The impact of intellectual heterogeneity on academic performance in business education

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ABSTRACT

This study extends previous lines of research which have identified academic achievement determinates among undergraduate business students by analyzing the impact of intellectual variance on business education. A quantile regression approach is utilized to estimate whether the returns on certain student characteristics, most notably the variance in intellectual ability as signaled by ACT score distribution across student cohorts in undergraduate business programs, differ along the conditional distribution of their Major Field Test in Business (MFT-B) test scores. A systematic examination of the relationship between academic ability (using the ACT as a proxy) and academic achievement (measured by the MFT-B) found no significant effects of either hetero- or homogeneity in academic ability variance on academic achievement for high ability students. There was also no support for contentions that high ability students might be disadvantaged by the presence of low ability colleagues. Quite interestingly a positive and significant effect was found for lower ability students from 20th to 50th percentile of the MFT-B distribution. While intellectual or academic ability, as signaled by the ACT, certainly appears relevant in terms of individual achievement, there is no indication that an admissions policy which creates cohorts with heterogeneity of innate intellectual ability has any significant impact on the academic achievement high ability individuals and may in fact benefit lower ability individuals within that cohort. Limitations and further research opportunities are discussed.

Key Words: Academic Achievement, Intellectual Capability, Quantile Regression

INTRODUCTION

Anyone who has made even the briefest visit to a college of business faculty lounge or attended one of their faculty meetings will have almost certainly encountered strongly held opinions regarding the impact of student intellectual ability variance on teaching and academic achievement. Strong contentions regarding the impact of students perceived to have intellectual capabilities at the tails of the distribution are often expressed. Advocates for higher admission standards may contend that low capacity students inhibit or hold back the learning of their intellectually better endowed, capable classmates. Is that true? We seek to answer this question by utilizing a large, multi-year sample collected from graduates of an Association to Advance Collegiate Schools of Business (AACSB) accredited college of business at a Carnegie I, land grant institution. This study seeks to extend previous lines of research which have identified academic achievement determinants among undergraduate business students (e.g. Bielinska-Kwapisz, *et al*., 2012) by analyzing the impact of intellectual variance on business education. This is enabled by the use of a quantile regression approach which reveals effects at different points of the distribution. The degree of variance in intellectual ability is measured by the variance in ACT scores in a particular student cohort.

Whatever the stock of decision factors utilized in a business student's selection of a major field of study, those preferences and inclinations will eventually interact with opportunity, options, and admission standards to create a cohort of students studying business with an emphasis on a particular discipline at a college of business. The unifying factor in the resultant cohort is, of course, the common interest in pursuing a certain field of study. However, admission standards' vagaries and imprecisions will inevitably create some degree of variation in intellectual capability across the cohort. We study the previously un-researched impact of that intellectual variation on the outcomes and academic achievement eventually realized by the individuals in a post-secondary student cohort. The uniqueness of the data set used lies in the fact that all students were tested by the same entry exam (ACT) and the same exit exam (MFT-B) but were organized into cohorts (majors) during their courses of study.

The Major Field Test in Business (MFT-B) is published by the Educational Testing Service (ETS), and is an assessment instrument designed for use in schools offering undergraduate business programs. The ETS describes the MFT-B as being constructed according to specifications developed and reviewed by subject matter expert committees so as to go beyond the mere measurement of factual knowledge and to evaluate students' ability to analyze and solve problems, understand relationships, and interpret material from their major field of study (Educational Testing Service [ETS], 2010). The ETS reports that the MFT-B was administered to 181,488 individuals at 685 different institutions between 2006 and 2010. Martell (2007) reported that, in 2006, 46% of business schools used the MFT-B test in their assessment of students' learning. The test contains 120 multiple-choice items covering the components of a common body of knowledge for undergraduate business education in the following proportions: accounting (15%), management (15%), economics (13%), finance (13%), marketing (13%), qualitative analysis (11%), information systems (10%), legal and social environment (10%), and international considerations of modern business operations (12% overlapping with the rest). The scores on the MFT-B range from 120 to 200 and ETS reports the mean score as 153.1 with a standard deviation of 14.1 from 2006 to 2010 (ETS, 2011).

A number of studies have examined the effect of students' characteristics on performance on the MFT-B (e.g. Bielinska-Kwapisz *et al.,* 2012a, Bielinska-Kwapisz 2012b; Zeis *et al*., 2009; Bycio and Allen, 2007; Bean and Bernardi, 2002; Stoloff and Feeney, 2002; Mirchandani, *et al*., 2001; Allen and Bycio, 1997). However, all previous researchers have relied on estimation using the Ordinary Least Squares (OLS) regression which estimates the mean effect of students' characteristics on their MFT-B scores. While estimating how "on average" students' characteristics effect performance is an important contribution to the understanding of the dispositional factors which predict or explain academic achievement, it is also interesting to see the effects at different points of the test score distribution. Quantile regression has two particularly attractive features as compared to OLS. First, it allows the examination of covariates effects on MFT-B scores along the entire MFT-B score distribution, providing a much more detailed data description and analysis. Second, while OLS is sensitive to the presence of outliers, quantile regression is more robust (Cameron and Trivedi, 2005).

The previously cited studies consistently identified ACT scores, GPA, gender, motivation, and business major as having a significant predictive relationship with MFT-B scores (for a complete literature review see Bielinska-Kwapisz *et al*., 2012a). While controlling for all these factors, we extend this line of research by including the variance in ACT scores to the list of predictors. In order to illuminate intellectual variance's impact on achievement, we are informed by the theoretical framework and extensive examination of this issue in the K-12 arena.

REVIEW OF LITERATURE

A review of the literature does not reveal any specific studies of the impact of intellectual variation on performance in undergraduate business programs, or in higher education generally for that matter. However, ability grouping, the practice of dividing students for instruction according to their learning capacity is a common practice in the K-12 arena and has been extensively studied. But after more than a half-century of analysis, ability grouping's educational impact remains in dispute. Proponents of ability grouping argue that it is an effective and appropriate response to intellectual variation among students, and that it allows teachers to provide appropriate instructional approaches for their students (National Education Association [NEA], 1990; Wilson and Schmits, 1978). On the other hand, opponents contend that ability grouping has significant undesirable consequence. They argue that when divided on the basis of academic ability, classes also tend to be segregated by social and economic characteristics (Oakes, 1990; Rosenbaum, 1976), and for a variety of reasons the low ability groups receive instruction inferior to that provided to high ability students (Oakes, 1985; Page, 1991). As an example, in a study of over 90 honors, regular, and remedial eighth and ninth grade English classes, Gamoran *et al.* (1995) concluded that both the quality of instruction and student outcomes were inferior in the low ability classes as compared to the high ability classes.

In 1997, Chicago public schools ended remedial classes and mandated college-preparatory coursework for all students, without regard to student ability or inclination. Nomi (2010), using an interrupted time series cohort design, concluded that although the policy resulted in more students completing the ninth grade with algebra and English course credits, failure rates increased, grades declined slightly, test scores did not improve, and students were no more likely to enter college. On the other hand, in a within-class grouping meta-analysis of 20 effect sizes, Lou *et al.* (1996) found a significantly positive learning effect of homogeneous ability grouping. Betts and Shkolnik (2000) found that a school policy of grouping students by ability had little effect on average math achievement growth and little or no differential effects of grouping for high-achieving, average or low-achieving students. Using a quasi-experimental cohort design Burris *et al*. (2006) examined the effects of providing an accelerated mathematics curriculum in heterogeneously grouped middle school classes and concluded that the probability of completion increased significantly across all achievement categories. Finally, two major sets of meta-analyses have been completed by Kulik and Kulik (1991) and Slavin (1987, 1990). By performing a re-analysis of findings from all the studies included in these two sets of studies, Kulik (2004) concluded that higher aptitude students usually benefit from ability grouping. The effect is small when little or no adjustment to the curriculum is made, but larger if special classes with accelerated curriculum are offered, while grouping has less influence on middle and lower aptitude learners.

Clearly, academic outcomes determinates are multifactorial and complex, but the K-12 experience does not seem to provide us with a clear indication of the contribution of ability grouping or intellectual variation on those outcomes. This unresolved debate, with logical positions and evidence both pro and con, does identify an element of the post-secondary educational setting which is presently unexamined and which, despite the absence of evidence, elicits strong opinions, contentions, and advocacy and seems deserving of more systematic consideration. The K-12 studies also provide examples of methodological approaches for that examination. For instance, another set of literature compares the impact of student diversity in K-12 education using international data. Michaelowa and Bourdon (2006) used the International PISA data and found no support for a negative impact of intellectual heterogeneity on performance, and in some cases the effect was even positive. Vandenberghe (2002) studied the peer effects and concluded that for a given level of the average peer effect, ability heterogeneity decreased students' achievement in both math and science. These results are in almost perfect opposite to those of Zimmer and Toma (2000). But despite what these studies lack in terms of agreement on findings, they do have a common methodology in that they examined the effect of diversity on an average student. The methodology is this study is similar to the one presented in these international studies; however, through the use of quantile regression approach, it was possible to determine the effects of heterogeneity on the high and low achieving students.

HYPOTHESES

The K-12 research on ability grouping, while still in process regarding the impact on academic achievement, informs this study of the impact of intellectual heterogeneity in post-secondary business education. Two hypotheses, one in regard to overall cohort impact and the other examining the specific impact on high ability students are derived.

Hypothesis 1: Academic cohorts with heterogeneous distributions of academic ability will have lower average levels of academic achievement than similarly situated academic cohorts with homogeneous distributions of academic ability.

Hypothesis 2: Students with high academic ability in academic cohorts with heterogeneous distributions of academic ability will perform less well than high ability students in academic cohorts with homogeneous distributions of academic ability.

METHODS AND DATA

Quantile regression models the relation between a set of independent variables and specific percentiles (or quantiles) of the dependent variable. Quantile regression was developed by Koenker and Bassett (1978) and Koenker and Hallock (2001), and is based on the minimization

of weighted absolute deviations for estimating conditional quantile functions. Unlike linear regression, in which the regression coefficient represents the change in the dependent variable produced by a one unit change in the independent variable associated with that coefficient, quantile regression parameters estimate the change in a specified quantile of the dependent variable produced by a one unit change in the independent variable. Linear regression estimates the mean value of the response variable for given levels of the predictor variables, while quantile regression estimates the return across the conditional distribution. Quantile regression makes use of the entire sample and is not equivalent to utilizing the dependent variable series of sub-samples and applying OLS to sub-samples. Therefore, quantile regression is not the same as dividing the data into different percentiles and then applying OLS to each percentile (e.g. Hallock *et al.*, 2008). The linear regression model in this study is in the following standard form: $y_i = \bar{x}_i\,\bar{\beta} + \epsilon_i$ where y_i is the dependent variable $\bar{x}_i$ is a vector of explanatory variables, $\bar{\beta}$ is a vector of their estimated coefficients, and ϵ_i is the independent and identically distributed error term (Reichstein *et al.*, 2010). The OLS estimator is found by minimizing the sum of the squared residuals: $\min_{\bar{\beta}\in R^k}\left[\sum_{i=1}^{n}\left(y_i - \bar{x}_i\bar{\beta}\right)^2\right]$. On the other hand, the quantile regression estimator is the vector β that minimizes:
$\min_{\bar{\beta}\in R^k}\left[\sum_{i\in\{i:y_i\geq\bar{x}_i\,\bar{\beta}\}}\tau\left|y_i - \bar{x}_i\,\bar{\beta}\right| + \sum_{i\in\{i:y_i<\bar{x}_i\,\bar{\beta}\}}(1-\tau)\left|y_i - \bar{x}_i\bar{\beta}\right|\right]$ where τ is the quantile defined as $Q_{Y|X}(\tau|x) = inf\{y: F_{X|Y}(y|x) \geq \tau\}$ in which τ is bounded between zero and one, and *y* is a random sample from a random variable Y, which have the distribution function F $(F(y) = P(Y \leq y))$. Notice that for τ = 0.5 the above equation becomes the absolute loss function determining the median regression.

Quantile regression has been frequently applied to issues in labor economics when examining wage differentials and wage discrimination (Fitzenberg *et al.*, 2001; Garcia *et al.*, 2001; Buchinsky, 2001). Quantile regression was also employed to study K-12 education by Eide and Showalter (1998) to estimate the relationship between school quality and student performance. Levin (2001) estimated an educational production function to investigate the effect of class size and peer effects. Prieto-Rodriguez *et al.*, (2008) studied educational approaches in 14 European countries. In the only study that uses college data, Escudero *et al.* (2009) examined the effects of gender, age, parent's education, and private or public school on the number of courses passed by students for accountancy and law students in Argentina.

In the context of this study, following Bielinska-Kwapisz *et al.* (2012a), ACT scores were used as a proxy for general cognitive capability (Koenig *et al.*, 2008), GPA as a measure of time input and effort, along with students' major field of study (accounting, finance, marketing, or management). The specific learning function used in this study is a fixed effects model presented as follows:

$$MFT\text{-}B_{ikt} = \beta_0 + \beta_1 ACT_{ikt} + \beta_2 GPA_{ikt} + \beta_3 Male_{ikt} + \beta_4 ExCredit_{ikt} + \eta_k + \delta_t + \varepsilon_{ikt} \quad (1)$$

where $MFT\text{-}B_{ikt}$ is the MFT-B score of student i in major k in term t; ACT_{ikt} is his/her ACT score; GPA_{ikt} is his/her overall GPA; $Male_{ikt}$ is a binary variable that takes the value of one if a student is male and zero if female; $ExCredit_{ikt}$ is a binary variable that takes the value of one if a student could receive extra points for a good performance; η_k are majors' fixed effects; δ_t are cohort fixed effects; β_i $(i=1\ldots4)$ are coefficients to be determined; and ε_{ikt} is the error term. Similar models were estimated in the previous literature on MFT-B scores by Bielinska-Kwapisz, *et al*. (2012a); Zeis, *et al*. (2009); Rook and Tanyel (2009); Bycio and Allen (2007);

Bagamery *et al.* (2005); Black and Duhon (2003); Bean and Bernardi (2002); Mirchandani *et al.* (2001); and Allen and Bycio (1997).

The unique contribution of this study is the examination of the impact of the effect of heterogeneity in the ACT scores on the MFT-B scores; the issue none of the previous literature explored. This study focuses on the composition of the students' ACT scores rather than the pure average of the ACT scores. To achieve this goal, a variance of students' ACT scores was included in Equation 1 in the following way:

$$MFT\text{-}B_{ikt} = \beta_0 + \beta_1 ACT_{ikt} + \beta_2 GPA_{ikt} + \beta_3 Male_{ikt} + \beta_4 ExCredit_{ikt} + \beta_5 VarACT_{kt} + \eta_k + \delta_t + \varepsilon_{ikt.} (2)$$

Variances in the ACT scores in a given class and major were utilized (Michaelowa and Bourdon, 2006; Vandenberghe, 2002; Zimmer and Toma, 2000). The Levene test for the equality of variances showed significant differences in variances between different majors-classes. The variance ranges from 5.44 for accounting in 2007 to 16.23 for management in 2006. Traditionally, Equation 1 was estimated by OLS. In this study, quantile regression, as described above, was utilized to uncover previously unobserved heterogeneity in the returns to education across quantiles.

The setting for the current study is an undergraduate college of business at a Carnegie Research I, land grant university, which has held continuous AACSB accreditation for over 25 years. The college is predominantly Caucasian, with a very small population of international and ethnic students. As part of an assessment of learning process, the college has administered the MFT-B every semester to every graduating senior from the summer semester 2005 to spring 2011. Background data identified in the research were directly obtained from student records. The total number of students in that population was 885 students. Full data, most notably MFT-B and ACT scores, were available for 845 students, primarily attributable to the fact that transfer students were not required to submit ACT scores. In addition, for each of the 845 students, the data includes university grade point average measured at graduation (GPA), gender, major area of study (finance, accounting, management, marketing), and graduating class (class 06, class 07, class 08, class 09, class 11). Starting in the spring semester 2008, students received extra credit points to incent their best efforts on the MFT-B (5 points for a 50th percentile score, 7.5 points for 75th percentile, and so on). Table 1 (Appendix) reports the full list of variables that were used, their definitions and descriptive statistics. Table 2 (Appendix) lists the observed correlations. There are no very high (above ±0.5) correlations between any pair of independent variables. Therefore, multicollinearity was of no consequence in the analyses. As the literature from the K-12 experience suggests, there may be a different effect of cohort heterogeneity on high and low achieving students. For example, high ACT variance may influence MFT-B scores differently for high-performing students than for low-performing students. However, since the previous literature produced mixed evidence, the sign and significance of this variable has to be determined empirically.

RESULTS

If, on average, increased cohort heterogeneity leads to reduced MFT-B scores, it would be expected that cohorts with a high ACT dispersion will return lower MFT-B scores. Figure 1 (Appendix) relates average MFT-B cohort scores to the heterogeneity of their ACT scores and provides no supportive for hypothesis 1.

However, the relationship has to be further investigated by controlling for other input variables through the regression analysis. Table 3 (Appendix) reports estimated coefficients for the model described in Equation 2 estimated by the ordinary least squares (OLS) and, therefore, reports estimate at the mean.

The model explains about 49% of the variation in the MFT-B scores. The results from the estimated regression show no significant effect of ACT dispersion on the average MFT-B scores. Thus no support was found for hypothesis 1, that higher cohort heterogeneity of academic ability as measured by ACT scores retards (or benefits) the average MFT-B scores.

Other coefficients are consistent in significance and magnitude with those reported in previous literature, for example in Bielinska-Kwapisz *et al.* (2012a) and Black and Duhon (2003). In particular, higher ACT score and GPA positively influence MFT-B scores. Male students score, on average, four points higher on the MFT-B (Bielinska-Kwapisz and Brown,in press). Finally, management and marketing students score, on average, lower than accounting students (accounting and cohort 2011 dummies were dropped from the equation to avoid perfect multicollinearity).

The shortcoming of the OLS regression is that it estimates coefficients at the mean values but the effect of the dispersion may influence top or bottom students differently than the average. As commonly suggested, high ACT students may be at an academic disadvantage in class with low performing students, or low ACT students may benefit by being in class with higher potential students. However, OLS cannot be used to answer these hypotheses; therefore quantile regression is utilized. In Table 4 (Appendix) , estimated coefficients at 0.05, 0.25, 0.50, 0.75, 0.95 quantiles of the MFT-B scores distribution are reported.

Of particular interest in this study are the coefficients of the dispersion. The coefficients for the top 5% (95^{th}) and top 25% (75^{th}) MFT-B students are small and insignificant. Clearly, the top students are not disadvantaged by being in heterogeneous cohorts. Thus there is no support for hypothesis 2 that students with high academic ability in academic cohorts with heterogeneous distributions of academic ability will perform less well than high ability students in academic cohorts with homogeneous distributions of academic ability.

Turning to lower performing students, there is also no significant observed effect of higher dispersion on the very bottom 5% of the students. However, quite interesting the coefficient is positive and significant from the bottom 20% students (20^{th}) to the median of the distribution (50^{th}). In fact, the impact is the largest at 25 percentile and decreases afterward. Clearly, these relatively low academic ability students benefited from being in heterogeneous cohorts.

Turning to the effect of other variables, the quantile regression results suggest some important differences across diverse points in the conditional distribution of MFT-B scores. The intercept is increasing along the MFT-B distribution, suggesting that the unexplained portion of the variation in MFT-B scores are the highest at the top of the distribution.

In this study ACT scores are used to represent cognitive intelligence and academic ability. A 1% increase in an ACT score is associated with an MFT-B score that is 23% higher at the median (50^{th}), but only 19% higher at the top (95^{th}) of the MFT-B distribution (all elasticities evaluated at sample means).Therefore, academic ability seems to have it biggest impact at the middle of the MFT-B distribution.

The larger the GPA coefficient, the greater is the impact of business education on students. If coefficients are not stable through the quantiles (i.e. changing along the MFT-B distribution), then there is inequality in education along the distribution. GPA should reflect students' general business knowledge and how well the academic business program prepares students for the exam. GPA slightly declines along the MFT-B distribution (Table 4). A 1% increase in GPA is associated with an MFT-B score that is 15% higher at the bottom of the distribution (5^{th}) and only slightly declines to 13% at the top of the distribution (95^{th}). Therefore, the GPA impact is pretty stable across the distribution.

In the study samples, students who took the MFT-B in spring 2008 and subsequently, received extra credit points to incent their best efforts on the MFT-B. The OLS results suggest a significant and positive effect of the extra credit. On average, the scores increased by 2.5 points (Table 3). The results from the quantile regression (Table 4) suggest that effect of extra credit was not the same at the considered points of distribution. The coefficients were significant at the top of the distribution only (75^{th} and 95^{th} percentile). The effect was the largest at the 5% top of the MFT-B distribution: 3.2 points (Bielinska-Kwapisz and Brown (in press) analyzed the effect of extra credit in more detail).

On average, male students in the study sample outperformed female students by 4.57 points on the MFT-B exam (Table 3), a phenomenon reported in many previous studies. However, the effect is much smaller at the bottom of the distribution (2.64) and the first quartile (3.99) (Table 4). The effect is the largest at the third quartile (5.74) and at the median (4.82) (Bielinska-Kwapisz and Brown (2in press) analyzed the effect of gender in more detail).

Interestingly, the lower score for management students compared to accounting was not significant at the top 5% of the distribution. Finance students significantly outperformed accounting students at the top 5% of the distribution by 4.06 points (even though the OLS coefficient is not significant).

CONCLUSION

This empirical study examines the impact of the degree of variation in academic ability on the academic achievement of student cohorts and the highest ability students in those cohorts. Significant differences in the variance of academic ability (utilizing variation in ACT scores as a proxy) were observed across field of study cohorts. Quantile regression was utilized to examine the impact of this dispersion, while controlling for other dispositional factors, on academic outcomes as measured by scores on the MFT-B. A systematic examination of that relationship found no significant effects of either hetero- or homogeneity in academic ability variance of academic cohorts on an average student. There was also no support for contentions that high ability students might be disadvantaged by the presence of low ability colleagues. An unexpected positive and significant academic achievement effect was found: from 20^{th} to 50^{th} percentile of the MFT-B distribution for lower ability students in heterogeneous cohorts.

The findings were determined through the use of quantile regression which examined relationships at various locations on the distribution curve. Previous research on the determinants of MFT-B scores estimated coefficients at the mean. However, it is useful to see the determinants of the MFT-B scores examined at different points of the distribution. The average impact may significantly differ from the impact at the top or a bottom of the distribution. Quantile regression would seem to substantially improve assessment of learning accuracy and contribute to a better and much more precise understanding of the dispositional factor contributions which impact academic achievement as compared to estimates of the coefficients on sample means obtained by the use of OLS.

The results of this empirical study do not provide any support for the oft-stated contention that intellectually less well-endowed students' presence in undergraduate business classrooms might inhibit the academic achievement of high capacity students. Probably the main implication of the study results can be applied to the methods and procedures by which students are assigned or admitted into universities, colleges, or particular fields of study.

While intellectual or academic ability, as signaled by the ACT, certainly appears relevant in terms of individual achievement, there is no indication that an admissions policy which creates cohorts with heterogeneity of innate intellectual ability has any significant impact on the academic achievement of either the cohort of the cohort's high ability students. In fact, study results suggest that a heterogeneous academic ability cohort may in fact benefit the lower ability individuals in that cohort without any deleterious impact on other members. Those looking for explanations for frustrations or academic performance below expectations should look at factors other than the presence of low ability students.

The findings of this study are of course bound by the validity of the proxy measures utilized: ACT as a measure of intellectual ability; GPA as a measure of time input and effort; and MFT-B scores as a measure of academic achievement. Generalization of the findings will be enhanced by replications in other institutional and disciplinary settings, something which is strongly hoped for and encouraged.

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APPENDIX

TABLE 1
Definitions and Descriptive Statistics (n=845)

Variable	Description	Mean	Std Dev.	Minimum	Maximum
MFT-B	Student MFT-B score on a scale of 120 to 200	160.86	12.16	129	194
ACT	Student ACT score on a scale of 1 to 36	23.39	3.42	14	34
GPA	GPA measured at the time of graduation	3.14	0.38	2.26	4.00
Var(ACT)	Variance of ACT scores in a given major and class	11.15	2.44	5.44	16.23
Male	Binary variable = 1 if male	0.55		0	1
ExCredit	Binary variable = 1 if extra credit was offered	0.43		0	1
Finance	Binary variable = 1 if finance major	0.17		0	1
ACCT	Binary variable = 1 if accounting major	0.21		0	1
MGMT	Binary variable = 1 if management major	0.34		0	1
MKTG	Binary variable = 1 if marketing major	0.28		0	1
Class 2006	Binary variable = 1 if class 2006	0.19		0	1
Class 2007	Binary variable = 1 if class 2007	0.18		0	1
Class 2008	Binary variable = 1 if class 2008	0.22		0	1
Class 2009	Binary variable = 1 if class 2009	0.22		0	1
Class 2011	Binary variable = 1 if class 2011	0.19		0	1

Table 2
Correlations (n=845)

	Variable	1	2	3	4	5	6	7	8	9	10
1	MFT	1.00									
2	ACT	0.57	1.00								
3	VarACT	0.02	-0.04	1.00							
4	GPA	0.45	0.46	-0.02	1.00						
5	Male	0.14	-0.04	0.12	-0.20	1.00					
6	ExCredit	0.08	-0.03	-0.23	-0.01	0.07	1.00				
7	ACCT	0.21	0.17	-0.24	0.21	-0.16	0.06	1.00			
8	FIN	0.26	0.08	0.01	0.03	0.15	0.03	-0.23	1.00		
9	MGMT	-0.15	-0.12	0.45	-0.09	0.13	-0.06	-0.37	-0.32	1.00	
10	MKTG	-0.25	-0.09	-0.27	-0.12	-0.12	-0.01	-0.32	-0.28	-0.45	1.00

TABLE 3
Ordinary Least Squares (OLS) Estimates (n=845)

	Estimate	t stat
Intercept	96.25	28.26
ACT	1.48	14.79
VarACT	0.24	1.52
GPA	7.84	8.56
Male	4.57	7.17
ExCredit	2.50	2.53
FIN	1.81	1.77
MGMT	-5.17	-5.37
MKTG	-5.91	-6.63
Class06	3.43	3.04
Class07	3.39	3.21
Class08	1.44	1.43
Class09	2.71	2.37
R-squared:	0.494	
Adjusted R-squared:	0.487	

TABLE 4
Quantile Regression (n=845)

Variable	5th		25th		50th		75th		95th	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	87.17	19.03	86.98	20.67	90.78	25.04	107.77	20.54	122.42	25.42
ACT	1.40	13.66	1.46	12.33	1.60	14.55	1.42	9.69	1.32	10.84
VarACT	0.10	0.78	0.48	2.32	0.31	1.86	0.31	1.18	-0.27	-0.96
GPA	7.93	9.36	8.02	7.21	7.92	7.96	6.93	5.12	6.82	6.55
Male	2.64	4.83	3.99	5.34	4.82	6.81	5.74	6.09	4.06	4.87
ExCredit	1.77	0.80	1.18	1.10	1.94	1.50	3.03	1.84	3.20	2.01
FIN	-0.81	-0.58	2.71	1.59	2.64	2.16	0.30	0.20	4.06	3.83
MGMT	-3.96	-3.91	-4.66	-3.79	-4.33	-3.97	-8.79	-5.53	-2.15	-1.35
MKTG	-6.06	-6.64	-4.86	-5.49	-5.06	-5.73	-8.54	-5.76	-4.95	-3.36
Class06	2.00	0.91	4.40	3.69	4.69	4.05	2.58	1.62	2.27	1.93
Class07	3.15	1.34	3.19	2.30	3.36	3.13	2.37	1.26	3.83	3.69
Class08	0.61	0.41	2.40	2.21	2.59	2.07	-0.05	-0.03	1.75	1.12
Class09	3.17	2.76	3.94	2.75	3.88	2.43	1.89	0.92	2.49	1.09

FIGURE 1. Average MFT-B Class Score and Variance in ACT Scores.