ignore the impact of lagging cohorts' sizes on expected rates of return. Thus it may be better to use the demographically measured cohort variables than the monetary returns that they affect.

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2 The differential tracking effect depends upon there being vintage effects in the labor market. That is, age groups (or, more relevantly, college graduation cohorts) are imperfect substitutes for each other. Connelly (1986) and Alsalam (1985) investigate the effects of cohort size at a more theoretical level. Connelly shows how the impact of cohort size is affected by the degree of substitutability one assumes among labor market groups and whether the group one belongs to is fixed or whether one can change it by changing one's schooling and labor market entry dates.

3 Whereas the cohort variable measures the height of the population density function, the two lead and lag cohort variables measure the slope of the density function at a particular cohort point.

A series of papers followed Wachter and Wascher and attempted to refine the impact of cohort size and position. Most of these were theoretical and basically refined the notions of Wachter and Wascher. For example, Stapleton and Young (1988) present a model that supports Wachter and Wascher's prediction that those early in the baby boom will increase their enrollment but disagree that those after the boom will decrease their enrollment. They show that the predicted impact of cohort size is affected by the way the researcher assumes that expectations are made. If individuals are myopic, baby boomers are more likely to go to college, for they mistakenly think that the high returns of the preceding cohort will persist. If they are semi-rational, they may predict that their size will affect returns and enrollment falls. If they are fully rational, and assume that their colleagues are, then Stapleton and young argue that cohort size would have little effect on enrollment, because they would expect people's reactions to changing expected circumstances to largely offset these effects in equilibrium. The empirical evidence does not support full rationality.

Falaris and Peters (1992) differ from Wachter and Wascher in the cohort definition, but keep the lag-lead cohort design. The difference between the two definitions lies in the band width and weighting scheme of younger and older cohorts. Falaris and Peters's "past" and "future" cohort variables are defined as follows: past cohort size is the ratio of own cohort size to the preceding cohorts averaged over five years; future cohort size is defined similarly with subsequent cohorts as the denominator. Hence, Falaris and Peters utilize a ten-year band centered on the own cohort. The ten years prior and subsequent to own cohort are then weighted in a declining manner. That is, the single-age group closest to own cohort is given a value of 1.0. Each subsequent single-age is given a weight of $1/n$, where n is the number of years removed from own cohort.

The measures of alternative cohort size variables found in these studies do not vary dramatically from one another given the fairly regular course of fertility movements, although they do differ somewhat in the width of the band over which the cohort is defined. Ahlburg, Crimmins and Easterlin (1981), for example, define cohort size as a five-year moving average. They use general fertility rates lagged 18 and 19 years for the 18 to 19 year old age group, and 20 to 24 year lags for the 20 to 24 year old age groups. Wachter and Wascher define their cohort variables as the ratios of the population ten years ahead or behind own cohort to own cohort population.

It seems clear that cohort size should be in a model designed to explain college enrollment. However, it is not clear what form the variable should take. Should it be simply the size of the cohort relative to that of its parents, as argued by Easterlin and used by Ahlburg, Crimmins, and Easterlin, or should it be a cohort variable split into leading-edge and trailing-edge variables as done by Wachter and Wascher, Stapleton and Young, and Falaris and Peters? The predictions of these models depend upon the elasticities of substitution among age and education cohorts. This is an empirical question over which there is some disagreement. From a forecasting perspective, the more important question is whether a model with cohort-lead, cohort-lag variables predicts better than a model with a standard relative cohort size variable.

Cost of College

Mattila (1982) develops a forecasting model which divides the cost of attending college into two components. First is tuition cost, which measures the actual cash disbursement paid to a university or college in order to attend classes. Second is the opportunity cost of attending college. In order to complete the usual four years of undergraduate work, students must forgo four years of labor market earnings. Mattila operationalizes these two definitions in constructing his rate-of-return to college variable. He measures opportunity cost (w) as the smoothed real income of males aged 18 to 24 who had completed only four years of high school. To measure tuition (Tu), he uses average tuition net of student aid. He further assumes that, due to part time and summer work, students incur only 75% of the opportunity cost. Hence, annual cost of college is $C = 0.75w + Tu$. This cost variable is then used in a calculation of rate of return.

Wachter and Kim (1982) use a measure of wages relative to the minimum wage to capture the opportunity cost of school in their enrollment equation. Specifically, they find that a measure of average wages relative to the minimum wage is negatively related to their schooling variable. This suggests that a higher opportunity cost may be negatively and significantly related to enrollments.

Macunovich (1993) includes a wage differential variable in her female enrollment equation. This variable measures the difference between the wages of women college graduates and women high school graduates. She finds the variable positive and significant, indicating that a positive wage differential for college graduates leads to higher enrollments. Secondly, she uses an unemployment rate measure as an inverse opportunity cost measure. Again, she finds this variable positive and significant.

Financing College

The costs of college in terms of tuition and opportunity cost are discussed above. The companion to costs in determining enrollment is the ability to finance those costs. Mattila (1982) notes that the financing of schooling has traditionally been done through the student's family. A higher family income, then, suggests a greater ability to finance college education. Mattila, following the practice in many of the structural models discussed earlier, operationalizes this by including a family income variable in his enrollment rate equations. Defining family income as mean real after-tax family income, he finds that it is positive and significant in three of five estimated models for males 18-19 and 20-24. For males 16-17, he finds income to be insignificant in all cases.

Ahlburg, Crimmins, and Easterlin (1981) include a variable measuring the median income of males aged 45-54 in their four age-sex models. They find it positive and significant across the four groups. Wachter and Wascher (1984) use the same measure as Ahlburg, Crimmins, and Easterlin in their college enrollment model and find it positive and significant in all cases. Although Macunovich (1993) does not include a family income variable in her models, we found in replicating her study that including a family income variable in her models yielded an insignificant effect on female enrollments.

The Military

Military service is expected to have offsetting effects on male college enrollment. On the one hand, those who enlist or are drafted into the military include individuals who otherwise would have enrolled in college. Therefore, military service can be expected to decrease college enrollments. Alternatively, the availability of student deferments, for example during the Vietnam era, may have increased the enrollment rates of college-aged males as a safe haven from the war was sought. In both cases, effects on some individuals may be permanent, while for others what is at issue is the timing of college attendance.

Several of the models reviewed examined the effect of military service on postsecondary school enrollment. Wachter and Kim (1982), for example, noted that in their model specifications an increased military-to-population ratio was associated with increased schooling.

Ahlburg, Crimmins, and Easterlin (1981) include a military draft variable in their male enrollment models. They define the draft variable as equal to zero from 1948 to 1959, equal to the number of inductees per thousand males sixteen and over at t+l for the period 1960 to 1972, and equal to zero from 1973 to 1976. The lead relationship of the draft variable to the enrollment variable results from the proposition that young males may enroll in college in anticipation of a large draft call in the year following their enrollment. They find, as expected, that the draft variable is positive and significant in explaining enrollment rates.

Mattila (1982) includes military-related variables in his male 18-19 and male 20-24 school enrollment models. He defines his draft variable as the ratio of annual draft inductions to the male civilian population aged 18 to 24. He also includes a variable, AF, measuring the proportion of each age cohort that is in the armed forces. This variable is hypothesized to have a negative sign. He finds the AF variable negative and significant in explaining enrollment in nine of the eleven models estimated. The draft variable is less robust, being positive and significant in only four of the eleven models. However, it was significant and positive in 3 of the 4 male 20-21 year old models.

Wachter and Wascher (1984) follow Mattila by including two variables to measure military service. As in Mattila's studies, these two variables measure the percentage of males inducted for service between 1960 and 1972 and the percentage of each cohort enlisted. Similar to Mattila, they find that the enlistment variable is more robust, being negative and significant in all models specified. The draft variable is positive and significant in only two of their six specifications.

Marriage

Macunovich (1993) notes that "primary responsibility for household activities has remained with females." She concludes, concurring with Easterlin (1980), that when male relative income is high, marriage and family formation are favored and there is less pressure to move toward two-income families. It is expected, then, that the college enrollment rate for females will be inversely related to the percentage of women married. That is, a more favorable market for marriage will lead to fewer women attending college.

Ahlburg, Crimmins, and Easterlin (1981) include a marriage variable in their female enrollment equations. In both the 18-19 and 20-24 year old cases, they find the marriage variable to be negatively signed and significant. Similarly, Wachter and Wascher (1982), using the same measure as Ahlburg, Crimmins, and Easterlin, find negative and significant coefficients on the marriage variable in their female enrollment equations.

One aside is interesting to note. If, as Korenman and Okun (1993) suggest, "marriage is losing its relevance as a determinant of fertility," it is conceivable that the strong association between marital rates and college enrollment rates may weaken. If families choose to remain childless after marriage, it is more likely that women may choose to continue their education beyond the secondary level.

Unemployment Rates

Several rationales exist for including unemployment rates in enrollment models. Mattila (1982) notes the offsetting effects of unemployment on enrollment. On the one hand, there may be a "discouraged worker" effect, where those unable to find work return to school. Alternatively, he posits an "added worker" effect where, when a parent is unemployed, children may not be able to afford to remain in school. The net impact of unemployment on college enrollment, then, is unclear. Including the unemployment rate for adult males 35-54 years old in his enrollment model, Mattila finds it generally insignificant in determining enrollment rates. He does, however, find a positive and significant effect for 2 of 3 models estimated for 18 to 19 year olds.

Wachter and Kim (1982) note that having a job may not be as desirable for some youth groups as being in school. This suggests the possibility that causality runs both ways between enrollment and unemployment. The opportunity cost of working, in this case, would be the benefits of attending school. They find that a cyclical unemployment variable is positively related to schooling in 8 of 9 cases.

Macunovich (1993) includes an unemployment variable in her female enrollment equations as an inverse measure of changes in the opportunity cost of obtaining a higher education. She finds the variable to be significant and positive, indicating that increased unemployment indicates a decreased opportunity cost, leading to higher female enrollment rates.

(3) *METHODOLOGY AND DATA*

There are two basic methodologies used in enrollment forecasting. The first is econometric modeling, either structural or quasi-reduced form. The second is trend modeling. In addition, some of the papers discussed build a simulation model using parameters directly estimated from a structural model of college enrollment. It is also possible to specify a simulation model using parameters obtained from a number of sources. Simulation models are not specifically designed for forecasting, although they can give insights that assist forecasting.

Econometric Forecasting Models

The econometric models attempt to identify the determinants of enrollment rates. Once these have been identified, forecast values of the independent variables can be entered into the regression equation to produce predicted values of the enrollment rates. Predicted values of the enrollment rates are then multiplied by the age-specific population projections of the U.S. Bureau of the Census to arrive at total enrollment projections. The econometric models can also produce prediction intervals that give the user a sense of the uncertainty of the enrollment rate forecast. But since we do not have information on the uncertainty of population projections, we cannot calculate the uncertainty of total enrollment forecasts.

As we noted earlier, most of the models surveyed in this study were primarily concerned with identifying the determinants of enrollment rather than in forecasting enrollment. Consequently, they did not give numerical enrollment forecasts or prediction intervals. At most, they discussed in qualitative terms whether enrollment or enrollment rates would rise or fall. For example, Wachter and Wascher (1984) predicted that the post-boom cohorts would attempt to distance themselves from the peak of the boom and thus expected the enrollment rate to fall "for several more years. Thereafter the effect should be positive." It turns out that enrollment rates rose, rather than fell as predicted by Wachter and Wascher. This does not necessarily invalidate their model because factors other than their cohort-position variables may explain the upturn in enrollments. This is possible for females, where marriage rates for females fell. However, there are no variables in the model that explain the rise in male enrollment rates. What is more damaging to their model is the finding of Falaris and Peters (1992) that in the upswing of the demographic cycle individuals tend to spend more time in school and increase the time to completion more than proportionately. The opposite is true for individuals in the down swing of the cycle. This is the reverse of the prediction of Wachter and Wascher and casts doubt on their hypothesis.

Ahlburg, Crimmins, and Easterlin (1981) provided point forecasts of enrollment rates and total enrollments, but not prediction intervals. They predicted enrollment rates to rise over the 1980s and 1990s under most scenarios. While the general trend in the four age-sex categories analyzed has been upward, there have been fluctuations. They predicted enrollment to rise for men and women aged 18 to 19. Enrollments did rise for both age groups through 1987, when male enrollment rates plunged. Females 18 to 19 increased enrollment rates through 1988, with rates declining in 1989. They also predicted steady increased enrollment for females 20 to 24 through 1995. Except for an enrollment decline in 1983, that pattern has occurred for this group. Finally, they posit a decline in male 20 to 24 year old enrollments from 1985 to 1995. In fact, enrollment rates declined from 1985 to 1986, but increased from 1986 through 1988, declining again in 1989.

Trend Models

The methodology of the trend models is straightforward. The forecasts are "based on extrapolations of recent trends for different groups, plus some educated guesses about future conditions** (Centra (1980)). Again, these models can be based on predicting the path of the college enrollment rate or total enrollment. The models can be statistical trend fitting models or can be based on "expert" judgment as to future rates of change.

Statistical trend fitting models have not been widely studied in the context of enrollment forecasting, particularly their forecast accuracy. More ad hoc trend models have a longer history in enrollment forecasting. In general, it is thought that trend models do not perform well. Why this is so is not clear. Even a cursory examination of the models in Centra (1980) shows that some of the trend models outperformed structural econometric models. In applications other than enrollment, trend models sometimes perform well. The forecast performance of the various trend models should be formally analyzed and a broader class of statistical trend models should be examined (see Armstrong (1985) for such models).

Simulation Models

Another methodology that is widely used elsewhere but is not well represented in the models discussed here is simulation. Stapleton and Young (1988) build a simulation model to investigate the impact of a baby boom. Stapleton and Young disagree with Wachter and Wascher and predict that those following after the baby boom will increase enrollment. This led them to predict rising enrollment rates. The Stapleton and Young model introduces a correlation between career choice and education that explains the difference in prediction.

Simulation models are very useful for carrying out "what-if" experiments, that is, evaluating the impact of alternative scenarios such as changes in funding on enrollment decisions. In general, simulation models do not forecast as well as more simplified structural forecasting models. This is not surprising, since forecasting models are specifically built to provide accurate forecasts rather than complete models of the behavior underlying the enrollment decision. In contrast, simulation models have a different function and this may inhibit their forecast ability.

Data

Most aggregate level studies use data on enrollment from the U.S. Bureau of the Census, Current Population Reports, Series P-20, School Enrollment[4]. The independent variables tend to be aggregate level data on income by age and percentage marrying, all from Census data. Some studies, such as Stapleton and Young (1988) and Macunovich (1993), use data constructed from the CPS.

The CPS suffers from certain well-known limitations. First, being based on a sample of persons of all ages, the subset of individuals of the relevant ages is fairly small, and making further divisions by, for example, race, gender, and income status, can produce unacceptably small sample sizes. CPS also does not permit distinctions among institutional types finer than public versus private, and its handling of postsecondary vocational enrollment is highly uneven.

The time series of enrollment data maintained by the Department of Education provides a potential alternative in time series modeling. This data series provides more detail on institutional type and control, but unfortunately does not permit subsetting by student age or income status. Also, except for the most recent years, its coverage of for-profit trade schools is highly uneven. It would be interesting to compare forecasting exercises using these data as a substitute for the CPS enrollment series.

The model of Falaris and Peters (1992) uses data on individuals from the National Longitudinal Survey and from the Panel Study of Income Dynamics. The data difference between this study and the others results from their focus on modeling individual decisions on education and time to completion.

(4) AN ASSESSMENT OF COMPARATIVE PERFORMANCE OF THE FORECASTING MODELS

The models of Ahlburg, Crimmins, and Easterlin (1981) and Macunovich (1993) were chosen for a systematic evaluation of forecast accuracy. The Ahlburg-Crimmins-Easterlin model (referred to below as ACE) was chosen on the basis of its good past forecast record and the Macunovich model because it

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4 For example, Ahlburg, Crimmins, and Easterlin (1981) and Wachter and Wascher (1984).

represents a refinement of this model. Tests of the efficiency of trend models compared to these models are also reported.

The ACE model was estimated separately for males and females and separately for ages 18-19 and 20-24. The estimation period was 1948-1986 and 1971-1986 (the latter for a direct comparison with Macunovich). The Macunovich model was estimated for females 20-24 for 1971-1986. The starting point of 1971 is dictated by the availability of the income data. We also estimated the Macunovich model for males 20-24. The construction of variables follows that of Macunovich (1993). So, for each age-sex group there are three basic models: the ACE model estimated 1948-1986 (ACE-long); the ACE model estimated 1971-1986 (ACE-short); and Macunovich estimated 1971-1986.

We also experimented with several different unemployment variables for each of these models. Two different unemployment variables were tested for both the male and female models. For males, a civilian unemployment rate for males 16 and over, and, following Macunovich (1993), a three-year moving average of the unemployment rate of male high-school graduates in the first five years of work experience were used. For females, we used a civilian unemployment rate for females 16 and over, and, again after Macunovich (1993), a one year lag of the unemployment rate of female high school graduates in the first year of work experience.

The fundamental task was to see which model predicted enrollment rates most accurately over the 1987-89 period, that is, how well the models did in forecasting beyond the period from which they were estimated. Since similar models had been used for females and males in the past literature, it was expected that a single model would dominate in this forecasting competition. This was not the case. For each different age-sex group a different model predicted enrollment rates over the period 1987-89 most accurately. The results of estimating the models are shown in the appendix. The mean absolute percentage forecast errors are presented in Table 1.

For females aged 18-19 years the most accurate model was ACE-short (assuming 0.5 percent annual income growth) with an average percentage error over the three year forecast of 2.2 percent (these are not enrollment percentage points, but percentage differences between actual and predicted enrollment rates). Estimating the model over the longer period almost doubled the forecast error. The most accurate model for females 20-24 is the Macunovich model. The percentage error of the forecast is 1.3 percent per year. The forecast error of the ACE models was at least four times as large. Various experiments adding a family income variable and a marriage variable to the Macunovich model produced less accurate forecasts.

For males 18-19 years the most accurate model was the ACE-long model (assuming once again 0.5 percent annual income growth). The forecast error was 6.2 percent per year.[5] The forecast error for the ACE-short models was one-third higher. The most accurate forecast model for males 20-24 years was ACE-long with income assumed to grow at 1.5 percent per annum. The forecast error was 1.2 percent.[6] The Macunovich model had a forecast error more than ten times larger.

To test the efficacy of trend models, models of the form:

$\mathrm{Enrollment}_i = \alpha_0 + a, \cdot t$ and

$\mathrm{Enrollment}_i = \alpha_0 + a, . t + \alpha_2 \cdot t^2$;t is a time trend variable,

were estimated for each age-sex group and the results are presented in Table 2. While the trend models performed better than some variations of the ACE and Macunovich models, in general they performed worse. In no case did the trend models outperform the best models.

Finally, to test whether the cohort lag-cohort lead framework of Wachter and Wascher (1984) and Falaris and Peters (1993) provides better forecast results, lead and lag cohort variables similar to Falaris and Peters were constructed. Specifically, we estimated the ACE model, replacing the

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5 Including the male unemployment rate as an explanatory variable lowers the forecast error to 5.1 percent per year.

6 The model with male unemployment rate had the same forecast error.

relative cohort size variable with past and future cohort size variables.

The lag-lead scheme did not improve the overall forecast performance. While it was an improvement in some model combinations, it hampered performance in others. In no age-sex groups did the lag-lead cohort variable models perform better than the previous best-forecast models. When tested in the best-forecast equations, inclusion of the lag-lead variables did not improve the forecasts and substantially reduced accuracy in most cases.

Returning to the results in Table 1, for males, the longer estimation period was associated with a more accurate forecast period while, for females, the shorter estimation period yielded a more accurate model for those in the 18-19 age range and the longer period worked better for the older group. This implies that the process determining male enrollment rates has been more stabke over time than the process determining female enrollment rates -- a result which is intuitively plausible in light of the important changes in women's roles in education and the labor force in recent decades. In addition, this exercise showed that models that fit the data better (that is, models with variables having statistically significant coefficients with the expected signs along with higher R-squared values) did not always predict most accurately. For example, as shown in the Appendix, the only significant coefficient (other than the constant term) for the ACE-Short model for females 18-19 was for the marriage variable and this equation had a R^2 value of 0.81. The ACE-Long model, on the other hand, had several correctly signed and significant coefficients and a R^2 value of 0.96. It is clear that the ACE-Long model is the "better" model of the two in a traditional statistical sense. However, when forecasts from the two were compared it was found that Mean Absolute Percentage Error of the ACE-Long model was roughly double that of the ACE-Short model.

Thus, the enrollment rate for each age-sex was most accurately predicted by a different model or a similar model but estimated over a different time period. No single model performed well for all groups.

(5) CONCLUSION

The literature includes a substantial amount of interesting work on enrollment determination and on enrollment forecasting. We have assessed that literature and have performed our own empirical investigation of the quality of several of the most promising models as instruments for out-of-sample forecasting.

It is clear that progress in understanding the structural determinants of college enrollment is not easily translated into an enhanced ability to forecast changes in college enrollment. To the contrary, the greatest predictive power may come from equations that appear to do a relatively poor job in accounting for past movement in enrollment rates.

Enrollment forecasting has tended to concentrate on the search for a "universal** model that is best for all groups at all times. This has been found to be a rather fruitless guest in the general forecasting literature and in the limited forecasting competition reported here. However, there are alternative ways to produce more accurate enrollment forecasts. In a large forecasting competition (with 1,000 series) Makridis et al. (1992) found that overall forecast accuracy can be improved by combining forecasts from models employing different methods. Armstrong and Collopy (1993) and Collopy and Armstrong (1992) found that integrating expert judgement and statistical models improved forecast accuracy. Combining the results from disaggregated forecasting models and trying alternative approaches is likely to be our best option for producing better predictions of higher education enrollments.

Table 1
Mean Absolute Percentage Errors--Basic Models*

		Males		Females	
		18-19	20-24	18-19	20-24
ACE-Long	0.5%**	6.2%	2.1%	3.7%	6.3%
	1.5%	7.8	1.2	4.7	6.3
ACE-Short	0.5%	8.2	4.2	2.2	14.5
	1.5%	8.0	5.4	2.3	14.1
Macunovich		---	14.4	---	1.3

* Mean Absolute Percentage Error calculated as

$$\left(\sum_{i=87}^{89} (\mathit{Forecast}_i - \mathit{Actual}_i)/\mathit{Actual}_i\right)/3$$

** The models assume either a 0.5% annual growth rate for income or a 1.5% annual growth rate.

Table 2

Mean Absolute Percentage Errors (MAPE)
Trend Models

		MAPE
Males 18-19	t	8.7%
	t, t^2	21.4
Females 18-19	t	2.4
	t, t^2	6.9
Males 20-24	t	5.2
	t, t^2	24.2
Females 20-24	t	2.8
	t, t^2	11.5

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Appendix

Basic Colleue Enrollment model--Ahlburg, Crimmins, Easterlin, Lonq
Dependent variable is enrollment rate for each age group

Model is ACE-Long	Males 18-19	Males 20-24	Females 18-19	Females 20-24
Constant	8.38 (2.73)	-1.36 (0.52)	28.14 (5.04)	16.37 (3.83)
Cohort Size 18-19	-0.13 (2.57)		-0.09 (2.49)	
Cohort Size 20-24		0.00 (0.03)		-0.01 (0.55)
Real Income	0.50 (10.61)	0.38 (12.38)	0.38 (10.03)	0.24 (18.07)
Draft	1.87 (6.63)	1.62 (6.60)		
Marriage			-0.66 (7.43)	-0.31 (9.01)
R-squared	0.90	0.91	0.96	0.98
N	39	39	39	39

Basic Collese Enrollment model--Ahlburg, Crimmins, Easterlin Short
Dependent variable is enrollment rate for each age group

Model is ACE-Short	Males 18-19	Males 20-24**	Females 18-19	Female8 20-24**
Constant	74.13 (6.89)	0.65 (7.19)	61.85 (4.15)	0.11 (3.83)
Cohort Size 18-19	-0.29 (4.72)		-0.11 (1.46)	
Cohort Size 20-24		-0.00 (4.68)		0.001 (1.30)
Real Income	-0.08 (0.77)	-0.00 (3.32)	-0.02 (0.18)	0.00 (0.61)
Draft	5.12 (2.19)	0.02 (1.01)		
Marriage			-0.58 (4.85)	-0.00 (2.69)
R-squared	0.75	0.85	0.81	0.82
N	16	16	16	16

** Note: The male 20-24 and female 20-24 year old dependent variables are Macunovich's enrollment rates. They are not multiplied by 100 to get a percentage, as are the ACE measures of enrollment.

Basic Colleqe Enrollment model--Macunovich
Dependent variable is enrollment rate for each age group

Model is Macunovich	Females 20 to 24	Males 20 to 24
Constant	0.20 (6.811	0.23 (5.14)
Wage Differential	0.14 (4.76;	-0.02 '(0.54)
Unemployment Rate	0.34 (4.82)	-0.38 (0.83)
Male Relative Income	-0.45 (13.13)	0.15 (1.56)
N	16	16
R-squared	0.94	0.28

t- **statistics are in parentheses**