ESSAYS ON LABOR MARKET AND EDUCATION

By

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ABSTRACT

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The first essay "Intergenerational Mobility in Korea" investigates intergenerational earnings mobility in Korea for sons born between 1958 and 1973 and compares Korea's mobility to that of other nations. It uses data from the Korea Labor and Income Panel Study and the Household Income and Expenditure Survey conducted by the Korean National Statistics Bureau. Since no single Korean dataset includes information on both sons' and their fathers' adult earnings, this study follows the two-sample approach previously applied in Korea by Ueda (2013), whose estimated intergenerational earnings elasticity is 0.22, and extends the analysis by using fathers' earnings from more approximal cohort. The estimate of around 0.4 is similar to estimates for some already-developed countries and smaller than typical estimates for recently-developing countries.

The second essay "College Enrollment over the Business Cycle: The Role of Supply Constraints" studies the impact of supply constraints on cyclicality in enrollment. Many studies on cyclicality of higher education examine the relationship between cyclical variation in labor market conditions, and changes in enrollment. Changes in enrollment are caused by changes on both the demand side and the supply side. However, much of the previous literature implicitly assumed elastic supply of enrollment. This study identifies institutions with supply constraints and investigates how those constraints have affected institutionsdecisions on enrollment, and how such effects vary across institutions. I find that, in the short run, institutions are different in capacity to absorb additional students, so that recessions have heterogeneous effects on enrollment size and on freshman achievement. During recessions, some capacity constrained institutions increase enrollment less than proportionately to the increase in the number of applications and, as a result, increase their admissions selectivity. Other institutions respond to increase in demand by accepting more students, resulting in a drop in new-student achievement.

Finally, the third essay "Racial Differences in Course-taking and Achievement Gap" investigates the black-white differences in course-taking and achievement in high school. Despite the overall increase in course-taking intensity in the last two decades, the achievement gap between black and white high-school students has persisted. Using nationally-representative data, this study examines racial differences in the course-taking pattern and its association with the achievement gap. Initial results show a racially-different course-taking pattern in mathematics courses, in that white students are more likely to be enrolled in advanced courses than black students are, in all high-school years, and that the difference begins occurring in the first mathematics course, and increases over the years. Moreover, the black-white test-score gap in Grade 12 differs by course level and by school year of mathematics course taken.

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CHAPTER 1
Intergenerational Mobility in Korea

1.1 Introduction

Intergenerational mobility refers to the persistence between parents' and children's outcomes. If parents' earnings do not impact much on their offspring's earnings, the degree of intergenerational earnings mobility is high, and it could be that relative economic disadvantages in the early years will persist to a lower extent in adulthood. That is, intergenerational earnings mobility explores the characteristics of inequality in economic opportunity as well. For a survey of relevant literature, see Solon (1999) and Black and Devereux (2011).

Korea experienced rapid and extensive economic growth in the past half century when real GDP per capita increased fifteenfold. At the same time, inequality in labor earnings steadily decreased from the 1970s to the 1990s. Because of these trends, a natural question is whether economic development with a consistent drop in inequality was accompanied by an overall increase in income the level of all market participants, or was shared by specific parties.

Because of a lack of longitudinal data spanning two generations, only a limited number of studies on intergenerational earnings mobility in Korea have been done. Recent studies in Korea by Kim (2009) and Choi and Hong (2011) employed co-residing father-son pairs in the initial round of panel data. However, as noted by Solon (2002), this sample may display a different intergenerational association than would a more representative sample.[1] Moreover, as in most other

[1] In fact, they further restricted the sample to those sons who moved out to form a new household. This sample selection approach has a potential risk of endogenous sample selection; non-coresidence sons during certain birth years are out of the sample and the way they moved out is endogenous. Moreover, if the average son's age in the sample is older than the average or median home-living son's age, then the sample over-represents sons who left home at late ages. Francesconi and Nicoletti (2006) in the UK found a downward bias of up to 25% in intergenerational elasticity when the sample is restricted to co-residence father-son pairs.

empirical studies, they estimated intergenerational earnings elasticities using short-run proxies for permanent earnings, which may generate downward biases in estimates.[2] An important exception avoiding this difficulty is Ueda (2013) who utilized a two-sample method to impute fathers' permanent earnings and showed relatively lower estimated intergenerational earnings mobility in Korea.

This study estimates intergenerational earnings mobility in Korea following the method presented in Ueda (2013) and extends empirical analysis in two dimensions. First, I use an additional national representative sample to better approximate the cohort of actual fathers so that fathers' missing permanent earnings are more accurately imputed, and carefully choose age ranges for each generation to minimize life-cycle bias.[3] Second, I compare my results to comparable results of other countries, Björklund and Jäntti (1997) in Sweden and in the U.S.; Fortin and Lefebvre (1998) in Canada; Nicoletti and Ermish (2008) in the UK; Leigh (2007) in Australia; Piraino (2007) and Mocetti (2007) in Italy; Lefranc et al. (2011) in Japan; Núñez and Miranda (2011) in Chile; Lefranc (2011) in France; Gong et al. (2012) in China; Ueda and Sun (2012) in Taiwan; and Cervini-Plá (2013) in Spain.

The remainder of this study is organized as follows: Section 2 presents the basic model to estimate intergenerational earnings persistence, and reviews previous empirical methods for estimation. Section 3 presents the data source, variables, and data selection process to generate the final sample for analysis. Section 4 shows estimation results with comparisons to other international countries' results. Section 5 concludes with remarks.

[2]See Solon (1992) for details.

[3]Earnings vary with observed age and a life-cycle pattern exists in the correlation between current observed and lifetime earnings, known as life-cycle bias. Studies showed estimates to be sensitive to not only the father's observed age but also to the son's age. If, for instance, the son's earnings are observed in the early stage of his career, it causes a downward effect on the estimate. Theoretical and empirical analyses of life-cycle bias are well documented in the U.S. by Haider and Solon (2006); in Sweden by Böhlmark and Lindquist (2006); and in Germany by Brenner (2010). The evidence from these studies shows that income measures in the age range between the early-30s and the mid-40s should be least affected by life-cycle bias when dependent variables are proxied. There is no study of life-cycle bias for any Asian countries nor for generated regressors; yet I adopted their results and within reason modified them based on Korean labor market features.

1.2 Literature Review and Method

In this section, I provide skeletal derivation of intergenerational mobility developed in Solon (1992) and Björklund and Jäntti (1997). The basic empirical approach in intergenerational mobility literature is to estimate earnings elasticity, which is to estimate ρ_1 in the following equation.

$$y_i = \rho_0 + \rho_1 x_i + \varepsilon_i \tag{1.1}$$

where y_i is the log of the permanent component of the son's earnings in family i, x_i is the log of the permanent component of the father's earnings in family i, and ε_i is a random disturbance uncorrelated with x_i. If y_i and x_i are observed directly from a random sample, one can estimate ρ_1 in equation (1.1) by applying least squares regression. Here the parameter ρ_1 is the intergenerational earnings elasticity and (1-ρ_1) can be interpreted as a measure of intergenerational mobility. Therefore, by comparing $\hat{\rho}_1$ of each country, comparisons of intergenerational mobility across countries are possible; the higher $\hat{\rho}_1$ is, the less mobile the society is.[4]

However, in most studies, available measures of the earnings variable are current earnings in repeated cross section samples, or in longitudinal samples, and in practice researchers have used short-run proxies of y_{it} for long-run economic status variables of y_i in time t,

$$y_{it} = \lambda_t y_i + h(Age_{it}) + \nu_{it} \tag{1.2}$$

where λ_t is the association between current and lifetime earnings at time t, which is allowed to vary over the life-cycle; and ν_{it}, the measurement error in y_{it} as a proxy for y_i, is assumed to be uncorrelated with y_i and ε_i. $h(Age_{it})$ is an arbitrary function of a son's age at time t such as a polynomial in age.

[4] An alternative way to measure the extent of intergenerational earnings mobility is to estimate intergenerational correlation, κ.

$$\kappa = (\sigma_0/\sigma_1)\rho_1$$

where σ_1 is the standard deviation of a son's log earnings and σ_0 is the same variable for his father. By construction, κ is equal to ρ_1 only if the standard deviations of log earnings are the same for both generations.

If one has an appropriate measure of a father's long-run earnings but is forced to use current earnings as a proxy for the son's long-run earnings, plugging equation (1.1) into equation (1.2) yields

$$y_{it} = \lambda_t \rho_0 + \lambda_t \rho_1 x_i + h(Age_{it}) + \eta_{it} \tag{1.3}$$

where η_{it} is equal to $\lambda_t \varepsilon_i + v_{it}$. Haider and Solon (2006) showed that the probability limit of the least squares estimator of the coefficient of x_i is equal to $\lambda_t \rho_1$, and suggested the age ranges be used for both father and son at their mid-careers, which more accurately would represent lifetime earnings.[5]

Another estimation problem exists when a single dataset containing earnings information for pairs of fathers and sons in a long-time series is unavailable. Björklund and Jäntti (1997) proposed a two sample method to impute fathers' missing earnings from an auxiliary sample of a father's generation on the basis of a son's report on a father, such as education, industry, and occupation.[6] Let z_i denote a set of fathers' socio-demographic variables such as education and occupation and assume that the permanent component of fathers' earnings is generated by the following relationship:

$$x_i = z_i \phi + \xi_i \tag{1.4}$$

where z_i is orthogonal to ξ_i by linear projection. From equation (1.4) fathers' long-run economic status variables are generated, $\hat{x}_i = z_i \hat{\phi}$, with age controls in the potential fathers' sample.[7]

Rewrite equation (1.1) as $y_i = \rho_0 + \rho_1 \hat{x}_i + \varepsilon_i + \rho_1 (x_i - \hat{x}_i)$ and plug into equation (1.2) gives

$$y_{it} = \lambda_t \rho_0 + \lambda_t \rho_1 \hat{x}_i + h(Age_{it}) + \omega_{it} \tag{1.5}$$

[5]In a classical errors-in-variables model when $\lambda_t = 1$, the OLS estimate of $\lambda_t \rho_1$ is unbiased even in the presence of the measurement error in the dependent variable. However, Haider and Solon (2006) showed that λ_t varies over a life-cycle, which needs not equal to one, and the estimator is biased by a factor of λ_t. Also see Solon (1992) for the attenuation bias when there is a classical measurement error in both son's and father's earnings.

[6]I impute fathers' missing earnings due to data availability but the issue of measurement error by using current earnings for long-run earnings is incidental.

[7]This two-sample approach is sometimes incorrectly labeled as TS2SLS. However it is not because not all exogenous second-stage regressors including the son's age variables are included in the first-stage in the equation (1.4).

where ω_{it} is equal to $\lambda_t \varepsilon_i + \nu_{it} + \lambda_t \rho_1 (x_i - \hat{x}_i)$. Under regularity conditions described in the Appendix, the probability limit of the least squares estimator of the coefficient of x_i is equal to

$$\text{plim}_{n\to\infty} \hat{\rho}_1 = \frac{\lambda_t \rho_1 Var(x_i) + Cov(x_i, \nu_{it})}{Var(x_i)} \tag{1.6}$$

which reduces to $\lambda_t \rho_1$ if $Cov(x_i, \nu_{it}) = 0$. (The proof can be reviewed in the Appendix.) However, the consistency still depends on λ_t even with the generated regressor and it calls for researcher caution in choosing the appropriate age range as Haider and Solon (2006) proposed.[8]

Finally, ordinary least squares regression is applied to equation (1.5) to estimate ρ_1.[9]

Generally, most studies with this methodology have two datasets: The first provides sons' economic status variables with sons' recollected information of fathers' education, industry and occupational characteristics at the son's particular age during childhood. Those variables are used to generate fathers' missing economic status variables. The second dataset contains potential fathers' economic status variables with socio-demographic characteristics. This supplementary sample is used to predict fathers' economic status variables like earnings, based on fathers' socio-demographic characteristics when sons were at a specific age as reported in the first dataset. Then ρ_1 can be estimated from equation (1.5) with predicted fathers' earnings, $\hat{x}_i$, in lieu of fathers' permanent earnings, x_i.

Similar to many other countries, Korea does not have a sufficiently long intergenerational panel

[8]Nybom and Stuhler (2011) provided an example when one suspects that lifetime earnings correlate within family, i.e., $Cov(x_{it}, \nu_{it}) \neq 0$. If measurement errors in earnings growth rates of fathers and sons are correlated, a father's lifetime earnings correlate with career outcomes and therefore the same shape of earning trajectories as his children.

[9]Note that ρ_1 in equation (1.3) will not be equal to ρ_1 in equation (1.5) as composite errors differ except for $x_i = \hat{x}_i$. One feasible expectation of the magnitude of ρ_1 is that ρ_1 in equation (1.5) would be larger than in equation (1.3) if there is a positive correlation between fathers' socio-demographic variables and sons' economic status variable; Björklund and Jäntti (1997) and Ueda (2013) used it as an upper bound on the true estimates. Except for fathers' education, it is not clear how other fathers' industry or occupation variables can affect sons' earnings. Moreover, the direction of bias is even more questionable when life-cycle bias comes into consideration. Thus in this study, I do not interpret $\hat{\rho}_1$ in equation (1.5) as an upper bound of $\hat{\rho}_1$ in equation (1.3). Hereafter the value of ρ_1 is denoted as ρ_1 in equation (1.5). Piraino (2007) tested orthogonality conditions for his set of predictors and confirmed that at least some of fathers' characteristics are correlated with the regression error term. The general approach by practitioners is to choose predictors such that the R^2 of the first step regression in equation (1.4) is as high as possible. Researcher caution is required to choose the appropriate standard errors of generated regressors. Murphy and Topel (1985) and Pagan (1984) showed that standard two-step procedures not accounting for generated regressor problems unambiguously underestimate standard errors of the consistent second-step estimators; and that corrected standard errors are larger than are their uncorrected counterparts, in some cases by a factor of two or more.

dataset where explicit information of father-son pairs' economic status variables are observed.[10] Several studies in Korea were done by employing the Korean Labor and Income Panel Study (KLIPS), which is only available from 1998 to 2008. Kim (2009) and Choi and Hong (2011) employed KLIPS data and estimated ρ_1 in Korea. They focused on father-son pairs who co-resided in 1998, and restricted sons who in subsequent years moved into a non-member household (for instance, through marrying). This homogeneous sample of co-resident father-son pairs is an endogenously selected sample and would demonstrate an intergenerational transmission of earnings different from in the population. They averaged available earnings to overcome attenuation bias because current earnings are proxied for permanent earnings. However, including younger sons - around 30 - and older fathers - in the late 50s - tends to lower estimates due to life-cycle bias. For monthly earnings, coefficients are 0.141 (0.042) and 0.349 (0.096) when the father's education is instrumented for the father's earnings.

Ueda (2013) also used KLIPS to estimate intergenerational mobility in Korea and employed a two-sample method to impute actual fathers' permanent earnings using sons' recollections of their fathers' educational levels and occupations when they were 14. Among working men with positive wages aged 25-54 for fathers and 30-39 for sons, Ueda restricted the sons' sample to 2006 and pooled annual earnings for the potential fathers' sample observed over the period 2003-2006. The coefficient is 0.223 (0.072) but Ueda imputed a too-recent earnings function instead of choosing the fathers' sample in actual calendar time.

[10]Another way to estimate ρ_1, taking into account the missing fathers' permanent earnings problem, could be by adopting the propensity score weighting estimation. But Nicoletti and Ermisch (2008) argued that it's usefulness is sensitive to data availability of father's earnings.

1.3 Data

KLIPS contains sons' earnings and their recollections of fathers when they were 14 and is the first Korean longitudinal survey on the labor market and income activities of households and individuals, collected from 1998 to 2008. During the first wave in 1998, a representative sample of 5,000 households and their members (15 and over), covering more than 13,000 individuals, was interviewed using the sampling frame from the census and they became the original panel of households and household members.[11]

In addition, Household Income and Expenditure Survey (HIES) is repeated cross section survey data that are the only publicly available at an individual level with economic status variables such as labor earnings, family income information of each household, and socio-demographic characteristics. Survey data are available since 1982; however, education information was added to the survey since 1985. HIES, as in KLIPS, used the sampling frame of the census, which supports the argument that both datasets are representative samples of the Korean labor market.

Monthly labor earnings are recorded pre-tax in HIES and net of taxes in KLIPS. However, pre-tax labor earnings in KLIPS can be calculated because tax on labor earnings is also available in KLIPS from 2004. One data limitation is that KLIPS records the income of self-employed workers by after-tax value whereas HIES does not provide income information for self-employed workers. This renders it harder to estimate accurate mobility when self-employed fathers are included. In this study, labor earnings are the main focus, because they enable international comparison of intergenerational mobility, as most previous studies used earnings; more, earnings mobility better measures mobility based an individual's merit than do other economic status variables.[12] Since

[11]Since the 2nd wave in 1999, household and individual sample are maintained by follow-up rules, which is typical in household panel surveys. Individuals who come to form blood and economic ties to original panel members are added to the original sample. For example, if a panel member marries and forms an independent household with his/her spouse, the latter becomes a 'new respondent' to the original panel and the couple is followed and interviewed thereafter. On the other hand, if for instance one of the panel members moves into a non-member household, via marriage for instance, he/she is also followed and his/her spouse's household members are interviewed. In this way, the size of the sample members grows and expands in waves. When a panel member moves out of the original household, for instance via divorce, he or she is also tracked as long as he or she lives with his or her children.

[12]See Björklund and Jäntti (2009) for more discussion on different income measures and their features.

HIES does not offer any income information for self-employed workers, sons whose fathers were self-employed during their childhood are excluded.[13]

KLIPS and HIES have recorded education, occupation, and industry in different categories. Especially occupation and industry variables are recorded with three digits in KLIPS, but in one digit and two digits in HIES, respectively. Since the categories used for industry and occupation in KLIPS are finer than those used in HIES, those variables are matched according to the HIES schedule. After recoding categories to have a homogeneous classification across samples, seven different levels of education, nine industry groups, and seven occupational groups are available to predict fathers' missing earnings. The number of predictors for fathers' missing earnings as well as the number of groups of each variable are relatively richer than in previous studies in other countries.[14]

In the analysis I use two waves of KLIPS for sons' sample and both KLIPS and HIES for potential fathers' sample. When replicating Ueda's empirical results, I use KLIPS in 2003 for sons' sample and KLIPS in 2006 for potential fathers' sample. Since the age gap between sons in KLIPS in 2003 and potential fathers in KLIPS in 2006 is three, to use more approximal cohorts of actual fathers, I retrieve sons' sample from KLIPS in 2008 and potential fathers' sample from HIES in 1985.[15]

Preferred age range for both generations is between 35 and 50 as errors-in-variables bias in sons' earnings stays small, following Haider and Solon (2006), given that Korean male workers generally enter the labor market about 3-5 years later than in the U.S. due to mandatory military service obligations.[16]

[13]Note self-employed sons are included when sons with self-employed fathers are excluded. If I exclude self-employed sons, I lose 50% of the sample, however, the estimates are similar.

[14]For instance, Björklund and Jäntti (1997) used fathers' education and occupation; Nicoletti and Ermisch (2008) used occupational prestige and education; and Lefranc (2011) used education.

[15]These two samples are 23 years apart thus enables matching of father's generation more closely to actual fathers than does using 2003 for potential fathers' sample. Using the average age difference between fathers and sons from the national census, potential fathers' age range in 1985 is set to 35-50 when the sons were 14, which covers around 95% of the father-son pairs. Table 1 demonstrates age differences between fathers and sons and it is clear that statistics for KLIPS 2005 and National Census 2005 are closely similar; this can be verified easily in Figure 1. This evidence justifies the use of KLIPS 2008 as a representative sample and restriction of samples based on the age information from KLIPS 2008.

[16]In fact, for sons 35-50 in 2008, their possible fathers were 34-68 in 1985; this covers 95% of fathers based on

Both KLIPS in 2008 and HIES in 1985 are restricted to working men age between 35 and 50 with positive wages, which leaves 1700 observations in KLIPS and 1780 in HIES.[17] Especially in HIES, the fathers' sample was further restricted to those with a positive number of children aged 6-19 in 1985. Fathers or sons who lived in foreign countries when their sons were 14 are excluded. Furthermore, employed sons whose fathers were self-employed also are excluded. Narrowing the sample to those with all education, industry, and occupation variables recorded, the number of observation drops to 675 in KLIPS and 1,577 in HIES.[18] Descriptive statistics of variables used for the main sample and the supplemental sample are summarized in Table **??**.

age difference information from census data in 2005. If I match the age range of 35-50 for fathers in 1985, I lose 20% of the sample; however, the estimates are similar. More information is provided in the next section.

[17]Between household head and non-head sons, differences exist in earnings and educational attainment. But excluding non-heads and restricting only to heads could be an endogenous selection. Moreover, there is no formal requirement to answer as a head but it is who represents the household. Thus I included all male workers and presented the results for both samples. In addition, national unemployment rate in Korea is around 5% in late 1980s and around 3.5% in 2000s, indicating that the excluding unemployed population is not troublesome.

[18]Total sample age between 35 and 50 in KLIPS is 3700 and 1897 are male; 1700 workers have positive wages; 1016 workers have self-employed fathers when they were 14, which leaves 684 workers. All have fathers' education information. The sample size decreases by six for missing fathers' industry information and by another three for missing occupation information, thus final sample size is 675. HIES has 1787 male workers aged between 35 and 50 and 1780 have positive earnings. The sample size drops by 223 when restricted to workers with children aged between 6 and 19. All have information on education, industry, and occupation.

1.4 Empirical Results

To extend the empirical results from Ueda (2013), the analysis starts by following his identification strategy of applying the two step method to a single dataset, KLIPS, and extends the analysis by introducing HIES for potential fathers' sample. Ueda (2013) averaged annual earnings between 2003 and 2006 for potential fathers and retrieved sons' earnings from 2006, and restricted ages for sons to 30-39 and for fathers to 25-54. To provide results similar to Ueda, I retrieve sons' earnings from KLIPS in 2006 and potential fathers' annual earnings from 2003, and restrict the same age ranges for sons and fathers. To implement the two-sample method, in the first step in equation (1.4), fathers' log earnings in 2003 are regressed on age, age squared, industry, occupation, and education variables followed by sample selection rules described in the previous section. Then, as in equation (1.5), sons' log earnings in 2006 from KLIPS are regressed on generated fathers' permanent earnings, age and age squared of sons.[19] Standard errors are estimated by the bootstrap method following Björklund and Jäntti (1997).[20] Table 1.B5 summarizes results and the estimate replicating Ueda's approach is 0.205 with a bootstrapped standard error of 0.050, which is similar to Ueda's baseline estimate of 0.223. Ueda used education and occupation to predict fathers' missing earnings and when I use those two variables as predictors, the estimate is 0.244 (0.054). When the later round in 2008 is used for sons' sample, the estimate is 0.310 (0.049).

Restricting to the preferred age range of 35-50 for both generations, the estimate in Panel D increases to 0.334 (0.057), partly due to excluding young fathers. Results are consistent with previous studies on life-cycle bias; inclusion of younger sons or older fathers lowers estimates. That is, the correlation between a father's age (son's age) at measurement and the size of $\hat{\rho}_1$ is

[19]Note that estimates of age controls such as age and age squared of fathers are not used to generate fathers' missing earnings. This is because I am not predicting earnings at a particular age, but are trying to predict fathers' long-run earnings, which requires the standardization on ages. Thus it is inappropriate to use re-age-adjusted fathers' earnings in the second step.

[20]First, I draw a bootstrap sample of fathers from KLIPS 2003, from which equation (1.4) is run to estimate parameters. Then I draw another bootstrap sample of sons from KLIPS 2006, from whose recollections data is used to generate fathers' earnings. I estimate ρ_1 in equation (1.5) and save estimates for 1000 replications. If a researcher ignores that fathers' earnings are generated and uses a bootstrap only in the second step, then standard errors are smaller than our approach, bootstrapping both steps, but still larger than those without bootstrapping in OLS.

negative (positive). The estimates are 0.144 (0.083) for sons with self-employed fathers and 0.218 (0.061) for sons with employed fathers, which frees concern that self-employment status of fathers might significantly affect the estimates.

This approach, however, implicitly assumes that potential fathers' characteristics in 2003 are close to those for actual fathers, and uses information from the younger-father generation. In other words, if the average age gap between fathers and sons is 30, then fathers' actual ages in 2003, whose sons are aged 30-39 in 2008, are 55-64 instead of 25-54. Moreover, occupation, industry, and education distribution in 2003, used for potential fathers' characteristics, are more similar to those for sons in 2008 than to those for actual fathers. Thus results of this approach are vulnerable if one supposes significant changes occurred in the wage structure in recent decades. To retrieve potential fathers' information from more approximal cohort of actual fathers, I use HIES and generate pseudo fathers' earnings based on sons' recollections on fathers' industry, seven categories of occupation, and education.

1.4.1 The Role of HIES

Estimates in Panels B and C in Table 1.B5 present the sensitivity of sons' sample between KLIPS 2006 and 2008, suggesting that detailed matching of potential fathers with actual fathers could be important. By retrieving potential fathers' information from HIES in 1985, the father-son age gap becomes more realistic and the distribution of earnings predictors including education, occupation, and industry, becomes closer to those of actual fathers remembered by sons than to those of potential fathers in KLIPS 2003.

Age ranges for both generations are restricted to 35-50 as it best reflects the feature of the Korean labor market that mandatory military service generally delays men from joining it. Moreover, the preferred age range better represents mid-career earnings, and this specification with three earnings predictors for fathers and age ranges for fathers and sons between 35 and 50 is served as the baseline model.[21] By excluding younger sons in their later 20s and early 30s and older fathers

[21] Key father's earnings predictors are chosen to maximize R^2 of the first stage regression and the results are summarized in Table 3. The adjusted R^2 in the first stage, 0.393, is relatively larger than other studies in Table 1.B7;

above 50, the estimate increases to 0.386 (0.059).[22]

Table 1.B6 urther reports regression results with several different sample specifications. Some concern might arise that the occupation distribution of potential fathers and real fathers are imperfectly matched. Although required information from the first step is the sample average of earnings in each predictor category, in Panel A the occupation categories are merged and reorganized to generate similar distributions. However, the number of categories does not change estimates significantly. In fact, estimates lie in the range 0.401 to 0.407 when the number of occupation categories is changed from 6 to 4, which indicates that the estimates are robust to occupation specifications. Thus different occupation category distribution has negligible impact on estimates.

The age range of 35-50 is chosen to have λ_t close to 1 so that measurement error is close to classical errors-in-variables. Many studies using current earnings to proxy for permanent earnings averaged earnings over years to deal with the measurement error following Solon (1992). Estimates of intergenerational earnings elasticity become larger as fathers' earnings are averaged over more years. Since potential fathers are taken from HIES in 1985 and HIES is repeated cross section data, which makes it harder to calculate missing fathers' average earnings, sons' earnings are averaged over years. Results in Panel B show that the estimates increase as earnings are averaged over more years.

In the base model, all three earnings predictors are used. If one changes the combination of earnings predictors and uses a subset of predictors, sample size increases by only nine, which frees the concern of having a smaller sample size in exchange for having more predictors. However, estimates change from 0.35 to 0.59, implying that researchers should pay attention when they choose appropriate predictors and especially when they compare with other countries' estimation

Piraino (2007) with 0.322, Mocetti (2007) with 0.301, Nicoletti and Ermisch (2008) with 0.289, and Ueda (2013) with 0.23. Preferred first step regression results are summarized in Table 1.B4 with age range of 35-50 for both generations using all three earnings predictors.

[22]If I match the age range of 34-68 for potential fathers in 1985 covering 95% of the father-son pairs, the estimate is 0.397, very similar to the estimate in the baseline model. Thus hereafter, age range of fathers in 1985 is fixed at 35-50 instead of 34-68. When self-employed sons excluded, the sample size decreases to 502, and the estimate is 0.409 (0.064). Further analysis shows that the estimate is robust to the treatment on the self-employment workers. In addition, for household heads, the sample size is 572 and $\hat{\rho}_1$ is 0.351 (0.062). Heads earn approximately 15% to 30% more than non-head members and this might result in a relatively lower estimate.

results. Results are summarized in Panel C.

When the industry variable is dropped, $\hat{\rho}_1$ is 0.392 (0.065). Most other countries' studies on intergenerational elasticity with two-sample estimation, documented in Table 1.B7, did not use an industry variable to predict fathers' earnings. However, it is not clear in which direction the estimate would move if an industry variable is included.[23]

1.4.2 International Comparison

In summary, the estimate of intergenerational elasticity is around 0.4, similar to already-developed countries and relatively lower than recently-developed or developing countries. A relatively higher extent of intergenerational mobility is shown in Korea, even higher than other developing countries (e.g., 0.69 in Brazil and 0.52 in Chile).[24]

Some studies, for instance Piraino (2007) in Italy, investigated the channels in the transmission of economic status and found parental education's contribution to the intergenerational mobility. In Korea, parent-child schooling correlation among 20-69 sons in 2008 is only 0.333,[25] one of the lowest values according to Hertz et al. (2008).[26] Some countries in Table 1.B7, for example Brazil and Chile, show a negative relationship between intergenerational schooling inheritance and intergenerational earnings mobility. More thorough examination on the relationship between education inheritance and intergenerational mobility in Korea is left for future research.

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[23] If I exclude the agriculture sector in industry and in occupation categories, which mostly considers the sample residing in urban areas, the estimate is 0.337, the lowest among all models. As a result, a reasonable claim is that intergenerational mobility is higher in urban areas than that in rural areas, accounting for job opportunities in those areas.

[24] Key comparable countries in Table 1.B7 have different age ranges for fathers and sons, and different sets of fathers' earnings predictors. Since each country has a different education-, industry-, and occupation structure and history, and different worker quality, precise international comparison is more challenged and no formal statistical test exists for comparison. Constructing a confidence interval for estimates for comparison is a possible option. However, those facts aside for simplicity, when I match age ranges and sets of predictors with corresponding countries in Table 1.B7, except for Chile where fathers' age-range information is unavailable, the relative mobility in Korea stay stable.

[25] Approximately 90% of sons are educated beyond high school, whereas as many as approximately 80% of their fathers have education less than high school.

[26] Hertz et al. (2008) documented international comparison of educational inheritance for sons 20-69. Some noticeable countries in Table 1.B7 are Brazil (0.59), Chile (0.6), China (rural, 0.2), Italy (0.54), Sweden (0.4), UK (0.31), and U.S. (0.46).

1.5 Remarks

This study examines intergenerational earnings mobility in Korea with the two-sample estimation method to generate father's missing permanent earnings by combining a panel dataset, which includes son's earnings and recollection information on father's socio-demographic characteristics, and a cross section dataset, which contains earnings and socio-demographic information of potential fathers.

This study shows that the measurement error in sons' current earnings as a proxy for permanent earnings is a source of inconsistency even when fathers' earnings are generated. Thus the working father-son sample is restricted to age 35-50 to be least affected by life-cycle bias, and the elasticity is around 0.4. Estimated intergenerational earnings elasticity is similar to estimates for some already-developed countries and smaller than typical estimates for recently-developing countries.

Previous studies on Korean intergenerational earnings mobility tend to have lower estimates than 0.4. Some included younger sons and older fathers in the sample, and those factors contributed to lower estimates. Moreover, focusing on a homogeneous sample of co-residing father-son pairs may result in lower estimates. Ueda (2013) also employed two-sample estimation; however, less attention was paid to detailed matching, as an inaccurate period of observation for potential fathers' sample was used for imputation.[27] Thus this study contributes to more-accute estimation of mobility, with two representative samples aiming to match pairs correctly by choosing the right age range for both generations, which better represents permanent earnings.

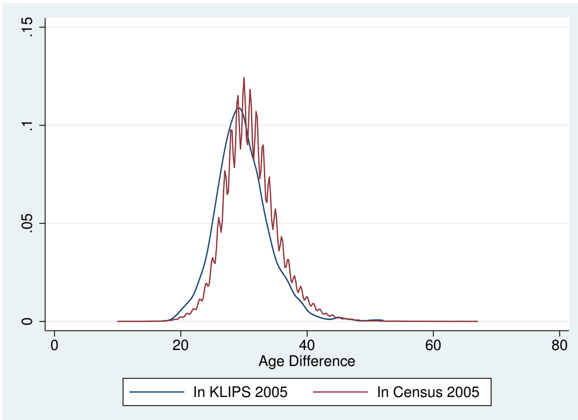
Perhaps one of the most important remaining issues to deal with is the life-cycle bias in Korea. Male workers in Korea generally have to serve in the army from their late teens, which on average delays labor market participation timing by three to five years compared to the U.S. Since data access is limited in Korea to analyze the framework as in Haider and Solon (2006), alternative approaches to studying life-cycle bias in Korea are required in future.

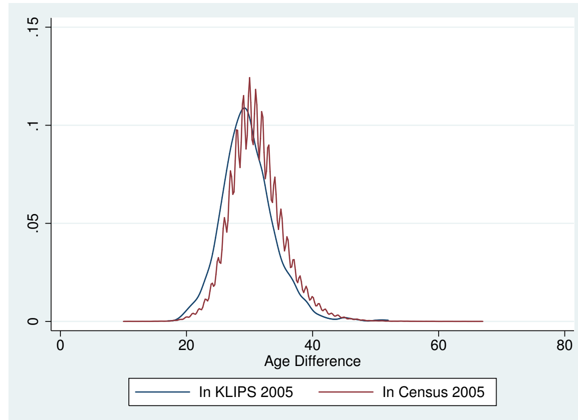
[27] Real GDP per capita in Korea increased more than three times between 1985 and 2003, implying that potential fathers' cohort in 1985, who are more proximal to actual fathers, are different from the cohorts in 2003.

APPENDICES

APPENDIX A
FIGURE FOR CHAPTER 1

Figure 1.A1 Average Age Difference between Fathers and Sons





Notes: Average age difference in the original samples is in the left. Average age difference when the difference between KLIPS 2005 and Census 2005 is corrected is in the right.

APPENDIX B

TABLES FOR CHAPTER 1

Table 1.B1 Father-Son Age Difference

	Census 2005	KLIPS 2005	KLIPS 2006	KLIPS 2008
Observation	139,832	2,654	2,655	2,564
Average Age Difference	30.54	29.79	29.74	29.79
Standard Deviation	4.25	4.25	4.22	4.21
Age Range for 90% of Observation	24-39	23-37	23-37	23-37
Age Range for 95% of Observation	22-41	22-39	22-39	22-39

Table 1.B2 Descriptive Statistics

	Actual Fathers Described by Sons	Potential Fathers in HIES	Sons
Mean Age	41		41
Education			
None	6.9	1.7	0.2
Elementary	26.1	15.4	1.8
Middle	20.8	23.7	4.1
High	29.2	34.8	30.6
Community College (2 Years)	2.0	2.4	18.2
University (4 Years)	13.7	20.4	34.3
Graduate School	1.4	1.7	10.8
Occupation			
Professional, Technical, Managerial	12.7	8.1	36.5
High-Rank Government Officer, Entrepreneur	2.6	0.7	2.6
Administrative Worker	16.7	24.9	19.2
Office Worker	5.2	7.7	3.7
Service Worker	3.2	5.3	3.5
Production Worker	37.4	51.1	33.3
Agriculture, Fishing, Forestry	22.3	2.2	1.2
Industry			
Agriculture, Fishing, Forestry	12.1	2.0	0.6
Mining	2.4	1.5	0.0
Manufacturing	18.2	30.3	28.6
Utilities	0.2	1.1	1.4
Construction	19.6	18.0	12.6
Wholesale and Retail Trade	10.3	8.8	11.6
Communication, Transportation	8.9	12.3	7.7
Banking, Business Service	5.0	4.1	17.8
Public Administration, Education	23.4	22.0	19.8

Notes: Age of father-son sample is restricted to 35-50.

Table 1.B3 Choice of Father's Earnings Predictors

Case	Earnings Predictors	F	R^2	Adj R^2	Root MSE
1	Industry	24.61	0.137	0.132	0.499
2	Occupation	80.22	0.293	0.289	0.451
3	Education	99.15	0.339	0.335	0.436
4	Ind & Occ	47.26	0.329	0.322	0.441
5	Occ & Edu	66.64	0.377	0.371	0.424
6	Ind & Edu	56.26	0.369	0.362	0.427
7	Ind & Occ & Edu	46.77	0.402	0.393	0.417

Notes: Age of father-son sample is restricted to 35-50.

Table 1.B4 First Step Regression

Dependent Variable: Log Father's Earnings	Coefficient	Std. Err
Education		
None	Omitted Dummy	
Elementary	0.2164	0.1032
Middle	0.3199	0.0999
High	0.4578	0.1006
Community College (2 Years)	0.7388	0.1230
University (4 Years)	0.7712	0.1043
Graduate School	0.7910	0.1313
Occupation		
Professional, Technical, Managerial	0.0735	0.1301
Administrative and Government Officer, Entrepreneur	0.0315	0.1923
Clerical Worker	0.1172	0.1247
Sales Worker	0.3916	0.1272
Service Worker	0.3992	0.1415
Production Worker	0.3119	0.1243
Agriculture, Fishing, Forestry	Omitted Dummy	
Industry		
Agriculture, Fishing, Forestry	Omitted Dummy	
Mining	0.2536	0.1711
Manufacturing	0.4053	0.1452
Utilities	0.4392	0.1933
Construction	0.1701	0.1486
Wholesale and Retail Trade	0.3348	0.1503
Communication, Transportation	0.3703	0.1478
Banking, Insurance, Business Service	0.3956	0.1547
Community, Social, and Personal Services	0.3885	0.1445

Notes: Age of father-son sample is restricted to 35-50.

Table 1.B5 Intergenerational Earnings Elasticity

Sons' Age	Fathers' Age	Sample Size	$\hat{\rho}_1$	Std. Err
Panel A: Original from Ueda				
30-39	25-54	809	0.223***	0.072
Panel B: Replication of Ueda Using KLIPS2006				
30-39	25-54	1142	0.205***	0.050
Panel C: Replication of Ueda Using KLIPS2008				
30-39	25-54	1083	0.310***	0.049
Panel D: Role of Age				
35-50	25-54	1911	0.307***	0.054
35-50	35-50	1666	0.334***	0.057
Panel E: Employed Fathers				
35-50	35-50	675	0.218***	0.061
Panel F: Self-Employed Fathers				
35-50	35-50	991	0.144*	0.083
Panel G: Potential Fathers from HIES				
35-50	35-50	675	0.386***	0.059

Notes: Sons' information is retrieved from KLIPS 2006 for Panel A - B, and from KLIPS 2008 for Panel C - G. Potential fathers' information is retrieved from KLIPS 2003 for Panel A - F and from HIES 1985 for Panel G. Bootstrapped standard errors are in parentheses.
***Significant at the 1% level.**Significant at the 5% level.
*Significant at the 10% level.

Table 1.B6 Sensitivity of Intergenerational Earnings Elasticity

	Sample Size	$\hat{\rho}_1$	Std. Err
Baseline	675	0.386***	0.059
Panel A: Role of Occupation Category			
Occupation Category			
6	675	0.401***	0.062
5	675	0.407***	0.061
4	675	0.405***	0.061
Panel B: Role of Averaging for Balanced Sample			
Period			
2007-2008	483	0.426***	0.058
2006-2008	459	0.445***	0.057
2005-2008	410	0.471***	0.060
Panel C: Predictor Combination			
Predictor			
Industry	678	0.585***	0.105
Occupation	675	0.398***	0.074
Education	684	0.354***	0.076
Ind & Occ	675	0.411***	0.063
Occ & Edu	675	0.392***	0.065
Ind & Edu	678	0.394***	0.065
Ind & Occ & Edu	675	0.386***	0.059

Notes: Baseline model uses industry, occupation, and education as predictors, and age of father-son sample is restricted to 35-50. Seven groups of occupation category are used and standard errors are bootstrapped.
***Significant at the 1% level.**Significant at the 5% level.
*Significant at the 10% level.

Table 1.B7 Comparable Intergenerational Earnings Elasticity with Two-Sample Estimation

Country	Authors	$\hat{\rho}_1$	Std. Err	Age^f	Age^s	Earnings Predictors
Australia	Leigh (2007)	0.41	0.137	25-54	25-54	Occ
Brazil	Dunn (2007)	0.69	0.014	30-50	25-34	Edu
Canada	Fortin and Lefebvre (1998)	0.22	0.051	40-50	17-59	Occ
Chile	Núñez and Miranda (2011)	0.52	N.A.	N.A.	23-65	Edu, Occ
China	Gong (2012)	0.63	0.117	48-74	30-42	Edu, Occ, Ind
France	Lefranc (2011)	0.50	0.028	25-60	28-50	Edu
Italy	Piraino (2007)	0.44	0.053	30-50	27-49	Edu, Occ, Ind
Italy	Mocetti (2007)	0.49	0.069	30-50	30-50	Edu, Occ, Ind, Region
Japan	Lefranc et al. (2011)	0.34	0.042	30-59	30-50	Edu, Occ, Ind
Spain	Cervini-Plá (2013)	0.40	0.042	37-57	30-50	Edu, Occ
Sweden	Björklund and Jäntti (1997)	0.28	0.094	43	30-39	Edu, Occ
Taiwan	Ueda and Sun (2012)	0.21	0.060	30-59	30-49	Edu, Occ
UK	Nicoletti and Ermisch (2008)	0.29	0.061	31-55	30-45	Edu, Occ
US	Björklund & Jäntti (1997)	0.42	0.121	N.A.	28-36	Edu, Occ

Notes: Leigh (2007) used predicted hourly wage for a 40-year old and the estimates in the table show results with the 1987 sample. When the 2004 sample is used, the estimate is 0.18 with standard errors of 0.043. Fortin & Lefebvre (1998) assumed 25-35 year difference between father and son. Björklund and Jäntti (1997) used the mean age of 43.

APPENDIX C
ADDITIONS FOR CHAPTER 1

I derive the consistency of OLS estimator $\hat{\rho}$ in equation (2.7), where dependent variable has a measurement error due to using the proxy and independent variable is generated from an auxiliary regression.

$$y_{it} = \rho_1 \hat{x}_i + \omega_{it} \tag{2.7}$$

where ω_{it} is equal to $\lambda_t \varepsilon_i + \nu_{it} + \lambda_t \rho_0 + h(Age_{it}) + (\lambda_t - 1)\rho_1 \hat{x}_i + \lambda_t \rho_1 (x_i - \hat{x}_i)$.

Write equation (1) as

$$y = x\rho + u \tag{2.8}$$

where $x = f(x_1, \theta)$, x_1 is a vector of variables from the first step that determines the unobservables, $f(\cdot)$, which is a $1 \times K$ vector of functions determined by the unknown vector θ, which is $Q \times 1$. Assume that $\mathbb{E}(u|x_1) = 0$ and errors are independent across observations. Further assume that $\hat{\theta}$ is a $\sqrt{N}$-consistent estimator of θ. Now let $\hat{\rho}$ be the OLS estimator from the equation

$$y_i = \hat{x}_i \rho + error_i \tag{2.9}$$

where $\hat{x}_i = f\left(x_{1i}, \hat{\theta}\right)$ and $error_i = u_i + (x_i - \hat{x}_i)\rho$, the ordinary least squares estimator is

$$\hat{\rho} = \left(\sum_{i=1}^{N} \hat{x}_i^{'} \hat{x}_i\right)^{-1} \left(\sum_{i=1}^{N} \hat{x}_i^{'} y_i\right) \tag{2.10}$$

Write $y_i = \hat{x}_i \rho + (x_i - \hat{x}_i)\rho + u_i$, where $x_i = f(x_{1i}, \theta)$, then plugging this in and multiplying through by $\sqrt{N}$ gives

$$\sqrt{N}(\hat{\rho} - \lambda_t \rho) = \left(N^{-1} \sum_{i=1}^{N} \hat{x}_i^{'} \hat{x}_i\right)^{-1} \left\{N^{-1/2} \sum_{i=1}^{N} \hat{x}_i^{'} \left[(x_i - \hat{x}_i)\lambda_t \rho + \xi_i\right]\right\} \tag{2.11}$$

where $\xi_i = \lambda_t \varepsilon_i + \nu_{it} + \lambda_t \rho_0 + h(Age_{it})$.

Under regularity condition stated in Theorem 1 in Murphy and Topel (1985) or Theorem 12.3 in Wooldridge (2010),[28] a mean value expansion of $\hat{\theta}$ gives

$$N^{-1/2}\sum_{i=1}^{N}\hat{x}_i^{'}\xi_i = N^{-1/2}\sum_{i=1}^{N}x_i^{'}\xi_i + \left[N^{-1}\sum_{i=1}^{N}\nabla_{\theta}f(x_1,\theta)^{'}\xi_i\right]\sqrt{N}(\hat{\theta}-\theta)+o_p(1) \tag{2.12}$$

Because $\mathbb{E}\left(\nabla_{\theta}f(x_1,\theta)^{'}\xi_i\right)=0$, it follows that $N^{-1}\sum_{i=1}^{N}\nabla_{\theta}f(x_1,\theta)^{'}\xi_i = o_p(1)$, and since $\sqrt{N}(\hat{\theta}-\theta)=O_p(1)$,

$$N^{-1/2}\sum_{i=1}^{N}\hat{x}_i^{'}\xi_i = N^{-1/2}\sum_{i=1}^{N}x_i^{'}\xi_i + o_p(1) \tag{2.13}$$

Using similar reasoning, by mean value expansion

$$N^{-1/2}\sum_{i=1}^{N}\hat{x}_i^{'}(x_i-\hat{x}_i)\,\lambda_t\rho = -\left[N^{-1}\sum_{i=1}^{N}(\rho\otimes x_i)^{'}\nabla_{\theta}f(x_1,\theta)\right]\sqrt{N}(\hat{\theta}-\theta)+o_p(1) \tag{2.14}$$

Now assume that

$$\sqrt{N}(\hat{\theta}-\theta) = N^{-1/2}\sum_{i=1}^{N}r_i(\theta)+o_p(1) \tag{2.15}$$

where I assume $\mathbb{E}[r_i(\theta)]=0$, which even holds for most estimators in nonlinear models.[29]

If I assume that $Cov(x_i, h(Age_{it}))=0$, then

$$\text{plim}_{n\to\infty}\hat{\rho} = \frac{\lambda_t\rho Var(x_i)+Cov(x_i,\nu_{it})}{Var(x_i)} \tag{2.16}$$

which reduces to $\lambda_t\rho$ if $Cov(x_i,\nu_{it})=0$. For consistency, replacing x_i with $\hat{x}_i$ in an OLS estimation causes no problem as in Wooldridge (2010).

[28](a) $D_0 \equiv \text{plim}_{n\to\infty}N^{-1}\sum_{i=1}^{N}\hat{x}_i^{'}\hat{x}_i = \mathbb{E}(x'x)$, (b) $f(\cdot)$ is twice continuously differentiable in θ for each x_1 with the sample second moments of $\partial f/\partial\theta$ uniformly bounded in the sense of $\text{plim}_{n\to\infty}\left(N^{-1}\sum_{i=1}^{N}\hat{x}_i^{'}\hat{x}_i\right)\left[N^{-1}\sum_{i=1}^{N}\nabla_{\theta}f(x_1,\theta)\xi_i\right]=D_1$, where $\nabla_{\theta}f(x_1,\theta)$ is the $K\times Q$ Jacobian of $f(x_1,\theta)^{'}$, and (c) $\hat{\theta}$ is a consistent estimator of θ.

[29]See Chapter 6 and 12 in Wooldridge (2010) for details.

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CHAPTER 2

College Enrollment over the Business Cycle: The Role of Supply Constraints

2.1 Introduction

Many studies on effects of recession on higher education have investigated the relationship between college enrollment and labor-market conditions, mainly measured by the unemployment rate, and have found clear countercyclicality; Manski and Wise (1983) found a weak relationship between four-year college applications and the local unemployment rate, Betts and McFarland (1995) found that public community college enrollments rise and fall in phase with the ups and downs of unemployment[1] and Barr and Turner (2013) claimed that the Great Recession has produced unambiguous increases in college enrollment.

Much attention has been paid to changes in enrollment demand when economic conditions changes, usually analyzing the relationship with individual level data. Some claimed that the opportunity cost of going to college decreases during a recession but the liquidity constraints also simultaneously becomes severe, and this limits the enrollment increase (Christian, 2004; Lovenheim, 2011). In this line of research the implicit assumption is that institutions have adequate flexibility to adjust to changes in demand, and that supply-side difficulties did not arise (Bound and Turner, 2007; Barr and Turner, 2012).

Some recent studies acknowledge that in the higher-education market, the supply-side is likely to be affected by local economic conditions and that enrollment can become inelastic if supply is inelastic despite demand cyclicality. If an institution faces a reduction in non-tuition revenue

[1] Some notable research on the theory of cyclicality on higher education includes Sakellaris and Spilimbergo (2000), Dellas and Koubi (2003), and Dellas and Sakellaris (2003).

including state/federal appropriations during a recession, it has fewer resources to spend on instruction; in turn, this decreases education quality. Further, if an institution has an enrollment capacity limit, it cannot accommodate all increases in demand and, in the short run, has only a limited quantity response. For instance, Lovenheim (2011) and Barr and Turner (2013) conjectured that supply elasticity might depend on residential programs, subsidies per student, and an institution's prestige. However, none have tested the hypothesis.[2] Motivated by their conjectures, this study collected data to identify institutions with supply capacity constraints in the short run, and showed that during recessions those institutions experienced limited adjustment in the quantity dimension; supply was inelastic.

Many previous studies on higher-education cyclicality focused on adjustment of the quantity dimension and analyzed how enrollment size responded to economic fluctuations. Simultaneously, those studies paid scant attention to what happens in the aspect of new student achievement, implicitly assuming that incoming student achievement, and/or that of produced human capital, are homogenous.[3] However, quality of human resource produced in higher education is affected by recessions and it relates to capacity constraints.

To present a more complete accounting of cyclical movement of college enrollment, this study introduces a simple conceptual model and derives implications of the role of capacity constraints on cyclical responses. Previous studies on cyclicality in higher education paid less attention to supply side and might have partially understood actuality. Among others, an institution's policy to provide housing for new freshmen captures capacity constraints on the supply-side, and during recessions produces different predicted adjustments in enrollment decisions. The model implies that institutions required to provide on-campus housing could have been supply elastic. During an economic downturn, these institutions become more selective, and cyclical variations in demand

[2] Lovenheim (2011) stated supply at top-ranked public and private schools is inelastic, and Barr and Turner (2013) argued that research universities and liberal arts colleges are most likely to be supply inelastic, and that supply is elastic for community colleges, open-access public 4-year institutions, and for-profit institutions.

[3] Christian (2004) used college-age cohort size as a source of change in demand for higher education and showed that state universities 1980-1995 tightened their admission policy, represented by a decline in acceptance rate, and experienced a drop in education quality, measured by expenditure per student, in response to the increase in demand for higher education.

do not turn into full-realization in enrollment. On the other hand, quantity expansion in the short run occurs at institutions without capacity constraints, i.e., those not required to provide housing for students such as community colleges and commuter universities.

This study presents compelling evidence that in fact the capacity constraints on the supply-side is binding, and that enrollment increase is disproportionate across institutions, depending on the constraints. In recessions, those institutions with limited quantity adjustment responded by a smaller increment in enrollment, elevating admission standards, and accepting students of higher achievement, whereas other institutions without the constraint tended to increase enrollment size, thus resulting in a decline in new freshman achievement.

This analysis begins with an introduction of a simple conceptual framework that illustrates an institution's maximization problem with different supply constraints, and derives implications of choices and results during recession. Section 3 presents data source, variables, and data selection process to generate the final sample for analysis. Section 4 describes changes in revenue resources and estimation results of the relationship between enrollment as well as new student achievement, and variations in labor market condition. Section 5 is the conclusion.

2.2 Conceptual Framework

Consider a simple world with two types of institutions. Each institution acts as one utility maximizing agent providing supply to the higher education market via decisions on enrollment subject to their own resources and has enrollment policy on how many and whom to accept.[4] [5] The number of enrolled students, n, serves as a source of revenue and cost to each institution at the same time.[6] Type A has no capacity constraints in supply in the short run, in the sense they are flexible in accepting students if demand increases. Thus supply of those institutions is elastic and demand-driven. Type A includes 4-year private commuting colleges, local public colleges, and community colleges, where most students likely live near campus and/or commute from home. On the other hand, Type B faces capacity constraints in the short run and has limited adjustment in enrollment when there demand increases. If enrollment exceeds capacity, these institutions need to consider building new housing or arranging extra contracts with other facilities. These have relatively inelastic supply such as elite 4-year private and public colleges, and are generally occupied by talented students. For example, these institutions require new freshmen to reside in on-campus housing - i.e., residence halls and/or off-campus facilities that have contracts with institutions - and in the short run have capacity constraints. These institutions place more emphasis on maintaining a relatively-high quality of enrolled students.

Institution i's decision-maker's utility function, $U(\cdot)$, is increasing in profit and the student quality.[7] Profit, π, is defined as the difference between revenue received and cost paid. Revenue,

[4] I use the individual institution as the agent that sets enrollment, student quality, and admission policy. Some previous studies, especially for public institutions, modeled states as a unit of analysis.(Lowry, 2001; Bound and Turner, 2007)

[5] Institutions pick the number of *admitted* students and employ all their resources in predicting the number of *enrolled* students. That is, enrollment is a function of the acceptance rate, which is the proportion of new applicants accepted, tuition, student quality, outside wages students can earn when they choose to work, and yield rate - i.e., the proportion of admitted students who enroll. For simplicity, ignore the possibility of interdependence between tuition, student quality, outside wage, acceptance rate, and yield rate. Also ignore any immigration-constraints in permission for international students to work except on campus or in off-campus work directly-related to their majors, and assume one market wage that college applicants can earn.

[6] Institutions choose the number of admissions and have sufficient experience in predicting actual enrollment. If enrollment is assumed to be a known function that behaved well for a long time, it is reasonable to pick n with uncertainty but uncertainty is not important in this context.

[7] Main focus of this study is on the choices of the number of undergraduate freshmen even though empirical results,

R, is the sum of tuition charged to enrolled students, $p \times n$, and non-tuition revenue, S, including government subsidy plus endowment payouts.[8] A school's cost depends on the number of students enrolled and the expenditure on educational quality. Assume that all schools, private and public, have the simple cost function $c(n)$.[9] Student quality, Q, decreases if enrollment size increases, all else equal.[10][11]

During an economic downturn, as in Dellas and Koubi (2003), the opportunity cost of education is procyclical and outside wage decreases. Thus, in the absence of severe liquidity constraints, educational pursuits ought to be countercyclical, which increases the total number of new applicants. At the same time, institutions receive less non-tuition revenue, which includes federal and state appropriations, and endowment earnings. Thus, a recession is modeled as a decline in S. With substantial decrease in appropriation and funding, institutions can increase tuition revenue by increasing enrollment size if prices are assumed stable in the short run.

During economic recession, institutions have heterogeneous responses in enrollment quantity. Schools without capacity constraint increase the enrollment size whereas institutions with limited capacity tend to have either no changes in enrollment or a smaller increment in enrollment. Type A colleges where on-campus housing is not necessary for freshmen show countercyclical responses: they increase enrollment size during recession. They can expand enrollment size ($\frac{\partial n}{\partial S}\mid_A < 0$) and offset the decrease in outside funding by maintaining a similar acceptance rate, which in turn in-

for instance De Groot et al. (1991) and Koshal and Koshal (2000), employed various types of cost function to capture synergies, or economies of scope, associated with the joint production of two or more products such as undergraduate and graduate education, and research.

[8] Note p in public institutions includes government per-student or per-credit subsidy. For simplicity, p represents tuition net of government subsidy if any. As long as tuition subsidy decreases during recessions, the distinction does not affect the model.

[9] $c(\cdot)$ includes expenditure per enrolled student plus custodial costs including faculty and staff salaries, and other costs associated with providing physical space to enrolled students, namely classroom buildings, residence halls, libraries, gathering spaces, administrative premises, etc..

[10] For example, $Q = \bar{Q} - a \times n$, where $\bar{Q}$ captures applicant quality if only one student is enrolled and a represents how quality is sensitive to the number of students, or by how much average quality drops with additional students.

[11] A Cobb-Douglas specification of utility function that places weight $1 - \alpha$ on student quality Q is

$$U = \pi^{\alpha} Q^{1-\alpha}; \alpha > 0$$

As α increases, an institution places more importance on profit, while that of student quality decreases. Both types of institutions have the same form of utility function for simplicity; however, they may have different weights on arguments. For example, Type A colleges may put more weight on profit dimension while Type B colleges may value student quality more, which implies $\alpha_A > \alpha_B$.

creases tuition revenue ($\frac{\partial \pi}{\partial S} \leqq 0$ at least with one equality). During a recession, marginal profit of \$1 is more valuable with the drop in S and student quality becomes less valuable as the quality of applicants increases, which provides enough incentives for these institutions to increase enrollment. On the other hand, Type B colleges, which have supply constraints in the short-run, need to build additional dormitories or contract with other housing facilities if they decide to accommodate the increase in demand by accepting student numbers higher than existing maximal. They in the short run choose not to have much response in the quantity dimension; they admit a similar number of students or a slightly more if they have soft constraints when they have a cut in outside funding ($| \frac{\partial n}{\partial S} |_A > | \frac{\partial n}{\partial S} |_B$, $\frac{\partial n}{\partial S} |_B \leqq 0$).

Differing impacts on student quality result from differing responses in quantity to an increase in demand. The effect of the increase in enrollment size on student quality is clear for Type B institutions: they elevate admission standards and accept students of higher quality. With an increase in number and quality of applicants during a recession, Type B colleges with supply constraints choose to maintain enrollment size around the capacity in the short-run, and elevate admission standards and admit students with better quality ($\frac{\partial Q}{\partial S} |_B < 0$). If the quality of applicant increases, these institutions become more selective and, from among the additional applicants, choose more talented students, which improves overall quality. On the other hand, colleges without capacity constraint accept more studentsand experience a decrease in overall quality of new students. With the increase in demand, some better students result but the majority of marginal students come from the lower tail of the quality distribution. Once they accept more lower-quality students than better-, overall quality declines ($\frac{\partial Q}{\partial S} |_A > 0$). Since the marginal utility of revenue decreases and that of student quality increases as enrollment increases, those institutions choose not to indefinitely increase enrollment.[12]

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[12]Another interesting approach would be by matching institutions with new students. Then the sign depends on the prestige of the school ($\frac{\partial Q}{\partial n} \lesseqgtr 0$). For top-ranked schools, the quality of marginal students due to the recession tends to be lower on average than that of their original students. Thus if they admit more students, student quality would decrease ($\frac{\partial Q}{\partial n} < 0$). If the school is less-selective and accepts only better-quality students, who would have enrolled in higher- tier school but could not due to the increase in admission standards, then student quality can increase ($\frac{\partial Q}{\partial n} > 0$). On the other hand, if they accept some marginal students who would have worked and who generally are less talented, it might decrease student quality ($\frac{\partial Q}{\partial n} < 0$); a similar result is expected for least-competitive colleges. If last two types

2.3 Data

2.3.1 IPEDS

This study investigates how an institution optimizes its resources in response to changes in demand. Institutional enrollment, prices, faculty, student achievement, and financial data are drawn from the Integrated Postsecondary Education Data System (IPEDS) since 1986, an annual survey by the U.S. Department of Education's National Center for Education Statistics (NCES). IPEDS provides aggregate information by institutions participating in Title IV federal financial aid programs. The dataset is used to explore the relationship between institutions' decisions on enrollment and changes in labor market conditions during recessions, and is suitable for in-detail observations of types of institutional responses. The number of institutions varies from 7,066 to 14,104 between 1986 and 2011. The final dataset is smaller because I excluded closed institutions, military institutions, tribal colleges, colleges not in the contiguous United States,[13] and extremely small institutions reporting fewer than 200 undergraduates.

2.3.2 Variables

2.3.2.1 Enrollment

Given the research interest - namely how supply constraints, i.e., the requirement to provide on-campus housing to freshmen affects decisions on enrollment - it is natural to use enrollment data for first-time first-year (FTFY) degree/certificate-seeking undergraduates who applied, were admitted, and enrolled (full time) for the most recent fall period available. Fall enrollment data is available from 1986. Other measures such as FTFY enrollment among high school graduates in the previous 12 months, and enrollment by age, residence state, or race, also are available.

of schools admit more less-talented students than better-qualified students, then the overall quality of new students would decrease when the enrollment size increases ($\frac{\partial Q}{\partial n} < 0$).

[13]These areas include Alaska, American Samoa, Guam, Federated States of Micronesia, Marshall Islands, Northern Mariana Islands, Palau, Puerto Rico, Virgin Islands, and Hawaii.

Figure 2.A1 plots the changes in the share of total enrollment by institution type and shows that the share of 2-year institutions and 4-year non-elite institutions is *procyclical* whereas the share of 4-year elite institutions is *countercyclical,* implying that the overall student achievement at each type of instituions is likely to be changed over the business cycle.[14][15]

2.3.2.2 Capacity Constraints

The variable to identify capacity constraints on the supply-side of higher education is constructed in multiple steps. The variable to represent the constraints is the on-campus housing requirement - i.e., dormitory, residence hall, or college-operated or -affiliated housing - which is equal to 1 (one) if all FTFY degree/certificate-seeking students are required to reside therein, or 0 (zero) if not. Institutions have exemption criteria on their residential policies, such as number of credits, proximity (commuting distance in actual miles or commuting minutes), age, marital status, custodial care of dependent children, dietary peculiarities, and religious constraints. Policies are subject to change, year to year, depending on spatial-, infrastructural-, and budgetary-constraints.[16]

Institutions required to provide residential accommodations for FTFY students cannot always change enrollment to cater to increase in demand. For example, they cannot add buildings and other infrastructure as rapidly as enrollment trends spike. Even if they do, recession or recovery or even boom may occur or may end earlier than expected. IPEDS provides information whether freshmen are required to live in on-campus housing and is recorded in Institutional Characteristics from 2004, which is long enough to cover the recession period. However, the variable in the governmental data system contains serious errors. Among the 1,059 institutions marked as having a firm on-campus housing residency policy at least once since 2004, 856 changed the answer from one to zero or *vice versa*, or mixed. For example, in IPEDS, Michigan State University

[14]Elite institutions include Top 200 National, Top 120 Public, Top 65 Private, and Top 180 Liberal Arts institutions, assembled from *US News and World Report* in 2005 and in 2013

[15]Many studies on cyclicality concluded that little cyclicality occurs at 2-year institutions, and weak cyclicality or almost none at 4-year institutions. Some studies further investigated the relationship based on student attendance status and claimed *procyclicality* in 2-year full-time enrollment and *countercyclicality* in 2-year part-time enrollment.

[16]One might be concerned that the policy adoption timing is dependent on local labor market conditions and changes in demand. However, a regression of the timing on lagged state unemployment rate (including time and institution fixed effects) yields an estimated coefficient close to and not statistically distinguishable from zero.

answered one, thus indicating that Michigan State University (MSU) requires freshmen to stay in dormitories, from 2004 to 2009, and changed the answer to zero since 2010 although MSU maintained the policy during the corresponding period.

Since it is impossible to detect any clear pattern of error being recorded, those 856 institutions were asked individually by phone and email whether they had freshmen dormitory residency requirement policies.[17] Table 2.B1 compares the number of institutions under the original variable from IPEDS with that of the revised one and the results are surprising: 242 institutions marked as having a dormitory residency policy in IPEDS responded that they never have had the policy, and after data collection the number of institutions that did have it during 2004-2011 changes from 203 to 724. For comparison, Carnegie Classification categorizes four-year institutions into highly residential, primarily residential, and primarily nonresidential. Fifty percent of institutions classified as residential have dormitory residency policies and around 70% of highly-residential classified institutions are found to have the policy.

The edited dormitory residency policy variable still does not reflect properly the supply constraints. Not all institutions having large residence halls or a high proportion of out-of-state students (or foreign students) compel freshmen to stay in on-campus housing. University of Michigan (UM), for example, does not have a dormitory residency policy, but provides dormitories for more than 10,000 students; currently, approximately 70% of UM freshmen reside in those. Other national schools such as Boston College, University of Wisconsin, and Cornell University are marked as not having the residency policies although in general they have a large share of out-of-state students many of whom reside in dormitories. Thus the constraint variable is revised considering dormitory capacity, ratio of FTFY enrollment to the capacity, and share of out-of-state freshmen.[18] Moreover, if an institution is reported to have had the policy for more than half the observed period, it is considered as a capacity constrained institution.[19] The capacity constraint variable captures

[17] As of September 15 2015, among 856 institutions, I collected dormitory policy information from 773 institutions. The revised list of colleges with the policy is available upon request.

[18] The capacity constraint variable is further restricted to have the ratio of freshmen to dormitory size smaller than one, dormitory size larger than 3500, and the ratio of out-of-state students greater than 0.45. If all of those conditions are satisfied, the constraint variable is set to one even though freshmen are not required to stay in on-campus housing.

[19] Other variables help identify supply constraints such as endowment size or faculty size. For example, during the

the different responses in changes of total enrollment share in Figure 2.A1; 80% of 4-year private elite- and 62% of 4-year public elite- institutions are categorized as capacity constrained.

Next, an additional constraint measure is generated retrospectively to 1986. Note that IPEDS started to question on-campus residency policy from 2004, thus a risk exists of misclassifying constrained institutions by extending back to 1986. However, data indicates the risk is relatively low. Between 2004 and 2014, only 92 of the 1,059 institutions adopted the residency policy, which implies that institutions with the policy are more likely to have maintained their policy. In fact, among 610 institutions reported as having the policy, more than 510 have had it since at least prior to 2004, and around 200 colleges responded they have had it for at least 20 years. An institution is defined as capacity-constrained in 1986 if it was marked as constrained either in 2004 or in 2004-2011. Finally, if a college is reported to experience a dramatic increase and decrease in enrollment, it is dropped.[20]

2.3.2.3 Student Achievement

Student quality is important since colleges both want and need to enroll students to be able to take advantage of the kinds of curricula, advising, and other program offered, and student quality affects future enrollment. Many studies measures to capture the school quality such as the number of (higher) degree awarded, the value of research grant, percent of faculty with PhD degree, and Barron's measure which are considered as long-term quality measures that colleges try to maintain. Instead, the quality of freshmen, measured by the achievement score, is used to capture the changes in student quality in the short-term. As in Epple and Romano (1998, 2008), to maintain the simplicity and highlight the role of peer groups, the student quality is determined exclusively by the mean ability of its peer group. If the achievement of freshmen, and that of enrolled students

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Great Recession when stock markets declined significantly, institutions that invested in risk assets lost large proportions of their endowment and might have become more supply constrained. Endowment earnings, however, stopped being reported to IPEDS in 1997 for Financial Accounting Standards Board (FASB) reporting institutions and in 2002 for Governmental Accounting Standards Board (GASB) reporting institutions.

[20] There are 12 schools whose maximum enrollment size is more than five time as large as the minimum enrollment size. Some schools were reported to have increase in freshmen enrollment more than 80 times 2004 - 2011. Examples are South University-Savannah 97 x, Ashford University 362 x, and University of Phoenix (online) 100 x.

are positively correlated via peer-effect, then choosing talented freshmen would mean an increase in overall quality. Hereafter the student quality in the short-run refers to the freshmen achievement score.

Student achievement is measured by Scholastic Aptitude Test (SAT) and American College Testing (ACT) scores, primarily considered to be predictors of students' performance, in reading (English and composition for ACT), math, and writing because scores can be compared both across colleges and over time.[21] Test scores are reported at percentiles 25 and 75, from 2001. One drawback of this achievement measure is that SAT/ACT scores are available for 75% of 4-year public-, 55% of 4-year not-for-profit private-, and more than 98% of national- or Top 120 public-, or Top 65 private- colleges, but mostly are unavailable for 4-year for-profit- and 2-year institutions.

2.3.2.4 Finance and Faculty

Finance variables, including average tuition and fees by student's residence, and net price, which is the so-called *sticker price* and fees less average financial aid from federal, state, and institution, are calculated by myself. Appropriation variables are accessible by local-, state-, and federal level, and other variables such as revenue, unrestricted revenue, and net tuition revenue, which is the difference between tuition and institutional grant and aid, are calculated by Delta Cost Project.[22] All price variables are adjusted to 2010 price level per the consumer price index.

Faculty variables include information of the number of current full-time/part-time faculty and the number of newly-hired faculty. For new-faculty variables, detailed information is accessible whether they are tenured or tenure-track, and data are available from 2001.

[21] Smith and Stange (2015), for example, used the average PSAT score of enrolled students in each institution to measure the institutional quality. However, in IPEDS, only SAT/ACT scores of freshmen are available.

[22] Delta Cost Project provides a longitudinal database derived from IPEDS finance, enrollment, staff, completions and student aid data for academic years 1986-87 through 2009-10; however, some variables in enrollment, institutional characteristics, and staff are not the same as in raw data files from IPEDS Data Center. For those mismatched variables, raw data files are preferred.

2.3.2.5 Unemployment Rate

Variables to measure the labor market condition are unemployment rate from the Bureau of Labor Statistics.[23] When it comes to the measure of unemployment rate, it seems natural for researchers to choose the unemployment rate of the state in which the institution is located, but it might be local labor market conditions in other states that affect an applicant's decision on enrollment. For example, from an institution's perspective, if outside funding such as state appropriation is fluctuating along with the labor market condition within a state, or if in-state students comprise the majority of enrollment, it is appropriate to use the unemployment rate of the state in which the college is located. On the other hand, from a college applicant's stance, the local labor market condition of where the applicant normally resides has more impact on the enrollment decision; this, in turn, changes the demand for higher education. For instance, high school students from Michigan would consider more about the local economy in Michigan than that in California if they are making college-going decisions.

This issue is dealt with by constructing an additional measure of the college-specific unemployment rate applicants face. This is average state unemployment rate among accepted students, weighted by their enrollment size by state. If a college is at national level, the weighted unemployment reflects various applicants' local economy conditions. For example, during the economic downturn in Michigan due to the decline of the automobile industry, the demand for UM, where more than 50% of students are from other states, was less likely to be affected by the local labor market condition than would be the demand for Eastern Michigan University, and is more likely to be affected by market conditions in other states.

Freshmen enrollment by state data are available from 1986 for almost every other year, but data submission was mandatory only in 2004, 2006, 2008, and 2010, where around 85% of institutions reported the enrollment by state, whereas the response rate varies from 35 to 65% when reporting

[23] Other measures include mass layoff statistics and average weekly earnings. Mass layoff numbers are from establishments with at least 50 initial claims for unemployment insurance (UI) filed against them during a 5-week period, however, over the past decade, only about one-third of the total unemployed, on average, received regular UI benefits. Moreover, there are variations in terms of UI across states and comparability issues with unemployment rate. See http://www.bls.gov/cps/cps_htgm.htm#laus for details.

was not mandatory. Accordingly, weighted measures cover a different number of institutions year by year and the sample size is smaller in estimation when weighted measures are used. So for each school, average weight by state is calculated with mandatory reporting years, and fixed weight is used to generate the institution-specific unemployment rate, which covers around 90% of 4-year public colleges and 65% of 4-year private colleges. When average fixed weight is calculated between 1986 and 2011, coverage increases to 92% for 4-year public and 73% of 4-year private institutions.

Table 2.B2 provides descriptive statistics by institution types, between 2004 and 2011 and is stratified by whether an institution is capacity-constrained, and by control. Statistics indicate institutions with constraints are mostly 4-year colleges and that FTFY enrollment size is about 40%-80% larger for constrained colleges. Moreover, those institutions have a 15-35% higher proportion of out-of-state students than do institutions without capacity constraints. Student achievement as measured by SAT and ACT scores, for capacity constrained institutions is 6-10% higher but the cost of attendance for constrained institutions as measured by *sticker price* is about 8% more expensive for public 4-year colleges and 40% more for private 4-year colleges. Another notable difference is the dependency on non-tuition revenue including various appropriations for capacity constrained public institutions.

Last, dormitory residency policy institutions account for 60% of land grant institutions and 70% of flagship institutions.

2.4 Responses to labor market shock in the higher education market

Given that this study's goal is to explore how institutions optimized their resources in response to the shock in the labor market along with the business cycle, and how constraints in the supply-side affected enrollment decisions, the analysis starts with periods from years prior to the onset of the recent recession, to years past the end of the recession, from 2004 to 2011. It mainly highlights the circumstances of 4-year public and private institutions, since the FTFY enrollment for 2-year public and private institutions with capacity constraints hardly exist, as described in Table 2.B2.[24]

A simple statistical model for describing cyclicality in higher education is

$$\ln n_{it} = \alpha_1 + \alpha_2 U_t + \varepsilon_{it} \tag{1.1}$$

where n_{it} is enrollment at institution i in year t, U_t is unemployment rate, and ε_{it} is a random error term. If the unemployment rate properly represents the labor market condition or cyclical variation, then $\alpha_2 \gtreqless 0$ as enrollment is countercyclical, noncyclical, or procyclical.

Equation (1.1) generally is estimated with OLS including time- and institution-fixed- effects; however, this approach has limitations in at least two aspects. First, the model is imprecisely specified in that it treated capacity constrained and non-capacity constrained institutions in the same manner. Second, if a researcher uses national unemployment rate, which is same across all institutions, with time-fixed effect, then one of year dummy automatically will be removed due to perfect multicollinearity. Thus, in practice, researchers use state variation to analyze cyclicality.

Figure **??** shows that the demand for higher education, measured by the number of applications, increased during the recession period across all types.[25] It indicates that there is cyclicality

[24] Within 4-year private institutions, there are for-profit- and not-for-profit- institutions. Not-for-profit institutions account for around 80% of non-capacity constrained and over 99% of capacity constrained institutions. In other words, less than 1% of 4-year private for-profit institutions is capacity constrained. Hereafter I mainly present results for not-for-profit for 4-year private institutions.

[25] Regression of the number of applications on unemployment rate and tuition fees yields a statistically significant positive coefficients on unemployment rate for all types of institutions implying that demand is countercyclical.

in demand,[26] which implies that the effect of the decrease in the opportunity costs of education outweighs that of the increase in liquidity constraints. During recessions, the demand for higher education is rising across all types of institutions; however, how it is served to supply, and the extent to which institutions are responding, would vary across types of institutions.

The empirical analysis begins with exploring the relationship labor market shock and institution revenue.

2.4.1 Budget

The most important sources of total revenue are from unrestricted revenues, which is the sum of tuition from students and appropriation largely from state and federal governments. Table 2.B2 indicates that the share of non-tuition revenue including appropriations is different across institution types. Lowry (2001) reported that the median share of all unrestricted revenues from these sources was 78% in 1994–95. Figure 2.C2 displays similar Full-Time Equivalent (FTE) appropriation and nontuition revenue patterns across all types of institutions and differences are only in terms of the level; public institutions are more dependent on nontuition revenues. Figures 2.C2 further indicate that the decline in appropriation and non-tuition share happened to every institution during the Great Recession, which implies that those institutions could try to increase tuition to recover some of the lost revenues.

Figure 2.C3 shows that all four-year institutions have the same increase-trend in tuition but that the rise in out-of-state tuition is relatively sharper for capacity constrained institutions during 2004-2010: 17% for both public and private colleges. For non-capacity constrained institutions, the increment is smaller: 17% for public institutions, 10% for private. While *sticker price* or posted tuition and fee has been increased, net price, i.e., the difference between *sticker price* and federal-, state-, and institution- financial aid, has remained relatively stable. Thus some institutions facing cuts in state/federal appropriation while simultaneously providing financial aid to students, have

[26] Yield rate in Figure 2.C1 is moderately decreasing over years, which might be due to the increase in competition with other institutions and to decrease in application fees, and is consistent with the assumption in the model that an institution can accurately predict the yield rate.

another option to make up the fall in appropriations: enroll additional students.

2.4.2 Enrollment

For institutions, one of the natural responses to recessions is to increase enrollment by either the need or the desire to increase tuition revenue as argued by Duffy and Goldberg (1998).[27] With larger enrollment, institutions can increase revenue; however, not all institutions are capable of serving more students; some schools requiring to provide housing to freshmen have to deal with the capacity constraints in the short-run. Table 2.B3 summarizes the empirical analysis of estimation of the elasticity of FTFY enrollment, defined as the natural log of FTFY enrollment, with respect to the unemployment rate, defined as the state unemployment rate. State unemployment rate in the same calendar year is used, since marginal students affected by labor-market conditions are less likely to apply to college early in the previous year. Panel A summarizes estimation results generally used in previous studies on cyclicality in higher education. Previous results did not consider any constraints in the supply side and estimates in the first row are consistent with previous studies: countercyclicality in 2-year institutions and weak cyclicality or almost none in 4-year institutions. By comparing Panels B and C, however, it is obvious that supply constraints plays a significant role in enrollment adjustment with respect to changes in the labor market; capacity constrained institutions experienced a smaller increase in enrollment size, although statistically insignificant, which is consistent with the model's prediction on supply constrained institutions.

Of interest is that positive coefficients for capacity constrained institutions, albeit statistically insignificant. If some of them increased enrollment size during recession, it might be that these colleges were not at capacity limit before recession and reached capacity limit with a small expansion. Or it might be they faced rather soft-constraints in the sense that institutions can accommodate more than on-campus housing limits as they can provide housing off-campus, which is

[27] It is assumed that tuition, p, and per-student resource, I, were chosen by the board before selecting the number of students, and institutions take those values as given. Some may argue that given non-tuition revenue received, I would decrease when enrollment increases thus decreases education quality. If I changes as student numbers change, institutions need to decide on at least three dimensions (quantity, quality, expenditure), which further complicates the analysis.

generally costlier than on-campus housing.[28] Certain institutions, where more freshmen arrived than on-campus housing capacity could accommodate, might have reserved extra space with off-campus facilities with whom they have contractual agreements. More discussion on the size of supply constraints and enrollment are provided in Section 4.5. Overall, results are consistent with the conjecture that non-capacity constrained institutions experienced larger increases in enrollment than did constrained institutions.

Table 2.D1 presents OLS estimation results focusing on 4-year institutions with different local unemployment measures between 2004 and 2011 since there are only 22 public 2-year colleges and five private 2-year institutions with capacity constraints. 4-year private for-profit institutions are excluded because only 25 schools are capacity constrained.[29] Panel A is estimated with state unemployment rate weighted in all reporting years and results are similar to those in Table 2.B3 in the sense that non-capacity constrained colleges have larger positive response in enrollment when local labor market conditions worsen, albeit insignificant.[30] Panel B is generated by excluding institutions with open admission policies that accept any FTFY students who apply and meet minimum requirements. The number of open 4-year private admission policy institutions increases from 114 in 1999 to 330 in 2011 and 7% of 4-year institutions with the policy are capacity constrained.[31] Since the majority of institutions with open admission policies are 4-year private for-profit institutions without the constraint, the difference of coefficients between Panels A and B is close to zero except for that for all 4-year. Since the freshmen enrollment size of for-profit institutions is 1/6 of public institutions and that of not-for-profit private is 1/4 of public institutions, equation (1.1) is estimated with weights on freshmen enrollment. Results in Panels C and D show that coefficients diminish across all types of institutions, and that institutions without open admission policies have

[28]Institutions can change the mixture of grade level in housing facilities and increase freshmen composition while providing less space for 2nd, 3rd, and/or 4th year students. This statement, however, is not testable due to data unavailability in IPEDS.

[29]Non-capacity constrained for-profit institutions have five times larger coefficient while the sample size is one third of not-for-profit institutions.

[30]When estimated from 2004 for only mandatory years for reporting enrollment by state or from 1986 for all years, similar patterns show: capacity constrained institutions experienced decrease or smaller increase in enrollment.

[31]4-year institutions with open admission policies have up to 0.6 times larger response to cyclical variation than do those without the policy; however, the difference is not statistically significant.

smaller response.[32]

Another way to recover the decline in appropriation is by increasing the number of out-of-state students. Figure 2.C4 plots enrollment by residency in 4-year institutions, and shows that the largest share of enrollment is from in-state students for public colleges whereas private colleges have the opposite composition. Public institutions with capacity constraints have a larger share of out-of-state enrollment FTFY students (47%) than do those without the constraint (41%), but have not steadily increased the share of out-of-state enrollment during recession. With lower appropriation, institutions could recover the loss by enrolling more of out-of-state students and capacity constrained institutions might have stronger incentive to change the mix of students; however, that mix remained stable during the recession. A possible reason could be that the increase in demand is mostly from in-state students who might choose in-state institutions as the marginal cost of attendance greater. That aspect is left for future research.

2.4.3 Student Achievement

With the countercyclicality of demand in higher education, numbers of applications increase during recessions. However, given that in the short-run capacity is fixed, institutions can choose an alternative dimension in enrollment: raise admission standards, which will increase new-student achievement. If we believe that the proportional increase in demand is lower for more-talented students and that they are more prone to have higher education and are less affected by local labor-market conditions, then most of the increase in demand might come from students of average- or low achievement.

In IPEDS, around 86% of schools that reported SAT scores also reported ACT scores at the same time. That is, if both measures are used to estimate changes in student achievement along with the business cycle, sample size increases by approximately 10-15% compared to when SAT measures alone are used. And analyzing different measures might improve our understanding of student achievement dimension. But ACT scores are widely reported to IPEDS since 2004,

[32] Alternatively one can use revised on-campus housing policy variable as an instrument for original policy variable in IPEDS but it gives similar estimates.

from approximately 700 institutions in 2001 to approximately 1000 in 2004, which renders SAT measures more favorable for analysis when the time horizon extends back to 2001. Another feature related to test scores is that the number of institutions reporting SAT scores varies up to 30% annually. To control for the composition of institutions in the analysis, the balanced sample is constructed to have both enrollment and test scores, which leaves 1042 institutions with SAT scores 2004-2011 and 772 institutions 2001-2011. When ACT scores are analyzed, the balanced sample size decreases from 955 to 443.[33]

Figure 2.A3 represents different changes in student achievement pattern across institution types, where student achievement is measured by average SAT scores of freshmen. For non-capacity constrained institutions, the student achievement level of high-ability (SAT 75th percentile) or that of low-ability students (SAT 25th percentile) is similar between public and private colleges. Changes in student achievement for those institutions occurred as expected in the model, and the overall achievement of new students has decreased during the recession; the pattern is most explicit for low-achievement students (SAT 25) in private 4-year institutions. Capacity constrained private institutions have higher SAT score on average, which supports the claim they are more selective, and exhibits the opposite pattern for changes in student achievement: a trend of increased achievement of students during the economic downturn. Figure 2.C5 displays changes in student achievement measured by ACT scores, patterns being similar to those with SAT scores. Note that the composition of institutions differ depending on the student achievement measure. On average, SAT and ACT scores are higher for private colleges except for SAT scores at public institutions in the second tier categorized by *US News and World Report*, which indicates that student achievement measured by ACT scores has more weight on low-tier public colleges.

Among various test-score measures, SAT Math percentile 25 and ACT Math percentile 25 scores are analyzed since i) the score was reported by most of the institutions, and ii) generally it is in the lower tail of student achievement distribution that marginal changes occur. Table 2.B4 sum-

[33]Only 2% of 4-year for-profit have either SAT or ACT (math) whereas 54% of not-for-profit have test scores. And only one institution with open admission policy reports test score. Thus if student achievement changes in response to unemployment, most variation comes from not-for-profit.

marizes results of the effect of local labor-market measures on the achievement of new students measured by SAT Math percentile 25 and ACT English percentile 25, focusing on the balanced panel of 4-year institutions that have both enrollment and test scores 2004-2011. Results with various unemployment measures indicate that capacity constrained institutions experienced an increase in student achievement, albeit statistically insignificant, whereas student achievement declined in most non-capacity constrained institutions. Table 2.D2 shows results when the time span is extended to 2001, where the number of institutions in balanced panel data decreased by 30-55%. The pattern of observing increase in student achievement for capacity constrained institutions is similar to that in the 2004-2011 sample. [34][35]

Changes in student achievement during the recession are determined not only by supply constraints, but also by institutional prestige. For example, some students at the margin, who are affected by cyclical variation in the labor market, might receive more rejections in recession due to stricter admission standards and now would need to choose a less-talented school. In lower-tier institutions, the effect on student achievement is ambiguous. There are some students who were not accepted from could-have-been accepted colleges with higher tier, some good students who would not have gone to colleges if market opportunity had been better, and others who are at the margin with relatively lower student achievement. Since public universities often seem less selective than private counterparts, freshman heterogeneity applies neither to selective colleges nor to private colleges, but mostly to public colleges. More discussion on the relationship between institutional prestige and changes in enrollment size and student achievement is offered in 4.6 below.

2.4.4 Faculty

In response to the transitory increase in demand, once institutions decide to expand enrollment, they need to hire extra faculty to provide a similar quality of education to new students, at least in

[34]Of interest is an increase in ACT scores even for non-capacity constrained institutions, although statistically not distinguishable from zero; however, by restricting to a balanced panel 2001-2011, the composition changed. In fact, the composition of institutions with ACT scores changed toward having fewer good *public* institutions and more good *private* institutions.

[35]For balanced panel, the analysis of log enrollment on weighted state unemployment provides similar pattern that non-capacity constrained institutions have larger increase.

terms of student-faculty ratio. Since hiring new tenured faculty can be considered as a long-term investment, institutions might adjust by hiring faculty with lower cost such as non-tenure-track, fixed-term faculty, adjunct faculty, or part-time faculty,[36] implying that those faculty are at the margin of employment.

Figure A.6(a) shows that institutions hired different types of faculty and how they responded to cyclical shocks. During the recession, 4-year institutions without the constraint, which experienced an increase in their enrollments, increased faculty size mostly in part-time positions. Moreover, in Figure A.6(b), these institutions hired less of new non-tenured faculty, implying that in short-term those institutions adjusted by hiring faculty with lower or zero fixed cost.[37] Table 2.B5 summarizes OLS estimation results of log faculty size on state unemployment rate and confirms that most types of institutions hired more part-time faculty and fewer higher-cost faculty, for example tenured or not tenured new faculty, both for in tenure track not in tenure track.

2.4.5 Size of Supply Constraints

Concern might arise that the enrollment adjustment in capacity constrained institutions with larger capacity would differ from those with smaller capacity. Institutions with smaller capacity can more easily increase enrollment, as the cost is relatively lower. Contrarily, institutions with larger capacity can increase enrollment if on-campus housing is under-utilized, or by additional contractual arrangements with off-campus housing that might be costlier.[38] Capacity constrained institutions are grouped by dormitory capacity size. Dormitory capacity of 700, 1400, 2600, and 6500 represents 25%, 50%, 75%, and 99% of observation, respectively. Figure 2.C7 displays enrollment and student achievement trends across different capacity and the responses in FTFY enrollment differ across dormitory capacity sizes. Many small-size institutions increased enrollment and ex-

[36]For long-run growth, quality/cost is higher with tenured faculty and institutions will be able to spread the investment cost over a longer period. Then it would be reasonable to hire them.

[37]In comparison with 2-year institutions, 4-year institutions hire more full-time than part-time faculty whereas public 2-year institutions hire more part-time faculty. Public 2-year institutions especially hired more non-tenure faculty not on tenure track, and not many full-time, who can be relatively readily employed temporarily at lower wages.

[38]Marginal cost for increasing capacity institutions might be U-shaped which implies that marginal cost decreases at first and then increases, especially when there are economies of scale.

perienced a drop in student achievement, whereas middle dormitory-size (2600∼6500) institutions relatively decreased enrollment and raised admission standards by limiting acceptance to students whose achievement seemed better.

Table 2.B6 summarizes OLS estimation results of different unemployment measures on enrollment size and student achievement of FTFY enrollment 2004-2011 among 4-year institutions that have both enrollment and SAT Math score, and indicates that the enrollment adjustment occurred at a different rate among institutions with dormitories. On average, institutions with dormitory size less than 1400 expanded class size during the economic downturn, although statistically not different from zero, and experienced a drop in student achievement. On the other hand, colleges with greater dormitory size between 2600 and 6500 decreased enrollment and relatively increased the achievement of freshmen measured by SAT Math percentile 25, albeit statistically insignificant. Results imply that small-capacity colleges have relatively lower cost of accepting additional students, and soft capacity constraints. On the other hand, institutions with large size of dormitories increased a smaller size of enrollment, implying that the constraints are binding relatively harder.

2.4.6 Prestige

At schools at national level, local conditions would less affect decisions on enrollment than at lower-tier schools, because many high-achievement students are from other states and their willingness for going to college is generally less influenced by labor-market conditions. Table 2.B7 presents different quantity and student achievement adjustment by prestige status 2004-2011. Prestige status is assembled from *US News and World Report* in 2005 and in 2013, grouped into Top 200 National, Top 120 Public, Top 65 Private, and Top 180 Liberal Arts institutions.

Results in Panel A show that majority of prestigious schools reacted to recession by decreasing enrollment, albeit statistically insignificant, while less-prestigious schools increased enrollment. Changes in student achievement by prestige type are described in Panels B. Coefficients on unemployment are negative for less-prestigious colleges, which implies that the overall achievement of new students has declined at those schools. On the other hand, elite institutions have positive coefficients indicating that the achievement of incoming students increased during recession, albeit statistically insignificantly, implying that elite schools became more prestigious. Panels C and D present results with weighted state unemployment rate, which provide a similar pattern except for SAT Math for national top private institutions; coefficients turned negative but are not statistically distinguishable from zero.

Table 2.D3 summarizes changes in quantity of enrollment and student achievement when both prestige status and capacity constraints are taken into account. Among non-capacity constrained institutions in Panels A and C, heterogeneity exists with respect to prestige status; less prestigious colleges experienced more increase in quantity and relatively more drop in student achievement. Overall, capacity constrained institutions in Panels B and F, reacted to recession by smaller increase or more decrease in quantity, and by less drop decrease or more increase in student achievement. And the effect of capacity constraints on enrollment is consistent among prestigious colleges; capacity constrained prestigious schools tend to have the largest decrease in quantity and the largest increase in frehmen achievement, although coefficients are statistically not different from zero.

2.4.7 Other Measures

Table 2.B8 presents OLS estimation results of various measures on weighted local labor market conditions. Panel A indicates that, during recession, full-time enrollment composition for white students increases across all types of institutions except for constrained public institutions, albeit insignificantly, which implies diversity among freshmen decreased. Specifically the increase in the share of white students was the largest among non-capacity constrained for-profit institutions.[39] The changes in share of federal grants beneficiaries during recession are summarized in Panel B. Results show that all types of institutions increased the share of freshmen receiving federal grants, and that non-capacity constrained institutions have greater increase in the share. Results from Panels A and B imply that the share of lower income white students increased in recession. Finally

[39] Excluding open-admission-policy schools provides similar results. When grouped by national, national-not-ranked, and not-national, the lowest tier (not-national) has the largest increase in whites share. Constrained schools tend to have smaller increase in whites share and only national institutions decreased whites share during recession.

Panel C presents results when analysis is extended back to 1986, and results are similar to those in Table 2.D1.

2.5 Conclusion

With worsening economic conditions, institutions experienced simultaneously a decline in outside financial resources and an increase in demand. Institutions maximizing the combination of student quality and profits, devised another means to compensate for lost revenue: accepting more students. By far, a majority of studies implicitly assumed that institutions are capable of enrolling more students, especially during recessions, but only acknowledged possible constraints on the supply-side, and not much attention was paid to changes in student quality.

This study presents how an institution chooses enrollment quantity and its effect on student achievement, and introduces a simple framework for institutions, from which implications are derived on the relationship between enrollment and student achievement when changes occur in labor-market conditions. Those implications are tested by using dormitory residency requirement policy variables from IPEDS, collected and further modified to represent the supply capacity constraints. Results show considerable heterogeneous responses by type of institutions in enrollment, changes in student quality, and adjustment in resources, when the constraints are taken into account.

Institutions without the capacity constraint tend to have increased enrollment compared to those with the constraints.[40] As a result, institutions with the constraints accepted new freshmen with higher achievement, whereas institutions without constraint faced decrease in student achievement and adjusted resources by hiring new faculty at lower cost such as non-tenured or not on tenure-track. Among capacity constrained colleges, responses to recessions differ, based on capacity size and prestige.

An empirical result that freshmen achievement is dependent on the business cycle has an interesting implication for studies on the effect of graduating in recessions. Recent studies showed initial adverse labor-market conditions have persistent effect on labor earnings, which recovers over time (Beaudry and DiNardo, 1991; Hershbein, 2012; Oreopoulos et al., 2012). Comparing

[40]Note that the changes in enrollment is not enriely driven by the capacity constraints as there are changes in demand of higher education during recession as well.

wages by cohorts across different labor market conditions implicitly assumes that students graduating across business cycles are homogeneous. If labor market conditions affect not only earnings after job-market entry, but also quality of human capital produced at higher education, recession's effect on long-term labor market outcomes might be underestimated. Similarly, return to education over time might be different for those graduating in expansion or in contraction.

An inference from the results is that if prestigious institutions face cuts in outside funding, institutions with supply capacity constraints might be much more selective and increase the achievement of new students. If that is the case, the achievement gap will widen between prestigious- and middle-ranked institutions. Another interesting topic would be an exploration of how the match between college prestige and applicant quality was altered when taking supply constraints into account.

Some recent studies have pointed out the expansion of non-residential programs and an increase in the entry of for-profit institutions. However, many for-profit institutions are not required to provide on-campus housing to freshmen, and receive negligible appropriations.[41] Thus those for-profit institutions are virtually not capacity constrained on the supply-side and more promptly can expand enrollment to meet increase in demand.

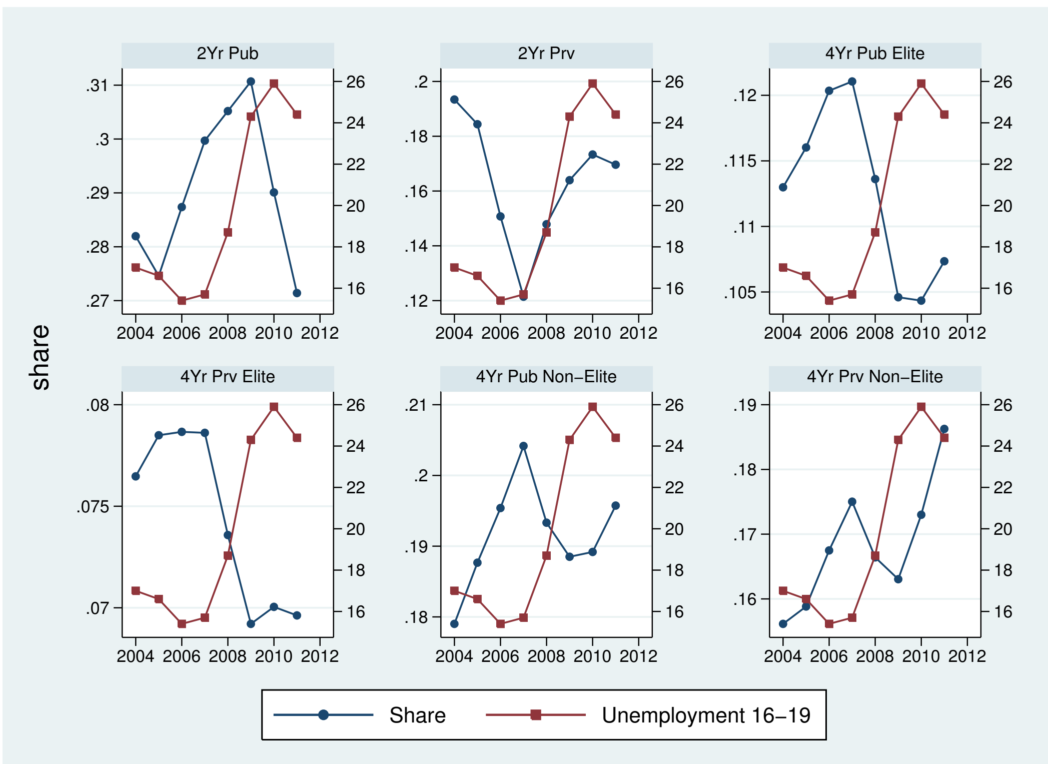
[41]Less than 0.01% of all for-profit institutions have on-campus residency requirement policies and they received on average US$285 of appropriation during 2004-2011.

APPENDICES

APPENDIX A

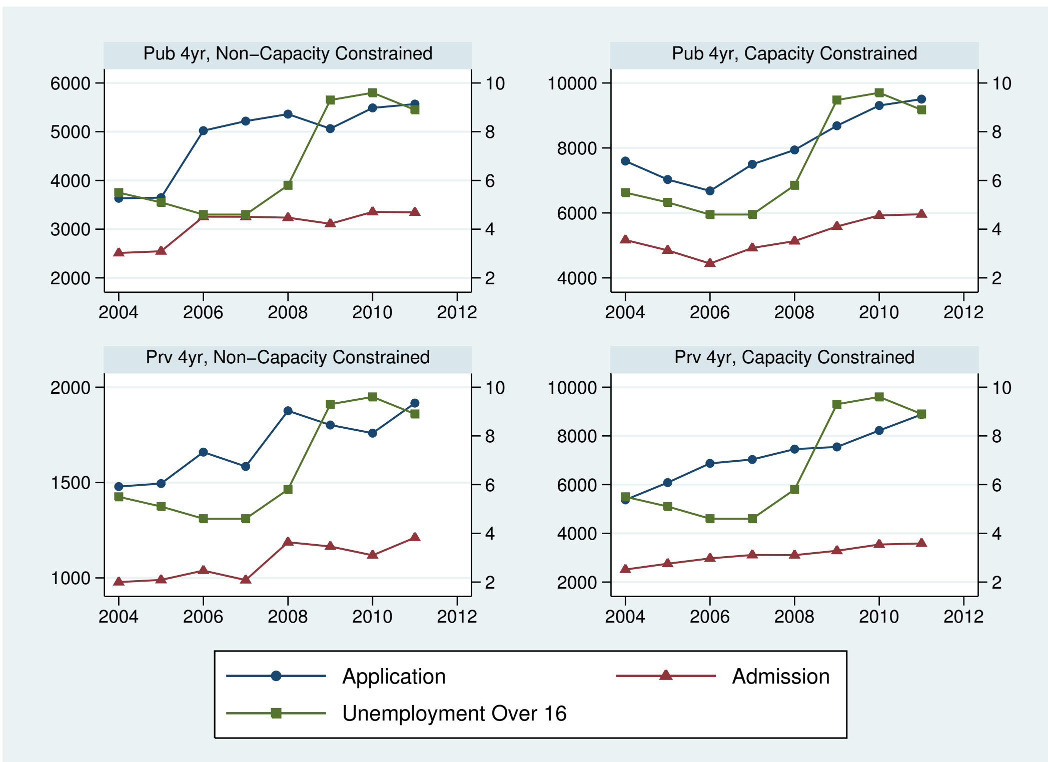
FIGURES FOR CHAPTER 2

Figure 2.A1 Changes in Share of Total Enrollment



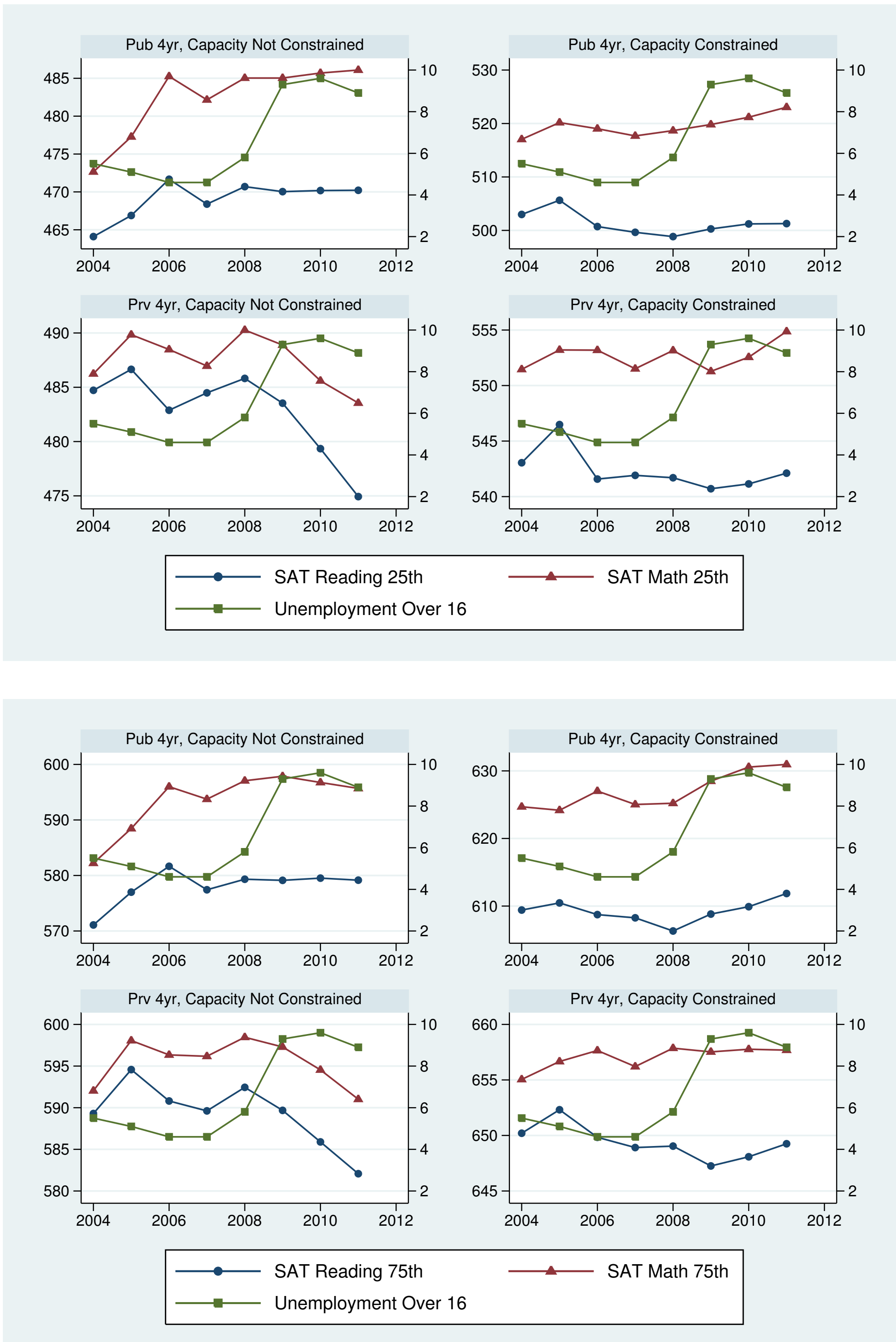
Notes: Left Y-axis represents share and right Y-axis represents unemployment rate..

Figure 2.A2 Application, Admission, and Enrollment]



Notes: Data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents application and admission, and right Y-axis represents unemployment rate.

Figure 2.A3 Student Achievement of FTFY by Institution Types



Notes: SAT data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents SAT score and right Y-axis represents unemployment rate.

APPENDIX B

TABLES FOR CHAPTER 2

Table 2.B1 Number of Observations with Dormitory Policy

		Revised Dormitory Variable									
		0	1	2	3	4	5	6	7	8	Total
	0	7,761	0	0	0	0	0	0	0	0	7,761
	1	107	2	5	4	1	0	1	1	52	173
	2	38	0	2	3	2	2	1	1	55	104
	3	21	1	2	1	4	3	5	0	68	105
Original	4	18	2	0	0	0	2	2	3	60	87
	5	21	1	2	0	1	5	3	2	80	115
	6	16	1	2	0	3	3	5	3	88	121
	7	21	0	1	4	1	1	2	3	118	151
	8	0	0	0	0	0	0	0	0	203	203
	Total	8,003	7	14	12	12	16	19	13	724	8,820

Notes: Each number indicates the number of institution with original and revised dormitory policy for corresponding years. *Original* refers to ALLOCAM variable in IPEDS and *Revised* refers to new dormitory policy variable after collecting information from each individual institution.

Table 2.B2 Descriptive Statistics (2004-2011)

		Capacity Constrained				Non-Capacity Constrained			
		Public		Private		Public		Private	
		4-year	2-year	4-year	2-year	4-year	2-year	4-year	2-year
Enrollment	FTFY Enrollment	1,975	364	542	234	1,365	810	304	235
	FTFY FTE	1,960	333	539	231	1,311	671	288	228
	Undergrad FTE	9,657	1,145	2,337	479	7,459	3,804	1,525	612
	In-State	53%	53%	34%	38%	59%	63%	51%	60%
	Out-of-State	47%	47%	66%	62%	41%	37%	49%	40%
	Application	5,093	82	3,212	657	2,280	47	898	73
	Admission	3,220	45	1,555	416	1,464	35	564	53
Dormitory	Capacity	3,766	456	1,512	480	1,825	320	746	235
Student Achievement	SAT Verbal 25%	480	437	502	389	447	404	460	405
	SAT Verbal 75%	589	563	615	499	554	514	570	524
	SAT Math 25%	494	449	505	393	456	397	460	401
	SAT Math 75%	601	591	616	506	566	509	571	511
	ACT English 75%	19	16	20	13	18	15	19	15
	ACT English 25%	25	23	27	19	24	21	25	22
	ACT Math 75%	19	17	20	15	18	16	18	15
	ACT Math 75%	25	24	26	19	24	20	24	21
Tuition	In-District	6,441	3,222	24,923	20,535	5,988	2,468	18,183	13,874
	In-State	6,442	3,377	24,923	20,535	5,996	2,949	18,184	13,874
	Out-of-State	15,358	7,330	24,923	20,570	14,288	6,416	18,185	13,875
Revenue	Total	310	17	143	11	240	44	40	9
	Unrestricted	239	15	141	13	186	38	44	9
	Net Tuition	93	4	56	7	72	11	31	9
Appropriation	Local	6	8	0	0	40	16	0	0
	State	104	7	8	0	90	16	1	0
	Federal	70	4	17	0	7	3	4	1
Faculty	Total	832	106	317	37	639	296	162	25
	New Tenured	6	2	5	1	4	4	4	9
	New Not Tenured	27	4	14	2	17	6	5	4
	New Not on Track	21	3	9	3	14	6	6	2
	Part-time / RA	885	1	343	0	472	16	47	5
Obs		242	22	545	5	381	1,063	890	851

Notes: Revenue and appropriation variables are measured in US$1-M.

Table 2.B3 Regression of Log Enrollment on Local Unemployment Rate

	All Institutions	4-year Institutions		2-year Institutions				
		All	Public	Private	Private Not for Profit	All	Public	Private
				Panel A: All Institutions				
Unemp	0.021***	0.015***	0.015***	0.016**	0.014**	0.022***	0.038***	0.018
	(0.005)	(0.006)	(0.005)	(0.008)	(0.006)	(0.009)	(0.008)	(0.016)
Obs	31,916	16,169	4,804	11,365	8,393	15,747	8,566	7,181
				Panel B: Non-Capacity Constrained Institutions				
Unemp	0.025***	0.022**	0.017**	0.025**	0.024*	0.023***	0.038***	0.019
	(0.006)	(0.009)	(0.007)	(0.013)	(0.013)	(0.009)	(0.008)	(0.016)
Obs	25,416	9,884	2,872	7,012	4,064	15,532	8,390	7,142
				Panel C: Capacity Constrained Institutions				
Unemp	0.003	0.004	0.006	0.005	0.005	0.016	0.005	-0.076
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.027)	(0.028)	(0.123)
Obs	6,500	6,285	1,932	4,353	4,329	215	176	39

Notes: Each specification includes a full set of fixed effects for individual institutions and years, between 2004 and 2011. All state unemployment rates are weighted by enrollment size by state. Robust standard errors clustered at the institution level are in parentheses.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.B4 Regression of Student Achievement on Local Unemployment Measures (4-year Institutions, 2004-2011)

	Non-Capacity Constrained			Capacity Constrained		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
	Panel A: State Unemployment Rate (SAT Math 25th)					
Unemp	-1.171*	-1.569**	-1.067	0.290	0.539	0.174
	(0.625)	(0.705)	(1.113)	(0.578)	(0.801)	(0.718)
Obs	3,653	1,661	1,960	4,375	1,259	3,110
	Panel B: Weighted State Unemployment Rate (SAT Math 25th)					
Unemp	-1.778**	-2.017**	-1.793	0.512	0.656	0.535
	(0.728)	(0.809)	(1.549)	(0.758)	(0.908)	(1.071)
Obs	3,487	1,620	1,838	4,184	1,240	2,939
	Panel C: State Unemployment Rate (ACT Math 25th)					
Unemp	-0.042	-0.010	-0.084	0.009	0.002	0.014
	(0.040)	(0.037)	(0.078)	(0.027)	(0.042)	(0.034)
Obs	2,387	1,128	1,243	3,497	1,200	2,284
	Panel D: Weighted State Unemployment Rate (ACT Math 25th)					
Unemp	-0.047	-0.010	-0.112	0.006	0.004	0.013
	(0.046)	(0.043)	(0.101)	(0.035)	(0.050)	(0.048)
Obs	2,292	1,103	1,175	3,342	1,177	2,154

Notes: Each specification includes a full set of fixed effects for individual institutions and years between 2004 and 2011. Robust standard errors clustered at the institution level are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.B5 Regression of Faculty on Weighted Local Unemployment Measures (4-year Institutions, 2004-2011)

	Non-Capacity Constrained			Capacity Constrained		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
			Panel A: Full Time Faculty			
Unemp	0.011	-0.002	0.008	0.003	0.007	0.001
	(0.007)	(0.004)	(0.009)	(0.003)	(0.004)	(0.004)
Obs	7,238	2,487	2,908	4,849	1,641	3,191
			Panel B: Part Time Faculty			
Unemp	0.016	0.043**	-0.013	0.012	0.063**	-0.011
	(0.015)	(0.022)	(0.024)	(0.014)	(0.031)	(0.015)
Obs	7,156	2,481	2,867	4,761	1,612	3,132
			Panel C: New Faculty (Tenured)			
Unemp	0.030	0.014	0.133	-0.076*	-0.062	-0.112
	(0.040)	(0.041)	(0.168)	(0.044)	(0.053)	(0.076)
Obs	1,019	815	200	1280	749	531
			Panel D: New Faculty (Not in Tenure Track)			
Unemp	-0.026	-0.059**	-0.006	-0.008	0.009	-0.022
	(0.018)	(0.024)	(0.028)	(0.019)	(0.034)	(0.022)
Obs	4,774	2,046	2,088	3,903	1,414	2,476
			Panel E: New Faculty (Not Tenured, Tenure Track)			
Unemp	-0.050**	-0.048*	-0.031	-0.001	-0.011	-0.008
	(0.022)	(0.026)	(0.036)	(0.021)	(0.036)	(0.025)
Obs	3,552	2,155	1,393	3,827	1,518	2,308

Notes: Each specification includes a full set of fixed effects for individual institutions and years between 2004 and 2011. Robust standard errors clustered at the institution level are in parentheses and faculty size is expressed in log value.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.B6 Changes in Enrollment and Student Achievement with Capacity Size (4-year Institution)

Size	Enrollment			Student Achievement		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
	Panel A: State Unemployment Rate					
Size 1	0.003	0.011	-0.002	-2.083*	-4.791**	-1.869
	(0.011)	(0.018)	(0.013)	(1.166)	(1.825)	(1.341)
Size 2	0.007	0.004	0.008	-0.227	-1.874	0.087
	(0.007)	(0.016)	(0.007)	(0.763)	(1.584)	(0.853)
Size 3	-0.005	-0.011	0.001	0.138	-0.738	0.631
	(0.008)	(0.017)	(0.007)	(0.662)	(0.820)	(0.944)
Size 4	-0.003	-0.003	-0.002	0.766	0.897	0.353
	(0.007)	(0.009)	(0.009)	(0.791)	(0.895)	(1.577)
Size 5	-0.016	-0.008	-0.058	-0.195	-0.175	-0.483
	(0.010)	(0.009)	(0.050)	(1.018)	(1.133)	(2.440)
	Panel B: Weighted State Unemployment Rate					
Size 1	0.003	0.019	-0.003	-2.532*	-6.457***	-1.723
	(0.013)	(0.019)	(0.015)	(1.362)	(2.083)	(1.638)
Size 2	0.010	0.008	0.010	-0.936	-2.223	-0.462
	(0.010)	(0.018)	(0.012)	(1.026)	(1.697)	(1.260)
Size 3	-0.004	-0.014	0.014	-0.18	-0.774	0.818
	(0.013)	(0.020)	(0.015)	(0.959)	(0.961)	(1.832)
Size 4	-0.002	-0.002	-0.005	1.655*	1.169	6.083***
	(0.010)	(0.011)	(0.015)	(0.978)	(1.016)	(2.294)
Size 5	-0.023*	-0.010	-0.265	-0.855	-0.852	-1.567
	(0.014)	(0.010)	(0.156)	(1.302)	(1.354)	(6.064)

Notes: Dormitory sizes are 1 (<700), 2 (<1400), 3(<2600), 4(<6500), and 5(>=6500).
Each specification includes a full set of fixed effects for individual institutions and years between 2004 and 2011. Log FTFY enrollment and SAT Math 25th percentile score are used for enrollment and student achievement measure. Robust standard errors are clustered at the institution level.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.B7 Changes in Enrollment and Student Achievement with Prestige (4-year Institution)

	Not Elite Institutions				Elite Institutions			
	Not National	Public Not Top120	Private Not Top65	Liberal Arts Not Top180	National	Public Top120	Private Top65	Liberal Arts Top180
Panel A: Changes in Enrollment								
Unemp	0.018***	0.023***	0.017**	0.03	-0.004	-0.007	-0.008	-0.003
	(0.006)	(0.006)	(0.008)	(0.021)	(0.005)	(0.005)	(0.007)	(0.006)
Obs	14,072	3,868	10,846	585	1,615	936	519	1,326
Panel B: Changes in Student Achievement (SAT Math 25th)								
Unemp	-0.369	-1.418**	-0.101	-0.790	0.005	0.388	0.420	1.599
	(0.534)	(0.672)	(0.654)	(2.878)	(0.626)	(0.759)	(1.177)	(1.066)
Obs	7,844	2,560	5,793	419	1,530	866	512	1,189
Panel C: Changes in Enrollment (Weighted State Unemployment)								
Unemp	0.025***	0.027***	0.025**	0.052	-0.006	-0.01	-0.01	-0.008
	(0.008)	(0.006)	(0.012)	(0.032)	(0.006)	(0.007)	(0.015)	(0.011)
Obs	13,238	3,749	10,103	550	1,580	924	506	1,248
Panel D: Changes in Student Achievement (SAT Math 25th, Weighted State Unemployment)								
Unemp	-0.88	-1.623**	-0.534	-1.536	-0.371	0.374	-1.189	1.303
	(0.663)	(0.713)	(0.945)	(3.806)	(0.833)	(0.884)	(2.195)	(1.803)
Obs	7,423	2,486	5,424	394	1,499	854	501	1,123

Notes: Each specification includes a full set of fixed effects for individual institutions and years between 2004 and 2011. FTFY enrollment and SAT Math 25th percentile score are used for enrollment and student achievement measure. Robust standard errors clustered at the institution level are in parentheses. Prestige variables is *assembled by US News and World Report* in 2005 and in 2013.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.B8 Regression of Various Measures on Weighted Local Unemployment Measures (4-year Institutions)

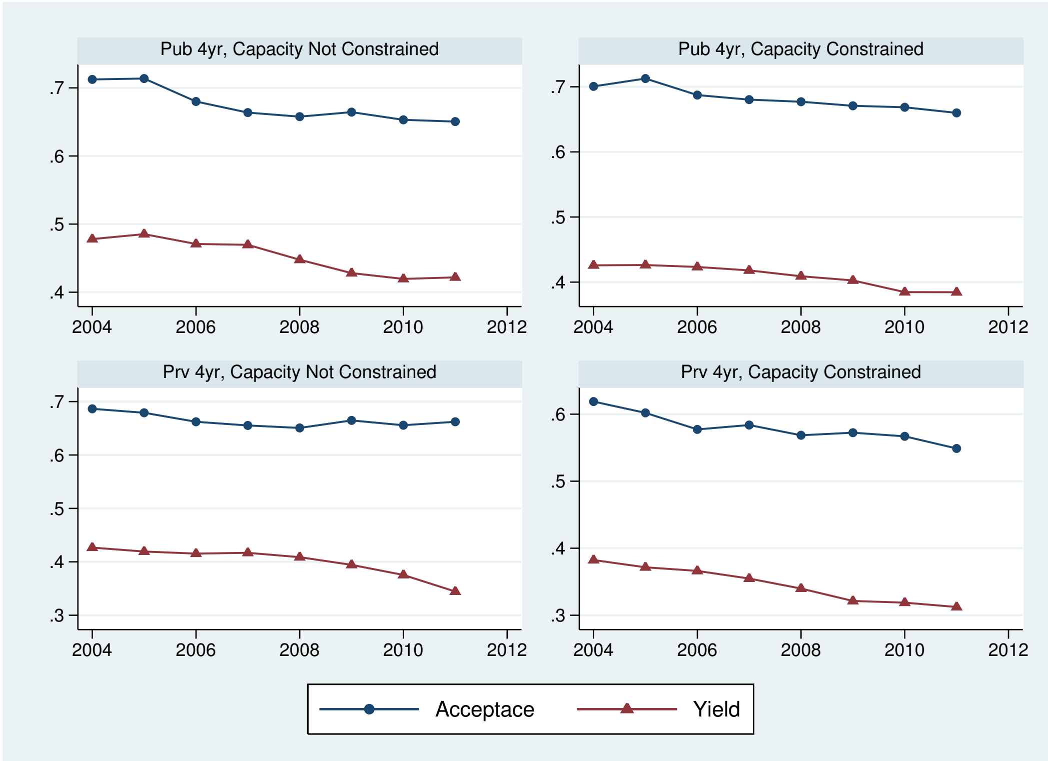
	Non-Capacity Constrained			Capacity Constrained		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
	Panel A: Changes in White Share					
Unemp	0.007**	0.006	0.004	0.006	-0.006	0.011
	(0.003)	(0.005)	(0.007)	(0.006)	(0.008)	(0.008)
Obs	9,289	2,774	3,788	5,990	1,899	4,070
	Panel B: Changes in Federal Grant Beneficiary Share					
Unemp	0.011*	0.010***	0.004	0.007***	0.007**	0.007
	(0.006)	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)
Obs	7,309	1,883	3,330	5,252	1,536	3,697
	Panel C: Changes in Enrollment Quantity (1986-2011)					
Unemp	0.015***	0.017**	0.007	0.005	0.014	-0.008
	(0.006)	(0.007)	(0.008)	(0.006)	(0.010)	(0.006)
Obs	25,513	9,073	12,636	17,788	5,195	12,567

Notes: Each specification includes a full set of fixed effects for individual institutions and years, between 2004 and 2011 for Panel A and B and between 1986 and 2001 for Panel C.
All state unemployment rates are weighted by enrollment size by state.
Robust standard errors clustered at the institution level are in parentheses.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

APPENDIX C

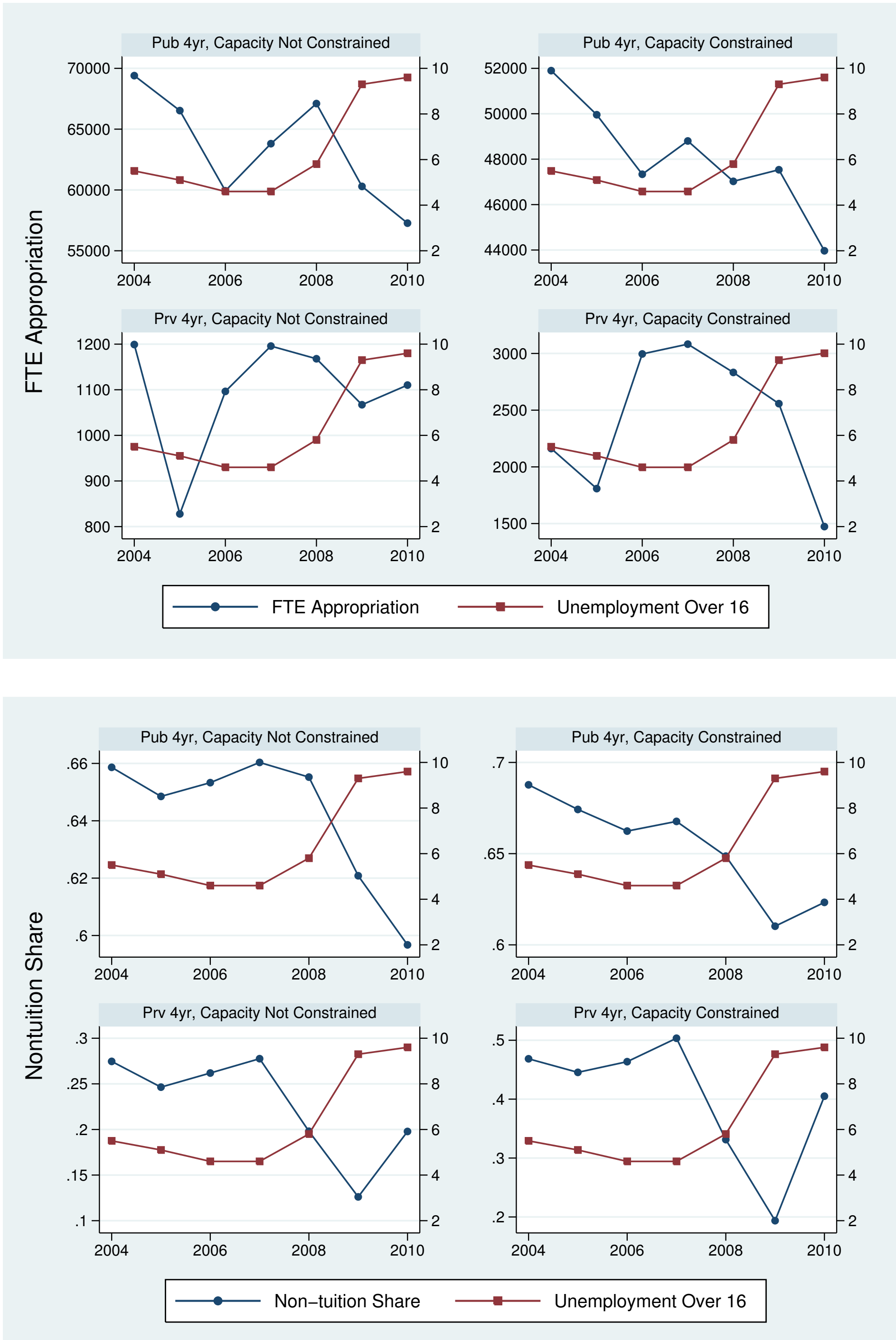
SUPPLEMENTAL FIGURES FOR CHAPTER 2

Figure 2.C1 Acceptance and Yield Rate by Institution Types



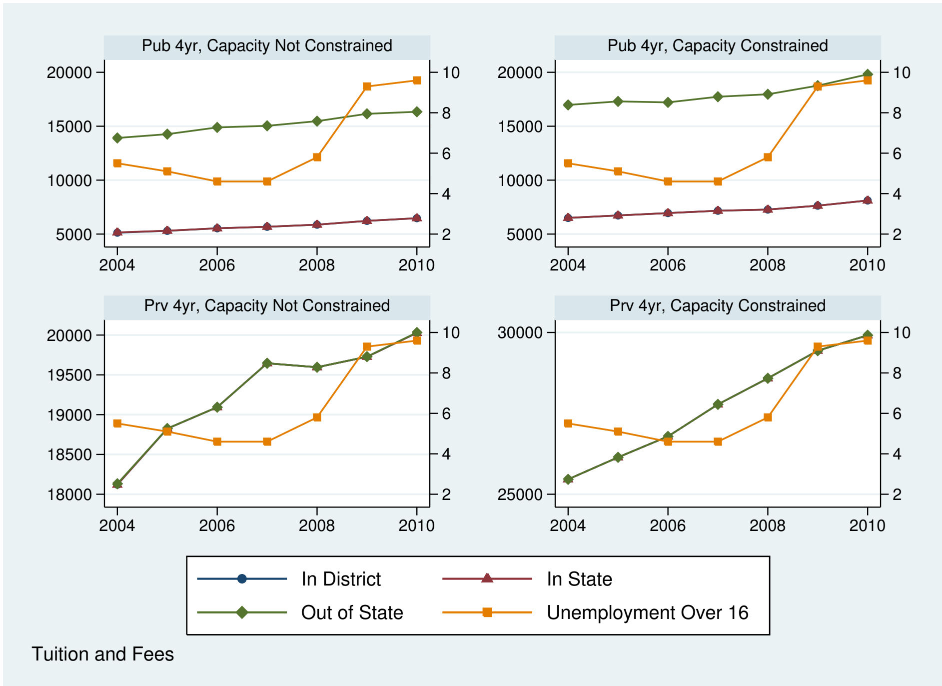
Notes: Data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents acceptance rate and right Y-axis represents unemployment rate.

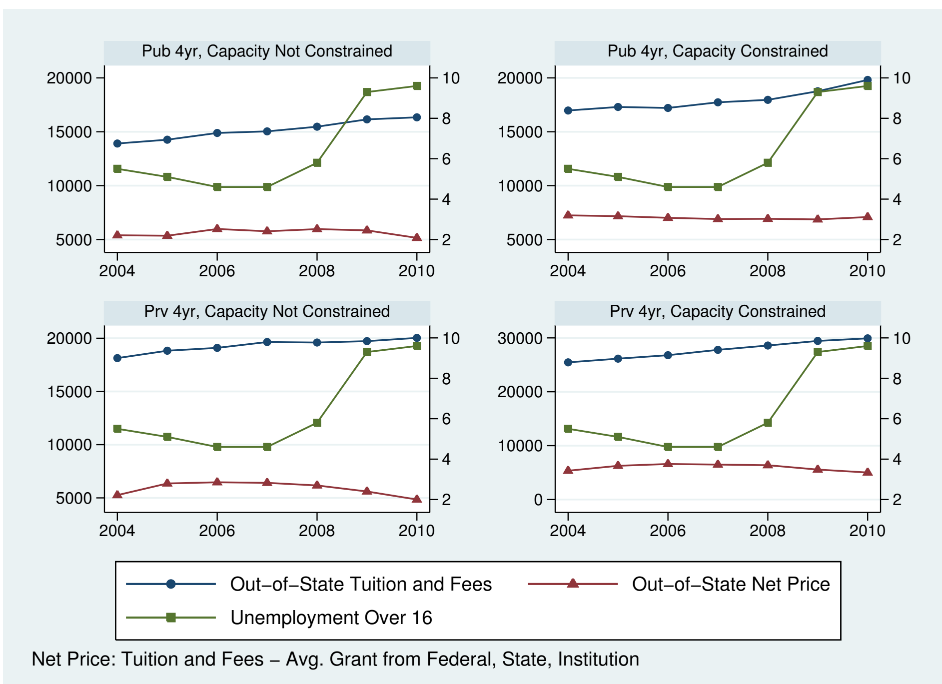
Figure 2.C2 FTE Appropriation and Non-Tuition Share by Institution Types



*Notes:*Data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. In Panel A, left Y-axis represents FTE appropriation and right Y-axis represents unemployment rate. In Panel B, left Y-axis represents non-tuition share and right Y-axis represents unemployment rate.

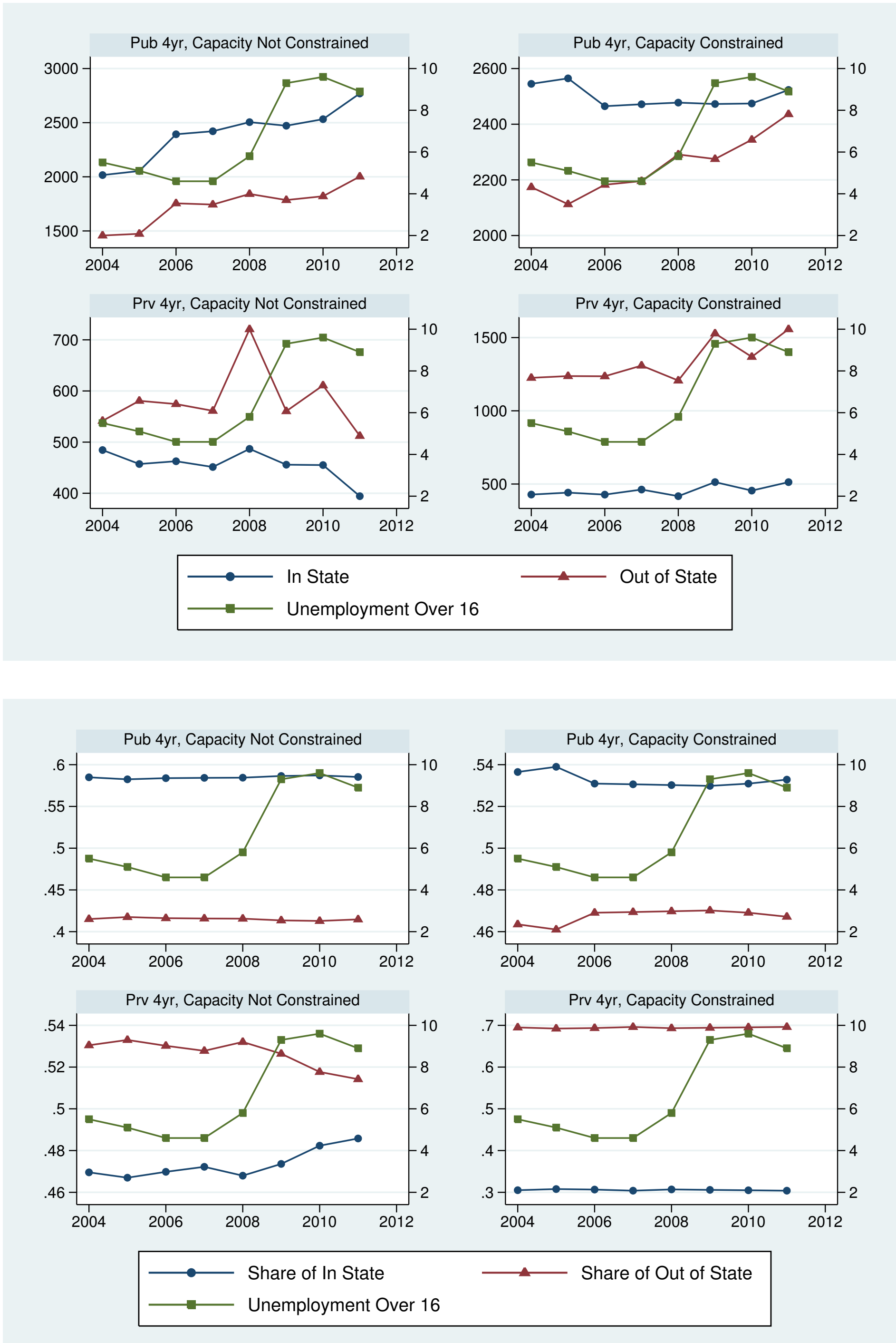
Figure 2.C3 Tuition and Net Price by Institution Types





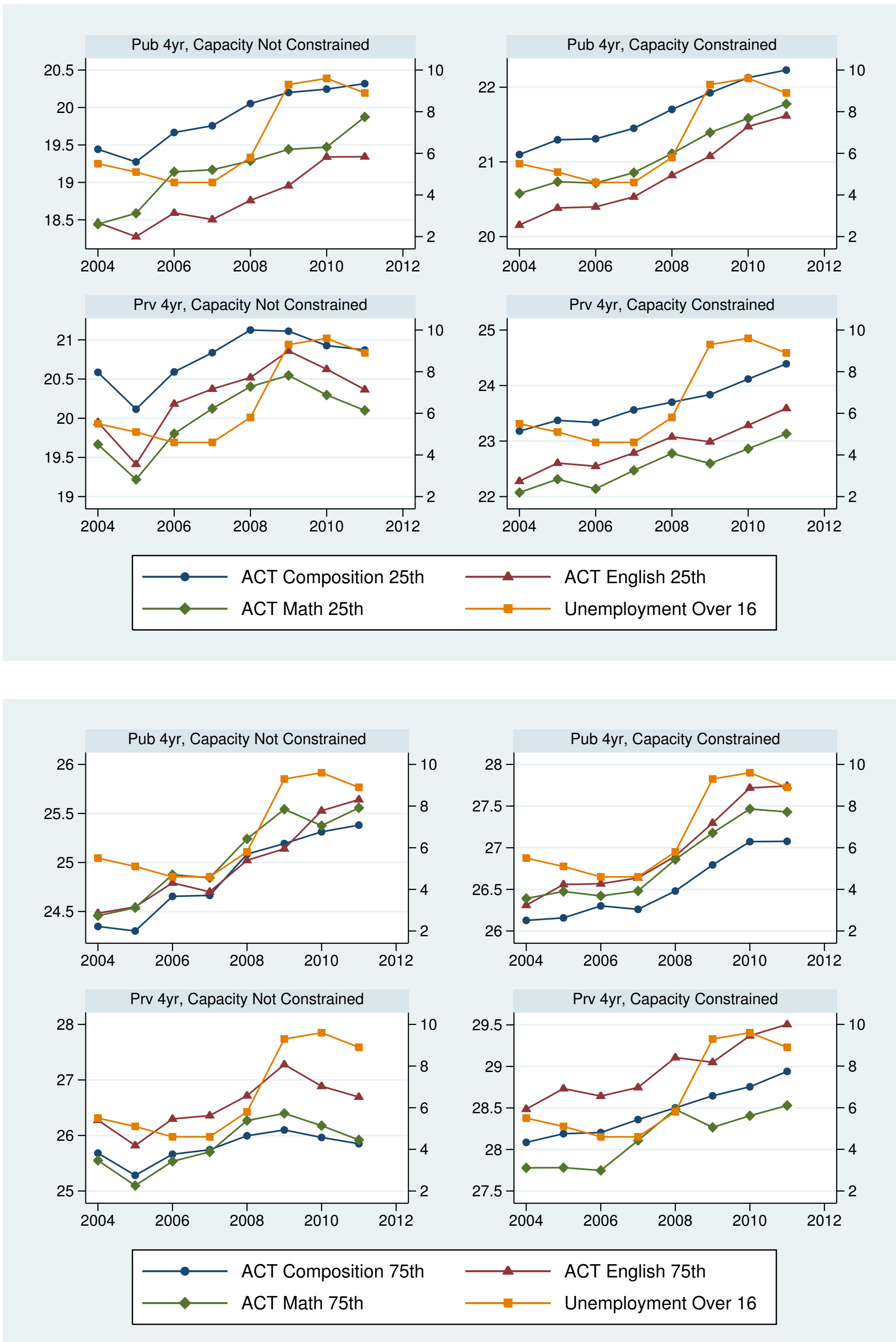
Notes: Data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents tuition and right Y-axis represents unemployment rate.

Figure 2.C4 Enrollment By Residence in 4-year Institutions



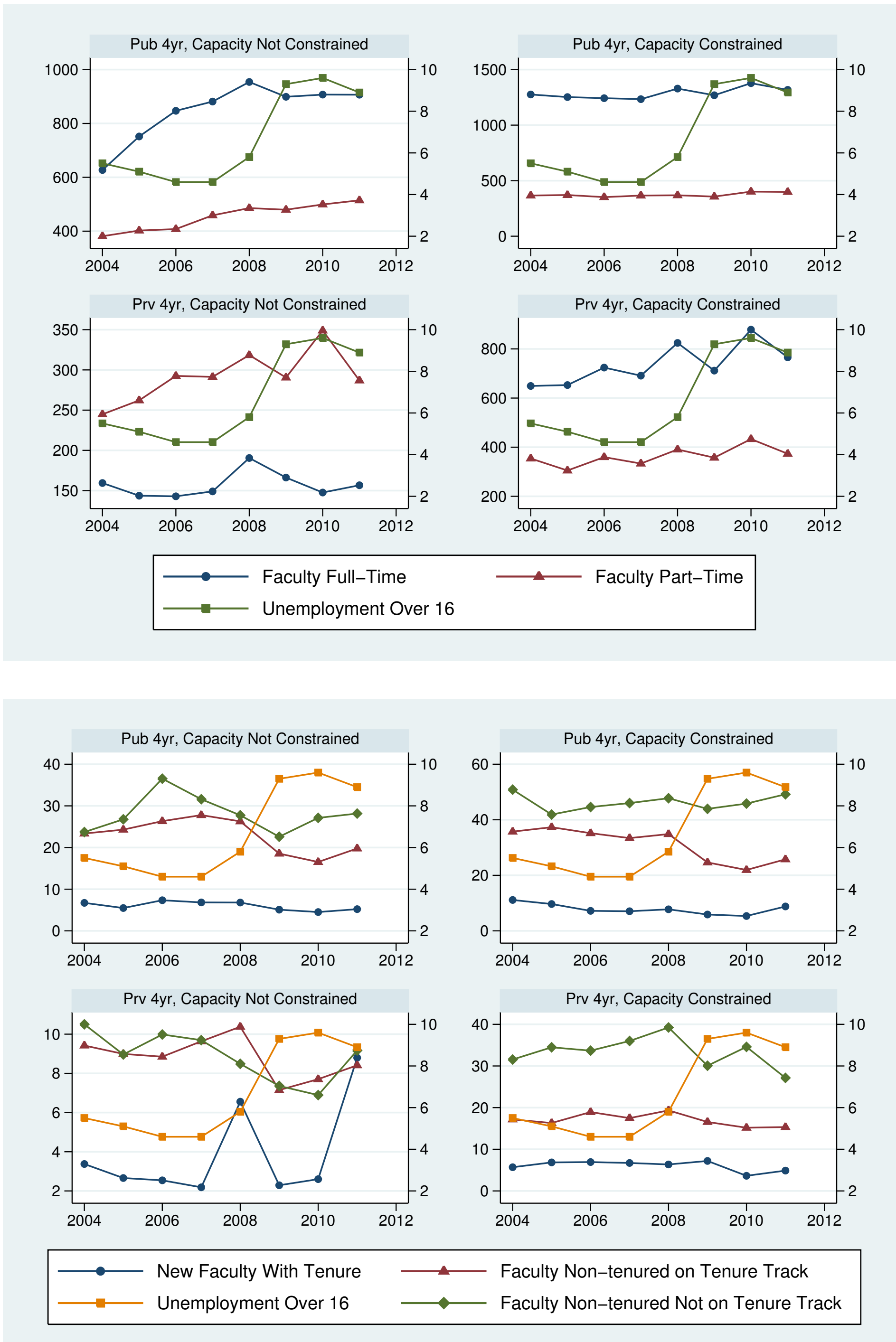
Notes: FTFY enrollment data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. In Panel A, left Y-axis represents enrollment and right Y-axis represents unemployment rate. In Panel B, left Y-axis represents share and right Y-axis represents unemployment rate.

Figure 2.C5 Student Achievement of FTFY by Institution Types



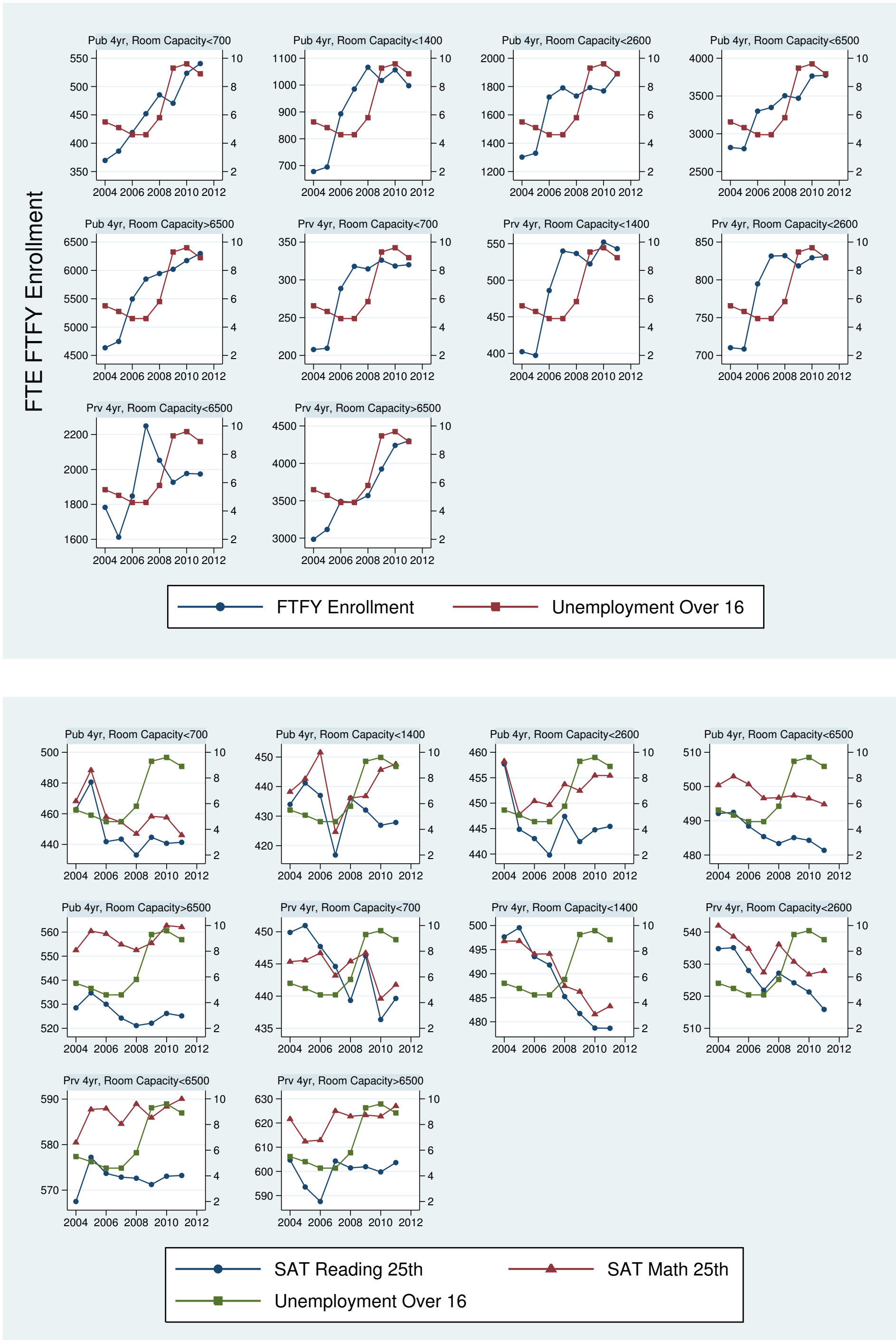
Notes: ACT data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents ACT score and right Y-axis represents unemployment rate.

Figure 2.C6 Faculty Employment by Institution Types



Notes: Faculty enrollment data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. Left Y-axis represents faculty size and right Y-axis represents unemployment rate.

Figure 2.C7 Enrollment and Student Achievement by Dormitory Capacity



Notes: FTE FTFY enrollment and SAT data are from this researcher's calculation using IPEDS weighted by FTFY enrollment size. In Panel A, left Y-axis represents enrollment and right Y-axis represents unemployment rate. In Panel B, left Y-axis represents SAT score and right Y-axis represents unemployment rate.

APPENDIX D

SUPPLEMENTAL TABLES FOR CHAPTER 2

Table 2.D1 Regression of Log Enrollment on Weighted Local Unemployment Measures (4-year Institutions)

	Non-Capacity Constrained			Capacity Constrained		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
	Panel A: State Unemployment Rate					
Unemp	0.027**	0.020***	0.032*	0.006	0.007	0.008
	(0.011)	(0.007)	(0.019)	(0.006)	(0.008)	(0.008)
Obs	9,292	2,774	3,788	5,990	1,899	4,070
	Panel B: State Unemployment Rate without Open Admission					
Unemp	0.020*	0.019**	0.035	0.006	0.008	0.007
	(0.011)	(0.009)	(0.022)	(0.006)	(0.008)	(0.008)
Obs	6,961	2,201	3,190	5,736	1,795	3,929
	Panel C: State Unemployment Rate weighted by Enrollment Size					
Unemp	0.018***	0.015**	0.023**	0.003	0.001	0.01
	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.007)
Obs	9,292	2,774	3,788	5,990	1,899	4,070
	Panel D: State Unemployment Rate weighted by Enrollment without Open Admission					
Unemp	0.012*	0.009	0.015	0.002	0.001	0.009
	(0.007)	(0.007)	(0.012)	(0.006)	(0.007)	(0.007)
Obs	6,961	2,201	3,190	5,736	1,795	3,929

Notes: Each specification includes a full set of fixed effects for individual institutions and years, between 2004 and 2011. All state unemployment rates are weighted by enrollment size by state. Robust standard errors clustered at the institution level are in parentheses.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.D2 Regression of Student Achievement on Local Unemployment Measures (4-year Institutions, 2001-2011)

	Non-Capacity Constrained			Capacity Constrained		
	All	Public	Private Not for Profit	All	Public	Private Not for Profit
	Panel A: State Unemployment Rate (SAT Math 25th)					
Unemp	-1.475**	-1.714**	-1.699	0.252	-0.373	0.399
	(0.698)	(0.73)	(1.315)	(0.656)	(1.011)	(0.785)
Obs	4,060	2,085	1,942	4,164	1,157	3,001
	Panel B: Weighted State Unemployment Rate (SAT Math 25th)					
Unemp	-2.371***	-2.336***	-3.375*	0.036	-0.458	0.476
	(0.781)	(0.827)	(1.808)	(0.933)	(1.213)	(1.307)
Obs	3,941	2,051	1,859	4,034	1,147	2,882
	Panel C: State Unemployment Rate (ACT Math 25th)					
Unemp	0.004	-0.033	0.057	0.018	-0.044	0.052
	(0.041)	(0.039)	(0.081)	(0.034)	(0.053)	(0.045)
Obs	1,859	954	896	2,712	1,023	1,684
	Panel D: Weighted State Unemployment Rate (ACT Math 25th)					
Unemp	-0.021	-0.040	0.020	0.003	-0.060	0.064
	(0.046)	(0.045)	(0.105)	(0.045)	(0.061)	(0.066)
Obs	1,812	937	867	2,636	1,015	1,617

Notes: Each specification includes a full set of fixed effects for individual institutions and years between 2001 and 2011. Robust standard errors clustered at the institution level are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 2.D3 Changes in Enrollment and Student Achievement with Prestige and Capacity Constraints (4-year Institution)

	Not Elite Institutions				Elite Institutions			
	Not National	Public Not Top120	Private Not Top65	Liberal Arts Not Top180	National	Public Top120	Private Top65	Liberal Arts Top180
	Panel A: Changes in Enrollment for Non-Capacity Constrained Institutions							
Unemp	0.025**	0.021***	0.026**	0.034	0.001	-0.002	-0.037	0.003
	(0.010)	(0.008)	(0.013)	(0.057)	(0.010)	(0.010)	(0.037)	(0.010)
Obs	9,045	2,555	6,944	217	469	317	68	237
	Panel B: Changes in Enrollment for Capacity Constrained Institutions							
Unemp	0.007	0.018*	0.006	0.027	-0.007	-0.013**	-0.004	-0.006
	(0.005)	(0.010)	(0.006)	(0.023)	(0.005)	(0.006)	(0.007)	(0.007)
Obs	5,027	1,313	3,902	368	1,146	619	451	1,089
	Panel C: Changes in Student Achievement for Non-Capacity Constrained Institutions (SAT Math 25th)							
Unemp	-0.713	-2.317***	0.178	0.670	-0.918	-0.477	-1.566	2.671
	(0.814)	(0.838)	(1.183)	(8.246)	(1.172)	(1.305)	(2.157)	(1.938)
Obs	3,853	1,646	2,545	120	435	290	64	217
	Panel D: Changes in Student Achievement for Capacity Constrained Institutions (SAT Math 25th)							
Unemp	-0.200	0.396	-0.183	-0.913	0.591	1.121	0.333	1.310
	(0.747)	(1.393)	(0.819)	(2.932)	(0.766)	(0.998)	(1.284)	(1.267)
Obs	3,991	914	3,248	299	1,095	576	448	972

Notes: Each specification includes a full set of fixed effects for individual institutions and years between 2004 and 2011. Log FTFY enrollment and SAT Math 25th percentile score are used for enrollment and student achievement measure. Robust standard errors clustered at the institution level are in parentheses. Prestige variables is assembled by *US News and World Report* in 2005 and in 2013.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

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CHAPTER 3

Racial Differences in Course-taking and Achievement Gap

3.1 Introduction

Over the past two decades, high-school graduates have been taking more credits in mathematics, and have shifted from taking lower-level math courses to taking more-advanced courses (Adelman, 2006; Dalton et al., 2007). In 2004 black and white students on average earned similar total credits in math, 3.7 and 3.6 respectively, but the racial/ethnic gap in enrollment in advanced mathematics courses persisted; black students are less likely than white students to be enrolled in high-track math courses (Kelly, 2009; Riegle-Crumb and Grodsky, 2010).

Despite the increase in course-taking intensity across gender and race, a substantial black-white achievement gap remains. Fryer and Levitt (2004, 2006) showed that the black-white test-score gap among incoming kindergartners is negligible after controlling for covariates but the gap widens over the first four-years of elementary school. They estimated that the gap in raw math score would be one standard deviation if black students continue to lose ground through Grade 9.

A majority of previous studies on course-taking used the number of math credits, and/or the highest level of math achieved, as a measure of course intensity. Credit units provide a general overview of student involvement in specific subjects to assess course-taking patterns but are unsuitable to gauge depth of learning. On the other hand, the highest level of math captures one dimension of the depth but does not consider the full history of the course-taking pattern and its association with changes in rigor-level over years.

This study examines one possible aspect to explain the racial gap in achievement - racial differences in course-taking - and differs from previous studies in that I construct a sequence of math courses completed by a high-school student, and measure racial differences in rigor level as well as in changes in the level within the sequence. If within a sequence any variation cannot be explained by the highest level or by the number of credits earned, this measure would improve our understanding on racial differences in course-taking and its relationship with the achievement gap.

The remainder of this paper proceeds as follows: Section 2 describes the background of math course-taking and achievement, and reviews previous literature. Section 3 describes and summarizes the data set. Section 4 presents basic results for the black-white math gap in course-taking and in achievement, and Section 5 discusses future works.

3.2 Background and Literature

Course-taking refers to enrollment in specific courses such as algebra or calculus and its effects on aspirations and attachment to school that accumulate over the schooling, and which contributes to a student's final educational attainment (Kelly, 2009). Between 1982 and 2004, on average, total math credits earned by high-school students increased from 2.7 to 3.6. At the same time, enrollment in advanced courses increased across categories of gender, race, and socioeconomic status (SES) but disparities among racial groups remained. For example, the share of high school graduates who completed pre-calculus or calculus increased from 10.7% in 1982 to 33% in 2004 but, in 2004, the share of whites was 37% whereas it was 19% for blacks and 22% for Hispanics (Dalton et al., 2007).[1]

When measuring racial differences in math course-taking, the number of credits earned and the level of math taken would give different answers in 2004; the total credits is similar - 3.7 for blacks, 3.6 for whites - but completion rate in the highest level, pre-calculus and calculus, is almost twice as large for white students. Issues with those measures are that the total credits fail to capture the level or content of the course, and the highest level completed pays no attention to variation within course sequence. For example, suppose student A took algebra I, geometry, and algebra II, and student B took pre-algebra, algebra I, geometry, and algebra II. Then in terms of the total credits, student B is taking a more-rigorous math track but both have the same highest math. If student C took algebra I, geometry, algebra II, and another basic course or a course from a another subject such as engineering or finance that may be counted as a math credit in order to meet statewide graduation requirements, then both measures provide the same answer, namely that student B and student C took math courses with the same intensity.

Previous studies on racial difference in course-taking showed that much of the variation in course-taking is attributed to prior achievement at the start of the year. For example, lower track

[1]Many states increased their requirements for high school graduation. For example, between 1987 and 2004, the number of states requiring at least 2.5 credits in mathematics grew from 12 to 26 and in 2004, 17 states required specific courses in math to graduate. These requirements appear to be reflected in high school student course-taking (Council of Chief State School Officers [CCSSO] 2005).

placement among black students are in part due to lower achievement scores (Lucas, 1999; Kelly, 2009). Family background also relates to course-taking and increases the black-white course-taking gap, especially in advanced math courses (Kelly, 2004, Dalton et al., 2007). Other key explanations include school quality measured by composition of race or disadvantaged student, number of courses offered, and teacher quality.

Ethnic differences in academic achievement have been studied since the 1960s and Coleman et al. (1966) showed that black-white score gap increased with student age. Fryer and Levitt (2004) summarized the explanations for racial gap in test scores; differences in genetic make-up, differences in family structure and poverty, differences in school quality, racial bias in testing or teachers' perceptions, and difference in culture, socialization, or behavior.

3.3 Data

This study uses the Education Longitudinal Study of 2002 (ELS:02), a nationally-representative sample of over 16,000 students who were high school sophomores in base year 2002, to examine racial differences in course-taking and gap in achievement. The first follow-up was in 2004, when most students were seniors. The second follow-up was in 2006. This study restricts the sample to students who had complete transcript information, and to on-time high school graduates.[2] Data collected from students include demographic and transcript data for all courses taken, their parents, and school administrators.

Students' high school transcripts are collected and coded using the Classification of Secondary School Course (CSSC) codes, updated from the 2000 National Assessment of Education Progress high-school transcript study. These were developed by the National Center for Education Statistics (NCES) and used in prior transcript studies such as the High School and Beyond of 1980 (HS&B) and the National Education Longitudinal Study of 1988 (NELS). Each CSSC course code contains six digits. The first two digits identify the main program area; the second two digits represent a subcategory of courses within the main program area; and the final two digits define the specific course. For example, regarding CSSC code 270405, the first two digits (27) define mathematics, the middle two digits (04) define the pure mathematics subcategory, and the final two digits (05) define the course algebra 2.

Using the CSSC codes, this study constructs course intensity or rigor level by employing math pipeline measures, introduced by Burkam and Lee (2003).[3] Pipeline measures are designed to capture the highest level of math completed but, for simplicity, this study assigns the rigor level of each course taken equivalent to the level of pipeline. For instance, algebra 1 and geometry are

[2]The procedure is documented in Dalton et al. (2007). The sample of on-time graduates excludes dropouts, who on average are likely to take lower-level courses, thus might over-represent relatively-high test scorers.

[3]Burkam and Lee (2003) divided math courses by level, into eight categories, moving from least to most advanced: (1) No mathematics; (2) Non Academic (e.g., general math or consumer math) mathematics; (3) Low Academic (algebra 1/plane, informal geometry); (4) Middle Academic (algebra 1, geometry/plane); (5) Middle Academic 2 (algebra 2); (6) Advanced 1 (algebra 3/trigonometry/analytic geometry); (7) Advanced 2 (pre-calculus); and (8) Advanced 3 (calculus).

assigned with the rigor level of 3.

Since the term in which the course was taken varies, quarter to year-long, and the number of courses taken per year also differs by students, one to eight courses, 3122 combinations arise from 61 math courses.[4] Thus this study restricts to math courses that are either year- or semester-long, which accounts for 80% of the courses, and drops other trimester-, quarter-long, and term-unknown courses. Additionally, this study generates measures of rigor level for each year such as the highest level or the average level of math per grade.[5] For example, when the highest level of math within a grade is used, a student is assigned with a sequence of middle-middle-middle 2-advanced 2 if he/she takes algebra 1 in freshman, geometry in sophomore, algebra 2 in junior year, and pre-calculus in senior year.

Transcript data cover 16,200 students with math courses; 13,900 students have both transcript and demographic information.[6] Among 11,450 on-time high school graduates taking 69,070 courses,[7] this study keeps courses with positive credits earned, which gives 11,410 students with 61,780 math courses. After restricting to year- and semester-long courses with pipeline measures available, and excluding students without pipeline measures, final data include 48,290 courses taken by 9350 students from 980 high schools.

Summary statistics for variables are presented in Table 3.B1, with white referring to non-Hispanic whites.[8] The upper panel on credit confirms previous results that there are no black-white differences in the number of math credits taken, nor in average credit taken per year. Since schools have different unit measures, standardized credits in Carnegie units are used**.** The next panel on course level describes that the highest level of math for white students is close to advanced 1,

[4]Since math courses are clearly sequenced and students in general take courses in order described by pipeline, the number of math course combinations is much smaller than all possible combinations of 61 courses.

[5]As many as 93% of students take either one or two math courses per academic year, and 6% take three or four courses. Less than 1% of students take five or more math courses per grade. This complicates generating a math sequence and comparison across ethnic groups.

[6]In compliance with National Center for Education Statistics restricted data-licensing agreements, the unweighted sample size in each specification is rounded to the nearest 10.

[7]Reasons for not graduating on-time are dropout, transferred, GED, still enrolled, withdrew, dismissed, health condition, incarcerated, and others. Dropout students accounts for 4% of the sample.

[8]Data include 470 students whose racial status is classified as “other”. These include mixed race, Native American, and Alaska Native students. Such students are included in regressions but not shown in the summary statistics table.

whereas that for black students is close to middle 2. Although there is no black-white difference in the level of first year math, it seems the gap is increasing over years so that the gap in the average level is .35 and the gap in the highest level of math is 0.5. The highest level of math is divided into three groups, low for levels 2 and 3, middle for levels 4 and 5, and advanced for levels 6, 7, and 8. 50% of blacks end up with middle level, whereas 40% of whites do, but the pattern differs for advanced level: 54% of white students and 65% of Asian students earned the highest level in advanced courses, whereas 42% of black and 39% of Hispanic students finished math courses in advanced level. Racial differences in course-taking patterns, especially in advanced levels of courses, might explain the gap in math test scores. Disparities in taking are most apparent in Advanced Placement (AP) courses, which include AP calculus and AP statistics: 11% for white and 5% for black.

Approximately 10% of high-school graduates achieved the highest level of math in their Grade 10, and more than 50% of students completed in Grade 12. Of interest is that the timing of completing the highest level of math is different between black and white students: 38% of blacks reach the highest level in Grade 11, while 32% of whites do, and the relationship is opposite for Grade 12. Since the proportion of missing math course in Grade 12 is not different between white and black, blacks might take lower level of course in Grade 12 than in Grade 11.

Course-taking pattern by grade is summarized in Table 3.D1. The black-white difference in the highest level is increasing over years, from 0.1 level in Grade 9 to 0.9 level in Grade 12, and the same pattern is observed for average level of math taken. Black students are more likely to take low-level courses in all high-school years, whereas the relationship is opposite for enrollment in advanced courses. For middle level courses, the pattern is mixed. In Grades 9 and 10, whites take more middle-level courses than their black peers do, but blacks in Grade 11 and 12 take more middle-level courses than do their Grades 9 and 10 white peers.

In sum, blacks and Hispanics are on average more likely to take lower-level courses than whites are. One possible explanation for whites and Asians taking less credits in lower-level courses, even in Grade 9, is that they already took those courses prior to Grade 9 so that they can take advanced courses such as pre-calculus, calculus or AP courses in high school.

Free reduced lunch (FRL) school is a categorical variable ranging from one to seven and it indicates that, on average, black students are enrolled in schools with relatively poorer peers than whites are.[9] White students are more likely to attend private schools. Parental education is coded one if the highest education level is higher than 4-year college, and zero otherwise. White students come from higher socioeconomic status families (parents more likely to be college-educated and wealthier than their black counterparts).

The key achievement variable is math standardized test scores in Grades 10 and 12. Among Grade 10 cohorts, whites score on average 2.1 point or 0.21 standard deviation higher than mean on the math exam, whereas blacks earn 6.2 point or 0.65 standard deviation lower than mean on that test, and the black-white achievement gap is 8.3 point or 0.86 standard deviation, which is close to what Fryer and Levitt (2004) predicted. Unconditional math test score gap slightly decreases to 8 point or 0.81 standard deviation among Grade 12 cohorts.[10]

Table 3.D2 describes the five most-common courses taken in high school years. Burkam and Lee (2003) showed that 14 courses have (unweighted) enrollment above 5% of the sample, using National Education Longitudinal Study of 1988 (NELS: 88). Ten years later, it turned out that 18 courses have (unweighted) enrollment above 1% of the sample, which in total comprises 90% of the sample, and only 4 courses have enrollment over 5% in the sample. No black-white difference exists in the top five common courses, but common courses by level show a different story. Whites take more advanced courses (19%) than do blacks (9%), and blacks take more low- or non-academic courses (20%) than do whites (7%); this is consistent with the course-taking pattern in Table 3.B1. Since students generally take upper-level courses by year, from low to middle, or from middle to advanced, the majority of courses are concentrated in middle level.

Table 3.B2 presents the five most common sequences, or course-taking patterns, based on highest level achieved in each year. Among 795 sequences, the top five common sequences comprises

[9]Categories corresponding to each FRL ratio are 1 for 0-5%, 2 for 6-10%, 3 for 11-20%, 4 for 21-30%, 5 for 31-50%, 6 for 51-75%, and 7 for 76-100%.

[10]Summary statistics including dropouts are presented in Table 3.D3. White students are less likely to drop and the overall unconditional black-white differences enlarge.

less than 30%, and it indicates more variety of sequences compared to Burkam and Lee (2003), who showed that nearly two-thirds of the students are reflected in only five patterns.[11] Comparing the common sequences between black and white, all students start in middle level courses in Grade 9 but the disparity in course level appears in Grade 10, in that white students start to take middle 2 courses, and those students take further advanced courses in their 11th and 12th grade, ending up with advanced 3 level. At least 19% of white students take four years of math courses and reach advanced level, whereas 12% of black students follow a similar pattern. Figure 3.A1 indicates the progress of highest-level math achieved by grade, and Figure **??** confirms that white and black students take a similar level of math courses in Grade 9, implying that pre-high school difference is not strong. Rather, the black-white difference in math level has developed over a number of years in high school.

[11] Algebra 1 only (12.4%), algebra 1 and geometry only (9.2%), algebra 1, geometry, and algebra 2 only (20.8%), algebra 1, geometry, algebra 2, and analysis/trigonometry only (10.9%), and calculus plus other courses (9.9%).

3.4 Empirical results

3.4.1 Racial Gap in Course Intensity

The black-white gap in course-taking among high-school graduates, and how the gap evolves over time, are estimated by the following model

$$Y_i = \beta_0 + \beta_1 Black_i + \beta_2 Hispanic_i + \beta_3 Asian_i + \beta_4 OtherRace_i + \varepsilon_i$$

where Y_i denotes for course-taking measure for student i. Since non-Hispanic white dummy is omitted, β_1, β_2, β_3 and β_4 captures the math course-taking gap between white and corresponding race. Other controls include gender, family SES and income, where family income, which is an ordinal indicator, is recoded by taking the midpoint of each income category. The analysis starts by looking at the differences in the number of credit taken by each grade, and results are summarized in Table 3.B3. Consistent with previous studies on intensity measures, the total credits relate positively to family background and no racial differences are evident when between-school variation is removed through school fixed effects. For comparison, Asian students are most likely to take math courses.

As in Table 3.D3, the high-school dropout rate is different between black and white students. Reasons for leaving high school vary, with women more likely to leave because of personal issues such as pregnancy or marriage and men more likely to leave to go to work; poor academic performance accounts for 7% (Rumberger, 1983). If dropout students have lower performance than on-time graduating students have, excluding dropouts would take out the left tail of performance distribution, thus the course-taking gap might be underestimated. For simple comparison, dropout students are included in the sample and their math credits are recorded as zero after they leave the school. Results in Table 3.B4 include dropouts and indicate that the black-white difference in the number of credits tends to drop among 9th and 10th graders, and to remain similar among 11th and 12th graders. Consistent with previous studies on dropout, the importance of parental education and family income to course-taking increases when dropout students are included, and dropout students tend to take fewer math courses.

As in previous studies, no meaningful differences exists in total math credits taken, but the quality of the course taken might be different. Table **??** summarizes ordinary least squares estimation results of racial differences in course-taking measured by rigor level. During high-school years, the highest level of math for black graduates is 0.5 level lower than white peers. When the average level of math course taken is calculated, black students on average take 0.2 level lower courses than white students take, which in turn accumulates to 2.4 level in four-years of high school. School fixed effect is included to account for across-school variation such as school SES, racial composition, and teacher quality, and the magnitude of the black-white gap in course-taking increases, except for total rigor, implying that the gap in course-taking is a within-school phenomenon. The black-white course-taking difference occurs from the first level of math course indicating that students enter high school with different levels of math preparation.

Each state has different policy for curriculum requirement for graduation, such as the number of minimum math credits and the list of courses to pass, and school fixed effects might not explain across-state differences. When state fixed effects are included, the black-white gap is identified from differences between blacks and whites attending school in the same state, and the pattern is similar, implying that the majority of variation is within-school: there is almost no change in coefficients for first-level, total rigor, and average rigor of math. But the coefficient on the highest-level of math increases, which is slightly smaller than the coefficient with school fixed effects.[12] The next step is to analyze in what level of course and in which grade the racial gap in course-taking exists.

3.4.2 Racial Gap in Course-Taking

Table 3.B5 shows that black students are more likely to enroll in low- and middle- level courses than their white peers, and less likely to take courses beyond middle 2 level, generally considered

[12] Hereafter only estimation results with school effects are presented unless controlling state unobservables provides different results.

the math threshold for college admission. Adelman (1999) showed that students who take courses beyond algebra 2 score higher on entrance examinations and have greater likelihoods of attending college in general (and more-selective colleges and universities in particular), as well as graduating from college, than students who meet but do not exceed the algebra 2 threshold. For example, Riegle-Crumb & Grodsky (2010) divided samples based on whether or not students completed any math course beyond algebra 2 and conduct separate analyses for each group. Moreover, the black-white gap in the enrollment level is more a within-school than a within-state phenomenon for low-level courses, but the relationship is opposite for middle level courses. Interestingly, there is almost no differences in taking pre-calculcus (advanced 2) or calculus (advanced 3) courses explained by within-school or between-state variation. Algebra 1 (middle) or algebra 2 (middle 2), on the other hand, seems mostly affected by between-state variation such as different math requirements for graduation.

Table 3.B7 presents how the disparity in rigor level of course-taking evolves over grades. It is clear that the black-white gap increases over time. Average rigor and the highest-rigor-per-grade provide almost the same estimates, since students generally are taking year-long course or semester-long courses with similar intensity levels.[13] Additionally, the positive association between course-intensity and family background also increases over years.

Table 3.B8 explores estimated racial disparities, which grows over high-school years, across course-intensity. Overall, when between-school variation is not considered, no black-white gap in course-taking appears for low-level course takers. Black students are more likely than white to take mid-level courses, and the relationship is opposite for advanced and AP courses. But mixed results appear for the pattern by grade. Black students are more likely than white students to take low-level courses in Grade 10. For mid-level courses, the relationship is mixed. Since black students start their Grade 9 with a lower level of math, they are less likely to take mid-level courses such as algebra 1, algebra 2, and geometry, in Grades 9 and 10, and more likely to take those

[13] Similar to results in Table **??**, the gap tends to be larger when school fixed effects are included than when state fixed effects are included, especially for Grades 9 and 11, implying that the increasing black-white gap in the level of course is more of a within-school than a within-state variation.

mid-level courses than white students in Grades 11 and 12. For advanced courses, there are no racial differences for 9th graders. But as whites and Asians are taking mid-level courses in Grade 9 and 10, a black-white gap in advanced course-taking appears in Grade10, and the gap increases over years. Panel D shows the course-taking pattern for AP courses such as AP Calculus and AP Statistics. Overall it shows that black students are less likely to take AP courses than white students are. In Grade 11, the black-white course-taking difference is negligible as 2% of whites and 1% of blacks are taking AP courses in their Grade 11. Notably Asians are significantly taking more AP courses in Grade 11. In Grade 12, blacks are significantly less likely to take AP courses than are whites.[14] Including school fixed effects remove between-school variations, and tend to increase the magnitude of black-white differences in all levels of math courses. Particularly, black graduates attending the same school are more likely to take low-level courses in all high school years.

3.4.3 Racial Gap in Timing of Highest-Level of Math

In general, high-school students applying for colleges do so at the end of Grade 11 and in early Grade 12, and submit the list of math courses taken, so have incentive to complete the highest-level by the end of Grade 11. At the same time, in general, national-level- or prestigious colleges require a course-taking plan in Grade 12 and students applying for those colleges might have more incentives to take advanced courses in Grade 12. Thus the timing of highest math level achieved might explain the persistent black-white gap in course-taking in Grade 12 and in advanced courses. To study racial disparity in the timing of highest-level obtained, the sample is divided by when they take the highest-level.

Students taking the highest-level in Grade 12 are of three possible types: i) no math course in Grade 11 and take highest-level in Grade 12; ii) lower-level in Grade 11 and more advanced level in Grade 12; iii) same level of math in Grades 11 and 12. Table 3.B9 shows that whites are more likely to achieve highest-level in Grade 12 albeit the estimate is statistically insignificant.

[14] Parents education and family income are negatively correlated with taking low-level courses. For mid-level course takers, students from better family background are more likely to take mid-level courses in 9th and 10th grade. The influence of family background on advanced course-taking is also increasing over years.

Interestingly, blacks who take highest-level of math in 12th grade are more likely than whites to miss math courses in Grade 11 whereas whites are more likely to take more advanced courses in Grade 12 than in Grade 11.

Similarly, students who take the highest-level in Grade 11 are divided into two groups: i) no math course in Grade 12; ii) lower-level in Grade 12. Consistent with results from 12th graders, blacks are more likely to take the highest-level in Grade 11. Specifically, black students are more likely than their white counterparts to miss math courses in Grade 12, and more likely to take lower-level math in Grade 12.

Once school fixed effects are included, all but one coefficient on blacks become statistically indistinguishable from zero, implying that the timing of taking the highest-level of math might relate to school characteristics.[15] Thus the sample is divided by school sector, public, private, and Catholic. Results are presented in Tables 3.B10 and 3.D4. The former show no racial differences in the timing of achieving the highest-level of math in Grade 12 in public and in private school. But black students in Catholic schools are less likely than their white peers to take math courses in Grade 11 and advanced courses in Grade 12. But once across-school variations are controlled, no racial differences appear in taking the highest-level of math in Grade 12 even among students in Catholic schools; this implies the presence of quality variations across Catholic schools.[16]

Similarly, in Table 3.D4 most variation in racial difference in the timing of taking the highest-level of math in Grade 11 occurs among students in Catholic high schools. Blacks are 16% less likely to take the highest-level of math in Grade 11 than white counterparts, where the national average is 5%, and are 14% more likely to miss math courses in Grade 12 than their white peers, whose national average is 3%.[17]

In conclusion, black-white difference in the timing of achieving the highest-level of math is

[15]Including state fixed effects increases the likelihood for whites to achieve the highest level of math in Grade 12; generally those students have lower level in Grade 11 and take more advanced courses in Grade 12; this might relate to different across-state policy.

[16]Although statistically insignificant, among private schools, between-state differences explain most of the black-white difference in the likelihood of taking the highest level of math in Grade 12.

[17]When across-state variation is controlled, the likelihood of black students achieving the highest level of math in their Grade 11 tends to increase for public and private school, albeit statistically insignificant.

mostly explained by between-school differences, and no statistically- and economically- meaningful differences within school are apparent. The between school differences in the timing is significantly large among Catholic schools, implying that school characteristics such as resources and teacher quality might affect students' decisions on course-taking pattern.

3.4.4 Achievement Gap

Table 3.B11 displays coefficients on black, Hispanic, and Asian race dummies, indicating differences relative to white, and results are consistent with previous studies on achievement gap; the black-white standardized math score gap of 0.647 in Grade 12, 1/8 standard deviation, is mostly explained by previous standardized test in Grade 10.[18] Next, the achievement gap is estimated by the level of math course taken in each grade, which is measuring the gap among students taking the same level of course in a certain period. For example, the coefficient of -1.704 in Panel A shows the black-white test gap in Grade 12 among students who took advanced-level course in Grade 11. The black-white test-score gap for students who in Grade 11 took mid-level math is -0.361, thus this test-score gap differs by course level. The black-white gap is relatively larger for students taking advanced course in all grades, about 2x– to 6x larger than the average gap. Of interest is that the test score gap is about 0.2 standard deviation among students taking the same advanced level in Grade 11 when average rigor level is controlled, whereas the gap is smaller than the average gap among 11th graders taking either mid- or low-level math courses.

The black-white test-score gap for students who in Grade 12 took mid-level math is -1.014, whereas (as we see above) the test-score gap for students who in Grade 11 also took mid-level math is -0.361, so this test-score gap differs by school year of taking mid-level math. Black students taking mid-level courses in Grades 9 and 10 are likely to have taken low-level courses in advance and can be regarded as college-track students. The test gap for those students is significant but the magnitude is smaller than 0.1 standard deviation. 95% of students earned credits in mid level courses and some passed the course by retaking or by taking credit recovery, which explains the

[18] General results on achievement gap are provided in Appendix A.

negligible achievement gap among students taking mid level courses. On the other hand, advanced level courses are harder to pass by retaking or by credit recovery.[19]

Additionally, simple analysis shows that, after controlling for test score in Grade 10, the correlation between black-white achievement gap in Grade 12 and course-taking, measured either by the average intensity or by the highest level of math, is around 0.25 and that around 10% of the variation in the test gap is explained by the variation in course-taking. Considering the fact that achievement is closely related to education attainment such as high school graduation and college going, different course-taking patterns are likely to have relationship with racial gap in attainment. More rigorous research on the casual path is left for future research.

Last, the black-white test gap in Grade 12 is about twice as large among students who take the highest level of math in Grade 12 than those completed in Grade 11. In Grade 12, on average, whites take more of advanced 1 level, while blacks take more of middle 2 level. This difference in course-taking intensity seems contributory to the test gap in Grade 12.

[19]When state fixed effects are substituted for school fixed effects, the score gap is larger for students taking advanced courses in their Grades 10, 11, and 12, as well as for those taking mid-level courses, implying that school-level heterogeneity exists within the same state.

3.5 Discussion

This study aims to explore the relationship between racial differences in math course-taking and achievement gap. Using ELS:02 Transcript Study data, this study constructed measures to capture course-taking patterns and analyzed the racial difference in math course-taking in high school. For example, average- or highest-level of rigor or intensity is calculated by grade and by course-level from a math sequence variable that a student took in high school. Moreover, the timing of highest-level of math achieved is used to identify students taking courses with rigor level continually increasing, who are retaking the course, and others who are choosing to opt out while on advanced track.

Racial difference in course-taking occurs not only in terms of the highest level of math or total number of math credits taken. Black students and white students start high school with different math levels and in following years take different math level, where the black-white difference in the level of math is increasing over the school years. Moreover, black and white high-school graduates tend to achieve the highest-level of math in different grades, which also contributes to the test-score gap in Grade 12. Thus the sequence variable is better suited to understand racial differences in course-taking patterns that change over years.

Between-school variations, such as school expenditure, number of courses offered, and teacher quality, seem to explain racial differences in course-taking. Once variations are controlled, the magnitude of black-white difference in course-taking generally increases, implying that the gap is a within-school phenomenon. Interestingly, substantial across-school variations exists among Catholic high schools.

Additionally, each state's policies for high school graduation differ. These include the number of math credits, levels of math course to complete, and exit exams. In 2013, at least 47 states have statewide requirements on the number of credits for high school graduation (National Center for Education Statistics, 2014). Comparison of empirical results controlling for school unobserved heterogeneity, and those with state unobserved heterogeneity, shows some degree of between-school variations among students attending school in the same state.

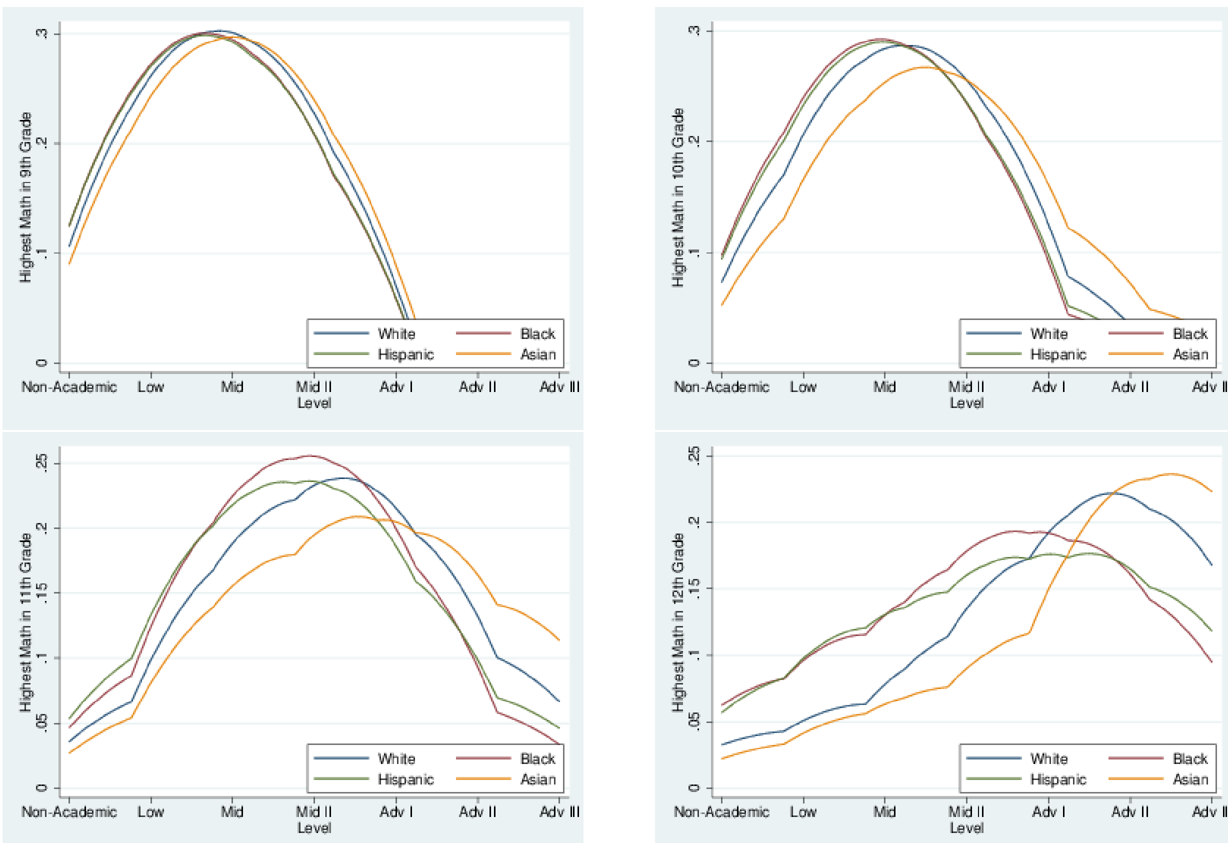
This study would be extended by using two other sets of nationally-representative data, NELS:88 and HS&B:82, to explore changes in course-taking patterns and achievement gap patterns. Some hypotheses to be tested: (1) White students outnumber black students in AP courses; (2) Black students enroll more in remedial courses than whites do; (3) Black students have more retention; and (4) Black students take more credit-recovery courses. Number 1 and 3 relate to opportunity structure, and 3 is linked to course preparation. By analyzing 2 and 4, this study can examine organizational responses to the *No Child Left Behind* policy, which might keep students in high school to graduate but not practically help their performance.

Fryer and Levitt (2004) predicted that the black-white achievement gap in Grade 9 will be one standard deviation in raw score if black students continue to lose ground at the rate experienced in the first two years of school. The 0.9 standard deviation difference in Grade 10 math score is a little smaller than their prediction but this implies that black students have lost ground since kindergarten. Black students' smaller response in math test score to family SES, a composite measure of parental education and occupation, in relation to white peers, seems to explain the lag in achievement because many black students have lower family SES, the cumulative impact of which is negative on achievement. This assertion, however, has to be further analyzed by continuous tracking of student achievement over the years.

APPENDICES

APPENDIX A
FIGURE FOR CHAPTER 3

Figure 3.A1 Progress in Math Level



Notes: Course-taking distribution by race in Grade 9 is in the upper left and that in Grade 10 is in the upper right. Course-taking distribution by race in Grade 11 is in the lower left and that in Grade 12 is in the lower right.

APPENDIX B

TABLES FOR CHAPTER 3

Table 3.B1 Summary Statistics by Race

Variable	Full Sample	White	Black	Hispanic	Asian
Credit:					
Total Credit	3.333	3.392	3.288	3.062	3.462
Average per year	0.703	0.723	0.753	0.636	0.625
Course Level:					
Highest Level of Math	5.747	5.838	5.327	5.292	6.407
Average per year	4.546	4.608	4.228	4.259	5.012
Level of First Course	3.834	3.866	3.734	3.685	4.011
Highest Level of Math:					
Low Level	0.049	0.041	0.065	0.077	0.033
Middle Level	0.429	0.405	0.514	0.538	0.314
Advanced Level	0.522	0.554	0.421	0.385	0.653
AP	0.122	0.116	0.046	0.070	0.329
Timing of Achieving Highest Level of Math:					
10th Grade	0.110	0.115	0.086	0.112	0.091
11th Grade	0.325	0.315	0.381	0.379	0.244
12th Grade	0.530	0.539	0.476	0.466	0.643
Missing Math Class in:					
9th Grade	0.090	0.075	0.120	0.114	0.101
10th Grade	0.089	0.071	0.150	0.136	0.066
11th Grade	0.145	0.140	0.158	0.169	0.123
12th Grade	0.387	0.381	0.409	0.448	0.307
Other Controls:					
Public	0.747	0.693	0.850	0.801	0.886
Private	0.098	0.126	0.041	0.038	0.060
Catholic	0.155	0.181	0.109	0.161	0.054
FRL School	2.076	1.716	3.240	2.912	1.804
Parent Education	0.444	0.479	0.361	0.281	0.545
Family Income	9.275	9.805	8.036	8.342	8.775
Test Score:					
10th Grade	52.090	54.144	45.890	47.433	53.416
12th Grade	51.302	52.933	44.953	46.906	55.039

Notes: The entries are means of student-level data on who are not missing math scores, race, and SES variable. The highest level of math is divided into three groups, Low for levels 2 and 3, Middle for levels 4 and 5, and Advanced for levels 6, 7, and 8. Free reduced lunch (FRL) school is a categorical variable ranging from one to seven corresponding to each FRL ratio (1 for 0-5%; 2 for 6-10%; 3 for 11-20%; 4 for 21-30%; 5 for 31-50%; 6 for 51-75%; and 7 for 76-100%.)
Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed.

Table 3.B2 Most Common Course Sequence

9th Grade	10th Grade	11th Grade	12th Grade	Percent
Full Sample				
Middle	Middle	Middle 2		7.94
Middle	Middle	Middle 2	Advanced 1	6.43
Middle	Middle	Middle 2	Advanced 2	6.37
Middle	Middle 2	Advanced 2	Advanced 3	5.01
Middle	Middle			2.2
White				
Middle	Middle	Middle 2	Advanced 1	7.48
Middle	Middle	Middle 2		7.47
Middle	Middle	Middle 2	Advanced 2	6.74
Middle	Middle 2	Advanced 2	Advanced 3	5.24
Middle	Middle			2.35
Black				
Middle	Middle	Middle 2		10.08
Middle	Middle	Middle 2	Advanced 1	6.85
Middle	Middle	Middle 2	Advanced 2	5.64
Middle	Middle	Advanced 1		2.59
Middle	Middle			2.41
Hispanic				
Middle	Middle	Middle 2		9.97
Middle	Middle	Middle 2	Advanced 2	4.98
Middle	Middle	Middle 2	Advanced 1	4.49
Middle	Middle 2	Advanced 2	Advanced 3	3.35
Middle	Middle 2	Advanced 2		2.7
Asian				
Middle	Middle 2	Advanced 2	Advanced 3	9.78
Middle	Middle	Middle 2	Advanced 2	7.36
Middle	Middle	Middle 2		5.6
Middle	Advanced 1	Advanced 2	Advanced 3	2.42
Middle 2	Advanced 2	Advanced 3	Advanced 3	2.42

Notes: Entries are means of student-level data of who are not missing math scores, race, and SES variable. Each entry is the highest-level of math in each grade.

Table 3.B3 Estimated Black-White Gap in Number of Credits

Variables	9th	10th	11th	12th	Total
Panel A: Credit and Race without School Fixed Effect					
Black	0.022* (0.011)	0.006 (0.010)	0.023* (0.010)	0.054*** (0.014)	-0.029 (0.034)
Hispanic	-0.031** (0.010)	-0.056*** (0.009)	-0.021* (0.010)	-0.050*** (0.013)	-0.248*** (0.032)
Asian	-0.010 (0.012)	-0.015 (0.010)	0.015 (0.011)	0.021 (0.014)	0.092* (0.036)
Female	-0.006 (0.007)	0.006 (0.006)	0.009 (0.006)	-0.016* (0.008)	0.084*** (0.021)
Parent Education	0.004 (0.007)	-0.001 (0.006)	0.004 (0.007)	0.016 (0.009)	0.190*** (0.022)
Family Income	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.000 (0.004)	0.071*** (0.009)
Adj. R^2	0.002	0.004	0.002	0.007	0.035
Panel B: Credit and Race with School Fixed Effect					
Black	-0.003 (0.018)	0.021 (0.014)	0.022 (0.015)	-0.006 (0.018)	-0.013 (0.042)
Hispanic	-0.020 (0.015)	-0.000 (0.011)	0.024 (0.013)	-0.018 (0.017)	-0.063 (0.038)
Asian	0.039* (0.017)	0.047** (0.015)	0.057*** (0.015)	0.064** (0.021)	0.261*** (0.044)
Female	-0.008 (0.007)	0.010 (0.006)	0.003 (0.007)	-0.009 (0.010)	0.085*** (0.020)
Parent Education	0.016* (0.008)	0.009 (0.007)	0.017* (0.008)	0.026** (0.010)	0.140*** (0.022)
Family Income	0.004 (0.003)	0.003 (0.004)	0.005 (0.003)	-0.002 (0.004)	0.047*** (0.010)
Adj. R^2	0.283	0.181	0.176	0.183	0.340
Number of observations[a]	8510	8520	8000	5730	9350

Notes: Dependent variable is the number of credits in unweighted sample. Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.
[a]In compliance with National Center for Education Statistics restricted data-licensing agreements, the number of cases in each of the cells of this table and all subsequent tables is rounded to the nearest 10.

Table 3.B4 Estimated Black-White Gap in Number of Credits with Dropout

Variables	9th	10th	11th	12th	Total
Panel A: Credit and Race without School Fixed Effect					
Black	0.009	-0.008	0.020	0.045**	-0.074*
	(0.012)	(0.012)	(0.011)	(0.014)	(0.034)
Hispanic	-0.048***	-0.078***	-0.036***	-0.058***	-0.293***
	(0.012)	(0.011)	(0.011)	(0.013)	(0.032)
Asian	0.002	-0.007	0.014	0.018	0.094*
	(0.013)	(0.012)	(0.012)	(0.014)	(0.037)
Female	0.001	0.015*	0.011	-0.016*	0.103***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.021)
Parent Education	0.031***	0.028***	0.012	0.019*	0.234***
	(0.008)	(0.007)	(0.007)	(0.009)	(0.022)
Family Income	0.013***	0.011**	0.007*	0.002	0.085***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.009)
Adj. R^2	0.009	0.013	0.005	0.007	0.047
Panel B: Credit and Race with School Fixed Effect					
Black	-0.001	0.010	0.023	-0.013	-0.025
	(0.020)	(0.018)	(0.016)	(0.019)	(0.044)
Hispanic	-0.039*	-0.028	0.001	-0.021	-0.099*
	(0.018)	(0.015)	(0.015)	(0.018)	(0.041)
Asian	0.042*	0.043**	0.051**	0.064**	0.263***
	(0.018)	(0.016)	(0.016)	(0.021)	(0.043)
Female	-0.001	0.019*	0.005	-0.008	0.104***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.021)
Parent Education	0.036***	0.032***	0.022**	0.028**	0.176***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.024)
Family Income	0.014***	0.010*	0.009**	0.000	0.062***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.011)
Adj. R^2	0.208	0.131	0.166	0.187	0.319
Number of observations	8840	8830	8120	5760	9790

Notes: Dependent variable is the number of credits in unweighted sample. Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B5 Estimated Black-White Gap in Course-Taking by Level

Variables	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Panel A: Course-taking by Level without School Fixed Effect							
Black	0.019**	0.026***	0.008	-0.007	-0.005	-0.024***	-0.018***
	(0.006)	(0.007)	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)
Hispanic	0.011	0.034***	0.012	-0.018***	-0.026***	-0.003	-0.010**
	(0.006)	(0.007)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)
Asian	-0.027***	-0.013	-0.059***	0.003	-0.010	0.036***	0.070***
	(0.007)	(0.007)	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)
Female	-0.014***	-0.009*	-0.005	0.010**	0.006*	0.007**	0.004
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
Parent Education	-0.035***	-0.047***	-0.044***	0.019***	0.027***	0.042***	0.039***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)
Family Income	-0.017***	-0.012***	-0.006**	0.008***	0.008***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.035	0.030	0.015	0.011	0.022	0.060	0.092
Panel B: Course-taking by Level with School Fixed Effect							
Black	0.046***	0.040***	-0.009	-0.014*	-0.025***	-0.018***	-0.018***
	(0.009)	(0.010)	(0.012)	(0.007)	(0.006)	(0.005)	(0.004)
Hispanic	0.037***	0.032***	-0.005	-0.022***	-0.014*	-0.016**	-0.011**
	(0.009)	(0.009)	(0.011)	(0.006)	(0.006)	(0.006)	(0.004)
Asian	-0.017*	-0.016	-0.058***	-0.002	-0.001	0.031***	0.063***
	(0.008)	(0.010)	(0.013)	(0.007)	(0.006)	(0.006)	(0.007)
Female	-0.015***	-0.012**	-0.001	0.014***	0.007*	0.007*	0.001
	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
Parent Education	-0.021***	-0.028***	-0.026***	0.012**	0.014***	0.025***	0.023***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)
Family Income	-0.011***	-0.010***	-0.000	0.004*	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.213	0.307	0.248	0.247	0.395	0.264	0.206
Panel C: Course-taking by Level with State Fixed Effect							
Black	0.023*	0.030**	0.019	-0.015	-0.015	-0.024***	-0.018***
	(0.011)	(0.009)	(0.012)	(0.009)	(0.008)	(0.005)	(0.003)
Hispanic	0.024*	0.031	-0.002	-0.020*	-0.010	-0.010	-0.012***
	(0.009)	(0.016)	(0.010)	(0.008)	(0.008)	(0.006)	(0.004)
Asian	-0.016	-0.029*	-0.075***	0.005	0.007	0.037***	0.072***
	(0.009)	(0.012)	(0.014)	(0.010)	(0.006)	(0.006)	(0.007)
Female	-0.014**	-0.009*	-0.004	0.012**	0.005	0.007	0.004
	(0.005)	(0.004)	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)
Parent Education	-0.033***	-0.048***	-0.040***	0.017***	0.027***	0.040***	0.037***
	(0.004)	(0.006)	(0.007)	(0.004)	(0.003)	(0.005)	(0.004)
Family Income	-0.017***	-0.011***	-0.006*	0.007**	0.008***	0.009***	0.009***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Adj. R^2	0.073	0.094	0.057	0.050	0.088	0.088	0.101
Number of Observations	9350	9350	9350	9350	9350	9350	9350

Notes: Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed. Level 2 (Non-Academic); Level 3 (Low); Level 4 (Middle); Level 5 (Middle 2); Level 6 (Advanced 1); Level 7 (Advanced 2); Level 8 (Advanced 3). ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B6 Estimated Black-White Gap in Course by Grade

Variables	9th Grade	10th Grade	11th Grade	12th Grade	9th Grade	10th Grade	11th Grade	12th Grade
Dependent Variable	Average Rigor by Grade				Highest Rigor by Grade			
Panel A: Rigor by Grade with School Fixed Effect								
Black	-0.187***	-0.241***	-0.365***	-0.631***	-0.185***	-0.233***	-0.332***	-0.611***
	(0.029)	(0.039)	(0.063)	(0.105)	(0.029)	(0.040)	(0.062)	(0.106)
Hispanic	-0.109***	-0.157***	-0.271***	-0.328***	-0.101**	-0.146***	-0.248***	-0.325***
	(0.031)	(0.038)	(0.062)	(0.097)	(0.033)	(0.039)	(0.061)	(0.098)
Asian	0.110**	0.355***	0.477***	0.672***	0.136***	0.377***	0.497***	0.699***
	(0.037)	(0.054)	(0.071)	(0.108)	(0.040)	(0.054)	(0.072)	(0.107)
Female	0.024	0.056**	0.076*	0.149**	0.021	0.058**	0.075*	0.136**
	(0.016)	(0.019)	(0.031)	(0.049)	(0.016)	(0.020)	(0.031)	(0.050)
Parent Education	0.109***	0.181***	0.358***	0.425***	0.115***	0.188***	0.362***	0.429***
	(0.017)	(0.021)	(0.036)	(0.054)	(0.018)	(0.021)	(0.037)	(0.055)
Family Income	0.056***	0.053***	0.111***	0.153***	0.055***	0.052***	0.111***	0.148***
	(0.008)	(0.009)	(0.015)	(0.027)	(0.008)	(0.010)	(0.015)	(0.026)
Adj. R^2	0.253	0.265	0.254	0.295	0.253	0.254	0.236	0.274
Panel B: Rigor by Grade with State Fixed Effect								
Black	-0.086**	-0.210***	-0.255**	-0.679***	-0.075*	-0.204***	-0.206**	-0.631***
	(0.031)	(0.046)	(0.078)	(0.118)	(0.030)	(0.045)	(0.074)	(0.116)
Hispanic	-0.088*	-0.117*	-0.196**	-0.459***	-0.092*	-0.120*	-0.180**	-0.448***
	(0.041)	(0.054)	(0.059)	(0.126)	(0.045)	(0.052)	(0.055)	(0.123)
Asian	0.189***	0.388***	0.532***	0.667***	0.205***	0.415***	0.565***	0.683***
	(0.036)	(0.050)	(0.078)	(0.091)	(0.030)	(0.054)	(0.079)	(0.082)
Female	0.032	0.047*	0.090**	0.137**	0.026	0.047*	0.088**	0.123**
	(0.017)	(0.020)	(0.030)	(0.043)	(0.017)	(0.021)	(0.031)	(0.042)
Parent Education	0.170***	0.288***	0.533***	0.668***	0.172***	0.287***	0.526***	0.655***
	(0.021)	(0.026)	(0.034)	(0.060)	(0.021)	(0.025)	(0.034)	(0.057)
Family Income	0.065***	0.081***	0.160***	0.211***	0.063***	0.080***	0.158***	0.202***
	(0.010)	(0.013)	(0.020)	(0.026)	(0.009)	(0.014)	(0.021)	(0.026)
Adj. R^2	0.081	0.113	0.123	0.146	0.080	0.110	0.118	0.140
Number of Observations	8510	8520	8000	5730	8510	8520	8000	5730

Notes: Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B7 Estimated Black-White Gap in Course by Grade

Variables	9th Grade	10th Grade	11th Grade	12th Grade	9th Grade	10th Grade	11th Grade	12th Grade
Dependent Variable		Average Rigor by Grade				Highest Rigor by Grade		
Rigor by Grade with School Fixed Effect								
Black	-0.187***	-0.241***	-0.365***	-0.631***	-0.185***	-0.233***	-0.332***	-0.611***
	(0.029)	(0.039)	(0.063)	(0.105)	(0.029)	(0.040)	(0.062)	(0.106)
Hispanic	-0.109***	-0.157***	-0.271***	-0.328***	-0.101**	-0.146***	-0.248***	-0.325***
	(0.031)	(0.038)	(0.062)	(0.097)	(0.033)	(0.039)	(0.061)	(0.098)
Asian	0.110**	0.355***	0.477***	0.672***	0.136***	0.377***	0.497***	0.699***
	(0.037)	(0.054)	(0.071)	(0.108)	(0.040)	(0.054)	(0.072)	(0.107)
Female	0.024	0.056**	0.076*	0.149**	0.021	0.058**	0.075*	0.136**
	(0.016)	(0.019)	(0.031)	(0.049)	(0.016)	(0.020)	(0.031)	(0.050)
Parent Education	0.109***	0.181***	0.358***	0.425***	0.115***	0.188***	0.362***	0.429***
	(0.017)	(0.021)	(0.036)	(0.054)	(0.018)	(0.021)	(0.037)	(0.055)
Family Income	0.056***	0.053***	0.111***	0.153***	0.055***	0.052***	0.111***	0.148***
	(0.008)	(0.009)	(0.015)	(0.027)	(0.008)	(0.010)	(0.015)	(0.026)
Adj. R^2	0.253	0.265	0.254	0.295	0.253	0.254	0.236	0.274

Notes: Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites.
The unit of observation is a student. Standard errors are in parentheses. Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed. ***Significant at the 1% level.
**Significant at the 5% level. *Significant at the 10% level.

Table 3.B8 Sensitivity Analysis of Course-Taking Gap

	Coefficient on Black for	Coefficient on Hispanic for	Coefficient on Asian for
By Level			
Low	0.042***	0.038***	-0.010
	(0.012)	(0.011)	(0.010)
Middle	0.072***	0.044*	-0.107***
	(0.020)	(0.021)	(0.023)
Advanced	-0.114***	-0.082***	0.117***
	(0.020)	(0.020)	(0.023)
AP	-0.048***	-0.033**	0.175***
	(0.011)	(0.013)	(0.021)
Panel A: Low Intensity			
Low in 9th Grade	0.088***	0.054**	-0.024
	(0.017)	(0.016)	(0.016)
Low in 10th Grade	0.060***	0.038**	-0.037*
	(0.015)	(0.014)	(0.015)
Low in 11th Grade	0.028*	0.023	-0.025*
	(0.013)	(0.012)	(0.011)
Low in 12th Grade	0.046***	0.024*	-0.016
	(0.013)	(0.011)	(0.011)
Panel B: Mid Intensity			
Mid in 9th Grade	-0.102***	-0.068***	0.002
	(0.021)	(0.019)	(0.020)
Mid in 10th Grade	-0.063**	-0.050**	-0.045
	(0.020)	(0.019)	(0.025)
Mid in 11th Grade	0.066**	0.021	-0.079**
	(0.022)	(0.021)	(0.026)
Mid in 12th Grade	0.053**	0.029	-0.037*
	(0.016)	(0.015)	(0.016)
Panel C: Advanced Intensity			
Advanced in 9th Grade	-0.014	-0.001	0.023*
	(0.007)	(0.008)	(0.010)
Advanced in 10th Grade	-0.026*	-0.020*	0.087***
	(0.010)	(0.010)	(0.019)
Advanced in 11th Grade	-0.097***	-0.064***	0.126***
	(0.018)	(0.018)	(0.022)
Advanced in 12th Grade	-0.082***	-0.048**	0.120***
	(0.020)	(0.018)	(0.024)
Panel D: AP Course			
AP in 11th Grade	-0.005	0.003	0.072***
	(0.005)	(0.006)	(0.014)
AP in 12th Grade	-0.045***	-0.033**	0.153***
	(0.011)	(0.013)	(0.021)

Notes: Specifications in this table are variations on those reported in Table **??**. Only the race coefficients are reported. School fixed effects are included. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B9 Estimated Black-White Gap in Timing of Highest-Level

	Coefficient on Black for	Coefficient on Hispanic for	Coefficient on Asian for
11th Grade			
Total	0.010	0.007	-0.076**
	(0.022)	(0.020)	(0.023)
No Math in 12th Grade	0.003	0.004	-0.045*
	(0.020)	(0.020)	(0.022)
Lower Level in 12th Grade	0.007	0.003	-0.031*
	(0.011)	(0.009)	(0.013)
12th Grade			
Total	-0.005	-0.014	0.093***
	(0.022)	(0.020)	(0.024)
No Math in 11th Grade	0.010	0.005	-0.021
	(0.010)	(0.009)	(0.011)
Lower Level in 11th Grade	-0.021	-0.031	0.066*
	(0.021)	(0.019)	(0.026)
Same Level in 11th Grade	0.007	0.012	0.047**
	(0.013)	(0.012)	(0.016)

Notes: Specifications in this table are variations on those reported in Table **??**. Only the race coefficients are reported. School fixed effects are included. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B10 Estimated Black-White Gap in Timing of Highest-Level in Grade 12

	Coefficient on Black for	Coefficient on Hispanic for	Coefficient on Asian for
Public School			
Total	-0.000	-0.010	0.112***
	(0.026)	(0.023)	(0.028)
No Math in 11th Grade	0.014	0.005	-0.022
	(0.012)	(0.010)	(0.013)
Lower Level in 11th Grade	-0.025	-0.038	0.091**
	(0.023)	(0.022)	(0.028)
Same Level in 11th Grade	0.010	0.023	0.043**
	(0.014)	(0.014)	(0.016)
Private School			
Total	-0.043	-0.011	-0.090
	(0.080)	(0.098)	(0.065)
No Math in 11th Grade	-0.024	-0.015	-0.008
	(0.024)	(0.032)	(0.029)
Lower Level in 11th Grade	0.014	-0.056	-0.210*
	(0.076)	(0.094)	(0.091)
Same Level in 11th Grade	-0.033	0.060	0.127
	(0.055)	(0.044)	(0.093)
Catholic School			
Total	0.004	-0.019	0.068
	(0.051)	(0.042)	(0.053)
No Math in 11th Grade	-0.004	0.010	-0.008
	(0.016)	(0.018)	(0.015)
Lower Level in 11th Grade	0.014	0.019	0.027
	(0.055)	(0.039)	(0.077)
Same Level in 11th Grade	-0.006	-0.048*	0.050
	(0.033)	(0.023)	(0.057)

Notes: Specifications in this table are variations on those reported in Table **??**. Only the race coefficients are reported. School fixed effects are included. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.B11 Estimated Black-White Gap in Grade 12 Test

Specifications	Coefficient on Black for	Coefficient on Hispanic for	Coefficient on Asian for
Total	-0.647**	-0.267	0.898***
	(0.226)	(0.198)	(0.266)
Panel A: By Course Level			
Low Level			
11th Grade	0.509	-1.005	-0.398
	(1.389)	(1.026)	(1.526)
12th Grade	1.179	1.977	1.272
	(1.190)	(1.153)	(1.859)
Mid Level			
11th Grade	-0.361	0.106	0.234
	(0.304)	(0.283)	(0.405)
12th Grade	-1.014	-0.309	0.312
	(0.945)	(0.854)	(1.197)
Advanced Level			
11th Grade	-1.704**	-0.462	1.426**
	(0.615)	(0.502)	(0.516)
12th Grade	-1.116**	-0.051	1.381***
	(0.374)	(0.348)	(0.399)
Panel B: Timing of Highest-Level Achieved			
In 12th Grade			
Total	-0.916**	-0.295	1.205**
	(0.308)	(0.296)	(0.367)
No Math in 11th Grade	-1.431	-2.247	0.036
	(1.980)	(2.341)	(5.178)
Lower Level in 11th Grade	-0.800*	0.005	1.143**
	(0.381)	(0.339)	(0.430)
Same Level in 11th Grade	-1.583	-0.751	1.62
	(1.565)	(1.350)	(1.482)
In 11th Grade			
Total	-0.408	-0.17	0.470
	(0.437)	(0.397)	(0.550)
No Math in 12th Grade	-0.371	-0.35	0.446
	(0.494)	(0.456)	(0.590)
Lower Level in 12th Grade	-0.358	0.093	-1.156
	(1.530)	(1.507)	(2.617)

Notes: Dependent variable is standardized math test score in Grade 12. Controls are gender, race, parental education, family income, and standardized math test score in 10th grade. Only the race coefficients are reported. School fixed effects are included.
***Significant at the 1% level. **Significant at the 5% level.
*Significant at the 10% level.

APPENDIX C

ADDITIONS FOR CHAPTER 3

C. Black-White Achievement Gap

Table 3.D5 summarizes ordinary least squares estimation results of racial math score gap in Grade 10 and unconditional black-white achievement gap is 8.61 point or 0.90 standard deviation and adding gender information does not change the gap significantly. When family SES and income are included, the black-white gap decreases by 30% and Hispanic-white gap decreases by 44%, and one standard deviation increase in family SES improves math score by 0.34 standard deviation.[20] Students from families, who regularly receive magazine and have both computer, and more than 50 books at home. have around 0.5 standard deviation score higher compared to those without magazine, computer, and more than 50 books at home. To capture bias in teacher's perceptions or interaction with students, teacher race dummy is included, which is equal to one when teacher and student have the same race. Students taught by math teachers with the same race have statistically-significantly higher score but the effect is relatively small: 0.07 standard deviation.[21] Addition of a series of covariates to the regression decreases the black-white gap by 42% and the Hispanic-white gap by 62% whereas the Asian-white gap enlarges. School fixed effect is included in column 6 to account for across school variation such as school SES, racial composition, and teacher quality, but changes in the black-white gap are not statistically distinguishable from zero.

Table 3.D6 presents estimation results for 12th graders to explore whether the racial gap in math achievement is changed in the last two years of high school. The black-white math score gap is similar in Grade 12 until 10th grade math score is added. Estimates in column 4 reflect how variation in learning between Grade 10 and 12 accounts for changes in math scores. Coefficients on black dummy drops by more than 90% and the effect is around 0.04 standard deviation, implying that the majority of the math achievement gap in Grade 12 is explained by previous test scores.[22] Family SES and income still contributes to the achievement gap over the last two years but the

[20]Estimates do not change significantly when a combination of parental education and occupation dummies are used in place of family SES.

[21]Note that 85% of white students have white teachers whereas 13% of blacks have black teachers. 6% of Hispanic and Asian students have teachers of the same race, and the estimates in column 5 might over-represent white students.

[22]When 9th grade GPA is included to estimate the score gap for 10th graders, the coefficient slightly changes from -4.975 (column 5 in Table 3.D5) to -4.661.

effects are not meaningfully large. When school fixed effect and other covariates are included, the black-white gap and the Hispanic-white gap become statistically not significant.

Table 3.D7 displays the sensitivity of estimated math achievement gaps. Each row is estimated separately and only coefficients and corresponding standard errors for each race dummy are reported. Baseline estimates refer to those in column 5 in Tables 3.D5 and 3.D6. Estimates are robust to sample weight and alternative test measures. Next, the sample is divided into several subgroups - gender, family SES quintile, family composition, and school sector. Male minority students seemed to perform better relative to whites than do females and it is most apparent among Hispanics. The relationship between family SES and test score gap is mixed across race. The black-white gap does not seem to relate significantly with family SES, whereas the Asian-white gap tends to enlarge for the highest SES subgroup. Family composition seems related to achievement gap; students living with both parents have smaller score gap than those living with a single mother, and the difference is largest among Hispanic students.[23] Black and hispanic children living with a single mother have the largest score gap relative to whites. When divided by school sectors to account for the fact that course-taking requirement and options vary significantly by sectors, the achievement gap is largest among public schools and smallest among private schools.

If there are heterogeneous responses in racial gaps to covariates by each racial group, full-sample analysis might understate or overstate the achievement gap. Table 3.D8 summarizes coefficient estimates that replicate column 5 in Table 3.D5 estimated separately by each racial subgroup. Responsiveness to gender does not seem to differ by race but that of family SES tells different story; one standard deviation improvement in family SES has the least impact on test score increase for black students. On the other hand, black students' math score is more responsive to an increase in family income than white peers'. Thus if one tries to analyze the effect of family background improvement, baseline results are likely to understate black-white test gap. Interestingly black students taught by black math teachers on average have lower test scores than their peers

[23]Among whites, 64% live with both parents, whereas 37% of black students do. Notably 38% of black students and 17% of Hispanics live with single mother.

taught by white, Hispanic, or Asian math teachers.[24]

Table 3.D9 shows the same analysis for 12th graders. The first column is the replication of column 5 in Table 3.D6. Black students benefit the least by one standard deviation improvement in family SES, and the effect endures for the last two-years of high school. Thus if family SES is improved by the same rate, unconditional test score gap between black and white students would be larger in Grade 12 than in Grade 10. Results show that black students taught by black math teachers increase math score by 1 point between Grade 10 and 12, which is somewhat different from results in Table 3.D8. But the mechanism of the effect of teachers' race on students' achievements remain for future research until further information on math teachers (what they teach and when they teach) become accessible.

[24]Since each student has one entry for math teacher's race, it is not certain when the teacher taught which math course.

APPENDIX D

SUPPLEMENTAL TABLES FOR CHAPTER 3

Table 3.D1 Highest Level of Math by Race and Grade

Variable	Full Sample	White	Black	Hispanic	Asian
Highest Level of Math:					
9th Grade	3.845	3.863	3.750	3.730	4.038
10th Grade	4.231	4.251	3.996	4.062	4.644
11th Grade	5.167	5.217	4.847	4.875	5.683
12th Grade	6.055	6.185	5.300	5.507	6.748
Average of Level of Math:					
9th Grade	3.814	3.838	3.712	3.694	3.983
10th Grade	4.192	4.213	3.952	4.027	4.584
11th Grade	4.192	4.213	3.952	4.027	4.584
12th Grade	5.107	5.169	4.746	4.812	5.604
Highest Level of Math- Low:					
9th Grade	0.188	0.177	0.229	0.235	0.136
10th Grade	0.114	0.102	0.149	0.150	0.070
11th Grade	0.070	0.064	0.082	0.097	0.047
12th Grade	0.060	0.053	0.097	0.078	0.040
Highest Level of Math- Middle:					
9th Grade	0.696	0.724	0.625	0.630	0.711
10th Grade	0.733	0.767	0.674	0.680	0.695
11th Grade	0.502	0.495	0.577	0.529	0.415
12th Grade	0.133	0.114	0.187	0.185	0.111
Highest Level of Math- Advanced:					
9th Grade	0.026	0.024	0.025	0.020	0.052
10th Grade	0.064	0.061	0.027	0.035	0.169
11th Grade	0.284	0.301	0.182	0.204	0.414
12th Grade	0.419	0.453	0.307	0.289	0.543

Notes: Entries are means of student-level data who are not missing math scores, race, and SES variable.

Table 3.D2 Most Common Courses

	Most Common Course			Most Common Level	
	Course Title	Course Level	Percent	Course Level	Percent
Full Sample					
	Geometry	Middle	19.97	Middle	42.59
	Algebra 2	Middle 2	17.83	Middle 2	19.48
	Algebra 1	Middle	17.73	Advanced 1	9.52
	Analysis, Introductory	Advanced 2	8.44	Low	8.62
	Algebra and Trigonometry	Advanced 1	3	Advanced 2	8.44
White					
	Geometry	Middle	20.37	Middle	42.7
	Algebra 2	Middle 2	18.43	Middle 2	19.99
	Algebra 1	Middle	17.5	Advanced 1	10.31
	Analysis, Introductory	Advanced 2	8.72	Advanced 2	8.72
	Algebra and Trigonometry	Advanced 1	3.15	Low	7.69
Black					
	Geometry	Middle	21.28	Middle	44.78
	Algebra 1	Middle	19.67	Middle 2	18.81
	Algebra 2	Middle 2	17.34	Low	11.49
	Analysis, Introductory	Advanced 2	5.05	Advanced 1	9.26
	Algebra and Trigonometry	Advanced 1	3.91	Non	8.48
Hispanic					
	Algebra 1	Middle	20.7	Middle	45.11
	Geometry	Middle	20.27	Middle 2	17.76
	Algebra 2	Middle 2	16.48	Low	12.45
	Analysis, Introductory	Advanced 2	7.48	Advanced 2	7.48
	Pre-Algebra	Low	3.92	Non	7.41
Asian					
	Algebra 2	Middle 2	17.03	Middle	36.72
	Geometry	Middle	16.27	Middle 2	19.45
	Algebra 1	Middle	13.33	Advanced 3	12.97
	Analysis, Introductory	Advanced 2	12.19	Advanced 2	11.99
	AP Calculus	Advanced 3	6.55	Advanced 1	8.88

Notes: Entries are means of student-level data of who are not missing math scores, race, and SES variable.

Table 3.D3 Summary Statistics Including Dropout by Race

Variable	Full Sample	White	Black	Hispanic	Asian
Credit:					
Total Credit	3.260	3.341	3.177	2.949	3.408
Average per year	0.703	0.723	0.752	0.633	0.627
Course Level:					
Highest Level of Math	5.656	5.767	5.222	5.177	6.343
Average per year	4.495	4.567	4.176	4.202	4.978
Level of First Course	3.810	3.844	3.704	3.671	4.002
Highest Level of Math:					
Low Level	0.063	0.052	0.086	0.094	0.034
Middle Level	0.437	0.411	0.517	0.547	0.330
Advanced Level	0.500	0.537	0.397	0.359	0.635
AP	0.117	0.112	0.043	0.065	0.319
Timing of Achieving the Highest Level of Math:					
10th Grade	0.127	0.127	0.110	0.138	0.102
11th Grade	0.319	0.311	0.367	0.370	0.244
12th Grade	0.509	0.523	0.453	0.436	0.626
Missing Math Class in:					
9th Grade	0.097	0.079	0.130	0.129	0.110
10th Grade	0.098	0.077	0.161	0.148	0.075
11th Grade	0.170	0.159	0.196	0.207	0.138
12th Grade	0.412	0.400	0.439	0.483	0.324
Other Controls:					
Public	0.756	0.700	0.857	0.815	0.885
Private	0.095	0.124	0.041	0.036	0.063
Catholic	0.149	0.176	0.102	0.150	0.052
FRL School	2.124	1.748	3.255	2.970	1.867
Parent Education	0.433	0.470	0.351	0.268	0.539
Family Income	9.206	9.747	7.983	8.286	8.707
Drop out	0.044	0.032	0.062	0.074	0.030
On-time Graduation	0.956	0.968	0.938	0.926	0.970
Test Score:					
10th Grade	51.715	53.875	45.453	46.886	53.245
12th Grade	48.906	51.121	41.852	43.196	53.397

Notes: Entries are means of student-level data on who are not missing math scores, race, and SES variable. The highest level of math is divided into three groups, Low for levels 2 and 3, Middle for levels 4 and 5, and Advanced for levels 6, 7, and 8. Free reduced lunch (FRL) school is a categorical variable ranging from one to seven corresponding to each FRL ratio (1 for 0-5%; 2 for 6-10%; 3 for 11-20%; 4 for 21-30%; 5 for 31-50%; 6 for 51-75%; and 7 for 76-100%.)
Parental education is coded one if the highest education level is higher than 4-year college and zero otherwise. Family income is recoded by taking the midpoint of each income category and log transformed.

Table 3.D4 Estimated Black-White Gap in Timing of Highest-Level in Grade 11

	Coefficient on Black for	Coefficient on Hispanic for	Coefficient on Asian for
Public School			
Total	0.006	-0.001	-0.087**
	(0.025)	(0.024)	(0.027)
No Math in 12th Grade	-0.005	-0.004	-0.051*
	(0.023)	(0.024)	(0.026)
Lower Level in 12th Grade	0.011	0.003	-0.036*
	(0.013)	(0.011)	(0.014)
Private School			
Total	0.008	0.047	0.028
	(0.078)	(0.100)	(0.067)
No Math in 12th Grade	0.032	-0.011	0.015
	(0.061)	(0.088)	(0.060)
Lower Level in 12th Grade	-0.023	0.058	0.013
	(0.042)	(0.037)	(0.050)
Catholic School			
Total	0.019	0.030	-0.087
	(0.051)	(0.036)	(0.046)
No Math in 12th Grade	0.028	0.041	-0.069
	(0.048)	(0.041)	(0.051)
Lower Level in 12th Grade	-0.009	-0.011	-0.017
	(0.016)	(0.019)	(0.030)

Notes: Specifications in this table are variations on those reported in Table **??**. Only the race coefficients are reported. School fixed effects are included. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.D5 Estimated Black-White Math Score Gap in Grade 10

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Black	-8.612***	-8.560***	-6.051***	-5.390***	-4.975***	-4.873***
	(0.289)	(0.288)	(0.275)	(0.299)	(0.353)	(0.445)
Hispanic	-6.683***	-6.662***	-3.751***	-2.988***	-2.529***	-2.183***
	(0.273)	(0.272)	(0.261)	(0.282)	(0.349)	(0.463)
Asian	0.706**	0.707**	2.080***	2.413***	2.874***	1.897***
	(0.309)	(0.308)	(0.288)	(0.304)	(0.368)	(0.503)
Female		-1.412***	-1.144***	-1.412***	-1.413***	-1.485***
		(0.178)	(0.165)	(0.172)	(0.172)	(0.189)
SES			2.965***	2.696***	2.698***	2.133***
			(0.118)	(0.126)	(0.126)	(0.148)
Family Income			0.363***	0.262***	0.262***	0.202***
			(0.051)	(0.055)	(0.055)	(0.061)
Magazine				0.763***	0.754***	0.628**
				(0.221)	(0.221)	(0.270)
Book				1.695***	1.688***	1.440***
				(0.261)	(0.261)	(0.278)
Computer				2.240***	2.231***	2.023***
				(0.327)	(0.327)	(0.363)
Teacher Race					0.584**	0.562
					(0.263)	(0.378)
School FE	N	N	N	N	N	Y
R^2	0.119	0.124	0.251	0.250	0.250	0.374
Number of observations	10280	10280	10280	9110	9110	9110

Notes: Dependent variable is standardized math score in unweighted sample. Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Magazine is equal to one if family regularly received magazine and zero otherwise. Book is equal to one if family has more than 50 books. Computer is equal to one if family has a computer. Teacher race is equal to one if teacher and student have the same race.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.D6 Estimated Black-White Math Score Gap in Grade 12

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Black	-8.443***	-8.381***	-5.600***	-0.351**	-0.471**	-0.256
	(0.300)	(0.299)	(0.283)	(0.156)	(0.199)	(0.274)
Hispanic	-6.416***	-6.391***	-3.181***	0.073	0.15	-0.042
	(0.284)	(0.283)	(0.269)	(0.146)	(0.196)	(0.229)
Asian	1.623***	1.625***	3.151***	1.346***	1.360***	1.198***
	(0.322)	(0.321)	(0.297)	(0.160)	(0.206)	(0.256)
Female		-1.691***	-1.395***	-0.403***	-0.514***	-0.547***
		(0.185)	(0.169)	(0.091)	(0.096)	(0.104)
SES			3.226***	0.653***	0.583***	0.368***
			(0.122)	(0.067)	(0.072)	(0.097)
Family Income			0.423***	0.108***	0.107***	0.067*
			(0.052)	(0.028)	(0.031)	(0.037)
Previous Test				0.868***	0.860***	0.850***
				(0.005)	(0.006)	(0.009)
Magazine					0.071	0.064
					(0.123)	(0.134)
Book					0.604***	0.563***
					(0.146)	(0.164)
Computer					0.168	0.246
					(0.183)	(0.197)
Teacher Race					-0.100	-0.044
					(0.147)	(0.168)
School FE	N	N	N	N	Y	Y
R^2	0.110	0.117	0.261	0.786	0.781	0.807
Number of observations	10280	10280	10280	10280	9110	9110

Notes: Dependent variable is standardized math score in unweighted sample. Non-Hispanic whites are the omitted race category, so all race coefficients are gaps relative to whites. The unit of observation is a student. Standard errors are in parentheses. Previous test refers to math standardized score in 10th grade. Magazine is equal to one if family regularly received magazine and zero otherwise. Book is equal to one if family has more than 50 books. Computer is equal to one if family has a computer. Teacher race is equal to one if teacher and student have the same race.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.D7 Sensitivity Analysis of Math Achievement Gap

Specifications	Coefficient on Black for 10th	12th	Coefficient on Hispanic for 10th	12th	Coefficient on Asian for 10th	12th
Baseline	-4.975***	-0.471**	-2.529***	0.15	2.874***	1.360***
	(0.353)	-0.199	(0.349)	-0.196	(0.368)	-0.206
Weighted	-5.109***	-0.559***	-2.546***	0.075	2.984***	1.526***
	(0.338)	(0.188)	(0.339)	(0.186)	(0.482)	(0.265)
Other test score measures:						
Math IRT estimated number right for 2002 scorers	-6.300***	-0.576***	-3.240***	-0.161	3.141***	-0.049
	(0.425)	(0.148)	(0.420)	-0.145	(0.442)	(0.153)
By Gender:						
Males	-4.565***	-0.758**	-1.521***	-0.363	3.417***	0.920***
	(0.553)	(0.311)	(0.533)	(0.298)	(0.554)	(0.311)
Females	-5.389***	-0.219	-3.425***	0.611**	2.357***	1.763***
	(0.455)	(0.259)	(0.459)	(0.259)	(0.489)	(0.275)
By SES quintile:						
Top	-5.198***	-0.886*	-2.202***	-0.265	3.451***	0.196
	(0.837)	(0.475)	(0.801)	(0.452)	(0.686)	(0.389)
Second	-4.840***	-1.023**	-1.910**	0.119	2.843***	1.505***
	(0.739)	(0.413)	(0.745)	(0.413)	(0.745)	(0.413)
Third	-5.495***	0.182	-2.942***	-0.264	2.259***	2.178***
	(0.670)	(0.372)	(0.695)	(0.382)	(0.817)	(0.448)
Bottom	-4.859***	-0.218	-3.586***	0.689*	1.822**	1.666***
	(0.671)	(0.385)	(0.653)	(0.372)	(0.740)	(0.420)
By Family Composition:						
Live with both Parents	-4.756***	-0.452	-1.638***	0.223	3.227***	1.442***
	(0.515)	(0.291)	(0.442)	(0.248)	(0.441)	(0.248)
Live with One Guardian and either with Father or Mother	-4.477***	-0.433	-3.536***	0.036	0.435	0.276
	(0.923)	(0.488)	(0.869)	(0.458)	(1.050)	(0.550)
Live with Single Mother	-5.371***	-1.060**	-3.968***	-0.062	3.253***	1.590***
	(0.710)	(0.424)	(0.859)	(0.507)	(1.048)	(0.616)
By School Sector:						
Public	-4.981***	-0.378*	-2.579***	0.178	3.210***	1.599***
	(0.399)	(0.223)	(0.406)	(0.225)	(0.415)	(0.231)
Private	-2.862*	0.399	-1.985	0.264	1.721	1.361*
	(1.489)	(0.939)	(1.420)	(0.894)	(1.310)	(0.825)
Catholic	-4.912***	-1.164**	-2.054**	-0.177	1.345	0.166
	(0.956)	(0.517)	(0.820)	(0.441)	(1.193)	(0.640)

Notes: Specifications in this table are variations on those reported in column 5 in Table B.1 and B.2. Only the race coefficients are reported. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.D8 Estimated Black-White Math Score Gap by Race in Grade 10

Variables	Full-sample	White	Black	Hispanic	Asian
Black	-4.975***				
	(0.353)				
Hispanic	-2.529***				
	(0.349)				
Asian	2.874***				
	(0.368)				
Female	-1.413***	-1.352***	-1.123**	-1.914***	-1.463**
	(0.172)	(0.210)	(0.493)	(0.525)	(0.648)
SES	2.698***	2.798***	1.844***	2.505***	2.679***
	(0.126)	(0.162)	(0.371)	(0.349)	(0.408)
Family Income	0.262***	0.218***	0.474***	0.348**	0.224
	(0.055)	(0.074)	(0.133)	(0.143)	(0.179)
Magazine	0.754***	1.211***	0.627	-0.017	0.028
	(0.221)	(0.297)	(0.572)	(0.573)	(0.704)
Book	1.688***	1.972***	1.276**	0.727	2.503***
	(0.261)	(0.366)	(0.598)	(0.620)	(0.889)
Computer	2.231***	2.725***	0.775	2.726***	5.245***
	(0.327)	(0.497)	(0.633)	(0.712)	(1.633)
Teacher Race	0.584**	1.231***	-2.197***	-0.210	-2.314*
	(0.263)	(0.295)	(0.715)	(1.096)	(1.380)
R^2	0.250	0.158	0.168	0.181	0.184
Number of Observations	9110	5780	930	1090	860

Notes: The dependent variable is standardized math score in Grade 10. The first column replicates column 5 in Table 3.B3. Other columns report estimates within a specific race. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 3.D9 Estimated Black-White Math Score Gap by Race in Grade 12

Variables	Full-sample	White	Black	Hispanic	Asian
Black	-0.471**				
	(0.199)				
Hispanic	0.150				
	(0.196)				
Asian	1.360***				
	(0.206)				
Female	-0.514***	-0.638***	-0.538*	-0.128	-0.162
	(0.096)	(0.118)	(0.278)	(0.291)	(0.361)
SES	0.583***	0.661***	0.551***	0.306	0.437*
	(0.072)	(0.093)	(0.211)	(0.197)	(0.232)
Family Income	0.107***	0.089**	0.132*	0.220***	0.100
	(0.031)	(0.042)	(0.075)	(0.079)	(0.099)
Previous Test	0.860***	0.871***	0.857***	0.831***	0.849***
	(0.006)	(0.007)	(0.019)	(0.017)	(0.019)
Magazine	0.071	0.356**	-0.561*	0.171	(0.346)
	(0.123)	(0.167)	(0.322)	(0.316)	(0.391)
Book	0.604***	0.686***	0.514	0.414	1.061**
	(0.146)	(0.206)	(0.337)	(0.342)	(0.495)
Computer	0.168	-0.132	0.318	0.301	0.434
	(0.183)	(0.279)	(0.356)	(0.396)	(0.912)
Teacher Race	-0.100	-0.287*	1.016**	0.063	-0.460
	-0.147	(0.166)	(0.404)	(0.605)	(0.767)
R^2	0.781	0.759	0.756	0.755	0.759
Number of Observations	9110	5780	930	1090	860

Notes: The dependent variable is standardized math score in Grade 12. The first column replicates column 5 in Table B.2. Other columns report estimates within a specific race. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

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