THREE ESSAYS IN APPLIED ECONOMICS: (1) SCHOOL FUNDING AND STUDENT PERFORMANCE IN ALABAMA, (2) NEWS AND VOLATILITY OF FOOD PRICES, AND (3) THE IMPACT OF NAFTA ON LABOR IN THE US

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Yuqing Zheng, son of Lingxiang Zheng and Yingdi Li, was born September 20, 1977, in Hangzhou, P. R. China. After graduating from Linpin High School in 1995, he attended Zhejiang University and graduated with a Bachelor of Science degree in Economics in July, 1999. He worked in Hangzhou for two years. First as an Investment Analyst in Guotai & Junan Investment Bank, then as a Project Manager in Hangzhou Venture Capital Funds. In August 2001, he entered Graduate School, Auburn University. He majored in Agricultural Economics and Rural Sociology. After graduating with a Master of Science degree in May 2003, he started pursing a Ph.D. degree in Applied Economics at the Department of Agricultural Economics and Rural Sociology. As a fulltime instructor, he taught principles of economics and business statistics at Auburn University Montgomery in 2005. He married Fei Ye, daughter of Caixiong Ye and Xiaoming Shen, on December 20, 2000.

DISSERTATION ABSTRACT

THREE ESSAYS IN APPLIED ECONOMICS: (1) SCHOOL FUNDING AND STUDENT PERFORMANCE IN ALABAMA, (2) NEWS AND VOLATILITY OF FOOD PRICES, AND (3) THE IMPACT OF NAFTA ON LABOR IN THE US

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This dissertation consists of three essays in economics on education, time series econometrics, and international economics. The first essay attempts to evaluate the impact of state funding on student performance in Alabama counties in a five-equation supply-demand framework. I also evaluate the impact of the *No Child Left Behind Act* (NCLB) on student performance and major school inputs, by estimating reduced-form equations using both Alabama county and US state level data. Results show that state funding, student median family income, school enrollment, and district poverty rate matter the most to student performance as measured by eighth-grade *Stanford* total test scores. State funding raises performance but is a strong substitute for local funding

because the benefits of an increase in state funding fall more heavily on the demand side which is less elastic. With other variables controlled, there is increase in Alabama in math test score, federal funding, instructional expenditure, and the teacher-student ratio by 8.8%, 25.1%, 6.4%, and 3.3% respectively, and decrease in average teacher's salary by 4.3%, most likely attributable to the implementation of NCLB. In contrast, NCLB increased US average teacher's salary by 5.5%. The second essay examines US food markets for asymmetric news effects based on the observation that financial markets exhibit an asymmetric news effect with unexpected low prices generating more price volatility than "news" of high prices. Analysis of 25 years of monthly data for 45 retail food items shows that price news destabilizes about a third of the markets with unexpected price increases more destabilizing, possibly because of increased concentration in distribution and retailing and larger firms, declining farmer share of final consumer spending, or menu cost. The third essay specifies a supply and demand model of the labor market to examine the effects of NAFTA on the US labor market. Regression results suggest that NAFTA decreased yearly unemployment growth by 6.8%. Equivalently, NAFTA brought a structural break to US state level unemployment. The second finding is that the labor market began feeling the impact of NAFTA immediately after its implementation and the labor market had continued to feel its beneficial effects through 2000.

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Style manual or journal used American Journal of Agricultural Economics.

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CHAPTER 1. SCHOOL FUNDING AND STUDENT PERFORMANCE IN ALABAMA

I. INTRODUCTION

America has the most competitive higher education system in the world but its students perform relatively poorly on international mathematics and science tests. For example in 2003, US students placed 24th among 29 OECD member countries in an international test that measured the mathematical literacy of 15-year-olds, scoring higher than only Portugal, Mexico and three other nations[1]. Economists worry that trailing other OECD countries on education measures may reduce US economic growth by as much as a half percentage point a year, attributable to decreases in productivity that determines economic growth[2].

The poor performance of American youngsters has attracted public attention since the publication of the widely cited report *A Nation at Risk* in 1983. Since then America and many of its states have undertaken comprehensive educational reforms. The *No Child Left Behind* Act of 2001 (NCLB Act) is an example of education reform at the federal level. One aim of the NCLB Act is to enhance reading ability for the youngest children.

The need to reform the educational system is more urgent in states with historically underperforming school systems, such as Alabama. In 1992, the average test score of the *Stanford* Achievement Test (eighth edition, *Stanford 8* hence) of the 8th grade students in Alabama was in the 38th percentile, 25% below the national average in the 50th percentile (see figure 1).

Poor performance has spurred proposals for educational reforms in Alabama. Beginning with the 1995-96 school year, all schools in Alabama have been required to be accountable for student achievement, according to the Education Accountability Plan. Each year, schools with poor performance in nationally normed tests will be put on "alert" requiring assistance from the State Department of Education. Meanwhile, in 1995, the Alabama legislature enacted the Foundation Program, a funding mechanism to calculate the cost for K-12 education, aiming to give local school systems maximum control of expenditures by apportioning funds in a "block grant" manner based on cost calculations using prior year data, such as average daily membership (ADM) [3]. Other educational reforms include the implementation of the Alabama Reading Initiative (ARI) in 1998 and Alabama Math, Science, and Technology Initiative (AMSTI) in 2002 by the State Department of Education. The goals of ARI and AMSTI are to significantly improve reading instruction and ultimately achieve 100% literacy among public school students and improve math and science teaching statewide.

In most cases, reforms come at the cost of higher levels of spending or diverting funds from other potential projects. Some policy makers, voters, and economists seem to assume that improved student performance would be a natural result of increased educational spending. However, there is no lack of debate among researchers on the effectiveness of school spending. The origin of the debate can be traced to the publication of the Coleman's Report in 1966. The best-known conclusion made by Coleman and his collaborators is that school resources play a negligible role in determining student outcomes while the socioeconomic background of the students has a more noticeable impact in explaining student success. Furthermore, most of the variation in student test scores cannot be explained by the variables included in the study.

Since Coleman's report, hundreds of studies have been carried out to determine the impact of teacher inputs, school spending, student family background and other factors on student performance. Also like Coleman, no consistent results can support the claim that increased spending matters for the K-12 education.

II. LITERATURE REVIEW

There are two measures of educational outcomes in the existing literature: a long-term measure of earnings after leaving school and a short-term measure of students' test scores. From an economist's perspective, earnings after school are more closely linked to a person's welfare and they are therefore considered as the long-term effects of schooling. The most famous research on the long-term effects of schooling is a study by David Card and Alan Krueger (1992). In addition, Betts (1996) provides a summary of such studies.

As to the short-term educational outcome measure, standardized test scores are arguably the best one (Munane, Willett, and Levy, 1995; Fergusan and Ladd, 1996). The prevalent approach to model students' test scores is a single production function. The production function treats the present student test scores as a joint product of input variables. The input variables include school inputs, student characteristics, and family and community background variables, and other variables that are hard to measure, such as student identity (Akerlof and Kranton, 2002). Some researchers argue that past achievements of student should be included in the subset of student characteristics since study is a cumulative process. When the model nests past student achievement, it is called value-added production function.

The most notable school inputs are expenditures per pupil, class size, teacher salary, teacher education, and teacher experience. No consensus has been reached on the effect of any of the school input variables on student performance.

Some researchers argue that school expenditure can have a nontrivial positive impact on student performance. Others advocate that money matters as long as the money is wisely spent, i.e., spent on instructional services. Papke (2005) finds that increases in spending have nontrivial and statistically significant effects on pass rates for fourth-grade math tests from 1992 through 1998 at Michigan schools. Jacques and Brorsen (2002) find that increases in the expenditures on instruction and instructional support lead to improvement of student test scores while higher spending on student support such as counseling and school administration has a reverse effect. Guryan's estimates (2001) suggest that increased spending improved 4^{th} grade test scores, but not on 8^{th} grade test scores in Massachusetts. Another finding of Guryan (2001) is that between 50 to 75 cents of state educational dollar were spent on schools.

Disagreement arises on the role of money with similar data sources but different methodologies. Using an ordered logit model, Jaggia and Kelly-Hawke (1999) find no systematic relation between higher levels of spending and student performance in Massachusetts. They argue that family background and stability matter more to student performance than educational spending. Similar results exist in the literature. Marlow (2000) examines the school spending and performance relationship in California argues that higher education spending does not improve student performance. Coate and VanderHoff's (1999) study in New Jersey has similar findings.

With respect to teacher salary, there is no lack of studies claiming it is ineffective in raising student performance. Loeb and Page (2000) argue that previous studies leading to the conclusion that teacher salary is unrelated to student performance "generally do not account for non-pecuniary job attributes and alternative wage opportunities, which affect the opportunity cost of choosing to teach." After adjusting for labor market factors, Loeb and Page estimate that an increase in teacher wages by 10% reduces high school dropout rates by 3% to 4%.

A considerable educational literature on the relationship between class size and student performance has produced mixed results at best. Class size is of particular interest to education researchers and administrators. Smaller classes arguably should help raise student performance. The intuition is that smaller class size means students can enjoy a better environment and more individualized instruction. In small classes, instructor can remember students' names and students may have the incentive not to disappoint the instructor. Class size is one of the few school input variables that administrators can change from term to term. In the empirical literature, Arias and Walker (2004), and Iacovou (2002) find evidence that small class size has a positive impact on student performance. Cooper and Cohn (1997) find a positive relationship between student achievement and class size in South Carolina. Borland, Howsen, and Trawick (2005) claim that the relationship between class size and student achievement is not only non-linear, but non-monotonic. They point out that one or more of the following four factors hinders the attempts to recover the true relation between class size and student performance. The factors are measurement error due to the use of a student/teacher ratio as the measure of class size, model misspecification resulting from the failure to control for family effects, endogeneity of class size, and incorrect functional form.

Hanushek has surveyed the literature on the estimated effects of key school resources on student performance in the education production function studies several times. In his 1986 survey, Hanushek find that the majority of the 147 education production function studies find statistically insignificant effect of class size, teacher education, teacher experience, teacher salary and expenditure per pupil on student performance. This pattern carries over to his updated 1996 survey in which the number of education production function studies reached 377, more than double that of 1986. Table 1 presents the summary of 377 available estimates for the bulk of production studies through the end of 1994. The remarkable finding from the 377 studies in 90 separate published works[4] is that neither the teacher related inputs including class size, teacher education, experience, and salary nor the school's expenditures measured at different levels are related systematically to student performance, which is a consistent theme in Hanushek's writing. For example, only 27% of the 163 studies find that expenditure per pupil is statistically significant and positively related to student performance. Meanwhile 66% of the 163 studies indicate that expenditure per pupil does not have a role in determining student performance, and even worse, 7% of the studies show increases in expenditure per pupil lower student performance. Hanushek interprets the mixed results in Table 1 as evidence of no systematic relationship between student achievement and school inputs.

Hanushek's interpretation has been challenged from different aspects. The first criticism of Hanushek's interpretation is the use of "vote counting" method in Table 1. Instead of the "vote counting" method, Hedges, Laine, and Greenwald (1994) apply a statistical procedure, meta-analysis, to the studies surveyed by Hanushek. They conclude that data shows that increased school inputs help improve student performance.

Other researchers believe that improved data sets and statistical methods can uncover the true relationship between school resources and student performance. Based on rich Texas school data, Ferguson (1991) argues that schools resources, i.e., teachers' language skill, teacher experience, class size, and percentage of teachers with a master's degree, all matter to average student scores on standardized tests. Similar results are found in Ferguson and Ladd's 1996 study in Alabama. With detailed district level data, Ferguson and Ladd (1996) find that better performance of teachers in the ACT college entrance exam, higher percentage of teachers holding a master's degree, smaller classes, and higher level on instructional expenditure per pupil all lead to improved student performance on standardized tests in Alabama. Both of the studies involve unusually rich data sets. The Texas study includes about 900 of Texas's districts. The Alabama study uses both district-level and disaggregated student-level data.

Another criticism of Hanushek's conclusion is that the endogeneity of some school resources can confound the correlation between school resources and average student achievement. Murnane (1991) attacks the validity of production function studies by pointing out that they do not fully address the endogeneity of some school inputs. As Murnane (1991, p. 458) puts it:

"Let me describe briefly two reasons why I find educational production function studies an inappropriate basis for determining whether money matters. First, these studies do not adequately address serious questions of causation. For example, many school districts have relatively high expenditure levels, including state and federal compensatory education funds, *because* they serve students with low achievement levels. The same is true for the allocation of compensatory education funds among schools within a given school district. Given this situation, any comparison of achievement levels across schools with different expenditure levels per pupil, or across schools within the same district, lends little insight into any beneficial impact of funding on student achievement. The statistical controls used to account for differing achievement levels among students remain inadequate in even the best studies."

Only a few studies address the endogeneity issue of school resources, with focus on compensatory spending and endogenous class size. Ferguson and Ladd (1996) acknowledge the existence of compensatory spending in Alabama in their study. Compensatory spending exists if a district receives more educational funding simply because students perform is poor in that district. One common approach to address endogeneity problem is to apply the Durbin-Wu-Hausman endogeneity test to the suspicious regressors and resort to the generalized instrumental variables estimator if endogeneity is found. To purge the reverse causation from poor student performance to more spending, Ferguson and Ladd use property value per pupil, per capita income, enrollment and number of schools in individual district as instrumental variables of the instructional expenditure per pupil and find that increased instructional expenditure per pupil improves student performance in Alabama. As for class size, Karen (1995) and Boozer and Rouse (2001) find that there are returns to investing in smaller classes after addressing the endogeneity of class size to student performance. With the endogeneity of spending and class size widely acknowledged, other potential endogenous variables are not fully addressed. Some candidates include teacher's salary, teacher education, and teacher experience etc. For example, endogeneity arises if schools financially reward teachers based on the improvement of student performance. Ferguson and Ladd (1996) find mixed results of endogeneity test on class size, teacher's experience and education and they treat these variables as exogenous by judgment. However, the detailed endogeneity test results are not reported in their study.

Murnane's (1991) second concern about the validity of production function studies is that the logic underlying the argument that money does not matter does not carry over to studies of similar organizations. He argues that other private organizations such as private schools and private firms in competitive markets also pay for inputs that are not directly related to student performance or productivity under competitive pressures, i.e., teaching experience beyond the first five years and reward for workers' attributes not directly related to productivity. Even though evidence shows worker experience does not contribute much to productivity, economists do not conclude that rewarding worker experience is inefficient because they believe that firms must have good reasons to do so to survive in competitive market. Nevertheless, economists interpret it as inefficiency in educational production function studies for public schools when teacher experience is found to be insignificant. Based upon the above argument, Murnane concludes that it is not appropriate to judge the effectiveness of school inputs solely on the results of educational production function studies. Other criticism of production function studies includes measurement error in school resources, and model misspecification, etc.

Since a number of difficulties plague education production function studies, this paper attempts to remedy part of these problems by offering a supply-demand approach using a rich panel dataset to fully address the endogeneity problem existing in school resources. This paper particularly addresses the effect of state funding on student performance in Alabama, with the intention to contribute to the literature in terms of methodology and data.

Most education studies focus on the expenditure, not revenue of school funding. Researchers and policy makers care about whether money is spent wisely. There are findings that higher instructional expenditure tends to have a more pronounced effect on student performance than total spending (Ferguson and Ladd (1996); Jacques and Brorsen (2002)). The policy implication is that money matters more if it is spent heavily on instruction and instructional support. On the other hand, the effect of state funding on student performance is rarely addressed. State funding has accounted for over half of the school revenues in the last decades in Alabama. However, not all state funding goes to increasing school expenditure. Guryan (2001) find that between 50 to 75 cents of each state educational dollar were spent on schools for Massachusetts. Guryan does not offer explanation for the above phenomenon. Kinnucan, Zheng and Brehmer (2005, and KZB hence) find that between 62 and 73 cents of the incremental Alabama state dollar goes to schools; the rest is absorbed by local taxpayers through incidence shifting and by the federal government through the compensatory mechanism. If not all of the state funding goes to school, the effect of state aid on student performance is discounted. In this paper, we update KZB's data to 2004 and continue to explore the impact of state funding on student performance.

Our data is an unusually rich Alabama county-level panel data covering years from 1996 to 2004. The description and source of the data are in Appendix A. Endogeneity of school resources including school spending and revenue by sources, teacher education, teacher's salary, and class size is fully tested in this paper. A supply-demand approach is specified to proxy the educational market in Alabama. Endogeneity test results reinforce the appropriateness of the approach taken here. Further policy implications, including the effect of the recent NCLB Act are discussed.

The paper is organized as follows. Section III is a replication of Ferguson and Ladd's study (1996) using our data. Section IV addresses several issues we uncover from the replication, focusing on endogeneity test. Section V presents a supply-demand system and compares the system estimates with production function estimates using the same panel data. Section VI is reduced form estimation with emphasis on the effect of the NCLB Act. Section VII concludes with policy implication.

III. REPLICATION OF FERGUSON AND LADD'S STUDY

The first step in this paper is to replicate Ferguson and Ladd's (FL hence, 1996) study on Alabama using our data, in the spirit of Tomek (1993) who suggests that improved scholarship can rise from confirmation and replication of previously published studies. Since FL conducted the most comprehensive and state-of-the-art study on Alabama's elementary education market, it is in our interest to see if their results are robust using our data. FL uses school data for the year of 1990. In this replication study we examine whether FL's results hold for a comparable year of 1992 and the panel from 1996 to 2004 in our data. However, we only have county level data, with which to replicate FL's district level study.

Model

Ferguson and Ladd's Value-added Production Function Approach

Specifically, FL models average student test scores in the i^{th} district in Alabama as follows:

(1) $$TS_i = \alpha + \beta S_i + \gamma X_i + \delta Z_i + \theta X_i^s Z_i^s + \mu_i$$

where the dependent variable TS_i is the present test score of students in the i^{th} Alabama district during the school year, 1989-1990. TS_i depends on a constant term α, a vector of school input variables in *S*, and a vector of student background characteristic variables in *X*, and a vector of school or district characteristics in *Z*, and a vector of $X_i^s Z_i^s$ which captures the interaction effects between a subset of student background variables (X_i^s)

and school or district variables (Z_i^s). The past test scores are subsumed in the vector *X* and hence the above model is a value-added production function indeed. The effects of those variables that are hard to measure, such as student motivation, should be reflected in the error term, μ_i.

FL extends the above model into three versions when it comes to testing the hypothesis that money has no effect on students test scores. The three versions of value-added models, version A, B and C are as follows:

$$
\begin{aligned}
Q8_i = {} & \alpha + \beta_1 ACT_i + \beta_2 EXP_i + \beta_3 MS_i + \beta_4 STR_i + \gamma_1 Q3_i + \gamma_2 ED_i + \gamma_3 \ln PCPI_i + \\
& \gamma_4 POV_i + \delta_1 ENROL_i + \delta_2 RACE_i + \delta_3 PUBLIC_i + \delta_4 URBAN_i \\
& + \theta_1 RACE_i * URBAN_i + \mu_{Ai}\,,
\end{aligned}
\tag{2A}
$$

where the dependent variable $Q8$ is the average composite of math scores from the *Stanford 8* for the eighth grade and from the Basic Competency Test (BCT) for the ninth grade during the 1989-1990 school year. All the test scores in FL's study are standardized[5] to have a mean of zero and a standard deviation of one across districts. The subscript *i* denotes the i^{th} district in Alabama, which includes 67 county and 62 city districts.

The school input variables include the average teachers' test scores from the ACT exams that teachers took in the process of applying to college (*ACT*), and the percentage of teachers with more than five years of experience (*EXP*), the percentage of teachers with a master's degree (*MS*), and the student-teacher ratio (*STR*). Student background variables include *Q3, ED,* ln*PCPI*, and *POV*. To implement the value added model, *Q3* is the average score of the third grade BCT and the fourth grade *Stanford 8* during the

1989-1990 school year, representing a proxy for past student achievement. *ED,* ln*PCPI* and *POV* are parental education, per capita income expressed in logarithm and poverty rate. Among the school district variables, *ENROL* is the total enrollment in thousands, and *RACE*, *PUBLIC* and *URBAN* are the percentage of students who are non-white, percentage of students in public schools and percentage of district that is urban respectively. Detailed variable definitions are summarized in Table 2. The last term, $RACE_i * URBAN$, is the interaction term which allows the interaction effect between *RACE* and *URBAN*. Previous studies justify the specification of the interaction term. There is literature suggesting that neighborhood characteristics influence educational attainment differently on black and white youth. Vartanian and Gleason (1999) find that neighborhood conditions, including growing up in neighborhoods with wealthier residents, more two parent families, and a greater percentage of workers in professional or managerial occupations lead to a substantial decrease in the high school dropout rate for black youth but do not help decrease the high school dropout rate for white youth.

Model (2B) replaces all the school inputs variables in model (2A) with instructional expenditure per pupil. FL proposes that we should treat the instructional expenditure as endogenous due to the existence of compensatory spending in districts where student performance is poor. In addition, a Durbin-Wu-Hausman endogeneity test clearly rejects the exogeneity of instructional expenditure per pupil. Therefore, FL uses the generalized instrumental variable estimator to purge the endogeneity of spending. As shown in equation (3A), four instrumental variables including log of property value per student, log of per capital income, enrollment, and number of schools in the district are used as regressors by ordinary least squares estimator to get the predicted values of log of instructional expenditure per pupil which is used as an explanatory variable ($\ln PI$) in model (2B). The results of instrumental variables estimation are reported in Table 3. FL also reports the results of instrumental variables estimation for log of non-instructional expenditure per pupil (ln*PNI*) for comparison purpose (see Table 3 for results of equation (3B)).

$$\text{(2B)} \quad \begin{aligned} Q8_i &= \alpha + \beta_1 \ln PI + \gamma_1 Q3_i + \gamma_2 ED_i + \gamma_3 \ln PCPI_i + \gamma_4 POV_i + \delta_1 ENROL_i + \delta_2 RACE_i + \\ &\delta_3 PUBLIC_i + \delta_4 URBAN_i + \theta_1 RACE_i * URBAN_i + \mu_{Bi} \end{aligned}$$

Model (2C) below adds a supplemental variable to the model (2B), $\ln PIA$, which equals the log of instructional expenditure minus its median value if the log of instructional expenditure is above its median and zero otherwise. By this nonlinear specification, FL aims to distinguish the effect of lower spending (below median spending) on student performance from that of higher spending.

$$\text{(2C)} \quad \begin{aligned} Q8_i &= \alpha + \beta_1 \ln PI + \beta_2 \ln PIA + \gamma_1 Q3_i + \gamma_2 ED_i + \gamma_3 \ln PCPI_i + \gamma_4 POV_i + \delta_1 ENROL_i + \\ &\delta_2 RACE_i + \delta_3 PUBLIC_i + \delta_4 URBAN_i + \theta_1 RACE_i * URBAN_i + \mu_{Ci} \end{aligned}$$

$$\text{(3A)} \quad \ln PI_i = \beta_0 + \beta_1 LnPV_i + \beta_2 LnINC_i + \beta_3 ENROL_i + \beta_4 SCHOOL_i + \xi_i$$

$$\text{(3B)} \quad \ln PNI_i = \beta_0 + \beta_1 LnPV_i + \beta_2 LnINC_i + \beta_3 ENROL_i + \beta_4 SCHOOL_i + \xi_i$$

Our Model for 1992 Data

We replicate FL's study using both the 1992 data and the panel data covering school years from 1996 to 2004. Table 2 contrasts the definitions of our variables with those in

FL's study. Our data only include the 67 counties in Alabama due to limited data availability.

For the school year of 1992, three versions of a model similar to equations (2A), (2B) and (2C) are posited as follows:

$$Q8_i = \alpha + \beta_1 MS_i + \beta_2 STR_i + \gamma_1 Q4_i + \gamma_2 ED_i + \gamma_3 \ln INC_i + \gamma_4 POV_i + \delta_1 ENROL_i + \delta_2 RACE_i + \delta_3 RURAL_i + \theta_1 RACE_i * RURAL_i + \nu_{Ai} \quad \text{(4A)}$$

$$Q8_i = \alpha + \beta_1 \ln PI_i + \gamma_1 Q4_i + \gamma_2 ED_i + \gamma_3 \ln INC_i + \gamma_4 POV_i + \delta_1 ENROL_i + \delta_2 RACE_i + \delta_3 RURAL_i + \theta_1 RACE_i * RURAL_i + \nu_{Bi} \quad \text{(4B)}$$

$$Q8_i = \alpha + \beta_1 \ln PI_i + \beta_2 \ln PIA_i + \gamma_1 Q4_i + \gamma_2 ED_i + \gamma_3 \ln INC_i + \gamma_4 POV_i + \delta_1 ENROL_i + \delta_2 RACE_i + \delta_3 RURAL_i + \theta_1 RACE_i * RURAL_i + \nu_{Ci} \quad \text{(4 C)}$$

where the dependent variable $Q8$ is the standardized eighth-grade students *Stanford 8* test scores (complete battery, percentile) during the 1991-1992 school year; *i* is the county index of Alabama which starts from 1 and ends with 67; MS is the percentage of teachers with a master's degree; STR is the student-teacher ratio with higher STR meaning larger class size; $Q4$ differs from $Q8$ only in the fact that $Q4$ is the standardized fourth-grade student *Stanford 8* test scores during the 1991-1992 school year; ED is the percentage of adults with college education; $\ln INC$ is the log of median family income representing a more accurate measure of family income than the variable of $\ln PCPI$ used in FL's study; POV is the percentage of all ages in poverty; $ENROL$ is the total enrollment in that district; $RACE$ is the percentage of students who are non-white; $RURAL$ is a rural dummy with one representing rural county and zero otherwise.

Note that differences exist between some of FL's and our variables. First, the dependent variables do not match. FL uses average composite of eighth-grade math scores from the *Stanford 8* and ninth-grade math BCT scores. We use eighth-grade *Stanford 8* total scores, which include a complete battery of reading, math, language, and social science. Differences could arise from the above two measures, even though both of them are standardized. Second, the data for teachers' ACT scores (*ACT*), teacher experience (*EXP*), and the percentage of students in public schools (*PUBLIC*) in FL's study are not available in our study. The third difference lies in the fact we use true median family income instead of using the personal income per capita as a proxy as FL does. To summarize, our variables are in bold if different from those in FL's study in definition in Table 2. One last note is that even the only four variables (*MS, STR, ENROL, and RACE*) that share common definitions differ due to different school years and sources of data. FL does not provide detailed data sources and whole data sources are documented in appendix A.

Our Model for the 1996-2004 Panel Data

For the panel data covering the school years from 1996 to 2004, we specify the following two-way fixed effects models (Wooldridge, 2002; Baltagi, 2001; Greene, 1993):

$$Q8_{it} = \alpha + \beta_1 MS_{it} + \beta_2 STR_{it} + \gamma_1 Q4_{it} + \gamma_2 ED_{it} + \gamma_3 \ln INC_{it} + \gamma_4 POV_{it} + \delta_1 ENROL_{it} + \delta_2 RACE_{it} + \delta_3 RURAL_{it} + \theta_1 RACE_{it} * RURAL_{it} + CS_i + TS_t + \nu_{Ait} \tag{5}$$

where i is the index for county with values of 1, 2,…, 67, and t is the index for year with values of 1996, 1997,…, 2004; *CS* (cross section) is a time invariant county-specific dummy and *TS* (time series) is a county invariant time-specific dummy variable. One-way and two-way fixed effects models denote models with *CS* only and both *CS* and *TS* dummies. The first observations in both *CS* and *TS* dummies are dropped to avoid perfect multicollinerity. Hence, the base county of the county-specific dummy is Autauga County and the base year of the time-specific dummy is 1996.

Fixed or Random Effects?

If the sampled sectional units were drawn from a large population, it would be appropriate to view individual specific constant terms as randomly distributed across cross-sectional units (Greene 1993, p. 479). For equation (5) without the *TS* dummy, it is called a random effects model if *CS* is a county-specific disturbance term. With an addition of a time-specific disturbance *TS*, equation (5) is then a two-way random effects model.

The fixed effects model applies to cases such as cross-sectional intercounty, interstate comparison while the random effects model applies to a longitudinal data set. The difference between fixed and random effects models lies in the handling of the individual effects. The fixed effects model treats the individual effects as estimable coefficients, and thus allows the individual effects to be correlated with other explanatory variables. The random effects model assumes no correlation between individual effects and other regressors; therefore the individual effects and the error disturbance constitute a composite error (Wooldridge 2002, p. 256). The tradeoff between these two is that the random effects model does not suffer the degrees of freedom loss as does the fixed effects model, but it imposes the unjustified assumption that individual effects do not correlate with other regressors (Greene 1993, p. 479).

To choose an appropriate model, Hausman (1978) proposed to test the hypothesis of no correlation between individual effects and other regressors. Since the fixed effects model is consistent when there is correlation between individual effects and other regressors, while the random effects specification is inconsistent, a statistically significant difference is interpreted as evidence against the random effects assumption of no correlation (Wooldridge 2002, p. 288). The Hausman test is performed and results suggest that the fixed effects model is preferable (Table 4).

Results

FL's Results

One theme stands out in FL's results: money matters to student performance. FL's results corresponding to equation (2A), (2B) and (2C) are reported in the left half of Table 4. We use the conventional 5% significance level to test the significance of the coefficients. The results of model A indicate that teacher ACT scores and class size matter to student performance[6]. The standardized teacher ACT scores have an estimated coefficient of 0.223. The estimated coefficient for the student-teacher ratio is -0.078. They are both significant in Model A, Table 4. However, the interpretation is different since the teacher ACT scores are standardized while the student-teacher ratio is not. For example, a one standard deviation increase in teacher ACT scores would increase student test scores by 0.223 standard deviations. If the student-teacher ratio decreases by one, then student test scores increase by 0.078. According to FL's explanation, the 0.223 coefficient for teacher ACT scores implies that a difference of one standard deviation in the distribution of teacher test scores would generate a difference of 0.223 standard deviations in the distribution of student test scores[7]. In contrast, the teacher experience and teacher education variables exert insignificant (significant only at 10% level) and weakly positive effects. Overall, all the school inputs variables show the expected signs.

Results in model B show that increased instructional expenditure per pupil exerts measurable positive impact on student test scores. The estimated coefficient for log of predicted instructional expenditure is 3.560 and statistically significant. Since it is a semi-log model, the coefficient suggests that a 10% difference in instructional expenditure (representing about one and one-half standard deviation in the distribution of predicted instructional expenditure across districts) would generate a difference of 0.356 (10% x 3.56) standard deviations in average scores across districts. The predicted instructional expenditure per pupil represents composite school inputs.

Furthermore, FL suggests that the effect of increased spending on student performance is concentrated among districts where spending is below the median level as indicated. In Model C, the effect of spending above the median is the sum of the estimates of ln*PI* and ln(*PI above median*). Spending above the median level has a small effect not statistically different from zero. Based upon above results, FL concludes that measurable school inputs affect student learning in Alabama. FL found similar results in their 1991 Texas study.

As for the student characteristics and school and district variables, *Q3, ENROL,* and *RACE*URBAN* are the variables that seem to matter. The positive coefficient of *Q3*, 0.339 in model B and 0.317 in model C means that a student's prior achievement carries over to following years. A positive enrollment coefficient, 0.018 for model A and 0.013

for model C, implies that students in large districts perform better than their peers in smaller districts with all else being equal (FL 1996, p. 277). Finally, the coefficient of -0.0001 for the interaction between race and urban residence indicates that differences in test scores between white and non-white students are larger in districts which are more urban (FL 1996, p. 276). Overall, student prior achievement plays an important role in determining student current performance and the enrollment and interaction effects are tiny. Given the cross-sectional data, all three models yield high R^2 levels of over 0.70.

Replication Results using 1992 Data

Our replication results of equations (4A) – (4C) using 1992 data are listed in the right half of Table 4. Surprisingly, our results do not support FL's argument that money matters in Alabama. In model A, neither percentage of teachers holding a master's degree nor student-teacher ratio exert significant effect on student performance. In addition, instructional expenditure per pupil has no effect in model B or C, a substantially different result from FL's.

Similar to FL, we find that fourth-grade student *Stanford 8* test scores have a positive effect on eighth-grade student *Stanford 8* test scores, i.e., 0.184 in model A, This confirms FL's finding that student previous achievement matters much for later performance. The adult educational attainment variable is significant in model A, indicating a 1% point increase in the percent of adults with college education would increase student test scores by 0.058 standard deviations. This is because families with higher levels of education usually demand better academic performance from their children. FL does not find a significant relation between parental education and student performance. Here, the median family income does not play any role in determining student test scores, similarly to its counterpart, capita income, in FL's study. Another result of this replication is that students in rural counties perform much better than students in non-rural areas. An estimated coefficient of 0.881 in model A suggests that the difference caused by location of district is large. The last finding is the negative relation between race and rural variables, which indicates non-white students in rural counties do not perform as well as their peers in non-rural counties, a result against FL's finding. The interaction effect is small at -0.015 in model A. Finally, we have high R^2 between 0.70 and 0.80, comparable to FL's.

To summarize, when applying FL's specification to our 1992 data, the results do not support FL's conclusion that measurable school inputs affect student learning in Alabama. Only the variable of previous student achievement remains significant in both studies. The fact that the two data are far from a perfect match should explain the disparity between FL's and our results to a large degree. Although both are standardized with zero mean and variance of one, the two dependent variables are different tests taken in different years. Teacher test score and teacher experience variables are not available in our study; therefore these two variables do not appear in our models A or B. Instead of per capita income, we use median family to represent the true family income[8]. Data differences exist in location and year in addition to the measurement. FL uses district data that includes most of Alabama counties and cities (a total of 127 districts), while our data is limited to Alabama's 67 counties. Our data is for the year of 1992, two years later than that of FL. In addition, from the equations that use instrumental variables to predict instructional expenditure, results do not match well. Table 3 (our 1992 data only) shows that the estimated coefficients of property value and median family income in our study are not as strong as their counterparts in FL's study. We also include the percent of non-white students in the instrumental variable lists.

Despite the difference in the two datasets, it remains surprising to see money matters in 1990 but not any more in 1992. We proceed to replicate using our panel data to see if this huge disparity continues.

Estimation of Panel Data without Fixed or Random Effects

Several variations of equation (5) are estimated for the panel data. Table 5 includes the regression results without using any panel data techniques such as fixed or random effects model. Estimates of models with and without the fourth grade test scores are both reported. Models A, B and C still refer to the specifications in which school inputs are measured by percentage of teachers holding a master's degree and student-teacher ratio, predicted instructional expenditure per pupil, and predicted instructional expenditure per pupil plus spending above the median respectively.

Again, money does not come into play in determining student test scores. In the left half of Table 5, the fourth grade test scores are not included in the explanatory variables. Teacher education measured by the percent of teachers with a master's degree and class size measured by student-teacher ratio do not show any effect on student performance. In addition, both model B and C suggest that increased instructional expenditure per pupil decreases student test scores while the effect of spending above median (sum of estimated coefficients of ln*PI* and ln(*PI above median*)) is insignificant.

The adult educational attainment shows a small and positive effect on student test scores, i.e., 0.014 in model B. The effect of the log of median family income is 1.471 in model B, a result not found in either FL's study or our 1992 replication. The results also indicate larger enrollment leads to better student performance. The negative and significant coefficients of percent of non-white students and the rural dummy indicate that non-white students do not perform as well as white students do and rural students do not perform as well as urban students do holding other conditions equal. The significant interaction term between the race and rural county variable suggests that non-white students in rural area perform better than non-white students in non-rural areas, an opposite finding to our study using 1992 data but consistent with FL's findings. Adjusted R^2's range from 0.66 to 0.68 for the three models, a reasonably good level for a single equation with about only 10 variables applied to a panel data with 603 observations.

The right half of Table 5 includes fourth grade test scores as an explanatory variable. When fourth grade test scores enter the production function, the coefficient is significant in all three models. The size of the coefficient is very close to that in FL's study, with 0.316 in our model B compared with 0.339 in FL's model B. The measurable school inputs and instructional expenditure per pupil are not significant in models A or B. Model C still indicates that instructional expenditure per pupil is negatively correlated with student test scores while spending above the median has no effect at all. The above results suggest that in this specification, money does not matter for student performance.

The adult's education variable and enrollment are no longer significant when fourth grade test scores enter the production function. The effects of median family income and race remain robust.

Estimation of Panel Data with One-way and Two-way Fixed Effects Models

Both the one-way and two-way fixed effects models are estimated and results are reported in Table 6. All the regressions are weighted by square root of enrollment to correct for cross-sectional heteroskedasticity. Estimates are weighted OLS results, so are those in Table 4 and 5. The two-way fixed effects model deserves the most attention by test statistics indicated. Here are the two steps that bring us to the above conclusion.

The first consideration is the choice of fixed or random effects model using the Hausman (1978) specification test (or *m* test) as a tool. In the random effects specification, the null hypothesis of no correlation between individual effects and regressors can be tested by the Hausman *m* test (SAS online documentation, 1999). The Hausman *m* test statistic is distributed as χ^2, with a significant *m* value indicating rejection of random effects. The highly significant Hausman *m* test statistic (χ^2 = 112.82) in model A under the one-way fixed effects model clearly rejects the use of random effects model.

The second step is to determine the use of one-way fixed effects or two-way fixed effects. Since the one-way fixed effects model is actually the two-way fixed effects model with all time dummies restricted to zero, a significant *F* test statistic for the null hypothesis of insignificant time dummies would reject the use of one-way fixed effects model. The values of *F* statistics for the above tests are listed under "*F* test for no *TS* effect" in Table 6. The significant *F* value of 11.61 rejects the hypothesis of no time effects in model A, so do other *F* statistics for model B and C. We also list the *F* statistics for hypotheses of no county-specific effects and none of county-specific or time-specific effects, which are 13.33 and 16.04 for model A for example.

There is strong evidence that fixed effects should be preferred over random effects model, and two-way fixed effects model should be preferred over one-way fixed effects model. Hence, we will focus on the interpretation of the results of the two-way fixed effects model unless noted. Meanwhile the results of one-way fixed effects are presented in Table 6 for comparison purpose.

Once again, school inputs and instructional expenditure per pupil do not come into effect in all the three versions of the two-way fixed effects model. None of the teacher education, class size and instructional expenditure per pupil variables is significant in any of the three models.

Student previous achievement has a positive significant effect at 0.210 in all the three models. The adult educational attainment and median family income show no effect here. The poverty rate is found to have a negative impact on student test scores with 1% point decrease in average poverty rate increasing average student test scores by 0.074 standard deviations in model A. The average poverty rate and its standard deviation during the 9 years are 18.19% and 5.56%. A difference of 1% point in average poverty rate represents about a difference of one sixth standard deviation in average poverty rate. Enrollment has a positive effect on student test scores as it does in FL's study.

We report time effects but not the 66 county effects, which are not informative to the interpretation of results. As 1996 is the base year, the negative time dummies in model A indicate that student test scores in the years 1998, 1999, 2000, 2002, 2003, and 2004 are worse than in 1996. The largest drop in test scores occurred in 2003 and 2004, when the test scores dropped by 0.591 and 0.699 standard deviations compared with those in 1996.

In Alabama[9], the *Stanford 9* was given during 1996-2002 and the *Stanford 10* was given starting from 2003. The *Stanford 9* is based on 1995 norms and the *Stanford 10*, a different test, is based on 2002 norms (Alabama Department of Education). The *Stanford 10* retains classic *Stanford 9* features, such as easy-hard-easy format and valid and reliable test items, but it differs from *Stanford 9* in many aspects. According to Florida Department of Education, general differences between *Stanford 10* and *Stanford 9* include new test content, full-color testing materials, clear navigation and the latest norms (2002) based on a national sample[10]. New test content means that all test questions in *Stanford 10* are new and unique, aligning to the most current state and national standards. The *Stanford 10* content is grade- and age-level appropriate and mirrors instructional activities and materials used in exemplary academic programs today. In the *Stanford 10* reading test, the test includes more items that address skills in critical analysis and strategies. Selections of poetry are now used at all levels of the test. In the *Stanford 10* mathematics test, more items require reasoning and problem solving. Estimation is now tested at all grade levels, and more two- and three-step problems are included. Finally, *Stanford 10* was normed in the spring and fall of 2002 with a large sample of the nation's K–12 student population.

Caution should be used when comparing *Stanford 9* and *Stanford 10* scores. Attempting to equate the two forms of the test would have been a major issue. Comparison within period with the same *Stanford Test* edition is out of question. For example, we are able to conclude that student performance in 1998 is worse than in 1996 and better than in 2002 and the student performance in 2004 is worse than in 2003, other factors held equal.

Another factor that could affect student test scores is the implementation of the *No Child Left Behind* (NCLB) Act in 2002. The impact of NCLB on student performance will be explored in more detail later in this essay. The adjusted R^2 is high at 0.89 for all the three models for this panel data.

Conclusion from Replication Study

We apply FL's three production function specifications to our 1992 data and 1996-2004 panel data in the hope that we could find similar results through replications. Huge disparity exists between FL's and our results, perhaps resulting from data differences. FL's result that measurable school inputs and instructional expenditure matter to student performance in Alabama does not carry over to our study. The only variable that is robust across all the studies is the student previous achievement, which has an effect on student test scores ranging from 0.180 to 0.340.

We also find evidence that the poverty rate matters to student performance in our panel data study. Finally, results indicate that the expensive NCLB Act does not have the expected positive effect on Alabama students.

IV. LEARNING FROM REPLICATION - SEVERAL ISSUES IN EDUCATION PRODUCTION FUNCTION STUDIES

From our literature review and replication study, we think there are three issues that could hinder the validity of production function studies of educational outcomes. They are lack of robustness of estimates, model misspecification, and endogeneity of school inputs and school funding.

Lack of Robustness – Lessons from Replication

Robustness of School Input Variables and Spending

The significant effects of school inputs and spending in FL's study do not hold in our replication study. With similar model specifications, these two studies provide opposite policy implications. This contradiction partly helps to explain the mixed results of production function studies in Table 1. Lack of robustness in the estimates suggests that a single production approach may not be the best tool to understand the educational market.

Robustness of Other Variables

Only the variable *Q4* stands robust across FL's and our studies. Mixed results occur for other variables when comparing our 1992 estimates data with FL's study. For example, the significant enrollment variable in FL's study is insignificant in our study. The rural variable has a positive effect on student performance in our study but has no impact in FL's study. Our panel data estimates match FL's results better in that they both find enrollment effect positive significant.

A disparity also exists within our replication studies. One example is the significant effects of the rural dummy variable and interaction between race and rural in the study using 1992 data disappear in the panel data study. One result in common is that both our studies do not support FL's argument that money matters in Alabama. The conflicts between our replication study and FL's study suggest that the estimates of a single production function may not withstand examination of robustness check. When applying similarly measured variables to the same model, the results do not remain similar.

Model Misspecification

The four different sets of panel data estimates in Table 5 and 6 have already shown how the sensitivity of results to model specification. For example, enrollment is positively significant in the models excluding the fourth grade test scores in Table 5. The effect of enrollment disappears in Table 5 when the fourth grade test scores enter the models. The enrollment continues to exert no effect in the one-way fixed effects model in Table 6. Finally, the positive effect of enrollment becomes significant in the two-way fixed effects model in Table 6.

Researchers have begun to examine alternatives to the production function approach to proxy the educational market. From a technical perspective, lack of robustness in the estimates could arise from model misspecification if a single production function is not the true model.

KZB proposes a supply-demand approach to model educational service in Alabama, arguing that observed school spending and outcome data are generated by an equilibrium process. An observed level of school spending should reflect the market equilibrium price, at which a market demand curve that defines parents/taxpayers willingness to pay for educational services intersects a supply curve that indicates the school district's marginal cost of providing those services. Since education is a public good and spending on education exerts positive externality, education is usually subsidized at federal and state levels. As a result, the observed school spending is the sum of the price buyers pay and the subsidy. Consider the equilibrium in Alabama's primary educational market in 2004, in which the school spending/funding per pupil is $4,291 and the local taxpayers' contributions to schools average $871 per pupil. The difference between school spending and local taxpayers' contributions comes from state subsidy, federal subsidy, and other funding at $2,400, $538, and $482 per pupil respectively[11]. If subsidies increase, it decreases the local funding as well as increasing the total school funding. This is the so called incidence problem in KZB'S paper.

In the present paper, we define Alabama's school funding as P_G consisting of local, state, federal and other funding (denoted P_N, SF, FF, and OF, respectively in Table 7). It would be proper to view P_G as the supply side price that schools face and P_N as the demand side price that measures local parents/taxpayers willingness to pay for educational services. According to the identity, $P_G = P_N + SF + FF + OF$, an increase in state or federal funding usually (upward slope supply and downward slope demand) leads to an increase in equilibrium quantity and total funding, as well as a reduction in local funding.

The summary statistics of the school revenues and expenditures by source are reported in Table 7 together with other school and student variables. Tables 8 and 9 list the decomposition of school revenues and expenditures by source over the last 13 years. For example, total school revenues per pupil in 2004 in Alabama is \$4,291, which consists of local funding of \$871, state funding of \$2,400, federal funding of \$538, and other funding of \$482 (Table 8). All the financial data are CPI deflated in the present study. Correspondingly, the school expenditures per pupil in 2004 in Alabama is \$4,104, which can be decomposed into \$2,589 of instructional expenditure and \$1,515 non-instructional expenditure. Table 9 differs from Table 8 only in that Table 9 lists the percentage distribution of the revenues and expenditures. Thus, the local, state, federal, and other funding in 2004 represent 20.29%, 55.94%, 12.54%, and 11.23% of the total revenues respectively. The percent of instructional and non-instruction spending is 63.09% and 36.91% in that year. Figures 2 and 3 include the plots of the Alabama school revenues and expenditures by source.

The bulk of production function studies in the literature of education economics mainly address questions such as “Does total school spending matter to student performance?”, “Is instructional expenditure more rewarding than non-instructional expenditure?”, “How to spend money wisely?” etc. However, questions such as “Do schools use state funding wisely?”, “Do schools get all the state funding?”, and “Does an increase in the state funding crowd out local funding?" are rarely raised. Issues about the effectiveness of state funding should deserve more attention as state funding consistently occupies over half of the total educational funding in the last 13 years in Alabama. Similarly, state funding is the lion's share of total educational funding in the US A supply-demand system allows us to address such revenue related questions in detail.

One advantage of adopting a supply-demand approach is its ability to distinguish demand shifters from supply shifters. By offering a supply-demand approach, it is possible to estimate the structural elasticities that are not available in the production function approach.

Taking family income as an example, we know from undergraduate Microeconomics class that income is a demand shifter in the market forces of demand and supply. The power of a supply-demand approach is its ability to distinguish demand shifters from supply shifters, by which we can have the structural elasticities. When putting all the related variables into a single production function, the estimated function is a quasi-reduced form, containing elements of supply, demand, and other structural relations.

Our supply equation differs from a typical production function in the fact that we use total revenues per pupil as school funding variable instead of total spending per pupil[12], and the demand shifters are excluded in the supply equation. The supply equation includes the total price (P_G), school inputs (*TSR, TPAY, TED*), and supply shifters (such as *ENROL, RURAL, POV,* Q_4). The demand equation includes the net price

(P_N) and demand shifters such as *INC, RACE, ED,* and *UNEMP*. The full model will be laid out shortly.

Endogeneity of School Inputs and School Funding

From Class Size and School Spending to Other Variables

Murnane (1991) questions the reliability of the estimates from production function studies by pointing out that the production function approach does not pay full attention to the endogeneity problem. Furthermore, our literature review shows that for those studies addressing endogeneity of school inputs and spending, their focus remains on class size and spending per pupil.

For example, FL applies the DWH test to other school inputs variables. Tests imply that teacher's test scores are exogenous to student performance while results for class size, teachers' experience and master's degree are mixed. Without listing and addressing the DWH test results in detail, FL presumably proceeds to treat these variables with mixed results as exogenous based on specification search. To cite FL's words:

"Results for class size, teachers' experience and master's degrees are more mixed, but our judgment is that these variables should also be treated as exogenous to student performance for the present analysis. When an instrumental variables estimate for class size is used along with the unadjusted numbers for the other variables, the estimated effects of class size are even larger than those reported here. Similarly, when instrumental variables estimates for teacher experience or master's degree are used, the measured effects are stronger for some, though not all, specifications. When instrumental estimates for class size, experience and master's degrees are entered together, an F-test for joint significance shows statistical significance but collinearity among the three that makes their separate effects difficult to distinguish."

With Murnane's sharp criticism in mind, we argue that it might be imprudent to assume exogeneity of school spending and other inputs without formal endogeneity tests.

The cause of endogenous class size could be that small classes are simply more often found in schools or classrooms that have high-achieving students. Endogeneity could also reside in other school-related variables such as teachers' salary. If schools reward teachers financially based on their teaching merit, then student performance would affect teacher's salary.

In our study, we list 12 variables that are suspected of being endogenous to student performance measured by eighth grade *Stanford* scores. The 12 variables are P_G, P_N, *SF, FF, OF, PI, PNI, TED, MS, TSR, TPAY,* and *Q4*. The first five variables (P_G, P_N, *SF, FF, OF*) are schools' total educational revenues per pupil and their sources. *PI, PNI* are schools' instructional and non-instructional expenditure per pupil. *TED, MS, TSR,* and *TPAY* are the teacher related school inputs and the last one *Q4* is student previous performance. If compensatory educational spending is existent in Alabama as FL points out, we expect some of the first seven spending/price variables to be endogenous with student performance. Other variables still could be endogenous, as schools with better-performed students might be more appealing to higher educated teachers or be more willing to offer higher salaries to attract better teachers.

Durbin-Wu-Hausman Endogeneity Test on 12 Variables

A DWH endogeneity test is performed on each of the 12 variables. Results are in Table 10. The DWH test involves two steps: an auxiliary regression in the first step and an augmented regression in the second step. Taking the total school funding as an example, the total school funding is regressed on a possible set of all strictly exogenous variables in the first step. The exogenous variables include income, other funding, 4th grade

Stanford Test scores, poverty rate, enrollment, rural dummy, percent of non-white students, appraised property value, unemployment rate, number of schools. The residuals in the auxiliary regression are saved. In the second step, an augmented regression is carried out where student performance is regressed on the residuals from the auxiliary regression, total school funding, teacher's salary, teacher -student ratio, teacher's education, income, adult education attainment, poverty rate, enrollment, rural dummy and percent of non-white students. The augmented regression is similar to a production function. The hypothesis that the total school funding is exogenous can be rejected if the residual from the auxiliary regression is significant in the augmented regression. The F statistics and p-values for the hypothesis that the residual variable is zero in the augmented regression are reported in Table 10, with a significant F statistic (or p-value < 0.05) indicating rejection of exogeneity. The value of the F statistic in the augmented regression for the total school funding is 5.89, indicating rejection of its exogeneity at 5% significance level. The detailed specifications of the auxiliary and augmented equations for other variables are also included in Table 10.

For school revenues, results indicate that total revenues and local funding are endogenous. State and other funding are exogenous to student performance while federal funding is weakly endogenous with a p-value of 0.058. The endogenous total school funding confirms the notion that student performance could partly influence the funding the schools get. The fact that local and federal funding are endogenous (federal is marginally significant) while state and other funding are not implies that compensatory distribution of funding in Alabama may reside at the local and federal level but not at the state level. Our results also suggest that instructional expenditure is endogenous but the non-instructional expenditure is not. This result corroborates FL's study as they also find instructional expenditure endogenous.

Of the four school inputs variables, we find teacher-student ratio and teacher's salary endogenous but not the percent of teachers holding a Ph.D. or master's degree. This confirms the previous finding in the literature that class size could be endogenous to student. For example, class sizes could be set purposefully by administrators. There are instances that administrators put the students most in need of help in smaller classes, which would lead to observed positive relationship between class size and student performance (Hanushek, 2004). Meanwhile, our results suggest that since endogeneity could exist between teacher's salary and student performance, treating teacher's salary as exogenous without a formal test is not sound.

The last finding in Table 10 is that *Q4* is exogenous which excludes the causation from the eighth grade test scores to the fourth grade student test scores.

Overall, this paper finds serious endogeneity (to student performance) problems existing in schools' educational revenues and expenditures at different levels, as well as in teacher-related school inputs. Given the fact that earlier production function studies do not pay full attention to the endogeneity problem, it is not surprising to see mixed results in Table 1. If endogeneity problem were not seriously addressed, production function studies could provide invalid policy implications, as pointed out by Murnane (1991).

V. FROM PRODUCTION FUNCTION TO SUPPLY-DEMAND SYSTEM

One obvious interpretation of the prevailing finding that money does not matter is that the underlying models are misspecified, resulting in biased estimates (Hanushek, 2004). Hanushek (2004) also hypothesizes that school resources could interact to determine student performance. More specifically, he proposes that unmeasured teacher quality could interact with other resources thus adding justification to the mixed results in Table 1.

To see how results can change with model specification and whether improvement can be achieved by the demand-supply over the production function approach, we model student performance using a classic production function, supply function and a supply-demand system respectively. Different estimators including Ordinary Least Squares (OLS), Weighted Least Squares (WLS), Weighted Two-Stage Least Squares (W2SLS), and Weighted Three-Stage Least Squares (W3SLS) are applied accordingly to the 1996-2004 panel data. The effects of state educational funding on student performance are estimated and highlighted for policy discussion.

We also test the existence of the interaction effects proposed by Hanushek (2004), with a focus on the interaction between teachers-related school inputs and poverty rate.

Production Function Estimates

Model

A classic production function with two-way fixed effects is specified as follows:

$$\begin{aligned} \ln Q8_{it} = {} & \alpha + \beta_1 \ln P_{Git} + \beta_2 \ln TED_{it} + \beta_3 \ln TSR_{it} + \beta_4 \ln TPAY_{it} + \beta_5 \ln Q4_{it} + \beta_6 \ln ED_{it} + \\ & \beta_7 \ln INC_{it} + \beta_8 \ln POV_{it} + \beta_9 \ln ENROL_{it} + \beta_{10} \ln RACE_{it} + \beta_{11} RURAL_{it} + \\ & \beta_{12} \ln POV_{it} * \ln TED_{it} + \beta_{13} \ln POV_{it} * \ln TSR_{it} + \beta_{14} \ln POV_{it} * \ln TPAY + \\ & \beta_{15} \ln POV_{it} * \ln ED_{it} + CS_i + TS_t + \upsilon_{it} \end{aligned} \tag{6}$$

where i is the index for county with values of 1, 2,…, 67, and t is the index for year with values of 1996, 1997,…, 2004. The production function includes total school funding per pupil, three teacher related school inputs, students' previous performance, adult educational attainment, median family income, poverty rate, enrollment, percent of non-white students, rural county dummy and the interaction between poverty rate and the three teacher related inputs and adult educational attainment. This function allows us to test the interaction between the measurable teacher inputs and poverty rate, which is pertinent to Hanushek's hypothesis.

The production function is estimated with OLS, WLS and W2SLS to see how results vary with hetetoscedasticity and endogeneity taken into consideration. Under each estimator, there are three versions. Model A is the full model of equation (6). Model B equals model A without interaction terms and model C equals model B without the three teacher inputs variables. Regression results together with F tests used to select the best of models A, B and C are reported in Table 11. In the replication study, we standardize all the test scores to see if the estimates have similar size as those of FL's. From now on, all the continuous variables are expressed in logarithms to make results easier to interpret. Therefore, estimated coefficients are structural elasticities.

OLS or WLS, and Interaction Effects

The square root of the log of total enrollment is used as a weight in this paper. When comparing WLS estimates with OLS estimates, results vary not much with difference most likely occurring in the third decimal place. For example, the elasticity for percent of teachers with a Ph.D. degree is 0.261 and 0.260 in the OLS and WLS models respectively, suggesting heteroscedasticity does not serious affect the magnitude of our estimates.

Given the fact that we are using a panel data and WLS is superior to OLS when heteroscedasticity is present, we prefer WLS to OLS in our study as FL does.

Since model A is the full model, a significant *F* statistic for the test A vs. B would reject the restriction imposed on model A by model B. The three *F* statistics in WLS for testing A vs. B, A vs. C and B vs. C are 4.92, 3.04, 0.50 respectively, indicating that model A should be preferred to model B or C and model B and C are indifferent to one another. The *F* tests indicate that overall interaction effects cannot be ignored.

Elasticities in WLS

The coefficient of total school funding per pupil is 0.027, but not significant at the 5% level. With a new production function specified, we still could not find a significant effect of total school funding on student performance.

The coefficients for teacher education (*TED*) and interaction between teacher education and poverty rate are 0.260 and -0.093. The positive coefficient of *TED* indicates that a higher percentage of teachers with a Ph.D. degree leads to improved student performance while the negative interaction between *TED* and *POV* implies that poverty counters the positive effects of *TED* on student performance. Therefore, the elasticity for teacher education is -0.010, which is the calculated result of 0.260 - 0.093*ln*POV* with poverty rate measured at its mean level. Above results suggests that higher percent of teachers with a Ph.D. degree exerts a positive effect on student performance in wealthy districts and a negative effect in poor districts in Alabama. Overall, the elasticity for *TED* on student performance is relatively small at -0.010.

The coefficients for teacher's salary and interaction between teacher's salary and poverty rate are -3.794 and 1.327 respectively. Similar to teacher's education in the method to calculate the overall elasticity, the elasticity of teacher's salary is equal to 0.056. The above results indicate that increased teacher's salary improves students test scores, with the effect amplified in districts with higher poverty rate.

We do not find that teacher-student ratio or the interaction between teacher-student ratio and poverty rate has any effect on student performance.

Other significant variables include Q_4, *ED, POV, ENROL, RACE* and *RURAL* with elasticities of 0.202, -0.264, -12.191, 0.098, -0.046, and -0.089 respectively.

2WSLS Estimates

In the Weighted Two-Stage Least Squares estimation, we allow the variables of P_G, *TPAY,* and *TSR* to be endogenous with *Q8*, as indicated by the DWH endogeneity test in Table 10. The instrumental variables are all the exogenous variables that include *SF, OF, Q4, INC, PV, ENROL, SCHOOL, UNEMP, RACE, POV, RURAL, BLACKBELT, ED, MS* and time dummies.

We can not reject model C as the true model for W2SLS, which means all the teacher related school inputs and the interaction terms may have no impact. In model C, the total education funding tends to have a weakly (only significant at the 10% level) positive effect on student performance with the elasticity of 0.084.

Other variables that matter to student performance in model C are *Q4, ED, POV, ENROL,* and *RURAL* with elasticities of 0.222, -0.376, -0.327, 0.098 and -0.109 for each.

Conclusions from the Production Function Study

Our production function study tells that the W2SLS estimates differ significantly from the WLS estimates. Teacher's education and salary are found to have a negative and positive effect on student performance in the WLS. When the school funding, class size and teacher's salary are endogenized in the W2SLS estimation, teacher's education and salary do not remain significant. Interaction between poverty rate and the teacher related school inputs, parental educational level are found in the WLS but not W2SLS estimation. The comparison illustrates how different conclusions can be reached before and after handling the endogeneity issue.

School funding remains insignificant throughout the OLS, WLS and W2SLS specifications. Some variables that remain robustly significant in WLS and W2SLS are *Q4, ED, POV, ENROL,* and *RURAL*. Adult educational attainment shows strong negative impact on student performance in most of the specifications. One reason for this lies in the fact that most of the *ED* data are interpolated since we only have *ED* data from the Bureau of Census for the years of 1990 and 2000.

Finally, the adjusted R^2 is impressively high, which ranges from 0.80 to 0.90 in this production function study.

Supply Function Estimates

Model

When pulling the demand shifters out of the production function, the supply function is specified as follows:

$$
\begin{aligned}
(7)\qquad \ln Q8_{it} &= \alpha + \beta_1 \ln P_{G\,it} + \beta_2 \ln TED_{it} + \beta_3 \ln TSR_{it} + \beta_4 \ln TPAY_{it} + \beta_5 \ln Q4_{it} + \\
&\beta_6 \ln POV_{it} + \beta_7 \ln ENROL_{it} + \beta_8 RURAL_{it} + \beta_9 \ln POV_{it} * \ln TED_{it} + \\
&\beta_{10} \ln POV_{it} * \ln TSR_{it} + \beta_{11} \ln POV_{it} * \ln TPAY + CS_i + TS_t + \pi_{it}
\end{aligned}
$$

The supply function actually is the production function with the three demand shifters *ED, INC, RACE* eliminated. Three specifications, OLS, WLS and W2SLS are estimated with results reported in Table 12. Again, the difference between the OLS and WLS estimates are not large. Focus remains on the WLS and W2SLS results only.

Results

When estimating the supply function alone, total educational funding continues to be uncorrelated with student performance in any specification.

WLS estimation suggests that model A is the true model, where teacher's salary is the only teacher related input that is significant. When interacted with poverty rate, teacher's salary has elasticity of 0.016 significant at the 5% level. Only coefficients significant at the 5% or 1% levels will be discussed later on. *Q4, POV, ENROL,* and *RURAL* all show significant effects in model A.

For the W2SLS, we cannot reject model C as the best model. Although teachers' salary is significant and has elasticity of 1.379 in model B, *F* test only allows us to weakly reject (p-value = 0.084) the restrictions of no teacher inputs effects imposed on model B by model C.

Comparing the supply function estimates with those from the production function, we find several characteristics in common. The first is that we could not find total funding to affect student performance. Second, teacher's salary is the only teacher-related input that tends to demonstrate a positive effect on student performance, while teacher's education and class size do not. The third finding is that interaction effects only exist in WLS estimates. When endogenous variables are instrumented in W2SLS, interaction effects become irrelevant to student performance. The fourth common characteristic is that student previous achievement and poverty rate are found to be the most robust variables across production and supply function studies. For instance, a 10% increase in fourth grade student test scores and 10% decrease in poverty rate will lead to an increase in eighth grade student test scores by 2.27% and 2.43%, taking the estimates in model C of supply function as an example. Last finding is that test scores are lower than that of 1996 for most of the years as indicated by the time dummies.

Supply-Demand System Estimates

Model

A supply-demand system based on the model proposed by KZB is as follows:

$$\ln Q8_{Sit} = \alpha_1 + \beta_{11} \ln P_{G\,it} + \beta_{12} \ln TED_{it} + \beta_{13} \ln TSR_{it} + \beta_{14} \ln TPAY_{it} + \beta_{15} \ln Q4_{it} + \beta_{16} \ln POV_{it} + \beta_{17} RURAL_{it} + CS_i + TS_t + \psi_{1it} \tag{8A}$$

$$\ln Q8_{Dit} = \alpha_2 + \beta_{21} \ln P_{N\,it} + \beta_{22} \ln INC_{it} + \beta_{23} \ln RACE_{it} + \beta_{24} \ln UNEMP_{it} + \psi_{2it} \tag{8B}$$

$$\ln TSR_{it} = \alpha_3 + \beta_{31} \ln SF_{it} + \beta_{32} \ln INC_{it} + \beta_{33} \ln ED_{it} + \beta_{34} \ln ENROL_{it} + \psi_{3it} \tag{8C}$$

$$\ln TPAY_{it} = \alpha_4 + \beta_{41} \ln SF_{it} + \beta_{42} \ln INC_{it} + \beta_{43} \ln TED_{it} + \psi_{4it} \tag{8D}$$

$$\ln FF_{it} = \alpha_5 + \beta_{51} \ln Q8_{it} + \beta_{52} \ln POV_{it} + \beta_{53} \ln ENROL_{it} + \psi_{5it} \tag{8E}$$

Equation (8A) defines the supply curve for educational services, which is hypothesized to be a function of the total educational funding (gross price). The supply shifters include the three teacher related inputs including teacher education, teacher-student ratio and teacher's salary and other supply shifters namely, the previous performance of the students, poverty rate, a rural county dummy, county and time dummy. The interaction between teacher input variables and poverty rate is not in the supply equation, as suggested by the W2SLS estimates in Table 12.

Equation (8B) is the demand curve for educational services, which is hypothesized to be a function of local educational funding (net price). The demand shifters include median family income, percent of non-white students and unemployment rate. Adult educational attainment variable is excluded due to its limited data availability and its insignificant presence in KZB's study.

Equations (8C) - (8E) account for the endogeneity of class size, teacher's salary and federal funding indicated in Table 10 (also see KZB for justification of the model).

The supply-demand approach has several advantages over a single production function. First, it disentangles supply and demand shifters. Second, endogeneity problem can be fully addressed by specifying equation (8C) - (8E) and the use of a 3SLS estimator. Furthermore, as argued by KZB, the supply-demand system allows state funding to affect student performance through its impact on class size and teacher's salary. The coefficient of *Q8* in equation (8E) also captures the compensatory funding noted by FL and Murnane (1991).

The system is closed by specifying the following equilibrium conditions:

(8F) $\ln Q8_{Sit} = \ln Q8_{Dit} = \ln Q8_{it}$

(8G) $P_{G\,it} = P_{N\,it} + SF_{it} + FF_{it} + OF_{it}$

Weighted Three-Stage Least Squares Estimates

The system was estimated using weighted 3SLS (W3SLS). The endogenous variables include *Q8*, P_G, P_N, *TPAY, TSR* and *FF,* and the instrumental variables include *SF, Q4, INC, PV, SCHOOL, UNEMP, POV, BLACKBELT, MS* and time dummies. A system estimator such as the W3SLS is our best choice given the heteroskedasticity in our panel data, cross-equation correlation in error terms, and the endogeneity existing in the different levels of funding and teacher inputs variables. Results are in Table 13 together with WLS estimates listed for comparison purpose.

The *F* test results for the overall models are all significant (for instance, *F* equals 47.77 in the supply equation using WLS). The overall results are satisfactory in terms of R^2 and significance. In the WLS estimation, the adjusted R^2 for the five equations is 0.86, 0.59, 0.18, 0.24 and 0.69. SAS reports a system weighted R^2 of 0.65 for the W3SLS estimation. Considering the fact that we have only a few variables in each equation (excluding the dummies in supply equation) for the nine-year-long panel data of 603observations, the R^2 for supply, demand and federal funding equations in WLS and the system weighted R^2 in W3SLS are satisfactory. The adjusted R^2 for *TSR* and *TPAY* equations in WLS are accepTable. Most of the variables in both OLS and 3SLS estimates are significant at the 5% level. We will focus on interpreting the results of the W3SLS and use WLS results for comparison only.

Supply Equation

The estimated supply elasticity (Q_8 with respect to P_G) is 1.319 and significant at the 5% level. The supply elasticity was estimated not significant in KZB's model using 1992 data. The fact that supply tends to be more elastic in the long run may reconcile the above conflict.

The percent of teachers with a Ph.D. degree and teacher-student ratio are not significant, indicating that the efforts to hire more teachers with a terminal degree[13] and to reduce class size are not rewarding to students in Alabama.

Teacher's salary is the only teacher-related input variable found pertinent to student performance. The teacher's salary elasticity is 3.252 and is strongly significant (t-ratio > 3), indicating a 10% increase in the teacher's pay would increase the student performance by 32.52%. Increasing teachers' salaries would be effectively improving student performance; however, the truth is that Alabama teachers' salaries have been stagnant in the last 9 years. There is a 2.19% decrease in teacher's salary from 2000 to 2004 (see Table 7). The average teacher's salary in 2004 is $19,961, only $540 more than that in 1996.

The coefficient for the fourth grade student *Stanford Test* scores is 0.167, significant at the 10% but not at 5%. Compared with its significant counterpart of 0.222 in the production function estimates (Model C, W2SLS, Table 12) and 0.217 in the WLS estimates in Table 13, *Q4* loses marginally in significance and size in the W3SLS estimates.

The coefficient of poverty rate is at -0.300 (t-ration > 3), which confirms its function as a robust supply shifter. *POV* also is significant in WLS estimates.

Enrollment is significant at 0.357, consistent with FL's result. The effect of *RURAL* is not significant. As for the time dummies, 7 out of 8 dummies are sigfnicant and negative. The three years with the largest drop in test scores compared with 1996 are 1999, 2004 and 2003, with elasticities of -0.318, -0.318, and -0.314 respectively. The least drop in score occurred in 1997 with the elasticity of -0.117 for the time dummy.

Demand Equation

The demand elasticity (Q_8 with respect to P_N) estimate is -0.048, indicating that local tax payers indeed demand fewer educational services when they have to pay more property taxes to support elementary education. However, people are not sensitive to a price change for the educational service given this inelastic demand. Our demand elasticity is only about a quarter the size of the demand elasticity (-0.192) estimated in KZB's study for 1992 in Alabama. It is counterintuitive to suppose that demand is less elastic in the long run, although educational service could be a special case. The implementations of NAFTA in 1994, increasing outsourcing of unskilled jobs, and intensive trade with China etc., all have widened the wage gap between skilled labor and unskilled labor. Nowadays education, such as attending college is more like a necessity to Americans than an option. Based on this, it is not surprising to see that Alabama taxpayers are becoming less sensitive to price changes in elementary education over the last nine years.

The highly inelastic demand for educational services limits the potential for outward supply shift on student test sores. Shifting the demand curve would be more effective in positively impacting student performance than moving down along the demand curve.

The income elasticity is highly significant at 0.525, a measurable impact on student test scores. The effect of the *RACE* variable on demand is small (-0.058) but highly significant (t-ratio = 14.34). This result indicates that in Alabama, districts with higher proportions of non-white students have a lower demand for educational services. Finally, the unemployment rate exerts no effect on demand.

TSR, TPAY and FF Equations

All the variables in the above three equations are highly significant except *INC* in the *TSR* equation and *POV* in the *FF* equation. For the *TSR* equation, results show that state funding plays a key role in determining class size. A 10% increase in state funding could lead to a 4.14% increase in the teacher-student ratio that is the inverse measure of class size. Given that an increase in the teacher-student ratio is not found to improve student performance in this paper, the above result suggests that state funding spent to reduce class size could be futile.

The elasticity for adults educational attainment is 0.079, which means that parents with a college degree would demand more educational service for their kids than less educated parents do. The impact of median family income on teacher-student ratio is only weakly significant at the 10% level, with a coefficient of 0.042. The fact that enrollment has negative effect (-0.022) on the teacher-student ratio are consistent with our expectations.

As to the *TPAY* equation, all coefficients of the three variables are positive. They are 0.181 for *SF,* 0.019 for *TED,* and 0.060 for *INC,* which means that state funding, teacher's education, and income are all positively related to teacher's salary in that county. The fact that teacher's education matters the least to teacher's salary indicates that wealth of local schools and local income level largely determine teachers' salaries. One thing in common between the *TSR* and *TPAY* equations is that state funding matters the most to class size and teacher's salary.

The estimates in the *FF* equation indicate the existence of compensatory funding in the level of federal funding. The elasticity of compensatory federal funding is quite large at -2.215, indicating a 10% increase in the 8^{th} grade student *Stanford Test* scores in one district would bring a 22.15% decrease in federal funding to that district. One last finding is that district with large enrollment tends to have lower federal funding per pupil.

VI. POLICY IMPLICATION

Total elasticities are derived from Table 13 to address some empirical questions in this section. We compute the total elasticities by simulating equations (8A) – (8E). Only significant coefficients in Table 13 are used in the simulation. The results are reported in Table 14. Additional simulations with demand elasticity set alternatively to -0.30 are conducted to gauge the sensitivity of results.

State Funding and Student Performance

When demand elasticity takes the value of -0.048 as estimated, the total elasticities for the seven exogenous variables on student performance are as follows in the descending order: *INC* (0.453), *SF* (0.201), *ENROL* (0.050), *RACE* (-0.047), *POV* (-0.043), *TED* (0.009) and *ED* (0.000). Income has the largest effect on student performance, most likely attributable to the highly inelastic demand and elastic supply.

State funding has a total elasticity of 0.201 on student performance, which means state funding indeed increases student test scores with a modest effect. When the demand elasticity is set to -0.300, the state funding effect increases to 0.631 but income effect shrinks to 0.301.

For the remaining exogenous variables, the effects are tiny, with the expected signs. The result that enrollment increases student performance is in accord with FL's findings. High percentage of non-white students decreases student performance, so does high poverty rate, although the effects are small.

When demand elasticity is -0.300, enrollment and poverty rate effects become more pronounced, at 0.156 and -0.134 respectively. This is mainly because these two supply shifters are more effective when demand is more elastic.

The overall conclusion from this simulation study is that median family income, state funding, enrollment and poverty rate are the factors that matter most to student performance.

Efficiency and Compensatory Effects, Incidence

The efficiency effect denotes the indirect impact of state aid on student performance via its effect on teacher-student ratio and teacher's salary. The "efficiency" means efficiency gains if teacher-student ratio or teacher's salary shifts supply curve to the right. Since teacher-student ratio is not significant in the supply equation (8A), the efficiency effect is represented by the effect of state funding on teacher's salary (β_{41}) in equation (8D). By "turning off" efficiency, we simply means assuming the coefficient of β_{41} is zero. The compensatory effect denotes the reverse causality between student test scores and school funding, represented by the β_{51} term in equation (8E).

Four controlled scenarios are simulated, including the presence of both effects, compensatory effect only, efficiency effect only, and presence of neither effect. Results are reported in Table 15. Results indicate that *Q8*/SF** reduces almost by half (from 0.201 to 0.117) without the efficiency effect. Meanwhile, the size of *Q8*/SF** only increased from 0.201 to 0.211 when the compensatory effect is not present. Based on Table 15, our conclusion is that the efficiency effect amplifies the positive impact of state funding to student performance while the compensatory effect matters little.

The total elasticities of the three endogenous funding variables with respect to state funding are converted to total derivatives in Table 16. When demand elasticity is -0.048 with the presence of efficiency, a $1 increase in state funding would cause decreases of $0.47, $1.39 and $0.08 in total educational funding, local funding and federal funding respectively. The reason why an increase in state funding decreases total education funding is that an increase in state funding shifts the supply curve to the right via its impact on teacher's salary, hence reducing the total educational funding. As theory predicts, the less elastic side of supply and demand bears more of the subsidy benefit. This explains the large decrease in local educational funding when state funding increases. The substitution between state and federal funding is relatively small.

When turning off the efficiency effect or using alternative demand elasticity of -0.300, the P_G */SF* term becomes positive. For example, a 1$ increase in state funding would cause the total funding to increase by \$0.45, local funding to decrease by \$0.41 and federal funding to decrease by \$0.15 for the last scenario in Table 16.

Our analysis is useful to answer several important policy questions:

Do Demand Elasticities Vary with Group Characteristic?

Since all the continuous variables in equations 8(A) – 8(E) are log transformed, constant demand elasticity is assumed. It is of our interests to relax this assumption and see if rich parents are more or less sensitive to a change in the price of education than are poor parents. Re-estimating the model in semi-log form allows us to address questions like above. Consider a semi-log demand equation in which the dependent variable is *lnQ8* and the independent variables are not log transformed. If the coefficient for the price is β, the demand elasticity is βP_N[14]. In the log-near model, the demand elasticity varies with the value of local funding.

Equations (8A) – (8E) are re-estimated without any of continuous variables log transformed except *Q8*. The coefficient for local funding P_N in the demand equation is -0.0001 and significant at 1% level. First, we sort local funding into two competing groups by variables of *INC, POV, BLACKBELT, RACE, RURAL ,*and *UNEMP* respectively. Then, the average local funding in each group multiplies -0.0001 to get the demand elasticity for that group (see note 14 for justification). For example, after sorting by income, we consider the 22 counties with the lowest income as low-income group and the 22 counties with the highest income as high-income group. In 2004, the average local funding for the low-income group (\$735) multiplies by -0.0001, getting demand elasticity of -0.074 for that group. The average local funding for the high-income group (\$1,054) multiplies by -0.0001, producing demand elasticity of -0.105 for high-income group in 2004. All the demand elasticities sorted by the above six characteristics are reported in Table 17. The period is 2000 - 2004.

The semi-log demand model allows demand to be more elastic corresponding to a higher level of local funding. Therefore, if income and local funding are positive correlated, demand is expected to be more elastic for high-income group. This turns out to be true in Table 17. Taking the year of 2004 as an example, results in Table 17 indicate that demand for education is more elastic for high-income counties (-0.105) than for low-income counties (-0.074); for counties with low poverty rate (-0.101) than for counties with high poverty rate (-0.073); for counties not in black belt (-0.093) than for counties in black belt (-0.071); for counties with low percentage of non-white students (-0.096) than for counties with high percentage of non-white students (-0.073); for non-rural counties (-0.101) than for rural counties (-0.083); for counties with low unemployment rate (-0.097) than for counties with low unemployment rate (-0.077). Similar results hold for the other years. Due to higher level of spending for education, high-income families tend to have higher demand elasticity for education than low-income families do. The demand elasticity for high-income counties is 21% higher than the average demand elasticity for all the 67 counties in 2004, -0.087. While the demand elasticity for low-income counties is 15% below that for all counties.

Demand or Supply Shift: Which One is More Efficient at Raising Test Scores?

Given the elastic supply and highly inelastic demand we found for the Alabama educational market, moving along the demand curve has little effect on equilibrium quantity unless they are accompanied by shifts in the curve, as noted by Brasington (2003). Income growth seems to the most effective way to raise student test scores in our paper, followed by increase in state funding and enrollment, and poverty reduction.

Does Money Matter in Alabama's Educational Market?

Yes. Increased stated funding has a measurable effect on student performance as long as the state funding goes into increasing teacher's salaries not into the reducing class size or increasing the percentage of teachers with a terminal degree.

What Explains the Change in student Performance between 1992 and 2004?

The *Stanford Test* scores of Alabama students in 1992, 1996, 2000 and 2004 are 37, 52, 51 and 46 respectively. The corresponding percentage changes from one period to the next period are 37.70%, -0.49% and -9.42%. Table 18 indicates how well our model explains the variation of the endogenous variable. The numbers under the column '% change' are percentage changes of the exogenous variables. For example, state funding increased by 25.21% from 1992-1996 and the total elasticity of *Q8* with respect to state funding is 0.201. The product of these two numbers yields the percentage change of *Q8* predicted by change in state funding, which is a 5.07% increase listed under the column 'Explained by'. Similarly, due to increases in real income, our model predicts that student test score would decrease by 1.33% from 1992 to 1996. The total percent change of student test score predicted by our model is an increase of 3.97%, as opposed to the real increase of 37.70%.

For the period from 1996 to 2000, the model predicts that average test scores would increase by 4.64% however, the fact is that they decreased by 0.49%. Our model works the best for the most recent period from 2000 to 2004. The model predicts that the test score would drop by 5.71% and the actual drop is 9.42%, which means our model explains about 61% of the variation in the endogenous variable.

The simulation results with demand elasticity set to -0.300 are also in Table 18, in which the state funding effect plays a much stronger effect in determining the change of test scores. Our model only explains 41.75% (15.74%/37.70%) of the student performance change from 1992 to 1996, 76.86% (-7.24%/-9.42) of the performance change from 2000 to 2004. The explanatory power for the periods of 1992-1996 and 2000-2004 both increases vastly and remains poor for 1996-2000.

Both simulation results indicate that our model works best for the 2000-2004 period, with high explanatory power for the variation in student test scores. Overall, results indicate that the increase in state funding explains part of the test score jump from 1992 to 1996. The decrease in state funding and median family income are responsible for the test score decrease over the 2000-2004 periods.

VII. NCLB AND SCHOOL INPUTS AND OUTPUTS

The NCLB Act is an expensive law with ambitious goals. In 2002, the first year of its implementation, NCLB awarded $20 billion of US education funding to various programs (among them education for the disadvantaged took the lion's share), a demonstrated increase from $14 billion in 2001[15]. The projected NCLB funding in 2007 is $22.5 billion. As stated in the 670-page-long law, one basic goals of NCLB is to improve the academic achievement of all students by holding schools, local educational agencies, and States accountable.

In this section, we measure the impact of NCLB on the measurable direct school outputs, standardized test scores, at both state and Alabama county level to tell whether NCLB turned out to be a nationwide success and how its impact is felt differently in Alabama from other states. A number of socio-economic variables were collected and used as control variables. In addition, the impact of NCLB on schools' inputs is addressed. The selected school inputs include schools' total funding, federal funding, instructional expenditure, teacher-student ratio, and teacher's salary. According to Table 10, they are endogenous variables. Comparing the impact of NCLB on schools' inputs and outputs is analogous to cost-benefit analysis therefore is of our interests.

Impact of NCLB on School Inputs and Outputs in Alabama

Based on the results of the endogeneity tests in Table 10, the following reduced form models are posited and estimated

(9A) $Q4S_{it}/Q8S_{it} = \mathrm{F}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3S_{it}/Q4S_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, POV_{it}, POV{*}SF_{it}, POV{*}OF_{it}, POV{*}TED_{it}, \mu_{Fit})$

(9B) $P_{G\,it} = \mathrm{G}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, \mu_{Git})$

(9C) $FF_{it} = \mathrm{H}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, \mu_{Hit})$

(9D) $PI_{it} = \mathrm{I}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, \mu_{Iit})$

(9E) $TSR_{it} = \mathrm{J}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, \mu_{Jit})$

(9F) $TPAY_{it} = \mathrm{K}(NCLB_{it}, SF_{it}, OF_{it}, TED_{it}, ENROL_{it}, SCHOOL_{it}, Q3_{it}, INC_{it}, PV_{it}, RACE_{it}, UNEMP_{it}, RURAL_{it}, \mu_{Kit})$

where i and t are the county and year indices, μ*'s* are random error terms. S is the index for *Stanford Test* subjects including reading (R), math (M), language (L), and total (T). For example, *Q4R* stands for the fourth-grade test scores in reading. Moreover, all continuous variables are specified in the logarithms, permitting the estimated coefficients to be interpreted as elasticities. The data used in estimation are pooled time-series/cross-section data for 1999-2004 since the subjects scores of *Stanford Test* are only available for this period.

One advantage of using the subject scores is that it allows conversion from *Stanford 9* to *Stanford 10* percentiles with Harcourt Assessment Percentile Rank Conversion Tables. All the *Stanford 9* percentiles are converted to *Stanford 10* percentiles therefore, making scores directly comparable for 1999-2004.

NCLB is a dummy that takes on the value of one for the period 2002-2004 and zero otherwise. Equations (9A) – (9F) were estimated as a two-way fixed effects model to control for county and time specific effects. The NCLB dummy would indicate if there is any residual time effect after taking into account systematic variation due to the passage of time[16]. The square root of enrollment is used in all equations as the weight to correct for heteroscedasticity.

Equation (9A) defines a production function for the subject scores of fourth and eighth graders. The existence of student previous test scores in equation (9A) makes it a value-added production function. One innovative feature of equation (9A) is to allow poverty rate to interact with the exogenous school inputs including state funding, other funding, and teacher's education. When estimating total test scores, model A includes the three interaction terms and model B excludes them. In equations (9B) – (9F), we are interested to see if NCLB has improved major school inputs in Alabama. Results are reported in Table 19 for fourth graders and in Table 21 for eighth graders.

Impact on Fourth Graders

Estimation results overall are satisfactory in both tables in that adjusted R^2 ranges from 0.71 to 0.96. For school inputs in Table 19, NCLB is statistically significant in *SF, PI*, *TSR*, and *TPAY* equations, with estimated elasticity of 0.251, 0.064, 0.033, and -0.043. Results suggest that federal funding to Alabama increased by a quarter attributable to NCLB. As a result, instructional expenditure increased by 6.4%. Class size shrank slightly, however, teacher's salary decreased by 4.3% due to NCLB. A large increase in federal funding did not bring up the total funding, mainly because federal was only 13% of total funding (in 2004) or federal funding is substitutive for state or local funding, or both.

The estimated NCLB effect is insignificant in any test subject for fourth graders. In contrast, median family income, corresponding third-grade test scores, state funding, teacher's education, and poverty rate exert strong influence on fourth-grade test scores.

For example, a 10% increase in median family income or third-grade reading test score will result in an estimated increase in fourth-grade reading test score by 6.68% or 2.25%.

Since the F test statistic is significant for the hypothesis of no interaction in all the four equations containing interaction terms, the model A is preferred over B. The elasticities of student performance with respect to state funding, teacher's education, and other funding are calculated using corresponding significant coefficients in model A for total score and they are reported in Table 20. For example, estimated state funding elasticity is 0.069 when poverty rate is measured at its mean level of 23.15% ($0.069 = -3.133 + 1.019 * \ln POV$). Since the coefficient for interaction between poverty rate and state funding is positive, the state funding elasticity increases as poverty rate increases, meaning state funding gets a bigger bang for the money for poorer districts. So does other funding but with a much smaller effect. State funding elasticity is -0.683 when poverty rate is 11.07% (two standard deviations below its mean) and 0.497 when poverty rate is 35.23% (two standard deviations above its mean). Conversely, the teacher's education elasticity decreases as poverty rate increases. Estimated teacher's elasticity is tiny at 0.003 for mean poverty rate and it goes to 0.104 or -0.055 when poverty rate goes two standard deviations below or above its mean, respectively. What Table 20 suggests is that state funding, other funding, or teacher's education has positive impact on student performance on average. However, state funding gets much more of its worth in districts where poverty rate is high while teacher's education works in the opposite way.

Impact on Eighth Graders

Since results for school inputs in Table 21 are very similar to those in Table 20, we skip discussion on this part and focus on the impact of NCLB on eighth-grade student test scores. First, NCLB is found to bring up eighth-grade math test score by 8.8%, a positive but surprising result since NCLB puts reading first. The effect of NCLB on eighth-grade reading or language, or total scores (model A or B) is insignificant. Among the five equations for test scores, we reject the hypothesis of no interaction effect only for the math equation. Effects of some other significant variables for fourth-grade student test scores in Table 19 seem to attenuate to a large degree for eighth-grade student. To name a few, median family income is insignificant in all the five equations; state funding and poverty rate are only significant in model B for the total score equation, with a positive and negative effect, respectively. Only student previous academic achievement holds a robust and positive effect in four of the five equations with smaller magnitude.

Overall, our results indicate that NCLB helped Alabama's eighth graders in math but not reading or language, and NLCB had no impact on performance of Alabama's fourth graders in any of the three *Stanford* subjects. Student previous academic achievement determines his/her current academic performance for both fourth- and eighth-graders. Family or district influence such as median family income and poverty rate mainly affects students in early grades. There is evidence found supporting that some school resources interact with poverty rate.

Impact of NCLB on State Level School Inputs and Outputs

This part evaluates the impact of NCLB on major school inputs and outputs using pooled state level data. We choose nonparametric linear regression in the presence of outliers in the state level data.

Data

Data on test score were obtained from the Nation's Report Card (the National Assessment of Educational Progress (NAEP)) produced by National Center for Education Statistics (NCES) at the US Department of Education. Test scores in reading and math are available for both fourth- and eighth-graders for the period of 1998, 2002, 2003, and 2005, and the period of 1996, 2000, 2003, and 2005, respectively. Data for 2005 is truncated since data for the majority of control variables are not available for this year. Data on schools' total, local, state, and federal funding, class size, teacher's salary, percentage of non-white students, school enrollment, and number of schools were obtained from the *Common Core of Data (CCD)* maintained by NCES. Data on adult educational attainment were obtained from *Statistical Abstract of the United States* at the US Census Bureau. Data on adult educational attainment are not available for 1996 and they were interpolated by data of their adjacent years. The data used for median family income and poverty rate came from *Small Area Income & Poverty Estimates 1996-2003* at the US Census Bureau. Unemployment rate data were obtained from the *Local Area Unemployment Statistics (LAUS) Program* at the Bureau of Labor Statistics.

Variable definitions and summary statistics are reported in Table 22. By comparing mean values in 2000, 2002, and 2003, most variables in Table 22 show a trend of increase over years among which include school funding by all sources (all financial data are in real terms), instructional expenditure, teacher's salary, adult educational attainment, poverty rate, percentage of non-white students, unemployment rate. Class size held steady at between 15 and 16. Note that teacher's salary increased by 4.7% while median family income dropped by 2.7% from 2000 to 2003.

Model

The following reduced-form models similar to equations (9A-F) are posited and estimated

(10A) $Q8S_{it} = \mathrm{F}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, Q4R_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Fit})$

(10B) $Q8M_{it} = \mathrm{G}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, Q4M_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Git})$

(10C) $P_{G\,it} = \mathrm{H}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Hit})$

(10D) $FF_{it} = \mathrm{I}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Iit})$

(10E) $PI_{it} = \mathrm{J}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Jit})$

(10F) $TSR_{it} = \mathrm{K}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Kit})$

(10G) $TPAY_{it} = \mathrm{L}(NCLB_{it}, SF_{it}, ENROL_{it}, SCHOOL_{it}, INC_{it}, RACE_{it}, UNEMP_{it}, POV_{it}, ED_{it}, \mu_{Lit})$

where *i* and *t* are the state and year indices, *μ's* are random error terms. *S* is the index for *Stanford Test* subjects including reading (R) and math (M). *NCLB* is a dummy that takes on the value of one for years later than 2002 and zero otherwise. *Q4* is excluded in equations for school outputs since it is insignificant in any of the equation for school output in Table 21.

Nonparametric Regression Estimation and Results

Equations (10A) – (10G) are expressed in double-log form and coefficients (elasticities) are estimated with R-package using the nonparametric linear regression proposed by Jaeckel, Hettmansperger and McKean. One-way fixed effects model is applied in which state specific effect is allowed. Existence of outliers justifies the use of nonparametric regression method over ordinary least squares estimator. For example, DC receives federal education funding but no state funding and students in DC always underperformed its peers in other states to a great extent in both reading and math tests. Once state test score is plotted, the test score corresponding to DC is obvious an outlier. There is no reason to exclude DC from our analysis. Non-parametric linear regression is much less sensitive to outliers than is simple linear regression based upon the least squares method. Results of nonparametric linear regression are reported in Table 23. For comparison purpose, estimated results using ordinary least squares methods are reported in Table 24. Results of state specific effects are suppressed due to space limit.

Turning to the impact of NCLB on school inputs first, Table 23 shows that NCLB increased schools' total funding, federal funding, instructional expenditure, teacher-student ratio, and teacher's salary by 11.5%, 30.6%, 11.4%, 5.1%, and 5.5%, respectively. Results are consistent with expectations since we found NCLB has the largest impact on federal funding. As a result, the state level school total funding and instructional expenditure increased by about 11% each. NCLB's impact on teacher-student ratio and teacher's salary is a positive and moderate increase of around 5.5%.

Highlights of estimation of other variables on school inputs include: increase in state funding is found to increase total funding, instructional expenditure, and teacher-student ratio and increase in school enrollment has a negative effect on any of these three variables mainly because enrollment is the denominator when calculating the three variables; the positive effect of number of schools on total school funding and instructional expenditure indicates that state with more schools tends to have higher level of school funding and instructional expenditure on a per pupil base; median family income is found to have a positive and significant effect on all the five school inputs. Higher median family income can lead to higher demand for education and teachers, resulting in higher level of school funding and spending, smaller class, and better teacher pay. The percentage of non-white students does not seem to have any impact on the five school inputs. One interesting finding is that higher poverty rates lead to higher levels of any of the first four school inputs, a sign indicating the education system is indeed practicing one purpose of NCLB that "distributing and targeting resources sufficiently to make a difference to local educational agencies and schools where needs are greatest". Finally, higher adult educational attainment shows positive effect on total funding, instructional expenditure, and student-teacher ratio, suggesting the better parents are educated, and the higher spending and smaller class size they demand for their kids, but not better pay for teachers in reality.

The *NCLB* dummy is not significant in either the reading or the math equation. Only student previous achievement plays a positive and significant role in both equations, indicating reading and math are accumulated learning process. In the math equation, fourth-grade math test score is the only significant variable. A 10% increase in the fourth-grade math test score will lead to an estimated increase of eighth-grade math test score by 6.08%, meaning accumulation is crucial to math study. Unlike math, we found that some other variables matter to eighth-grade reading test score in addition to fourth-grade reading test score.

First, states with larger enrollments are found to have lower reading test scores. Second, the negative correlation between reading score and percentage of non-white students indicates that students with various racial backgrounds have different tastes in education. Black students tend to have lower demand for reading skills. Third, higher adult educational attainment is found to increase student test score in reading, probably due to higher demand from parents for education. Last, unemployment is found to be positively related with student reading test score with answer remaining unclear. Once ranked by size, fourth-grade student reading test score and adult educational attainment play key influence on eighth-grade student reading test score. The impact of school enrollment and racial mix is tiny.

Finally, there are a number of differences between the nonparametric results in Table 23 and OLS results in Table 24. For example, the *NCLB* dummy is significant and negative for math equation in Table 24 but not significant in Table 23. Table 23 is preferred over Table 24 due to the existence of outliers.

VIII. CONCLUSION AND FUTURE RESEARCH

The present essay aims to make the following contribution to the economics of education literature. The first contribution is the improved dataset. Our dataset provides a wide range of district-level variables for Alabama for the period 1996-2004. Variables include fourth- and eighth- student *Stanford Test* scores, school funding and expenditures by source, teacher's salary and education, class size, number of schools in each district, racial composition of students, and enrollment etc that are school related. Non-school related variables include personal income per capita, median family income, adult educational attainment, poverty rate, unemployment rate, property valuation, and so on.

Completing the panel data entails abstracting data from various issues of Alabama Department of Education Annual Reports, individual county school report cards, communicating with personnel from the Alabama Department of Education and Alabama Department of Examiners of Public Accounts, and referring to a number of internet data sources. It took us half a year to complete the collection of the data. The rich dataset is used in the present paper to address the effectiveness of state funding and NCLB (federal funding) in improving student test scores; furthermore, it can also be used for our future research and by other researchers who are interested in Alabama's K-12 education.

The second contribution of the present essay lies in the methodology. We start with a replication of Ferguson and Ladd's 1996 production function study on Alabama primary education market but the model does not support the conclusion they have that spending matters to student performance. After the replication study, estimates are shown to be very sensitive to a single function specification. We argue that if not carefully addressed, the endogeneity problem among school funding and teacher-related variables could plague the validity of production function studies. Endogeneity is detected in school total, local, and federal funding, class size, and teacher's salary, which helps justify the adoption of the KZB's (2005) five-equation supply-demand approach.

By estimating the five-equation system with three stage least squares estimator, the system produces consistent estimates with KZB's study on Alabama using 1992 data. We find that state educational funding, teacher's salary, and student median family income matter the most to student performance. Another finding is that the rightward shifting of the demand curve seems to be a better tool than moving along the demand curve to improve student performance, since demand for education is highly inelastic and supply is elastic in Alabama.

The last contribution of the present paper is the up-to-date evaluation of NCLB impact. The impact of NCLB on student performance is being hotly debated. Our quantitative analysis based on large dataset over a long period provides sound evidence that NCLB is doing well for Alabama students. The present dataset makes other hypotheses feasible to test. For our future research, there is a lot that can be done. The NCLB Act is a continuous research topic that is of great interest. The 2005 data will be collected to better measure the impact of NCLB Act on student performance since 2005 is another year in which *Stanford 10* is adopted. One natural application of the current dataset is an analysis of the factors affecting the supply and demand for teacher quality. Consider the number of highly qualified teachers in Alabama to be at its equilibrium level determined by demand and supply. Highly qualified teachers can be approximated by the number/percent of teachers with a terminal degree or with at least a Master's degree[17]. Teacher demand can be hypothesized to be a function of teacher's salary, local median family income, the community's demand for a particular level of teacher quality measured by adult educational attainment, percent of students who are non-white as a measure of racial mixture, and school instructional expenditure and non-instructional expenditure. Teacher supply can be hypothesized to be a function of teacher's salary, population, the unemployment rate, a rural dummy variable, a black belt county dummy variable, and student characteristics that can be measured by test scores[18]. The empirical model is as following:

(11A) $TED = D(TPAY, INC, ED, RACE, PI, PNI)$

(11B) $TED = S(TPAY, POP, UNEMP, RURAL, BLACKBELT, Q4)$

where (11A) and (11B) are the conceptual models for demand and supply. The model disentangles the supply and demand forces that determine the level of highly qualified teachers in a county. Besides the demand and supply elasticities, we are interested in several empirical questions such as "are teachers less willing to relocate to black belt counties in Alabama?'.

Overall, we have completed a rich dataset and applied a supply-demand approach instead of classic production function approach to model Alabama primary educational market. I am interested in educational finance and reforms and this is my first attempt at tacking empirical educational issues. I will continue my efforts in my future research career.

CHAPTER 2. NEWS AND VOLATILITY OF FOOD PRICES [19]

I. INTRODUCTION

The present essay examines whether unexpected price changes or news affects the variance of prices for 45 retail US food items. Price volatility generates losses for consumers and producers as developed by Newberry (1989). The hypothesized link between news and volatility of prices is motivated by the seminal work of Engle and Ng (1993) who develop a news impact curve that measures how new price information is incorporated into volatility. For assets, estimated news impact curves are typically asymmetric with news of low prices having a larger impact on volatility.

Studies of asymmetric news impacts in the macroeconomic literature include Braun, Nelson and Sunier (1995) and McKenzie (2002). The most common explanation is the asset leverage effect of Braun, Nelson, and Sunier (1995) and Chen and Wang (2004). McKenzie (2002) attributes the asymmetry in foreign exchange markets to central bank intervention. Other explanations for asymmetry include the reduced serial correlation of prices during periods of high volatility as developed by Shiller (1984), non-synchronous trading of Lo and MacKinlay (1987), and firm size effects of Chueng and Ng (1992). Attribution theory offers a theoretical background for asymmetric news effects based on risk aversion as in Mizerski (1982), Chang and Kinnucan (1991), and Richards and Patterson (2005).

The extent to which food price news contributes to volatility may have some practical or policy interest. Tomek (2000) notes the variance of farm prices increases from harvest to summer attributing the increase to crop uncertainty during the growing season. Time varying variances are noted in some retail and farm prices. Bénabou and Gertner (1993) note that increased volatility may reduce the incentive for consumer search and magnify retailer market power. Samuelson (2005) notes food and energy are the most volatile components of consumer prices. The importance of price news is emphasized by the recent mad cow scares discussed by Burton and Young (1996), Lloyd, McCorriston, Morgan, and Rayner (2001), Verbeke and Ward (2001), Pennings, Wansink, and Meulenberg (2002), Jin and Koo (2003), Sanjuán and Dawson (2003), Piggott and Marsh (2004), and McCluskey, Grimsrud, Ouchi, Wald (2005).

Price volatility at the farm level has received attention, for instance by Yang, Haigh, and Leatham (2001), Apergis and Rezitis (2003a), Yang, Zhang, and Leatham (2003), and Bose (2004). Studies of retail price volatility focusing on its transmission through the marketing channel include Kesavan, Aradhyula, and Johnson (1992), Jha and Nagarajan (2002), Apergis and Rezitis (2003b), and Rezitis (2003).

The present paper contributes to this literature with its test of asymmetric volatility. The exponential generalized autoregressive conditional heteroskedastic (EGARCH) model of Nelson (1991) allows a straightforward test of the asymmetry hypothesis. The present analysis of 45 food markets suggests that price news exacerbates volatility in a number of markets with news of high prices more destabilizing.

II. THE NEWS IMPACT CURVE

Following Engle and Ng (1993) let y_t be the first difference of the natural log of price. Let $F_{t\text{-}1}$ be the past information set containing realized values of all relevant variables. Consumers know the information in $F_{t\text{-}1}$ when they make consumption decisions at that time. The expected price change and volatility are the conditional expected value of y_t and the conditional variance of y_t given $F_{t\text{-}1}$ denoted $m_t \equiv E(y_t|F_{t\text{-}1})$ and $h_t \equiv var(y_t|F_{t\text{-}1})$. The unexpected price change at time t is $\varepsilon_t = y_t - m_t$. Engle and Ng (1993) state that ε_t may be treated as a collective measure of news at time t. If $\varepsilon_t > 0$ (< 0) price is higher (lower) than expected. With the maintained hypothesis that predictable volatility depends on past news, the ARCH specification of Engle (1982) is

(12) $$h_t = \omega + \Sigma^{p}_{i=1} \alpha_i \varepsilon^2_{t\text{-}i}$$

where p is the number of lags and α_i and ω are parameters. An implicit assumption is that older news has less impact on current volatility than more recent news, $\alpha_i < \alpha_j$ for $i > j$. News that arrived more than p periods ago has no effect on current volatility.

The GARCH (p, q) model introduced by Bollerslev (1986) generalizes the ARCH (p) model by including the persistence term

(13) $$h_t = \omega + \Sigma^{p}_{i=1} \alpha_i \varepsilon^2_{t\text{-}i} + \Sigma^{q}_{i=1} \beta_i h_{t\text{-}i}$$

where q is the number of lags for the lagged variance term and the β_i are coefficients. This GARCH model is an infinite order ARCH model. Most empirical applications use the GARCH(1,1) implying the effect of the shock declines geometrically over time.

As noted by Engle and Ng (1993) a drawback of (12) and (13) is the implicit assumption that low or high price news has symmetric effects. The exponential GARCH or EGARCH model of Nelson (1991) relaxes this assumption,

(14) $\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \gamma\, (\varepsilon_{t-1}/h_{t-1}^{\frac{1}{2}}) + \alpha\, [(|\varepsilon_{t-1}|/h_{t-1}^{\frac{1}{2}}) - (2/\pi)^{\frac{1}{2}}]$

where ω, β, γ, and α are coefficients with asymmetry captured by γ. If $\gamma = 0$ there are symmetric effects but if γ is positive (negative) high (low) price news generates more volatility. The EGARCH model embeds a parametric test of the asymmetry hypothesis.

The news impact curve of Engle and Ng (1993) is based on (13) and (14). Comparing the GARCH(1,1) and EGARCH(1,1) models with one lag, the relation between ε_{t-1} and h_t is the news curve relating past news to current volatility and measuring how new information is incorporated into volatility.

Graphs of the GARCH(1,1) and EGARCH(1,1) models in Figure 4 highlight key differences. First, the news impact curve implied by the GARCH model is symmetric with respect to the centering point $\varepsilon_{t-1} = 0$ while the graph for the EGARCH model is skewed right implying high price news produces more volatility. The graph illustrates $\gamma > 0$ and for $\gamma < 0$ there would be left skew.

A second difference is the EGARCH curve rises faster than the GARCH curve moving away from the origin, implying that "big news" is more destabilizing in the EGARCH model than in the GARCH model. This feature is due to the functional forms with the exponential EGARCH tending to overtake the quadratic GARCH as they extrapolate beyond the minimum point at $\varepsilon_{t-1} = 0$.

Jagannathan and Runkle (1993) relax this magnification feature of the EGARCH model in the Glosten model $h_t = \omega + \beta\, h_{t\text{-}1} + \alpha\, \varepsilon^2_{t\text{-}1} + \gamma\, S^-_{t\text{-}1}\, \varepsilon^2_{t\text{-}1}$ where $S^-_t = 1$ if $\varepsilon_t < 0$ and $S^-_t = 0$ otherwise. There is little difference between present estimates of this GJR model and the EGARCH (1,1) as presented.

The model is completed by mean and error equations,

(15) $y_t = \mu + \Sigma^k_{i=1}\, \rho_i\, y_{t\text{-}k} + \varepsilon_t$

(16) $\varepsilon_t = v_t\, h_t^{2}$

where y_t is the first difference of log price, k is the lag length, and v_t is a white noise process with unit variance. The lagged terms in the autoregressive AR(k) process (14) capture the predictable components of price change. The error term ε_t reflects a random component or shock. The conditional variance of the shock in (16) h_t forms the basis for the dependent variable in (14).

III. EMPIRICAL RESULTS

The present data of monthly retail food prices from 1980 to 2004 is from the US Bureau of Labor Statistics for 45 food items that account for the bulk of the US Consumer Price Index (CPI). Prices for items with limited data availability are excluded as are prices for different package sizes of items such as sugar, coffee, and cola. The most representative package size is chosen. The sample yields 300 observations but with incomplete reporting actual sample sizes in some instances are less, most notably pork with 80 and broccoli, cola, and wine with 110.

The EGARCH model requires a stationary data generating process and the Dickey and Fuller (1981) test for unit roots is

(17) $\Delta \ln p_t = a + b\, \Delta \ln p_{t-1} + c\, T + e_t$

where T is a unit step variable. These test results (reported in Table 25) indicate that each log series is difference stationary in (15), $y_t = \ln(p_t/p_{t-1}) = \Delta \ln p_t$. For 19 products, however, both b and c are significant at the 5% level and the dependent variable in (15) is set to $y_t = \Delta \ln p_t - c\, T$ to remove the trend.

The system (14) - (16) is an AR(k)-EGARCH(1,1) model with the autoregressive parameter k selected to produce the most parsimonious specification for (14) using Box-Jenkins strategy. An AR(1) or AR(2) provides good approximation to the data generating processes. Maximum likelihood estimates of α, β, and γ are in Table 26. The 5% significance level is used unless indicated otherwise.

There is evidence of time varying variance with either α or β significant for 40 of the 45 items. The exceptions are cola, eggs, ground beef, peanut butter, and sirloin steak and their constant variance is evidence of mature markets. The parameter α in (14) is significant for 25 items (55% of the sample) indicating news effects on volatility, and the parameter γ is significant for 23 (51%) of the items indicating asymmetric news affects.

A joint test for the significance of ARCH/GARCH effects in the three parameters α, β, and γ is provided by the Lagrange Multiplier LM statistic reported in the last column of Table 26. These LM effects are insignificant for 16 items (36%). The LM test has low power in the sense of high probability of a Type II error of failing to reject a false null hypothesis. It is not intuitive for a significant asymmetry effect of γ with insignificant

ARCH/GARCH effects as occurs for cabbage, celery, cucumbers, flour, pork, and turkey. To err on the conservative side, asymmetry is considered significant only if γ and the LM statistic are jointly significant.

Table 27 lists these significant items along with coefficients for high and low price news. In the EGARCH(1,1) model the effect of high price news on conditional variance is $\alpha + \gamma$ and the low price effect is $\alpha - \gamma$. For apples, estimated effects are 0.44 and 0.02. An unexpected price increase measured by a unit increase in the standardized residual $|\varepsilon_{t\text{-}1}|/h_{t\text{-}1}{}^{2}$ with $\varepsilon_{t\text{-}1} > 0$ increases volatility 44%. In contrast, an unexpected price decrease with $\varepsilon_{t\text{-}1} < 0$ increases volatility 2%. For apples, the news impact curve is upward sloping for both high and low price news with high price news more destabilizing. The mean effect for the 16 items for high price news is 0.45 and for low price news 0.04. The *t*-value computed under the null hypothesis that the mean responses are equal is 3.06, and the mean news impact curve for these 16 items mimics apples. The mean conceals variation across items and a number of anomalies but illustrates the asymmetry in Figure 4. The EGARCH(1,1) curve in Figure 4 corresponds to equations $\ln(h_t) = -.8 + \ln h_{t\text{-}1} + .45\ \varepsilon_{t\text{-}1}/h_{t\text{-}1}{}^{½}$ when $\varepsilon_{t\text{-}1} > 0$, and $\ln(h_t) = -.8 + \ln(h_{t\text{-}1}) + .04\ (\varepsilon_{t\text{-}1}/h_{t\text{-}1}{}^{½})$ when $\varepsilon_{t\text{-}1} < 0$ given $h_{t\text{-}1} = 1$. The symmetric GARCH(1,1) curve corresponds to $h_t = -.55 + h_{t\text{-}1} + .004\ (\varepsilon_{t\text{-}1}{}^{2})$.

High price news for T-bone steaks has no effect on price volatility but low price news has a pronounced effect of 0.22. T-bone price surprises are different from other beef cuts, and ice cream is similar to T-bones. Regular consumers of T-bone steaks and ice cream might be insensitive to high price news but potential consumers are sensitive to unexpected low prices.

There are instances of downward-sloping news impact curves but this is more common for low price news. For onions, the coefficient of high price news is 0.45 and the low price coefficient is -0.43 implying that an unexpected jump in the retail price has a destabilizing effect while an unexpected fall stabilizes price. There is a similar pattern for carrots, chicken, grapefruit, lettuce, potatoes, and tomatoes. The market responds to unexpected price increases but does not notice unexpected price declines. When these prices jump unexpectedly the markets attract attention, but with an unexpected fall in price there is decreased volatility.

For 10 of the 16 items in Table 27 coefficients of high price news are larger than the absolute values of the low price news coefficients, consistent with the hypothesis that consumers respond disproportionately to high price news. Of the total sample, there are significant price surprise effects in the first two columns of Table 28 for only a quarter of the items. Of these 16 items, high price news is destabilizing for about half. For the remaining items, either there are no price news effects or there is no effect on variance.

Inferences based on GARCH-type models can be fragile as discussed by Jones, Lamont, and Lumsdaine (1998) and an additional test on asymmetry is the regression

(18) $s_t^2 = \delta_0 + \delta_1 s_{t-1} + \delta_2 s_{t-2} + \delta_3 s_{t-3} + v_t$

where $s_t = (\varepsilon_t/h_t^2)'$, the predicted standardized residual from (15). A statistically significant value of F for the null hypothesis $\delta_1 = \delta_2 = \delta_3 = 0$ indicates remaining asymmetry effects as developed by Enders (2004). In that case the model is misspecified in that sources of asymmetry are omitted. To make the test as complete as possible (18) is estimated for all items in Table 26 that have a significant γ. Results suggest the EGARCH model is well specified in the sense that asymmetric effects are fully accounted for in 22 of the 23 cases in Table 29. The exception is potatoes with the null hypothesis rejected at the 1% probability level. For the other commodities computed F-statistics are very small providing confidence that (18) has no explanatory power and the noted asymmetry effects are legitimate.

IV. CONCLUSION

Price volatility is welfare decreasing and may reduce competition by increasing consumer search costs. There is time varying variance for all but 5 of the 45 food prices from the US Consumer Price Index over the past 25 years. Price news affects variance for only 16 of the items and there is asymmetric volatility with larger effects for high price news for 10 of those items. Low price news stabilizes price in 7 of the markets.

The present results have implications for food markets in light of recent highly publicized instances of food safety. A food scare that lowers price might amplify price volatility, a neglected issue in the food contamination literature exemplified by Richards and Patterson (2005). Present results indicate the amplifying impact of news is an issue for about a third of the food markets.

It is worth noting that food price volatility has been declining over the period. The coefficient of variation in monthly food prices for these 45 items declined from 11% during the 1980s to 9% during the 1990s to 7% during 2000-04. There is increased concentration in distribution and retailing and larger firms are able to absorb price changes pricing to market. The declining farmer share of final consumer spending suggests farm price volatility is not passed along to consumers. Unexpected high prices, however, have an asymmetric effect on volatility in a number of markets. For the third of the food markets that have constant variance, the suggestion is that the markets are mature.

CHAPTER 3. THE IMPACT OF NAFTA ON LABOR IN THE US[20]

I. INTRODUCTION

The political rhetoric in the United States over trade liberalization points to a clear divergence between how economists and the general public view the relationship between international trade and unemployment. Some economists have historically taken the point of view that trade and unemployment are unrelated[21]. This is evidenced most clearly by the fact that the overwhelming majority of international trade models assume full employment. The prevailing view may be that unemployment is largely determined by macroeconomic variables and not by microeconomic forces that determine trade patterns and factor returns. However, politicians, the media, and the general public hold the opinion that trade and unemployment are closely related.

During a visit to a textile mill in North Carolina in July 2005, US President George W. Bush speaking of the Central American Free Trade Agreement (CAFTA) said that CAFTA is a "pro jobs bill" and that "this is a good deal for workers"[22]. This point of view is not unique to recent policy debates. One only has to recall Ross Perot's talk of the North American Free Trade Agreement's "giant sucking sound" during the 1992 Presidential campaign.

There is a growing literature that suggests that trade and unemployment may have strong linkages. Hoon (1994) and Matusz (1996) both integrate efficiency wage based unemployment into the standard model of intra-industry trade. Both show that moving from autarky to trade reduces the economy's unemployment rate. Janson and Turini (1995) reach a similar conclusion using search based unemployment in a model of intra-industry trade. Davidson, Martin, and Matusz (1999) integrate search based unemployment into a simple two-good, two-factor model of comparative advantage. They show that a large capital abundant country that that trades with a small labor-abundant country may see their unemployment rate increase when they open to trade[23].

There is mixed empirical evidence on the impacts of trade on employment levels. Revenga (1992) shows that decreased industry level import price indices lead to decreases in employment using US data. Revenga (1995) finds similar results using data from Mexico. Matusz and Tarr (2000) summarize a number of papers concerning trade liberalization and employment in less developed countries. Their conclusion is that the existing data shows a positive relationship between trade liberalization and employment levels. Finally, Davis, Haltiwanger, and Schuh (1996) find no evidence that exposure to trade has any impact on flows of job creation and job destruction. Empirically, there is no consensus on the issue of trade and unemployment.

An additional concern that is at the heart of the general public's fear of trade is that of labor market adjustment. A great many workers fear that international trade will create short term spells of unemployment and that there may be significant costs of retraining and relocating. A real question of concern is the length of the adjustment period. Davidson and Matusz (2000) construct a model of labor market search where workers have an incentive to retrain after trade liberalization. Using simulations they show that their model implies an adjustment period of four years following liberalization, a significant but perhaps not extreme time period. Matusz and Tarr (2000) review a large number of empirical papers on adjustment costs and find a similar conclusion. Adjustment costs tend to be small relative to the size of the gains from trade.

A natural starting place to begin to examine the effects of trade liberalization on the US economy is the NAFTA agreement. The signing of NAFTA provides one of the few points in time where the United States has an obvious and significant trade liberalization event. The present chapter adds to both the literature on trade and unemployment and the literature the adjustment to trade liberalization. This chapter first estimates the effects that NAFTA on unemployment in US states then follows these effects through time to estimate the length of the adjustment period. To preview the results we find that NAFTA had a positive effect on unemployment in 16 of the 49 US states and pooled estimates suggest that NAFTA reduced state level unemployment. We also find that the labor market began to feel the effects of NAFTA two years following is implementation and the labor market has continued to feel its effects through 2004, the last year of our data.

II. THEORY

The following section develops a supply and demand model of the labor market to examine the effects of trade on the labor market across US states. Labor demand in state k is assumed to depend on the wage (W), income (Y), the business tax rate (B), the union membership density (M), the level of unemployment insurance (R), and the degree of trade openness (T) in the general function,

(19) $L_D = D(W, Y, B, M, R, T)$.

The quantity of labor demanded is assumed to depend negatively on the wage, the business tax rate, and unemployment insurance, and positively on gross state product.

Unions have an ambiguous effect on labor demand. Unions can increase labor demand by supporting and lobbying for programs that increase product demand, influence the prices of related inputs, and increase the number of firms that employ union workers (McConnell, Brue and McPherson, 2006). However, they can also influence labor demand through their effects of productivity. The evidence concerning unions and productivity is mixed. The meta-analysis by Doucouliagos and Laroche (2003) on the existing literature shows that the mean effect of unions on productivity is a positive 3%. However, there are as many studies reporting negative effects as positive effects.

Labor demand may depend either positively or negatively on openness depending on whether the state specializes more heavily in exporting or importing industries.

Labor supply is assumed to depend on the wage (W), the population (P), the individual income tax rate (I), the union membership density (M) and the level of unemployment insurance (R)

(20) $L_S = S(W, P, I, M, R)$

Labor supply depends positively on both the wage and the population. Labor supply depends negatively on the individual income tax rate, the union membership density, and the level of unemployment insurance. Labor supply depends negatively on union membership density because of union ability to restrict the supply of labor through exclusive unionism or occupational licensure. Labor demand depends negatively on unemployment insurance because it may provide an incentive for firms to lay off workers instead of lowering wages. Furthermore, unemployment benefits provide an income effect which also tends to reduce the supply of labor (Reynolds, Masters, and Moser, 1991).

Frictions in the labor market exist such that, in equilibrium, there is some amount of unemployment

(21) $$L_S = L_D + U$$

where U is the number of unemployed workers.

The model in (19)-(21) can be expressed in terms of percentage changes

(22) $$\hat{L}_D = \eta\hat{W} + \eta_Y\hat{Y} + \eta_B\hat{B} + \eta_M\hat{M} + \eta_R\hat{R} + \eta_T\hat{T}$$

(23) $$\hat{L}_S = \varepsilon\hat{W} + \varepsilon_P\hat{P} + \varepsilon_I\hat{I} + \varepsilon_M\hat{M} + \varepsilon_R\hat{R}$$

(24) $$\hat{L}_S = (1-\mu)\hat{L}_D + \mu\hat{U}$$

where "hats" indicate percentage changes. In (22), the η's are the demand side elasticities, and η is the elasticity of labor demand with respect to the wage and η_k for k = Y,B,M,R,T is a structural elasticity that indicates the relatively horizontal shift in the labor demand curve for a small increase in variable k. In (23), the ε's are the supply side elasticities; ε is the elasticity of labor supply with respect to the wage, and ε_j for j = P,I,M,R is a structural elasticity that indicates the relative horizontal shift in the labor supply curve for a small increase in variable j. In (24) $\mu = U/L_S$ and $1-\mu = L_D/L_S$ are parameters that indicate the share of unemployed and employed workers in the labor force. The term μ is the unemployment rate.

Substituting equations (22) and (23) into (24) and rearranging yields the quasi-reduced form

$$(25) \qquad \hat{U} = \beta_1\hat{W} + \beta_2\hat{Y} + \beta_3\hat{B} + \beta_4\hat{M} + \beta_5\hat{R} + \beta_6\hat{P} + \beta_7\hat{I} + \beta_8\hat{T}$$

where $\beta_1 = (\varepsilon - (1-\mu)\eta)/\mu$, $\beta_2 = -\eta_Y (1-\mu)/\mu$, $\beta_3 = -\eta_B (1-\mu)/\mu$,

$\beta_4 = (\varepsilon_M - (1-\mu)\eta_M)/\mu$, $\beta_5 = (\varepsilon_R - (1-\mu)\eta_R)/\mu$, $\beta_6 = \varepsilon_P/\mu$, $\beta_7 = \varepsilon_I/\mu$, and

$\beta_8 = -\eta_T (1-\mu)/\mu$.

Equation (25) defines equilibrium in the labor market. The predicted signs of the coefficients are as follows. An increase in the wage, the business tax rate, or the population are predicted to increase unemployment. An increase in income or income taxes are predicted to decrease unemployment. Increases in union density, unemployment benefits, or trade openness have ambiguous effects on unemployment.

III. EMPIRICAL MODEL

All data range from 1977 to 2004. The data used for wages come from the Quarterly Census of Employment and Wages (QCEW) program at the Bureau of Labor Statistics (BLS). The wage data measures the average annual pay per worker in each state. The data used to measure income is gross state product (GSP) per capita. The GSP per capita is calculated by taking the GSP from the Bureau of Economic Analysis divided by its population from the same source. Both wages per employee and GSP per capita are deflated using the consumer price index (CPI).

The state business tax rate is a state total composite tax rate composed of general sales, individual income, corporate income, motor fuels, licenses, and all other taxes. It is from the table of State and Local Tax Burdens by State, 1970-2005 of the Tax Foundation. Hirsch, Macpherson and Vroman (2001) provide the estimates of union membership density by state, defined as the percentage of non-agricultural wage and salary employees (including public sector employees) who are union members.

The data used to measure unemployment insurance is the unemployment insurance replacement rate, calculated by dividing the average weekly benefit paid for unemployment by average total weekly wage in covered employment from the Unemployment Insurance Financial Data Handbook of the BLS. A higher the unemployment insurance replacement rate raises assistance the unemployed receive.

The state population and individual income tax rate data are from the Bureau of Economic Analysis. Dividing current personal income taxes that go to state governments by personal income yields the individual income tax rate. Annual unemployment and the unemployment rates are the average of seasonally adjusted monthly data across years from the Local Area Unemployment Statistics (LAUS) program of the BLS. Hawaii and Alaska are excluded from the data.

The empirical implementation of equation (25) is

$$\begin{aligned} \mathrm{dln}Unemp_{iT} &= \beta_0 + \beta_1 \mathrm{dln}Wage_{iT} + \beta_2 \mathrm{dln}GSP_{iT} + \beta_3 \mathrm{dln}BTax_{iT} + \\ &\beta_4 \mathrm{dln}Union_{iT} + \beta_5 \mathrm{dln}UI_{iT} + \beta_6 \mathrm{dln}Pop_{iT} + \beta_7 \mathrm{dln}ITax_{iT} + \beta_8 N5 + e_{iT} \end{aligned} \tag{26}$$

where i and T are the state and year indices. And, all the variables except trade openness are expressed in the first difference of logarithm (log). For instance, $\mathrm{dln}Unemp_{iT}$ is the difference of the natural log of unemployment of state i between time T and time T – 1.

β_0, $\beta_1 - \beta_8$, e_{iT} are the constant, coefficients, and error terms respectively. And, N5 is a trade dummy that takes on a value of one for the year 1994 and the five subsequent years, zero otherwise. Equation (26) is a test for a structural break in unemployment[24] due to NAFTA after controlling for other relevant variables. A significant β_8 indicates the impact of NAFTA on the yearly growth of unemployment, or equivalently, the existence of a structural break in unemployment attributed to NAFTA.

Several issues regarding equation (26) need to be addressed prior to estimation. First, is the construction of the N5 variable. The specification of the trade dummy follows the methodology in Wacziarg and Wallack (2004). Although NAFTA was signed in 1992, the agreement was not fully implemented until 1994. For this reason we select 1994 as the base year for the NAFTA dummy. The openness of U.S (the trade to GDP ratio) in this time period supports our choice. Openness increased from 22% in 1994 to 23.4% in 1995, a demonstrated year-to-year increase of 6.8%. Compared to the slight increase from 20.7% in 1992 to 20.9% in 1993 it would appear that this is the year when the economy began feeling the effects of NAFTA. The 6.8% increase in openness from 1994 to 1995 is consistent with the de facto trade liberalization criterion adopted by Sachs and Warner (1995) and approaches the 7% used by Tornell (1998).

Equation (26) with N1 and N are two alternative specifications of NAFTA dummies for comparison. N1 takes on a value of one for the year 1994 only and N takes on a value of one for 1994 – 2004, and zero otherwise.

Second, note that we have not explicitly modeled technological change. However, all the variables in equation (26), with the exception of the NAFTA dummy, are in difference form. With this specification it is not necessary to specify a technology variable since the constant term, β_0, captures the effect of technology on labor demand assuming technology increases linearly over time.

Third, one might be concerned that the wage is endogenous to unemployment. A Hausman-Wu-Durbin endogeneity test confirms this finding. Therefore, OLS estimates will be biased. To correct this problem we use a two-stage least squares (2SLS) estimator. In the first stage, the wage is predicted using instrumental variables. The selected instrumental variables include the individual income tax rate, the Consumer Price Index, union membership density, the gross state product, and the gross domestic product. In the second stage, equation (26) is estimated with the use of the predicted value of the wage from the first stage.

IV. ESTIMATION RESULTS

We estimate equation (26) in three ways. First, is model A with OLS estimator applied to the pooled state level data for comparison purpose. N5 is used in model A. Second, by pooling the state level data the 2SLS estimator applies to all the three NAFTA specifications in model B. Finally, the 2SLS estimator applies at the national level using gross domestic product used instead of gross state product in model C. N5 is used in model C. The purpose of estimating the above different models is to check if data aggregation or NAFTA dummy specification matters in determining trade impact. Results for the three models are in Table 30. Models A and B are estimated using one-way fixed effects model to control for state specific effect. Turning from model A to model B with N5, the business tax rate gains significance with 2SLS used instead of OLS estimator. In the presence of endogenous wage, our discussion will focus on the estimates of the 2SLS estimator which are models B and C, especially model B with N5.

Comparison within model B and between model B and C yields two findings regarding the impact of NAFTA on unemployment growth. First, the negative and significant N5 and N1 in model B imply that NAFTA decreased state level unemployment growth. The pooled regression provides reliable results with degrees of freedom equal to 1,240. The estimates in model B with N5 suggest that NAFTA decreased the yearly state unemployment growth rate by 6.8%. This suggests that trade liberalization, at least in the case of NAFTA in the United States, tends to be a "pro jobs" policy, contrary to what is often reported in the popular press. One interesting result reflected in model B is that N (NAFTA dummy with value of one for 1994 – 2004 and zero elsewhere) is insignificant, indicating that NAFTA might have unequal impact on unemployment growth. The yearly impact of NAFTA on unemployment growth will be traced in the present paper to address this issue.

The second finding is that N5 is insignificant in model C in which country level data is used. The fact that NAFTA matters to the state level but not to the national level data shows that data aggregation matters in uncovering the adjustment of labor to changes in trade policy.

In model B with N5, higher gross state product, and individual income tax rates are predicted to decrease unemployment growth[25]. And, increases in wages, business taxes, the unemployment insurance replacement rate, and population are predicted to increase unemployment growth. Furthermore, the adjusted R^2 is at a moderate level 0f 0.386.

With the estimated coefficients of the β's in model B with N5 in Table 30 and given unemployment rates, the structural elasticities, the η's and ε's, in equations (22) and (23) are solved for and reported in Table 31. Recovering the structural elasticities for the wage and unemployment insurance replacement requires simulation methods since these variables appear on both the demand and supply sides.

Assuming perfectly inelastic supply for simplicity, the demand elasticity with respect to the wage is -0.053 which falls some short of the range of labor demand elasticity estimates in the literature. As summarized by Hamermesh (1986), the long-run labor demand elasticity is in the range of -0.15 to -0.50 for most industries and for the economy as a whole. The demand elasticity of GSP indicates that a 10% increase in GSP would raise labor demand by 1.6%, all else equal. The demand elasticity with respect to business taxes suggests that a 10% increase in business taxes will decrease labor demand by 0.18%. We find a negative effect on labor demand and supply for changes in unemployment insurance. A 10% increase in the unemployment insurance replacement rate will decrease labor demand by 0.78%[26]. Such a result suggests that unemployment insurance may provide an incentive for firms to lay off workers. The demand elasticity of NAFTA shows that NAFTA increased labor demand by 0.04%, a positive but small number.

On the labor supply side, the supply elasticity suggests that a 10% increase in the population would increase labor supply by 2.18%. Individual income taxes have a negative effect on labor supply. A 10% increase in individual income taxes are predicted to decrease labor supply by 0.05%. Finally, the supply elasticity of the unemployment insurance replacement rate suggests that a 10% increase in the unemployment insurance replacement rate will decrease labor supply by 0.23%[27]. Our results confirm the theoretical expectation that unemployment insurance can decrease labor demand and supply at the same time. However, the reductions in labor demand and supply have opposing impacts on unemployment. Given the combined effect we found in equation (26) that unemployment insurance increased unemployment growth, we conclude that unemployment insurance has a larger impact on labor demand than on labor supply.

The second objective of this paper is to estimate the length of the adjustment period. That is, how many years following its implementation in 1994 are the effects of NAFTA felt? Equation (27) is posited as follows to achieve this end

$$\begin{aligned}\text{(27)}\quad \mathrm{dln}\mathit{Unemp}_{iT} &= \gamma_0 + \gamma_1 \mathrm{dln}\mathit{Wage}_{iT} + \gamma_2 \mathrm{dln}\mathit{GSP}_{iT} + \gamma_3 \mathrm{dln}\mathit{BTax}_{iT} + \gamma_4 \mathrm{dln}\mathit{Union}_{iT} \\ &+ \gamma_5 \mathrm{dln}\mathit{UI}_{iT} + \gamma_6 \mathrm{dln}\mathit{Pop}_{iT} + \gamma_7 \mathrm{dln}\mathit{ITax}_{iT} \mathrm{dln} + \sum_{m=1994}^{2004} \theta_{\mathrm{m}} D_m + \omega_{iT}\end{aligned}$$

where m is a year index starting with 1994 and ending with 2004; D_m is a year dummy that takes on the value of one when the year is equal to m, and zero otherwise. For example, D_{1994} is equal to one for 1994 only and zero for all other years. By specifying such a setting, the 11 year dummies trace the impact of NAFTA on unemployment growth on a yearly basis. The estimated coefficients of the γ's and the θ_m are listed Table 32.

The coefficients for the yearly dummies are significant and negative in 1994, 1995, 1998, and 2000. This indicates that labor market began to feel the effects of

NAFTA immediately following its implementation. It is not unusual to see NAFTA had immediate impact on labor market since it was signed two years ahead of its implementation. What is a bit puzzling is that the signs of the time dummies switched to positive for 2001 – 2003. Incidentally, this switch coincided with the September 11 tragedy. The adjustment of US unemployment to NAFTA is calculated as follows and plotted in Figure 5. The average state unemployment in 1993 was 182,318 and unemployment was at a random walk process before 1994 which is indicated by the insignificant constant term γ_0 in Table 32. With other factors held constant, the estimate of -.079 for θ_{1994} and -.066 for θ_{1995} indicates that in 1994 NAFTA helped decrease unemployment to 167,915 calculated by 182,318*(1-.079) and in 1995 to 156,833 calculated by 182,318*(1-.079)*(1-.066), and so on. Unemployment remains unchanged if θ_m is insignificant for m equals 1994 to 2004. Figure 5 shows that the labor adjustment to NAFTA displays a U-shape over time. NAFTA was shown to decrease unemployment growth for four of seven following years after it took effect, but increased unemployment growth in the three years starting from 2001. The U-shape adjustment curve corroborates our earlier finding that N5 but not N is significant in model B.

V. Conclusion

There is no consensus on the effect of trade liberalization on the labor market in the empirical literature. The present paper specifies a supply and demand model of the labor market to examine the effects of NAFTA on the US labor market outcome. Regression over pooled state level data suggests that NAFTA decreased yearly unemployment growth by 6.8% increasing labor demand by 0.04%. NAFTA brought a structural break to US state level unemployment. The result that NAFTA has a positive and small effect on labor demand holds at the state level but not country level data, justifying the recent trend of using disaggregated data to detect labor movement due to trade liberalization[28].

The second finding of this paper is that the labor market impact of NAFTA started immediately following its implementation and the beneficial impact of NAFTA was felt for the period of before 2001. The issue of labor adjustment period to trade liberalization has been raised by Davidson and Matusz (2000) but the period has not empirically tested.

The present results exclude the concern of unemployment due to the peso devaluation in 1995. It provides evidence to support the argument of De Janvry (1996) that NAFTA helped offset negative impact of peso crisis that would otherwise have impacted trade between the US and Mexico.

Table 1. Percentage Distribution of Estimated Effects of Key Resources on Student Performance, Based on 377 Studies

Resources	Number of estimates	Statistically significant		Statistically insignificant		
		Positive	Negative	Positive	Negative	Unknown
Teacher-pupil ratio	277	15	13	27	25	20
Teacher education	171	9	5	33	27	26
Teacher experience	207	29	5	30	24	12
Teacher salary	119	20	7	25	20	28
Expenditure per pupil	163	27	7	34	19	13
Administrative inputs	75	12	5	23	28	32
Facilities	91	9	5	23	19	44

Source: Hanushek (1996).

Table 2. Variable Definitions for FL's Study and Our Replication Study[a]

Variables	FL's study on school year of 1990	Variables	Our study on school years of 1992, 1996-2004
Dep. Var.			
Q8	The average composite of math scores from the *Stanford 8* for the eighth grade and from the BCT for the ninth grade for the 1989-1990 school year. All the test scores are standardized to have zero mean and variance of one.	***Q8***[b]	Eighth grade *Stanford 8* test scores (complete battery), i.e., reading, math, language, social, science during the school year of 1992, 1996-2004. All the test scores are standardized to have zero mean and variance of one too.
School inputs			
ACT	Average teachers' test scores from the ACT exams that teachers took in the process of applying to college	***ACT***	N/A
MS	The percentage of teachers with a master's degree	*MS*	The percentage of teachers with a master's degree
EXP	Percentage of teachers with more than five years of experience	***EXP***	N/A
STR	Student-teacher ratio	*STR*	Student-teacher ratio
Student background			
Q3	Average of the third grade BCT and the fourth-grade *Stanford 8* during the 1989-1990 school year. Standardized	***Q4***	Fourth grade *Stanford 8* test scores for the 1991-1992 school year. Standardized
ED	Various year of parental education	***ED***	Percentage of adults college educated
PCPI	Per capita income	***INC***	Median family income
POV	Poverty rate, the percentage of families with children ages 5 to 18 living in poverty	***POV***	Poverty rate, percentage of all ages in poverty
School or district			
ENROL	Total enrollment, in thousands	*ENROL*	Total enrollment, in thousands
RACE	Percentage of students who are non-white	*RACE*	Percentage of students who are non-white
PUBLIC	Percentage of students in public schools	***PUBLIC***	N/A
URBAN	Percentage of the district that is urban	***RURAL***	Rural County dummy, 1 = Rural
Interaction			
RACE URBAN*	Interaction between RACE and URBAN	***RACE* RURAL***	Interaction between RACE and RURAL

Note: a. FL's study includes 127 public school districts (counties and cities), while our study focuses on the 67 counties in Alabama due to data limit.

b. Our variables are in bold if different from those in FL's study in definition. Some other variables such as *STR,* even sharing the same definition in both studies, differ due to different years and sources of data. FL did not report data sources. Our data sources are in Appendix A. All the financial data in the present study are CPI deflated.

Table 3. Determinants of Instructional and Noninstructional expenditure per Pupil, 1992

	FL's study		Our study			
	School year of 1990		School year of 1992		School years of 1996-2004	
Dep. Var.	ln(instructional spending per pupil)	ln(noninstructional spending per pupil)	ln(instructional spending per pupil)	ln(noninstructional spending per pupil)	ln(instructional spending per pupil)	ln(noninstructional spending per pupil)
ln*(PV)*	0.079***[a]	0.111***	0.019	0.058	0.072***	-0.017
	(3.68)[b]	(3.59)	(1.29)	(1.16)	(5.61)	(0.74)
ln*(INC)* [c]	0.192***	0.035	0.053	0.258	-0.063*	0.241***
	(5.16)	(0.65)	(0.96)	(1.38)	(1.69)	(3.71)
ENROL	-0.005***	-0.012***	-0.002**	-0.002	0.000	-0.004***
	(4.55)	(7.25)	(2.33)	(0.85)	(0.15)	(3.84)
SCHOOL	0.003***	0.007***	0.001***	0.000	0.000	0.002***
	(3.35)	(6.59)	(3.00)	(0.33)	(0.12)	(3.61)
RACE	--	--	0.001***	0.003**	0.001**	0.002***
	--	--	(3.71)	(2.39)	(2.50)	(4.26)
Constant	4.683***	5.743***	6.846***	4.149**	7.617***	4.984***
	(16.08)	(13.68)	(12.15)	(2.18)	(19.81)	(7.42)
R^2	--	--	0.31	0.11	0.08	0.05
Adjusted R^2	0.45	0.40	0.25	0.04	0.07	0.04
df	122	122	61	61	597	597
N	127	127	67	67	603	603

Note: a. ***, **, and * denote significance level at 1%, 5% and 10% respectively.
b. Absolute values of t statistics are in parentheses.
c. ln*(PCPI)* for FL's study.

Table 4. Replication of FL's Study using the 1992 School Year Data in 67 Alabama Counties[a]

	FL's study, school year 1990[b]				Our study, school year 1992		
Variables	Model A	Model B	Model C	Variables	Model A	Model B	Model C
ACT	0.223***[c]	--	--		--	--	--
	(3.19)[d]	--	--		--	--	--
EXP	0.859	--	--		--	--	--
	(0.96)	--	--		--	--	--
MS	1.430*	--	--	*MS*	0.017*	--	--
	(1.81)	--	--		(1.78)	--	--
STR	-0.078***	--	--	*STR*	-0.029	--	--
	(2.94)	--	--		(0.53)	--	--
ln*PI*	--	3.560***	8.810***	ln*PI*	--	0.164	-3.863
	--	(2.72)	(3.19)		--	(0.07)	(0.67)
ln*(PI above*	--	--	-9.190**	ln*(PI above*	--	--	5.574
median)	--	--	(2.15)	*median)*	--	--	(0.75)
Q3	0.187	0.339***	0.317***	*Q4*	0.184**	0.207**	0.181*
	(1.58)	(2.84)	(2.69)		(2.22)	(2.43)	(1.95)
ED	0.032	0.011	0.021	*ED*	0.058**	0.046*	0.045*
	(1.32)	(0.48)	(0.87)		(2.21)	(1.82)	(1.77)
lnPCPI	-0.484	--	--	*lnINC*	-0.145	0.239	0.328
	(0.56)	--	--		(-0.10)	(0.16)	(0.22)
POV	-0.004	0.010	0.018	*POV*	-0.004	0.003	-0.001
	(0.21)	(0.64)	(1.10)		(0.12)	(0.08)	(0.03)
ENROL	0.018***	0.008*	0.013**	*ENROL*	0.004	0.002	0.001
	(3.38)	(1.77)	(2.55)		(0.67)	(0.43)	(0.27)
RACE	-0.002	-0.005	-0.005	*RACE*	-0.011*	-0.012*	-0.012*
	(0.28)	(0.91)	(0.85)		(1.74)	(1.97)	(1.81)
URBAN	-0.005	0.004	0.002	*RURAL*	0.881***	0.810***	0.735**
	(1.30)	(1.10)	(0.40)		(3.44)	(3.01)	(2.56)
*RACE**	-0.0001*	-0.0001*	-0.0001**	*RACE**	-0.015**	-0.014**	-0.013*
URBAN	(1.77)	(1.80)	(2.41)	*RURAL*	(2.41)	(2.23)	(1.91)
Constant	0.164	-28.200***	-65.130***	Constant	0.845	-3.945	25.913
	(0.02)	(2.66)	(3.24)		(0.06)	(0.19)	(0.58)
R^2	--	--	--	R^2	0.79	0.77	0.77
Adjusted R^2	0.71	0.73	0.73	Adjusted R^2	0.75	0.73	0.73
df	108	113	112	df	56	57	56
N	127	127	127	N	67	67	67

Note: a. Weighted OLS estimates (WLS), using square root of enrollment as weight.

b. FL reports eight series of results depending on class size linearity, inclusion of scores for grade 3 and 4, spending linearity. We only report three representative series here, which correspond to "With scores for grade 3 and 4" under linear class size in FL's Table 8A-2, "linear and nonlinear spending" under with scores for grade 3 and 4 in Table 8A-3.

c. ***, **, and * denote significance level at 1%, 5% and 10% respectively.

d. Absolute values of t statistics are in parentheses.

Table 5. Determinants of Eighth Grade SAT Complete Battery Scores without Fixed or Random Effects, 1996-2004[a]

	Without the fourth grade test scores			With the fourth grade test scores		
Variables	Model A	Model B	Model C	Model A	Model B	Model C
MS	-0.0004	--	--	-0.002	--	--
	(0.10)	--	--	(0.54)	--	--
STR	0.003	--	--	0.011	--	--
	(0.33)	--	--	(1.08)	--	--
ln*PI*	--	-1.641**	-6.109***	--	-0.982	-5.734***
	--	(2.32)	(5.70)	--	(1.44)	(5.63)
ln*(PI above median)*	--	--	6.533***	--	--	6.986***
	--	--	(5.45)	--	--	(6.12)
Q4	--	--	--	0.329***	0.316***	0.328***
	--	--	--	(7.83)	(7.51)	(8.03)
ED	0.010*[b]	0.014**	0.018***	0.003	0.005	0.009
	(1.72)[c]	(2.31)	(3.06)	(0.57)	(0.83)	(1.57)
ln*INC*	1.781***	1.471***	0.937***	1.538***	1.427***	0.854***
	(5.61)	(4.34)	(2.71)	(5.06)	(4.40)	(2.60)
POV	0.019	0.014	0.004	0.014	0.014	0.003
	(1.46)	(1.03)	(0.28)	(1.13)	(1.07)	(0.24)
ENROL	0.005**	0.005**	0.006***	0.002	0.002	0.003*
	(2.22)	(2.48)	(2.99)	(0.95)	(1.23)	(1.72)
RACE	-0.028***	-0.028***	-0.028***	-0.017***	-0.017***	-0.017***
	(13.01)	(13.13)	(13.47)	(6.87)	(7.03)	(7.09)
Rural	-0.234**	-0.270***	-0.224**	-0.173*	-0.192**	-0.139
	(2.56)	(2.93)	(2.47)	(1.97)	(2.17)	(1.61)
*RACE*RURAL*	0.010***	0.010***	0.009***	0.006***	0.006***	0.005**
	(4.47)	(4.69)	(4.29)	(2.83)	(2.98)	(2.45)
Constant	-16.965***	-1.124	38.678***	-14.791***	-6.018	36.352***
	(5.27)	(0.15)	(3.72)	(4.80)	(0.83)	(3.67)
R^2	0.67	0.67	0.69	0.70	0.70	0.72
Adjusted R^2	0.66	0.67	0.68	0.69	0.70	0.71
df	593	594	593	592	593	592
N	603	603	603	603	603	603

Note: a. Weighted OLS estimates (WLS), using square root of enrollment as weight.
b. ***, **, and * denote significance level at 1%, 5% and 10% respectively.
c. Absolute values of t statistics are in parentheses.

Table 6. Determinants of Eighth Grade SAT Complete Battery Scores with Panel Data Techniques, 1996-2004[a]

	one-way fixed effects model			two-way fixed effects model		
Variables	Model A	Model B	Model C	Model A	Model B	Model C
MS	0.014***[b]	--	--	0.005	--	--
	(3.21)[c]	--	--	(1.00)	--	--
STR	0.006	--	--	0.009	--	--
	(0.81)	--	--	(1.18)	--	--
ln*PI*	--	-3.268**	-6.156***	--	1.152	2.122
	--	(2.04)	(3.71)	--	(0.69)	(1.05)
Ln*(PI above median)*	--	--	4.488***	--	--	-1.298
	--	--	(5.23)	--	--	(0.86)
Q4	0.174***	0.180***	0.179***	0.210***	0.210***	0.210***
	(4.65)	(4.81)	(4.90)	(5.72)	(5.75)	(5.75)
ED	-0.210***	-0.179***	-0.150***	-0.065*	-0.061*	-0.063*
	(9.72)	(6.76)	(5.67)	(1.88)	(1.78)	(1.83)
ln*INC*	1.609***	1.023**	0.517	-0.714	-0.797	-0.824
	(4.03)	(2.36)	(1.19)	(1.09)	(1.21)	(1.25)
POV	-0.032**	-0.041***	-0.035***	-0.074***	-0.076***	-0.077***
	(2.58)	(3.20)	(2.72)	(5.17)	(5.30)	(5.36)
ENROL	0.017	0.011	0.013	0.025**	0.037***	0.037***
	(1.50)	(0.95)	(1.10)	(2.29)	(3.13)	(3.17)
RACE	0.004	0.002	-0.002	0.002	0.002	0.004
	(0.32)	(0.19)	(0.15)	(0.24)	(0.22)	(0.35)
Rural	-0.160	-0.149	-0.187	-0.171	-0.135	-0.126
	(0.56)	(0.52)	(0.66)	(0.64)	(0.51)	(0.47)
*RACE*RURAL*	-0.007	-0.008	-0.007	-0.004	-0.005	-0.006
	(0.99)	(1.04)	(0.94)	(0.64)	(0.79)	(0.80)
Constant	-11.761***	19.819	46.675***	10.098	2.390	-4.801
	(2.72)	(1.36)	(3.08)	(1.55)	(0.17)	(0.29)
TS97	--	--	--	0.024	0.017	0.048
	--	--	--	(0.41)	(0.28)	(0.70)
TS98	--	--	--	-0.183**	-0.235***	-0.245***
	--	--	--	(2.56)	(3.74)	(3.83)
TS99	--	--	--	-0.231***	-0.259***	-0.233***
	--	--	--	(3.32)	(3.57)	(2.98)
TS00	--	--	--	-0.190**	-0.236***	-0.215**
	--	--	--	(2.41)	(2.91)	(2.54)
TS01	--	--	--	-0.142	-0.197**	-0.184*
	--	--	--	(1.63)	(2.16)	(1.98)
TS02	--	--	--	-0.258**	-0.316***	-0.309***
	--	--	--	(2.58)	(2.91)	(2.85)
TS03	--	--	--	-0.591***	-0.657***	-0.669***
	--	--	--	(5.20)	(5.32)	(5.39)
TS04	--	--	--	-0.699***	-0.767***	-0.809***
	--	--	--	(5.44)	(5.47)	(5.46)
F test for no *CS* effects	15.64	14.00	13.71	13.33	13.38	13.32
	[<0.0001]	[<0.0001]	[<0.0001]	[<0.0001]	[<0.0001]	[<0.0001]

F test for no *TS* effects	--	--	--	11.61	12.31	8.58
	--	--	--	[<0.0001]	[<0.0001]	[<0.0001]
F test for neither existence	--	--	--	16.04	15.96	14.59
of *CS* or *TS* effects	--	--	--	[<0.0001]	[<0.0001]	[<0.0001]
Fixed VS Random	112.82[d]	--	--	--	--	--
	[<0.0001]	--	--	--	--	--
R^2	0.89	0.89	0.90	0.91	0.91	0.91
Adjusted R^2	0.88	0.88	0.88	0.89	0.89	0.89
df	526	527	526	518	519	518
N	603	603	603	603	603	603

Note: a. Weighted OLS estimates (WLS), using square root of enrollment as weight.
b. ***, **, and * denote significance level at 1%, 5% and 10% respectively.
c. Absolute values of t statistics are in parentheses.
d. Hausman *m* test statistic for fixed effects. A significant *m* value indicates rejection of random effects.

Table 7. Variable Definitions and Summary Statistics, 67 Alabama Counties

Var.	Definition	1992			1996			2000			2004		
Student Test Score		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Q8	Eighth-grade test score, national percentile [a]	37	16	58	52	23	70	51	29	67	46	32	65
Q4	Fourth-grade test score, national percentile	44	28	65	51	28	68	55	38	74	54	32	70
School Revenues													
P_G	Total educational revenues, dollars/pupil [b]	2,698	2,283	3,849	3,186	2,820	3,721	3,830	3,268	4,580	4,291	3,262	10,538
P_N	Local funding, dollars/pupil	409	144	953	450	150	1,027	843	460	1,991	871	439	1,831
SF	State funding, dollars/pupil	1,779	1,585	2,813	2,227	1,991	2,737	2,551	2,113	2,979	2,400	1,906	2,922
FF	Federal funding, dollars/pupil	396	189	1,007	373	177	967	415	197	1,069	538	240	1,477
OF	Other funding, dollars/pupil	114	24	252	135	41	844	21	0	127	482	8	6,123
School Expenditures													
PE	Total educational expenditures, dollars/pupil [c]	2,754	2,143	4,802	3,231	2,650	4,338	4,000	3,186	5,307	4,104	3,103	6,872
PI	Instructional expenditures, dollars/pupil	1,489	1,293	1,754	1,686	1,442	2,015	2,545	2,257	2,860	2,589	2,195	3,097
PNI	Non-instructional expenditures, dollars/pupil	1,265	849	3,048	1,545	1,208	2,322	1,455	929	2,447	1,515	909	3,775
School Inputs													
STR	Inverse of *TSR* (teacher-student ratio)	18.76	16.70	21.70	17.43	15.40	20.40	15.30	13.50	17.00	15.14	4.76	50.05

TPAY	Teacher's salary exc. principals, dollars	18,716	17,487	20,447	19,421	17,630	20,703	20,398	19,541	21,084	19,961	19,248	20,975
TED	Teachers with a Ph.D. degree or equivalent specialized education training beyond the Master's level, percent	5.72	1.64	11.30	5.53	1.71	11.42	5.29	0.80	11.00	4.92	0.90	13.30
MS	Teachers with a master's degree, percent	47.49	29.20	63.43	48.88	31.33	66.03	48.81	32.70	61.30	48.66	31.50	59.60
Student background													
ED	Adults college educated, percent	11.24	4.70	30.10	12.59	6.14	33.68	13.49	7.10	36.80	14.39	6.78	39.92
INC	Median family income	18,157	10,909	30,327	17,624	10,795	33,108	18,087	10,925	34,524	16,416	9,782	34,180
POV	Poverty rate, percentage of all ages in poverty	20.48	7.70	49.00	19.71	6.95	38.95	17.16	6.40	31.00	17.82	6.30	34.60
School or District													
BLACK BELT	Black Belt county, dummy variable, 1 = Black Belt county	0.28	0	1	0.28	0	1	0.28	0	1	0.28	0	1
ENROL	Total enrollment	7010	1803	65593	7145	1790	63292	7250	1668	65067	7269	1419	65037
PV	Appraised property valuation, dollars/pupil	22,819	2,153	96,279	24,374	9,982	82,741	31,914	10,507	126,024	36,653	13,628	93,408
RACE	Percentage of students who are non-white	37.73	0.08	99.79	37.72	0.04	99.91	38.26	0.13	99.92	39.17	0.42	99.93
RURAL	Rural County, dummy variable, 1 = Rural	0.69	0	1	0.69	0	1	0.76	0	1	0.76	0	1
UNEMP	Unemployment rate, percent	6.63	2.50	13.50	6.26	1.70	15.90	5.71	1.50	11.80	7.07	2.30	15.70

Note: a. Complete battery scores from *Stanford Test* series given in April.

b. Expressed on an average daily attendance basis. All monetary variables are in real terms real, which means that they are CPI deflated.

$P_G = P_N + SF + FF + \text{OF}$,

c. PE = $PI + PNI$.

Table 8. Alabama School Revenues and Expenditures by Source

Var.\Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Q8	37.45	--	--	--	51.57	52.81	50.70	50.79	51.31	51.06	49.72	47.16	46.48
School Revenues													
P_G	2697.83[a]	2743.05	2798.06	3086.73	3185.63	3411.94	3498.90	3978.25	3829.85	3913.90	4069.91	4004.22	4290.60
P_N	408.79	426.80	426.73	451.12	450.09	748.13	783.95	833.88	842.89	870.78	888.97	872.14	870.73
SF	1778.86	1789.73	1863.21	2138.16	2227.36	2282.78	2333.82	2447.42	2550.76	2416.12	2491.98	2452.34	2400.02
FF	396.25	414.70	397.43	376.11	373.33	381.04	381.14	391.42	415.48	433.55	485.58	479.88	538.02
OF	113.93	111.82	110.68	121.35	134.84	--	--	305.52	21.21	193.45	203.38	199.87	481.83
School Expenditures													
PE	2754.14	2837.21	2911.15	3053.05	3230.58	3460.60	3828.98	3888.70	4000.38	3982.77	3948.66	3941.28	4104.26
PI	1488.91	1491.24	1571.41	1674.48	1685.52	2219.21	2316.45	2438.96	2545.10	2549.52	2527.99	2509.30	2589.26
PNI	1265.23	1345.97	1339.74	1378.57	1545.06	1241.39	1512.53	1449.74	1455.28	1433.24	1420.68	1431.98	1515.00

Note: a. All the monetary variables in this study are CPI deflated.

Table 9. Percentage Distribution of Alabama School Revenues and Expenditures by Source

Var.\Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Q8	37	--	--	--	52	53	51	51	51	51	50	47	46
School Revenues													
P_G	2697.83	2743.05	2798.06	3086.73	3185.63	3411.94	3498.90	3978.25	3829.85	3913.90	4069.91	4004.22	4290.60
P_N	15.15	15.56	15.25	14.61	14.13	21.93	22.41	20.96	22.01	22.25	21.84	21.78	20.29
SF	65.94	65.25	66.59	69.27	69.92	66.91	66.70	61.52	66.60	61.73	61.23	61.24	55.94
FF	14.69	15.12	14.20	12.18	11.72	11.17	10.89	9.84	10.85	11.08	11.93	11.98	12.54
OF	4.22	4.08	3.96	3.93	4.23	--	--	7.68	0.55	4.94	5.00	4.99	11.23
School Expenditures													
PE	2754.14	2837.21	2911.15	3053.05	3230.58	3460.60	3828.98	3888.70	4000.38	3982.77	3948.66	3941.28	4104.26
PI	54.06	52.56	53.98	54.85	52.17	64.13	60.50	62.72	63.62	64.01	64.02	63.67	63.09
PNI	45.94	47.44	46.02	45.15	47.83	35.87	39.50	37.28	36.38	35.99	35.98	36.33	36.91

Table 10. Durbin-Wu-Hausman Endogeneity Test on Several Key Variables, 1996-2004

Variables[a]	F Statistics	
P_G	5.89[d]	*P_G =F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*[b]
	[0.016][e]	*Q8=H(RESIDUAL, P_G, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*[c]
P_N	16.89	*P_N =F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[<0.0001]	*Q8=H(RESIDUAL, P_G, P_N, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
SF	0.00	*SF=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.961]	*Q8=H(RESIDUAL, P_G, SF, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
FF	3.61	*FF=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.058]	*Q8=H(RESIDUAL, P_G, FF, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
OF	0.70	*OF=F(INC, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.403]	*Q8=H(RESIDUAL, P_G, OF, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
PI	15.27	*PI=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[<0.0001]	*Q8=H(RESIDUAL, P_G, PI, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
PNI	0.98	*PNI=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.322]	*Q8=H(RESIDUAL, P_G, PNI, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
TED	1.61	*TED=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.204]	*Q8=H(RESIDUAL, P_G, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
MS	0.91	*MS=F(INC, OF, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.341]	*Q8=H(RESIDUAL, P_G, TPAY, TSR,MS, INC, ED, POV, ENROL, RURAL, RACE)*
TSR	6.74	*TSR=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.001]	*Q8=H(RESIDUAL, P_G, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
TPAY	33.04	*TPAY=F(INC, OF, Q4, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[<0.001]	*Q8=H(RESIDUAL, P_G, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*
Q4	0.02	*Q4=F(INC, ED, POV, ENROL, RURAL, RACE, PV, UNEMP, SCHOOL, RESIDUAL)*
	[0.880]	*Q8=H(RESIDUAL, P_G, Q4, TPAY, TSR, TED, INC, ED, POV, ENROL, RURAL, RACE)*

Note: a. All continuous variables are expressed in logarithms.
b. Auxiliary Regression.
c. Augmented Regression.
d. F statistic of the hypothesis that the RESIDUAL variable is zero in the augmented regression.
The RESIDUAL variable is the error term in the auxiliary regression.
e. p-values in brackets. A low p-value indicates rejection of exogeneity.

Table 11.Production Function Estimates using Two-way Fixed Effects Model, 1996-2004

	OLS			WLS			W2SLS[a]		
Var.	Model A	Model B	Model C	Model A	Model B	Model C	Model A	Model B	Model C
P_G	0.029	0.014	0.015	0.027	0.012	0.014	0.101	0.100	0.084*
	(0.86)	(0.42)	(0.46)	(0.81)	(0.37)	(0.03)	(1.64)	(1.58)	(1.82)
TED	0.261**[b]	-0.015	--	0.260**	-0.014	--	0.176	-0.013	--
	(2.33)	(1.17)	--	(2.34)	(1.10)	--	(1.42)	(0.86)	--
TSR	-0.182	0.015	--	-0.160	0.011	--	-0.389	-0.438	--
	(0.92)	(0.32)	--	(0.82)	(0.24)	--	(0.84)	(0.92)	--
TPAY	-3.785***	0.117	--	-3.794***	0.121	--	1.164*	1.191*	--
	(3.15)	(0.60)	--	(3.19)	(0.63)	--	(1.85)	(1.93)	--
Q4	0.200***	0.217***	0.221***	0.202***	0.218***	0.221***	0.197***	0.208***	0.222***
	(5.09)	(5.53)	(5.66)	(5.10)	(5.53)	(5.64)	(3.48)	(3.62)	(5.63)
ED	0.871**	-0.360***	-0.371***	0.825**	-0.354***	-0.364***	0.398	-0.369***	-0.376***
	(2.31)	(3.94)	(4.09)	(2.22)	(3.86)	(4.00)	(0.97)	(3.10)	(4.09)
INC	0.040	0.078	0.081	0.049	0.083	0.084	0.102	0.147	0.120
	(0.33)	(0.66)	(0.71)	(0.41)	(0.71)	(0.74)	(0.64)	(0.95)	(1.04)
POV	-12.071***	-0.352***	-0.359***	-12.191***	-0.348***	-0.356***	-0.090	-0.304***	-0.327***
	(3.15)	(5.57)	(5.78)	(3.22)	(5.57)	(5.77)	(0.12)	(3.28)	(5.10)
ENROL	0.099***	0.101***	0.095***	0.098***	0.098***	0.094***	0.077*	0.073*	0.098***
	(3.01)	(3.11)	(3.33)	(3.06)	(3.10)	(3.38)	(1.80)	(1.80)	(3.50)
RACE	-0.046**	-0.038*	-0.037	-0.046**	-0.038*	-0.037	-0.035	-0.035	-0.043*
	(2.02)	(1.67)	(1.63)	(2.04)	(1.67)	(1.64)	(1.31)	(1.26)	(1.88)
Rural	-0.088***	-0.099***	-0.103***	-0.089***	-0.099***	-0.103***	-0.095***	-0.099***	-0.109***
	(4.08)	(4.56)	(4.82)	(4.13)	(4.60)	(4.84)	(3.64)	(3.76)	(5.03)
*POV*TED*	-0.094**	--	--	-0.093**	--	--	-0.064	--	--
	(2.53)	--	--	(2.53)	--	--	(1.56)	--	--
*POV*TSR*	0.074	--	--	0.064	--	--	0.006	--	--
	(0.92)	--	--	(0.81)	--	--	(0.25)	--	--
*POV*TPAY*	1.321***	--	--	1.327***	--	--	0.052	--	--
	(3.36)	--	--	(3.41)	--	--	(0.68)	--	--
*POV*ED*	-0.391***	--	--	-0.375***	--	--	-0.256*	--	--

	(3.25)	--	--	(3.16)	--	--	(1.94)	--	--
Constant	37.165***	2.369***	3.498***	37.338***	2.283	3.474***	-12.081*	-10.753	2.478**
	(3.17)	(0.99)	(3.01)	(3.23)	(0.97)	(3.02)	(1.79)	(1.62)	(1.97)
TS97	0.002	0.002	0.002	0.002	0.002	0.002	-0.013	-0.011	-0.002
	(0.12)	(0.13)	(0.15)	(0.12)	(0.13)	(0.16)	(0.83)	(0.66)	(0.16)
TS98	-0.050***	-0.045***	-0.040***	-0.050***	-0.045***	-0.040***	-0.054**	-0.049**	-0.046***
	(3.66)	(3.32)	(3.10)	(3.68)	(3.34)	(3.15)	(2.55)	(2.30)	(3.53)
TS99	-0.050**	-0.044**	-0.041***	-0.049**	-0.044**	-0.041***	-0.113*	-0.093	-0.053***
	(2.20)	(2.04)	(2.67)	(2.19)	(2.05)	(2.66)	(1.99)	(1.63)	(3.30)
TS00	-0.043**	-0.034*	-0.025	-0.042**	-0.034*	-0.026	-0.058	-0.038	-0.035**
	(2.01)	(1.69)	(1.56)	(2.00)	(1.72)	(1.61)	(1.02)	(0.68)	(2.12)
TS01	-0.014	0.002	0.014	-0.013	0.002	0.012	-0.040	-0.019	0.002
	(0.58)	(0.11)	(0.76)	(0.56)	(0.08)	(0.70)	(0.68)	(0.31)	(0.12)
TS02	-0.037	-0.020	-0.011	-0.036	-0.019	-0.011	-0.062	-0.042	-0.022
	(1.51)	(0.84)	(0.52)	(1.46)	(0.84)	(0.53)	(1.46)	(1.00)	(1.06)
TS03	-0.091***	-0.073***	-0.063***	-0.089***	-0.072***	-0.063***	-0.117***	-0.096**	-0.072***
	(3.32)	(2.85)	(2.77)	(3.29)	(2.86)	(2.80)	(2.61)	(2.16)	(3.17)
TS04	-0.103***	-0.079***	-0.071***	-0.101***	-0.079***	-0.072***	-0.091**	-0.070	-0.084***
	(3.55)	(2.91)	(2.78)	(3.52)	(2.92)	(2.81)	(2.03)	(1.61)	(3.22)
F test A vs. B	--	5.04	--	--	4.92	--	--	1.42	--
	--	[0.001]	--	--	[0.001]	--	--	[0.227]	--
F test A vs. C	--	--	3.13	--	--	3.04	--	--	1.63
	--	--	[0.004]	--	--	[0.004]	--	--	[0.125]
F test B vs. C	--	--	0.56	--	--	0.50	--	--	1.80
	--	--	[0.632]	--	--	[0.681]	--	--	[0.146]
R^2	0.90	0.88	0.88	0.89	0.89	0.89	0.85	0.85	0.88
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.83	0.82	0.87
df	514	518	521	514	518	521	514	518	521
N	603	603	603	603	603	603	603	603	603

Note: a. WLS means Weighted Least Squares estimates. W2SLS means Weighted Two-Stage Least Squares estimates. Endogenous variables include *Q8*, P_G, *TPAY*, and *TSR*. Instrumental includes *SF, OF, Q4, INC, PV, ENROL, SCHOOL, UNEMP, RACE, POV, RURAL, BLACKBELT, ED, MS* and time dummies.
b. ***, **, and * denote significance level at 1%, 5% and 10% respectively. Absolute values of t statistics are in parentheses.

Table 12.Supply Function Estimates using Two-way Fixed Effects Model, 1996-2004

	OLS			WLS[a]			W2SLS[b]		
Var.	Model A	Model B	Model C	Model A	Model B	Model C	Model A	Model B	Model C
P_G	0.013	0.011	0.013	0.012	0.010	0.012	0.168	0.298	0.194
	(0.38)	(0.32)	(0.40)	(0.32)	(0.29)	(0.37)	(0.33)	(0.56)	(1.53)
TED	0.211*[c]	-0.020	--	0.210*	-0.019	--	0.195	-0.018	--
	(1.90)[d]	(1.57)	--	(1.71)	(1.51)	--	(1.63)	(1.16)	--
TSR	-0.156	-0.004	--	-0.127	-0.008	--	0.125	-0.171	--
	(0.84)	(0.09)	--	(0.04)	(0.17)	--	(0.10)	(0.13)	--
TPAY	-3.280***	0.162	--	-3.268***	0.167	--	1.241*	1.379**	--
	(2.79)	(0.83)	--	(2.82)	(0.85)	--	(1.91)	(2.11)	--
Q4	0.208***	0.223***	0.226***	0.209***	0.223***	0.226***	0.168**	0.193**	0.227***
	(5.22)	(5.63)	(5.75)	(5.46)	(5.63)	(5.73)	(2.05)	(2.28)	(5.49)
POV	-11.225***	-0.346***	-0.349***	-11.252**	-0.345***	-0.348***	-0.944	-0.187**	-0.243***
	(2.96)	(9.31)	(9.62)	(2.51)	(9.41)	(9.70)	(1.30)	(2.22)	(3.83)
ENROL	0.085***	0.056*	0.053**	0.084***	0.056*	0.054**	0.043	0.041	0.040
	(2.88)	(1.95)	(2.07)	(3.87)	(1.98)	(2.17)	(1.17)	(1.15)	(1.29)
Rural	-0.080***	-0.075***	-0.079***	-0.081***	-0.075***	-0.079***	-0.049	-0.055	-0.066***
	(3.81)	(3.54)	(3.76)	(4.69)	(3.59)	(3.80)	(1.36)	(1.47)	(2.94)
*POV*TED*	-0.077**	--	--	-0.077*	--	--	-0.072*	--	--
	(2.10)	--	--	(1.86)	--	--	(1.81)	--	--
*POV*TSR*	0.069	--	--	0.055	--	--	0.003	--	--
	(0.90)	--	--	(0.08)	--	--	(0.12)	--	--
*POV*TPAY*	1.133***	--	--	1.132**	--	--	0.092	--	--
	(2.97)	--	--	(2.52)	--	--	(1.22)	--	--
Constant	34.951***	1.928	3.516***	29.743***	1.884	3.513***	-10.065	-13.003	1.937
	(3.01)	(0.95)	(8.17)	(2.61)	(0.94)	(8.30)	(0.89)	(1.12)	(1.63)
TS97	-0.002	-0.004	-0.004	-0.002	-0.004	-0.004	-0.025	-0.032	-0.013
	(0.15)	(0.32)	(0.33)	(0.02)	(0.33)	(0.33)	(0.84)	(1.03)	(0.84)
TS98	-0.056***	-0.056***	-0.050***	-0.056***	-0.056	-0.050***	-0.080***	-0.083***	-0.061***
	(4.15)	(4.15)	(3.91)	(3.67)	(4.19)	(3.96)	(3.87)	(3.81)	(3.52)
TS99	-0.058***	-0.062***	-0.060***	-0.057**	-0.062	-0.059***	-0.188***	-0.180***	-0.088***

	(2.60)	(2.88)	(4.07)	(2.24)	(2.91)	(4.08)	(3.30)	(3.03)	(3.04)
TS00	-0.055***	-0.060***	-0.052***	-0.054**	-0.060	-0.052***	-0.146*	-0.131*	-0.074***
	(2.83)	(3.19)	(3.50)	(2.10)	(3.25)	(3.57)	(1.92)	(1.66)	(2.85)
TS01	-0.032	-0.036*	-0.025*	-0.032	-0.036	-0.026*	-0.154**	-0.139*	-0.058**
	(1.56)	(1.79)	(1.73)	(0.29)	(1.84)	(1.81)	(2.16)	(1.88)	(2.07)
TS02	-0.060***	-0.065***	-0.056***	-0.059	-0.065	-0.056***	-0.163***	-0.165***	-0.092***
	(3.19)	(3.50)	(3.70)	(1.63)	(3.53)	(3.74)	(3.38)	(3.26)	(2.88)
TS03	-0.119***	-0.126***	-0.116***	-0.118***	-0.126	-0.117***	-0.226***	-0.226***	-0.150***
	(6.13)	(6.68)	(7.82)	(4.22)	(6.76)	(7.91)	(4.73)	(4.51)	(4.95)
TS04	-0.137***	-0.140***	-0.134***	-0.136***	-0.139	-0.134***	-0.216***	-0.220***	-0.177***
	(7.53)	(7.85)	(8.37)	(4.95)	(7.94)	(8.46)	(4.85)	(4.75)	(4.87)
F test A vs. B	--	4.40	--	--	4.27	--	--	1.45	--
	--	[0.005]	--	--	[0.005]	--	--	[0.228]	--
F test A vs. C	--	--	2.69	--	--	2.60	--	--	1.87
	--	--	[0.014]	--	--	[0.017]	--	--	[0.084]
F test B vs. C	--	--	0.96	--	--	0.92	--	--	2.07
	--	--	[0.411]	--	--	[0.432]	--	--	[0.103]
R^2	0.88	0.88	0.88	0.88	0.88	0.88	0.86	0.84	0.86
Adjusted R^2	0.86	0.86	0.86	0.87	0.86	0.86	0.83	0.82	0.83
df	517	520	523	517	520	523	517	520	523
N	603	603	603	603	603	603	603	603	603

Note: a. Weighted Least Squares estimates.
b. Weighted Two-Stage Least Squares estimates. Endogenous variables include *Q8*, P_G, *TPAY,* and *TSR.* Instrumental variables include *SF, Q4, INC, PV, SCHOOL, UNEMP, POV, RURAL, BLACKBELT, MS* and time dummies.
c. ***, **, and * denote significance level at 1%, 5% and 10% respectively.
d. Absolute values of t statistics are in parentheses.

Table 13. Parameter Estimates of Supply-Demand Model, 1996-2004

	WLS					W3SLS[a]				
Var.	$Q8_S$	$Q8_D$	*TSR*	*TPAY*	*FF*	$Q8_S$	$Q8_D$	*TSR*	*TPAY*	*FF*
P_G	0.018	--	--	--	--	1.319**	--	--	--	--
	(0.52)	--	--	--	--	(2.05)	--	--	--	--
P_N	--	-0.006	--	--	--	--	-0.048***	--	--	--
	--	(0.37)	--	--	--	--	(2.85)	--	--	--
SF	--	--	0.482***	0.181***	--	--	--	0.414***	0.181***	--
	--	--	(8.67)	(9.88)	--	--	--	(7.64)	(9.98)	--
TED	-0.023*[b]	--	--	0.019***	--	0.001	--	--	0.019***	--
	(1.81)[c]	--	--	(7.47)	--	(0.07)	--	--	(7.88)	--
TSR	-0.019	--	--	--	--	-2.586	--	--	--	--
	(0.42)	--	--	--	--	(1.64)	--	--	--	--
TPAY	0.248	--	--	--	--	3.252***	--	--	--	--
	(1.25)	--	--	--	--	(3.25)	--	--	--	--
Q8	--	--	--	--	-0.834***	--	--	--	--	-2.215***
	--	--	--	--	(11.49)	--	--	--	--	(20.20)
Q4	0.217***	--	--	--	--	0.167*	--	--	--	--
	(5.48)	--	--	--	--	(1.85)	--	--	--	--
ED	--	--	0.091***	--	--	--	--	0.079***	--	--
	--	--	(7.67)	--	--	--	--	(6.95)	--	--
INC	--	0.508***	0.025	0.060***	--	--	0.525***	0.042*	0.060***	--
	--	(11.99)	(1.05)	(8.89)	--	--	(13.73)	(1.82)	(9.01)	--
POV	-0.244***	--	--	--	0.625***	-0.300***	--	--	--	0.039
	(4.08)	--	--	--	(12.75)	(3.11)	--	--	--	(0.64)
ENROL	0.021	--	-0.018***	--	-0.063***	0.357***	--	-0.022***	--	-0.047***
	(0.66)	--	(2.82)	--	(4.66)	(8.46)	--	(3.47)	--	(3.65)
RACE	--	-0.062***	--	--	--	--	-0.058***	--	--	--
	--	(13.39)	--	--	--	--	(14.34)	--	--	--
RURAL	-0.061***	--	--	--	--	-0.031	--	--	--	--
	(2.80)	--	--	--	--	(1.01)	--	--	--	--
UNEMP	--	0.020	--	--	--	--	-0.011	--	--	--

	--	(1.13)	--	--	--	--	-0.730	--	--	--
CONSTANT	1.097	-0.854**	-6.846***	7.891***	7.979***	-49.095***	-0.696*	-6.427***	7.887***	14.895***
	(0.54)	(2.05)	(12.68)	(43.08)	(19.23)	(2.58)	(1.91)	(12.23)	(43.52)	(25.49)
TS97	-0.001	--	--	--	--	-0.117***	--	--	--	--
	(0.06)	--	--	--	--	(3.17)	--	--	--	--
TS98	-0.051***	--	--	--	--	-0.123***	--	--	--	--
	(3.77)	--	--	--	--	(4.62)	--	--	--	--
TS99	-0.056***	--	--	--	--	-0.318***	--	--	--	--
	(2.65)	--	--	--	--	(4.40)	--	--	--	--
TS00	-0.052***	--	--	--	--	-0.154*	--	--	--	--
	(2.78)	--	--	--	--	(1.68)	--	--	--	--
TS01	-0.038*	--	--	--	--	-0.201**	--	--	--	--
	(1.92)	--	--	--	--	(2.32)	--	--	--	--
TS02	-0.063***	--	--	--	--	-0.284***	--	--	--	--
	(3.43)	--	--	--	--	(4.52)	--	--	--	--
TS03	-0.124***	--	--	--	--	-0.314***	--	--	--	--
	(6.67)	--	--	--	--	(5.11)	--	--	--	--
TS04	-0.136***	--	--	--	--	-0.318***	--	--	--	--
	(7.75)	--	--	--	--	(7.15)	--	--	--	--
F-statistic	47.770	215.11	33.450	63.670	442.810	--	--	--	--	--
R^2	0.88	0.59	0.18	0.24	0.69	--	--	0.65[d]	--	--
Adjusted R^2	0.86	0.59	0.18	0.24	0.69	--	--	--	--	--
df	520	598	598	599	599	520	598	598	599	599
N	603	603	603	603	603	603	603	603	603	603

Note. a. Weighted three-stage least squares estimates. Engodenous variables include *Q8*, P_G, P_N, *TPAY, TSR* and *FF*. Instrumental variables include *SF, Q4, INC, PV, SCHOOL, UNEMP, POV, BLACKBELT, MS* and time dummies.

b. ***, **, and * denote significance level at 1%, 5% and 10% respectively.

c. Absolute values of t statistics are in parentheses.

d. System Weighted R^2 reported by SAS.

Table 14. Total Elasticities for Alternative Values of the Long-Run Demand Elasticity[a]

Endogenous	Exogenous Variables						
Variables	*SF*	*INC*	*RACE*	*ED*	*TED*	*ENROL*	*POV*
Demand Elasticity = -0.048							
Q8	0.201	0.453	-0.047	0.000	0.009	0.050	-0.043
P_G	-0.294	0.196	-0.036	0.000	-0.040	-0.233	0.195
P_N	-4.192	1.490	-0.229	0.000	-0.183	-1.040	0.891
FF	-0.446	-1.004	0.104	0.000	-0.020	-0.158	0.095
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.181	0.060	0.000	0.000	0.019	0.000	0.000
Demand Elasticity = -0.300[b]							
Q8	0.631	0.301	-0.024	0.000	0.028	0.156	-0.134
P_G	0.032	0.080	-0.018	0.000	-0.026	-0.152	0.126
P_N	-2.103	0.747	-0.115	0.000	-0.092	-0.522	0.447
FF	-1.398	-0.666	0.052	0.000	-0.061	-0.394	0.297
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.181	0.060	0.000	0.000	0.019	0.000	0.000

Note: a. Computed using structural elasticities given in Table 13.
b. Alternative demand elasticity.

Table 15. Total Elasticities with and without Efficiency and Compensatory Effects[a]

Endogenous	Exogenous Variables						
Variables	*SF*	*INC*	*RACE*	*ED*	*TED*	*ENROL*	*POV*
Both effects (efficiency effect = 0.181 and compensatory effect = -2.215)							
Q8	0.201	0.453	-0.047	0.000	0.009	0.050	-0.043
P_G	-0.294	0.196	-0.036	0.000	-0.040	-0.233	0.195
P_N	-4.192	1.490	-0.229	0.000	-0.183	-1.040	0.891
FF	-0.446	-1.004	0.104	0.000	-0.020	-0.158	0.095
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.181	0.060	0.000	0.000	0.019	0.000	0.000
No efficiency effect (efficiency effect = 0 and compensatory effect = -2.215)							
Q8	0.117	0.453	-0.047	0.000	0.009	0.050	-0.043
P_G	0.089	0.196	-0.036	0.000	-0.040	-0.233	0.195
P_N	-2.444	1.490	-0.229	0.000	-0.183	-1.040	0.891
FF	-0.260	-1.004	0.104	0.000	-0.020	-0.158	0.095
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.000	0.060	0.000	0.000	0.019	0.000	0.000
No compensatory effect (efficiency effect = 0.181 and compensatory effect = 0)							
Q8	0.211	0.476	-0.049	0.000	0.009	0.052	-0.045
P_G	-0.286	0.213	-0.037	0.000	-0.040	-0.231	0.193
P_N	-4.397	1.028	-0.181	0.000	-0.192	-1.090	0.934
FF	0.000	0.000	0.000	0.000	0.000	-0.047	0.000
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.181	0.060	0.000	0.000	0.019	0.000	0.000
Neither effect (efficiency effect = compensatory effect = 0)							
Q8	0.123	0.476	-0.049	0.000	0.009	0.052	-0.045
P_G	0.093	0.213	-0.037	0.000	-0.040	-0.231	0.193
P_N	-2.564	1.028	-0.181	0.000	-0.192	-1.090	0.934
FF	0.000	0.000	0.000	0.000	0.000	-0.047	0.000
TSR	0.414	0.000	0.000	0.079	0.000	-0.022	0.000
TPAY	0.000	0.060	0.000	0.000	0.019	0.000	0.000

Note: a. Computed using structural elasticities given in Table 13.

Table 16. Incidence Shifting With and Without the Efficiency Effect

Demand	Marginal Effects of State Funding		
Elasticity	P_G /*SF*	P_N/*SF*	*FF/SF*
	With Efficiency Effect = 0.181		
Elas.= -0.048	-0.47	-1.39	-0.08
Elas.= -0.300	0.05	-0.70	-0.25
	Without Efficiency Effect		
Elas.= - 0.048	0.14	-0.81	-0.05
Elas.= -0.300	0.45	-0.41	-0.15

Note: a. The total derivatives in this Table are evaluated at the mean data points of P_G, *SF*, P_N, and *FF* over 1996-2004.

Table 17. Various Demand Elasticities in a Semi-log System

Year		2000	2001	2002	2003	2004
Demand Elasticity		-0.084	-0.087	-0.089	-0.087	-0.087
INC	Low[a]	-0.066	-0.068	-0.071	-0.071	-0.074
	High	-0.105	-0.110	-0.113	-0.109	-0.105
POV	Low	-0.104	-0.110	-0.095	-0.104	-0.101
	High	-0.064	-0.069	-0.079	-0.070	-0.073
BLACKBELT	Yes	-0.065	-0.069	-0.078	-0.068	-0.071
	No	-0.092	-0.094	-0.093	-0.095	-0.093
RACE	Low % non-white	-0.098	-0.099	-0.092	-0.099	-0.096
	High % non-white	-0.065	-0.069	-0.084	-0.072	-0.073
RURAL	Yes	-0.079	-0.080	-0.081	-0.079	-0.083
	No	-0.102	-0.109	-0.115	-0.113	-0.101
UNEMP	Low	-0.101	-0.103	-0.102	-0.101	-0.097
	High	-0.070	-0.074	-0.076	-0.074	-0.077

Note: a. Low-income and high-income groups denote the 22 counties with the lowest and highest income.

Table 18. Change of Student Performance Explained by Exogenous Variables

Variable	% change, 92-96	Explained by	% change, 96-00	Explained by	% change, 00-04	Explained by
Q8	37.70		-0.49		-9.42	
Demand elasticity=-0.048						
SF	25.21	5.07	14.52	2.92	-5.91	-1.19
INC	-2.94	-1.33	2.63	1.19	-9.24	-4.19
RACE	-0.04	0.00	1.45	-0.07	2.36	-0.11
ED	11.99	0.00	7.14	0.00	6.66	0.00
TED	-3.28	-0.03	-4.35	-0.04	-6.94	-0.06
ENROL	1.94	0.10	1.46	0.07	0.26	0.01
POV	-3.75	0.16	-12.98	0.56	3.90	-0.17
% Total Explained		*3.97*		*4.64*		*-5.71*
Demand elasticity=-0.300						
SF	25.21	15.91	14.52	9.16	-5.91	-3.73
INC	-2.94	-0.88	2.63	0.79	-9.24	-2.78
RACE	-0.04	0.00	1.45	-0.03	2.36	-0.06
ED	11.99	0.00	7.14	0.00	6.66	0.00
TED	-3.28	-0.09	-4.35	-0.12	-6.94	-0.19
ENROL	1.94	0.30	1.46	0.23	0.26	0.04
POV	-3.75	0.50	-12.98	1.74	3.90	-0.52
% Total Explained		*15.74*		*11.77*		*-7.24*

Table 19. Coefficient Estimates of Reduced-Form Model to Test the Effects of the No Child Left Behind Act on Fourth-Grade Test Scores, Funding, Class Size, and Teacher Pay in Alabama's County Schools[a]

	Endogenous Variable									
	Fourth Grade Test Scores					Total Funding Per Pupil	Federal Funding Per Pupil	Instruct. Spending Per Pupil	Teacher-Student Ratio	Teacher's Salary
				Total						
Exogenous Variable	Reading	Math	Language	Model A	Model B					
NCLB	0.068	-0.020	-0.005	0.012	-0.014	0.053	0.251***	0.064***	0.033***	-0.043***
	(1.74)	(0.51)	(0.15)	(0.36)	(0.44)	(1.64)	(6.50)	(4.11)	(2.85)	(11.58)
SF	-3.971***	-2.96**	-2.68***	-3.133***	0.052	0.669***	0.212	0.144***	0.110***	0.001
	(3.67)	(2.64)	(3.10)	(3.45)	(0.54)	(7.09)	(1.88)	(3.18)	(3.23)	(0.11)
OF	-0.048	-0.050	-0.057**	-0.052	0.001	0.060***	0.002	0.001	-0.001	0.000
	(1.49)	(1.53)	(2.25)	(1.94)	(0.51)	(20.94)	(0.56)	(0.68)	(0.63)	(0.51)
TED	0.566***	0.365	0.418***	0.433***	-0.016	0.001	-0.013	0.007	0.015**	0.003
	(2.95)	(1.85)	(2.73)	(2.69)	(0.88)	(0.06)	(0.63)	(0.83)	(2.25)	(1.44)
ENROL	0.053	0.120	0.134	0.113	-0.058	-0.231	-0.447**	-0.172**	0.075	0.037
	(0.24)	(0.53)	(0.77)	(0.62)	(0.33)	(1.35)	(2.19)	(2.09)	(1.21)	(1.86)
SCHOOL	0.132	0.114	0.129**	0.123	0.161**	0.002	-0.040	-0.001	0.017	-0.011
	(1.77)	(1.47)	(2.15)	(1.96)	(2.52)	(0.04)	(0.53)	(0.03)	(0.73)	(1.50)
Q3R	0.225***	--	--	--	--	--	--	--	--	--
	(5.94)	--	--	--	--	--	--	--	--	--
Q3M	--	0.245***	--	--	--	--	--	--	--	--
	--	(5.95)	--	--	--	--	--	--	--	--
Q3L	--	--	0.220***	--	--	--	--	--	--	--
	--	--	(6.23)	--	--	--	--	--	--	--
Q3	--	--	--	0.226***	0.257***	-0.016	0.090**	0.027	0.034**	-0.010**
	--	--	--	(5.95)	(6.74)	(0.42)	(2.00)	(1.47)	(2.51)	(2.30)
INC	0.668**	0.670**	0.571**	0.644**	0.579**	0.249	-1.025***	-0.247	-0.406***	0.041
	(2.14)	(2.07)	(2.29)	(2.46)	(2.17)	(0.94)	(3.25)	(1.95)	(4.25)	(1.35)
PV	-0.059	-0.086	-0.054	-0.065	-0.051	-0.076	-0.019	-0.003	0.007	-0.007
	(1.07)	(1.51)	(1.23)	(1.41)	(1.09)	(1.64)	(0.35)	(0.14)	(0.42)	(1.27)
RACE	-0.011	-0.029	-0.008	-0.015	-0.028	-0.033	0.079	0.014	0.030	0.000
	(0.21)	(0.52)	(0.19)	(0.33)	(0.59)	(0.71)	(1.43)	(0.63)	(1.80)	(0.06)

UNEMP	0.029	-0.013	0.026	0.015	0.014	0.062**	0.054	0.005	0.006	-0.002
	(0.89)	(0.39)	(0.99)	(0.53)	(0.49)	(2.23)	(1.64)	(0.39)	(0.60)	(0.76)
RURAL	0.014	0.027	0.01	0.016	0.021	-0.065	0.006	-0.021	0.004	-0.011**
	(0.36)	(0.64)	(0.30)	(0.46)	(0.60)	(1.89)	(0.14)	(1.29)	(0.29)	(2.71)
POV	-9.961***	-7.110***	-6.432***	-7.642***	0.051	0.030	-0.259***	-0.013	-0.099***	0.021**
	(3.77)	(2.60)	(3.04)	(3.45)	(0.61)	(0.36)	(2.65)	(0.34)	(3.35)	(2.27)
*POV*SF*	1.321***	0.955***	0.858***	1.019***	--	--	--	--	--	--
	(3.88)	(2.70)	(3.14)	(3.56)	--	--	--	--	--	--
*POV*OF*	0.015	0.017	0.019**	0.017**	--	--	--	--	--	--
	(1.49)	(1.62)	(2.31)	(1.99)	--	--	--	--	--	--
*POV*TED*	-0.179***	-0.118	-0.129***	-0.137***	--	--	--	--	--	--
	(3.04)	(1.95)	(2.74)	(2.76)	--	--	--	--	--	--
ED	0.091	0.346	0.263	0.247	0.325	0.034	0.406	-0.190**	-0.216***	0.065***
	(0.43)	(1.58)	(1.56)	(1.40)	(1.82)	(0.19)	(1.93)	(2.25)	(3.39)	(3.21)
Constant	25.846***	17.041	15.856**	18.832**	-3.510	2.952	17.360***	11.049***	0.274	9.070***
	(2.76)	(1.76)	(2.11)	(2.40)	(1.22)	(1.04)	(5.12)	(8.12)	(0.27)	(27.74)
R^2	0.91	0.84	0.80	0.88	0.87	0.79	0.97	0.84	0.77	0.92
Adjusted R^2	0.89	0.80	0.75	0.84	0.84	0.74	0.96	0.79	0.71	0.90
F test of no interaction	7.78	3.81	6.21	6.78	--	--	--	--	--	--
	[0.0001][d]	[0.011]	[0.0001]	[0.0001]	--	--	--	--	--	--
s.e. regression	0.13	0.14	0.11	0.11	0.11	0.11	0.13	0.05	0.04	0.01

Note: a. Model was estimated as a two-way fixed effects model using pooled time-series/cross-section data for 1996-2004; coefficient estimates for county and time dummy variables are suppressed.

b. *** and ** denote significance level at 1% and 5% respectively.

c. Absolute values of t statistics are in parentheses.

d. p-value in bracket.

Table 20. Elasticity of Test Scores with Respect to State Funding, Other Funding and Teacher's Education with Varying Poverty Rates

Poverty Rate	$\partial \ln Q4/\partial \ln SF$	$\partial \ln Q4/\partial \ln OF$	$\partial \ln Q4/\partial \ln TED$
11.07% (mean - 2*sd)	-0.683	0.041	0.104
23.15% (mean)	0.069	0.053	0.003
35.23% (mean + 2*sd)	0.497	0.061	-0.055

Table 21. Coefficient Estimates of Reduced-Form Model to Test the Effects of the No Child Left Behind Act on Eighth-Grade Test Scores, Funding, Class Size, and Teacher Pay in Alabama's County Schools[a]

	Endogenous Variable									
	Eighth Grade Test Scores					Total Funding Per Pupil	Federal Funding Per Pupil	Instruct. Spending Per Pupil	Teacher-Student Ratio	Teacher's Salary
				Total						
Exogenous Variable	Reading	Math	Language	Model A	Model B					
NCLB	-0.038	0.088**[b]	0.046	0.033	0.021	0.052	0.258***	0.066***	0.036***	-0.044***
	(1.10)	(2.04)[c]	(1.33)	(1.03)	(0.67)	(1.62)	(6.65)	(4.24)	(3.05)	(11.74)
SF	-0.015	-0.437	-0.366	-0.153	0.336***	0.669***	0.235**	0.150***	0.117***	-0.002
	(0.01)	(0.36)	(0.37)	(0.17)	(3.71)	(7.11)	(2.08)	(3.31)	(3.42)	(0.17)
OF	-0.026	-0.076**	-0.016	-0.036	0.001	0.060***	0.002	0.001	-0.001	0.000
	(0.93)	(2.15)	(0.57)	(1.40)	(0.32)	(20.96)	(0.59)	(0.69)	(0.61)	(0.45)
TED	0.393**	0.642***	0.102	0.343**	0.001	0.001	-0.014	0.007	0.015**	0.003
	(2.28)	(3.01)	(0.58)	(2.17)	(0.06)	(0.04)	(0.64)	(0.83)	(2.24)	(1.49)
ENROL	0.343	0.375	0.420**	0.355**	0.199	-0.235	-0.431**	-0.167**	0.081	0.035
	(1.77)	(1.54)	(2.13)	(2.00)	(1.21)	(1.37)	(2.10)	(2.03)	(1.30)	(1.76)
SCHOOL	-0.017	0.023	-0.084	-0.034	-0.027	0.007	-0.025	0.002	0.019	-0.013
	(0.26)	(0.27)	(1.23)	(0.55)	(0.45)	(0.10)	(0.32)	(0.06)	(0.83)	(1.82)
Q4R	0.152***			--	--	--	--	--	--	--
	(3.18)			--	--	--	--	--	--	--
Q4M	--	0.098		--	--	--	--	--	--	--
	--	(1.71)		--	--	--	--	--	--	--
Q4L	--	--	0.121**	--	--	--	--	--	--	--
	--	--	(2.00)	--	--	--	--	--	--	--
Q4	--	--	--	0.162***	0.192***	-0.034	0.015	0.012	0.020	0.003
	--	--	--	(3.10)	(3.84)	(0.66)	(0.23)	(0.47)	(1.05)	(0.45)
INC	0.074	-0.011	0.031	-0.001	-0.078	0.264	-0.973***	-0.237	-0.397***	0.032
	(0.26)	(0.03)	(0.11)	(0.00)	(0.30)	(0.99)	(3.05)	(1.86)	(4.10)	(1.04)
PV	0.064	0.016	0.005	0.031	0.039	-0.077	-0.023	-0.004	0.007	-0.006
	(1.31)	(0.27)	(0.11)	(0.70)	(0.86)	(1.66)	(0.41)	(0.16)	(0.40)	(1.14)
RACE	0.016	-0.045	-0.025	-0.020	-0.031	-0.034	0.083	0.015	0.032	-0.001
	(0.32)	(0.74)	(0.51)	(0.44)	(0.70)	(0.73)	(1.49)	(0.69)	(1.89)	(0.13)

UNEMP	0.042	-0.007	0.062**	0.034	0.028	0.063**	0.046	0.003	0.003	-0.001
	(1.44)	(0.19)	(2.10)	(1.27)	(1.07)	(2.28)	(1.40)	(0.21)	(0.31)	(0.46)
RURAL	-0.031	-0.033	0.018	-0.016	-0.016	-0.064	0.005	-0.022	0.003	-0.011***
	(0.86)	(0.72)	(0.51)	(0.49)	(0.49)	(1.86)	(0.12)	(1.32)	(0.24)	(2.68)
POV	-0.843	-2.022	-2.058	-1.358	-0.246***	0.030	-0.240**	-0.009	-0.094***	0.019**
	(0.35)	(0.68)	(0.85)	(0.62)	(3.12)	(0.37)	(2.45)	(0.22)	(3.15)	(2.00)
*POV*SF*	0.104	0.260	0.242	0.163	--	--	--	--	--	--
	(0.33)	(0.68)	(0.77)	(0.57)	--	--	--	--	--	--
*POV*OF*	0.009	0.025**	0.005	0.012	--	--	--	--	--	--
	(0.98)	(2.19)	(0.56)	(1.42)	--	--	--	--	--	--
*POV*TED*	-0.128**	-0.193***	-0.031	-0.106**	--	--	--	--	--	--
	(2.41)	(2.94)	(0.57)	(2.18)	--	--	--	--	--	--
ED	-0.391**	-0.536**	0.025	-0.320	-0.332	0.044	0.416	-0.190**	-0.217***	0.062***
	(2.08)	(2.27)	(0.13)	(1.85)	(1.94)	(0.25)	(1.96)	(2.23)	(3.37)	(3.03)
Constant	0.193	5.226	2.847	2.334	1.067	2.889	16.717***	10.901***	0.110	9.165***
	(0.02)	(0.50)	(0.33)	(0.30)	(0.39)	(1.02)	(4.91)	(7.99)	(0.11)	(27.82)
R^2	0.91	0.86	0.82	0.90	0.89	0.79	0.97	0.84	0.77	0.92
Adjusted R^2	0.89	0.82	0.77	0.87	0.87	0.74	0.96	0.79	0.71	0.90
F test of	2.04	4.15	0.33	1.98	--	--	--	--	--	--
no					--	--	--	--	--	--
interaction	[0.108][d]	[0.009]	[0.806]	[0.117]						
s.e. regression	0.12	0.15	0.12	0.11	0.11	0.11	0.13	0.05	0.04	0.01

Note: a. Model was estimated as a two-way fixed effects model using pooled time-series/cross-section data for 1996-2004; coefficient estimates for county and time dummy variables are suppressed.

b. *** and ** denote significance level at 1% and 5% respectively.

c. Absolute values of t statistics are in parentheses.

d. p-value in bracket.

Table 22. Variable Definitions and Summary Statistics, 51 States, 2000-2003

Variable	Definition	2000			2002			2003		
NCLB	NCLB dummy, before 2002=0	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Student Test Score										
Q4R	Fourth-grade reading	271	235	287	--	--	--	277	243	291
Q4M	Fourth-grade math	224	192	234	--	--	--	234	205	243
Q8R	Eighth-grade reading	--	--	--	263	240	272	262	239	273
Q8M	Eighth-grade math	271	235	287	--	--	--	277	243	291
School Funding and Spending, $/Pupil										
P_G	Total funding[a]	$4,627	$3,079	$7,070	$4,971	$3,291	$8,391	$5,032	$3,204	$7,949
P_N	Local funding	$2,012	$96	$5,240	$2,169	$106	$7,348	$2,182	$104	$6,860
SF	State funding	$2,260	$0	$3,950	$2,392	$0	$5,073	$2,407	$0	$5,538
FF	Federal funding	$355	$153	$1,390	$410	$230	$1,043	$443	$265	$1,089
PI	Instructional expenditure	$2,410	$1,639	$4,003	$2,591	$1,688	$4,496	$2,633	$1,681	$4,677
Teacher-related School Inputs										
TSR^{-1}	Inverse of teacher-student ratio	15.7	12.3	22.0	15.5	11.8	21.8	15.5	11.7	21.8
TPAY	Average teacher's salary	$27,098	$19,676	$41,840	$28,354	$20,441	$43,025	$28,376	$20,261	$43,752
Student background										
ED	Adults college educated, percent	25.2	15.3	38.3	26.4	15.9	44.4	26.7	15.3	46.4
INC	Median family income	$24,118	$17,530	$30,772	$23,422	$17,062	$30,535	$23,463	$17,607	$30,657
POV	Age 5-17 in families in poverty, percent	13.8	5.2	27.5	14.6	6.2	29.8	15.1	5.7	30.0
RACE	Non-white students, excluding Asians and Pacific Islanders, percent	26.7	0.8	94.5	28.7	2.7	94.4	28.9	2.6	94.1
School or District Variables										
ENROL	School enrollment	918,768	77,194	6,038,590	943,719	75,392	6,247,726	944,766	76,166	6,353,667
UNEMP	Unemployment rate, percent	3.8	2.3	5.7	5.4	3.3	7.6	5.6	3.5	8.1
SCHOOL	Number of schools	1,804	185	8,578	1,851	198	8,916	1,883	203	9,100

Note: a. $P_G = P_N + SF + FF$. All financial variables are CPI deflated.

Table 23. Nonparametric Coefficient Estimates of Reduced-Form Model to Test the Effects of the No Child Left Behind Act on Eighth-Grade Test Scores, Funding, Class Size, and Teacher's Salary using NAEP Data

	School Outputs		School Inputs				
	Eighth Grade Test Scores		Total	Federal	Instruct.	Teacher-	Teacher's
Variable	Reading	Math	Funding Per Pupil	Funding Per Pupil	Spending Per Pupil	Student Ratio	Salary
NCLB	-0.002	-0.010	0.115***	0.306***	0.114***	0.051***	0.055***
SF	-0.002	0.000	0.061***	0.062	0.068***	0.043***	-0.015
ENROL	-0.072**[a]	-0.041	-0.507***	-0.016	-0.474***	-0.264***	0.017
SCHOOL	-0.034	0.031	0.259***	-0.284	0.267***	0.057	-0.004
Q4R	0.399***	--	--	--	--	--	--
Q4M	--	0.608***	--	--	--	--	--
INC	-0.010	-0.003	0.674***	1.591***	0.363***	0.249***	0.243***
RACE	-0.022***	-0.004	0.001	0.041	0.002	-0.001	0.005
UNEMP	0.015***	0.006	-0.068***	-0.083	-0.082***	-0.055***	-0.006
POV	0.022	-0.015	0.151***	0.304***	0.146***	0.115***	-0.030
ED	0.197***	0.021	0.435***	0.399	0.369***	0.350***	-0.132
Constant	4.547***	2.681***	5.157***	-9.572***	7.166***	-3.049***	7.701***
df	67	68	187	187	187	187	187

Note: a. *** and ** denote significance level at 1% and 5% respectively.

Table 24. OLS Coefficient Estimates of Reduced-Form Model to Test the Effects of the No Child Left Behind Act on Eighth-Grade Test Scores, Funding, Class Size, and Teacher's Salary using NAEP Data[a]

	School Outputs		School Inputs				
	Eighth Grade Test Scores		Total Funding Per Pupil	Federal Funding Per Pupil	Instruct. Spending Per Pupil	Teacher-Student Ratio	Teacher's Salary
Variable	Reading	Math					
NCLB	-0.003	-0.011**[b]	0.121***	0.307***	0.119***	0.048***	0.055***
	(1.05)	(2.20)[c]	(11.66)	(13.31)	(11.93)	(5.99)	(5.63)
SF	-0.007	-0.002	0.049***	0.028	0.054***	0.036***	-0.008
	(0.59)	(0.22)	(2.93)	(0.76)	(3.38)	(2.79)	(0.48)
ENROL	-0.080**	-0.051	-0.490***	-0.02	-0.435***	-0.274***	0.034
	(2.32)	(1.83)	(4.62)	(0.08)	(4.24)	(3.37)	(0.33)
SCHOOL	-0.029	0.030	0.227***	-0.322	0.210***	0.048	-0.019
	(1.19)	(1.54)	(2.70)	(1.72)	(2.58)	(0.74)	(0.24)
Q4R	0.403***	--	--	--	--	--	--
	(6.94)	--	--	--	--	--	--
Q4M	--	0.607***	--	--	--	--	--
	--	(8.03)	--	--	--	--	--
INC	-0.021	-0.021	0.598***	1.523***	0.320***	0.200**	0.256**
	(0.38)	(0.70)	(5.46)	(6.25)	(3.03)	(2.38)	(2.47)
RACE	-0.023**	-0.004	0.000	0.04	0.001	0.002	0.004
	(2.02)	(1.56)	(0.03)	(1.28)	(0.05)	(0.21)	(0.27)
UNEMP	0.016**	0.012	-0.075***	-0.072	-0.085***	-0.048***	-0.005
	(2.45)	(1.80)	(3.26)	(1.41)	(3.85)	(2.73)	(0.25)
POV	-0.012	-0.022	-0.077**	-0.173**	-0.032	-0.075***	0.011
	(0.98)	(1.81)	(2.45)	(2.47)	(1.07)	(3.14)	(0.37)
ED	0.027	-(0.02)	0.115**	0.261**	0.155***	0.101**	-0.033
	(1.82)	(1.32)	(2.13)	(2.18)	(2.99)	(2.45)	(0.65)
Constant	4.749***	3.056***	6.321***	-7.810***	7.655***	-2.110**	7.405***
	(8.36)	(5.62)	(4.76)	(2.64)	(5.96)	(2.07)	(5.89)
R^2	0.97	0.98	0.9758	0.95	0.98	0.96	0.97
Adj. R^2	0.95	0.97	0.9685	0.93	0.97	0.95	0.96
df	67	68	187	187	187	187	187

Note: a. Square root of log enrollment was used as a weight to correct for heteroscadasticity.
b. *** and ** denote significance level at 1% and 5% respectively.
c. Absolute values of *t* statistics are in parentheses.

Table 25. Dickey-Fuller Unit Root Test

Δln(Commodity)	a_0[a]	γ	a_2	df	Commodity	a_0	γ	a_2	df
Apples	-0.08***[b]	-0.15***	0.0003***	290	**L**emons	-0.05**	-0.14***	0.0003**	293
	(-4.39)[c]	(-4.86)	(4.06)			(-3.44)	(-4.76)	(3.90)	
Bacon	0.01	-0.02	0.0001	293	Lettuce	-0.35***	-0.47***	0.0008***	290
	(1.96)	(-1.78)	(1.64)			(-8.39)	(-9.53)	(6.06)	
Bananas	-0.25***	-0.25***	0.0004***	290	Milk	0.00	-0.03	0.0001	212
	(-6.11)	(-6.25)	(5.11)			(1.58)	(-1.67)	(1.67)	
Bread	-0.03	-0.04	0.0001	293	Orange Juice	0.02	-0.03	0.0000	293
	(-2.19)	(-2.41)	(2.31)			(2.66)	(-2.38)	(0.75)	
Broccoli	-0.35**	-0.63***	0.0016***	107	Onions	-0.19***	-0.16***	0.0003	208
	(-3.91)	(-7.05)	(4.18)			(-4.01)	(-4.34)	(2.48)	
Butter	0.01	-0.02	0.0001	293	Peanut Butter	0.02	-0.03	0	245
	(1.23)	(-1.55)	(1.52)			(2.59)	(-2.15)	(0.00)	
Cabbage	-0.33***	-0.25***	0.0006***	246	Pork	0.11	-0.12	0.0001	77
	(-5.66)	(-5.92)	(4.09)			(1.77)	(-2.18)	-1.44	
Carrots	-0.23***	-0.20***	0.0004***	246	Potatoes	-0.13	-0.10**	0.0002	216
	(-5.12)	(-5.24)	(4.55)			(-3.27)	(-3.65)	(2.41)	
Celery	-0.29***	-0.32***	0.0006***	240	Potato Chips	0.13***	-0.15***	0.0002***	293
	(-6.42)	(-6.78)	(4.37)			(5.20)	(-5.05)	(4.43)	
Cheese	0.07**	-0.09**	0.0002**	224	Rice	-0.02	-0.03	0.0000	240
(American)	(3.73)	(-3.73)	(3.54)			(-1.63)	(-1.74)	(0.36)	
Cheddar	0.12**	-0.12**	0.0002**	228	Round Roast	0.04	-0.04	0.0001	293
Cheese	(3.71)	(-3.78)	(3.49)			(2.18)	(-2.26)	(2.43)	
Chicken	-0.03**	-0.10**	0.0002**	293	Sausage	0.02	-0.04	0.0001	269
	(-3.50)	(-3.89)	(3.52)			.(2.77)	(-2.49)	(1.74)	
Chuck Roast	0.03	-0.05	0.0001	185	Spaghetti	-0.04**	-0.12**	0.0001	245
	(1.60)	(-1.87)	(1.76)			(-3.64)	(-3.95)	(3.35)	
Coffee	0.03	-0.03	0.0000	293	Steak Round	0.05	-0.05	0.0001	293
	(1.94)	(-2.07)	(0.97)			(2.52)	(-2.53)	(2.33)	
Cola	-0.04	-0.40***	0.0002	107	Steak Sirloin	0.14**	-0.13**	0.0003	168
	(-1.76)	(-5.05)	(2.57)			(3.47)	(-3.45)	(2.99)	

Cookies	0.03	-0.04	0.0001	293	Steak T-Bone	0.16***	-0.13***	0.0004***	264
	(3.05)	(-2.65)	(1.63)			(4.34)	(-4.28)	(4.17)	
Cucumbers	-0.26***	-0.34***	0.0007	212	Sugar	-0.06**	-0.06**	0.0000	293
	(-5.72)	(-6.51)	(3.33)			(-3.46)	(-3.79)	(1.02)	
Eggs	-0.02	-0.12***	0.0001	293	Tomatoes	-0.16***	-0.41***	0.0012***	290
	(-2.74)	(-4.37)	(2.54)			(-6.23)	(-8.69)	(6.85)	
Flour	-0.16**	-0.10**	0.0002**	293	Tuna	0.04	-0.05	-0.0001	293
	(-3.93)	(-3.97)	(3.50)			(2.77)	(-2.75)	(-2.55)	
Ground Beef	0.00	-0.02	0.0001	245	Turkey	-0.01	-0.25***	0.0001**	293
	(0.40)	(-1.36)	(1.72)			(-2.79)	(-6.49)	(3.61)	
Grapefruit	-0.13***	-0.13***	0.0003	293	Wine	0.93***	-1.06***	0.0037***	107
	(-4.18)	(-4.52)	(3.42)			(10.08)	(-10.96)	(10.08)	
Ham	0.02	-0.12**	0.0003	200	Yogurt	-0.15***	-0.22***	0.0003***	216
	(3.01)	(-3.68)	(3.29)			(-4.95)	(-5.07)	(4.57)	
Ice Cream	-0.10***	-0.15***	0.0003***	291					
	(5.04)	(-4.96)	(4.76)						

Note: a. A Dickey-Fuller test is in the form of $\Delta \ln y_t = a_0 + \gamma \Delta \ln y_{t-1} + a_2 t + e_t$.

b. "***" and "**" indicate 1%, 5% significance level respectively.

c. t tatios in parentheses.

Table 26. **Maximum Likelihood Estimates of EGARCH(1,1)**

Item	α	β	γ	LM Statistic[a]
Apples	0.23*	0.87*	0.21*	22.9*
	(2.35)[b]	(21.1)	(3.45)	
Bacon	0.27*	0.67*	0.18*	25.6*
	(2.74)	(5.38)	(2.76)	
Bananas	0.09	0.98*	0.05	2.58
	(1.94)	(55.2)	(1.42)	
Bread	0.24*	-0.87*	-0.07*	21.6*
	(4.47)	(-16.3)	(-2.23)	
Broccoli	0.01	0.53*	0.37	2.01
	(0.21)	(2.47)	(0.99)	
Butter	0.26*	0.99*	-0.05	15.3*
	(5.33)	(154.7)	(-1.17)	
Cabbage	0.01	0.88*	0.03*	6.92
	(1.46)	(11.8)	(2.30)	
Carrots	0.25	0.55*	0.26*	14.2*
	(1.94)	(3.92)	(3.08)	
Celery	-0.26*	0.82*	0.17*	2.12
	(-2.13)	(12.5)	(2.37)	
Cheese, American	0.13	0.93*	-0.15	7.36
	(1.31)	(25.0)	(-1.95)	
Cheese, cheddar	0.39*	0.97*	-0.13	44.9*
	(4.88)	(60.7)	(-1.83)	
Chicken	0.28*	0.39*	0.42*	37.0*
	(3.72)	(3.17)	(5.94)	
Chuck roast	0.46*	0.12	-0.03	13.8*
	(2.87)	(0.28)	(-0.19)	
Coffee	0.98*	0.11	0.32*	49.1*
	(6.04)	(0.84)	(2.38)	
Cola	0.17	0.39	-0.19	6.34
	(0.64)	(0.80)	(-1.31)	
Cookies	0.24*	-0.93*	-0.02*	8.05*
	(6.44)	(-78.3)	(-2.54)	
Cucumbers	-0.43*	0.41*	0.35*	2.94
	(-2.84)	(2.73)	(3.18)	
Eggs	0.28	0.52	0.04	5.30
	(1.61)	(0.78)	(0.49)	
Flour	0.02	0.97*	-0.11*	4.26
	(0.40)	(95.2)	(-3.87)	
Ground beef	-0.04	-0.03	-0.21*	7.61
	(-0.18)	(-0.11)	(-2.12)	
Grapefruit	-0.17*	0.82*	0.39*	8.24*
	(-2.79)	(22.1)	(5.79)	
Ham	0.48*	-0.28	-0.14	1.49
	(2.47)	(-1.19)	(-1.44)	
Ice cream	0.12	0.99*	-0.05*	14.3*
	(1.32)	(104.8)	(-2.96)	
Lemons	0.00	-0.61*	0.11	11.3*
	(-0.31)	(-2.03)	(0.87)	
Lettuce	0.06	0.76	0.26*	11.4*

	(0.79)	(12.7)	(3.47)	
Milk	0.27*	0.97*	0.00	33.8*
	(3.87)	(52.7)	(0.00)	
Orange juice	0.47*	0.52*	0.07	19.2*
	(3.48)	(3.15)	(0.81)	
Onions	0.01	0.67*	0.44*	14.3*
	(0.61)	(7.91)	(2.99)	
Peanut butter	0.25	0.35	0.21	9.87*
	(1.62)	(1.12)	(1.48)	
Pork	0.11	0.96*	-0.23*	2.03
	(1.05)	(34.0)	(-2.64)	
Potatoes	0.05	0.86*	0.42*	20.7*
	(0.78)	(16.5)	(4.41)	
Potato chips	0.01	0.98*	-0.06*	39.2*
	(0.92)	(122.7)	(-2.11)	
Rice	0.31*	-0.21	-0.03	9.59*
	(2.53)	(-0.57)	(-0.34)	
Round roast	0.21*	0.95*	-0.06	24.0*
	(3.04)	(26.8)	(-1.31)	
Sausage	0.11	0.72*	-0.12	1.96
	(0.60)	(4.52)	(-1.80)	
Spaghetti	0.46*	-0.06	0.01	10.4*
	(3.12)	(-0.13)	(0.05)	
Steak, round	0.47*	0.77*	0.07	26.5*
	(3.76)	(6.72)	(0.98)	
Steak, sirloin	-0.00	0.62	0.13	3.25
	(-0.23)	(1.27)	(1.02)	
Steak, T-bone	0.11	-0.88*	-0.11*	14.6*
	(1.72)	(-20.5)	(-2.66)	
Sugar	0.47*	0.93*	-0.001	86.6*
	(4.35)	(31.6)	(-0.02)	
Tomatoes	0.16*	0.88*	0.26*	18.1*
	(2.15)	(19.1)	(3.67)	
Tuna	0.43*	0.85*	0.06	23.4*
	(3.09)	(9.13)	(0.98)	
Turkey	-0.37*	0.70*	-0.25*	2.96
	(-4.70)	(7.54)	(-3.20)	
Wine	1.12*	0.69*	0.40*	81.4*
	(5.45)	(6.49)	(2.94)	
Yogurt	0.27*	0.99*	-0.07	5.99
	(2.51)	(67.7)	(-1.57)	

Note: [a]Lagrange Multiplier statistic computed under the null hypothesis that α, β, and γ are jointly zero.
[b]Numbers in parenthesis are asymptotic *t*-ratios. Asterisk indicates significance at the 5% level or less.

Table 27. Effect of News on Monthly Retail Food Price Volatility

Food Item	High Price News ($\alpha + \gamma$)	Low Price News ($\alpha - \gamma$)
Apples	0.44	0.02
Bacon	0.45	0.09
Bread	0.17	0.31
Carrots	0.51	-0.01
Chicken	0.70	-0.14
Coffee	1.30	0.66
Cookies	0.22	0.26
Grapefruit	0.22	-0.56
Ice cream	0.07	0.17
Lettuce	0.32	-0.26
Onions	0.45	-0.43
Potatoes	0.47	-0.37
Potato chips	-0.05	0.07
Steak, T-bone	0.00	0.22
Tomatoes	0.42	-0.10
Wine	1.52	0.72
Mean (μ_i)	0.45	0.04
Std. Deviation sd_i	0.41	0.35
Sample size (n_i)	16	16
t-value under null hypothesis that means are equal:[a]		3.04

Note: [a]Calculated with $t = (\mu_1 - \mu_2)/(Psd*N)$ where $N = (1/n_1 + 1/n_2)^2 = 0.353$ and $Psd = 0.381$ is the pooled estimate of the common standard deviation computed using the formula in Spurr and Bonini (1973, p. 297).

Table 28. Classification of Food Price Variance Response

News Effects		No News Effects		
Symmetric effects	Asymmetric effects	Insignificant LM statistic	No news effects EGARCH model	Constant variance
*Apples	*Carrots	Cabbage	Bananas	Cola
*Bacon	*Chicken	Celery	Broccoli	Eggs
Bread	Grapefruit	Cucumbers	Butter	Ground beef
*Coffee	*Lettuce	Flour	American cheese	Peanut Butter
Cookies	*Onions	Turkey	Cheddar cheese	Steak, sirloin
Ice cream	*Potatoes		Chuck roast	
Potato chips	*Tomatoes		Ham	
Steak, T-bone			Lemons	
*Wine			Milk	
			Orange juice	
			Rice	
			Round roast	
			Sausage	
			Spaghetti	
			Steak round	
			Sugar	
			Tuna	
			Yogurt	

* Disproportionate responses to high price news

Table 29. Diagnostic Regression

Item	F-Statistic for H_N: $\delta_1 = \delta_2 = \delta_3 = 0$	Probability
Apples	1.62	0.18
Bacon	0.02	0.99
Bread	0.86	0.46
Cabbage	0.15	0.93
Carrots	1.01	0.39
Celery	0.32	0.81
Chicken	0.22	0.88
Coffee	0.03	0.99
Cookies	0.09	0.97
Cucumbers	1.73	0.16
Flour	0.99	0.40
Ground beef	0.33	0.80
Grapefruit	1.81	0.15
Ice cream	1.57	0.20
Lettuce	0.40	0.76
Onions	0.36	0.78
Pork	0.62	0.60
Potatoes	6.26	0.0004
Potato chips	2.23	0.08
Steak T-bone	0.77	0.51
Tomatoes	2.15	0.09
Turkey	1.45	0.28
Wine	1.45	0.23

Table 30. The Effect of NAFTA on US Unemployment

Variable		Constant	Wage	GSP	Btax	Union	UI	Pop	Itax	N5	N1	N		
Symbol			W	Y	B	M	R	P	I					
Coefficient		β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_8	β_8	Adj. R^2	df
Model A: OLS, pooled state data														
N5	94 - 99 = 1,	0.030[a]	1.328***	-2.650***	0.169	0.034	0.411***	3.234***	-0.082***	-0.077***	--	--	0.395	1240
	0 else	(0.023)[b]	(0.235)	(0.121)	(0.126)	(0.034)	(0.077)	(0.522)	(0.023)	(0.009)	--	--		
Model B: 2SLS[c], pooled state data														
N5	94 - 99 = 1,	0.017	0.840**	-2.542***	0.280**	0.030	0.401***	3.669***	-0.086***	-0.068***	--	--	0.386	1240
	0 else	(0.023)	(0.373)	(0.145)	(0.125)	(0.034)	(0.077)	(0.528)	(0.023)	(0.009)	--	--		
N1	94 = 1,	0.008	-0.004	-2.375***	0.369***	0.023	0.419***	3.220***	-0.093***	--	-0.089***	--	0.363	1240
	0 else	(0.024)	(0.361)	(0.147)	(0.128)	(0.035)	(0.079)	(0.535)	(0.024)	--	(0.018)	--		
N	94 - 04 =1,	0.005	-0.355	-2.346***	0.362***	0.017	0.413***	2.863***	-0.090***	--	--	0.007	0.349	1240
	0 else	(0.024)	(0.438)	(0.158)	(0.132)	(0.035)	(0.080)	(0.542)	(0.024)	--	--	(0.008)		
Model C: 2SLS, country data														
N5	94 - 99 = 1, 0 else	-0.008	0.966	-3.632**	0.920	-1.166	0.888	4.347	-0.992**	-0.036	--	--	0.785	18
		(0.139)	(1.753)	(1.262)	(1.125)	(0.660)	(0.605)	(12.334)	(0.372)	(0.033)	--	--		

Note. a. **, and *** denote significance level at 5% and 1% respectively.

b. Standard errors are in parentheses.

c. Instrumental variables include individual income tax rate, CPI, union membership density, GSP and GDP.

Table 31. Structural Elasticities

Parameter	Structural Elasticities								
Unemp. rate[a]	Wage	GSP	Btax	Union	UI	N5	Pop	Itax	UI
μ	η (ε=0)	η_Y	η_B	η_M	η_R (ε_R=-0.05)	η_T	ε_P	ε_I	ε_R (η_R=-0.05)
0.059	-0.053	0.160	-0.018	--	-0.078	0.004	0.218	-0.005	-0.023

Note. a. State average for 1977-2004.

Table 32. Adjustment Period of US Unemployment with Respect to NAFTA

γ_0	θ_{1994}	θ_{1995}	θ_{1996}	θ_{1997}	θ_{1998}	θ_{1999}	θ_{2000}	θ_{2001}	θ_{2002}	θ_{2003}	θ_{2004}	Adj. R^2	df
-0.006	-0.079***[a]	-0.066***	0.012	-0.015	-0.045**	-0.021	-0.051***	0.150***	0.216***	0.082***	-0.011	0.464	1230
(0.022)	(0.017)[b]	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.019)	(0.018)	(0.017)		

Note. a. **, and *** denote significance level at 5% and 1% respectively.

b. Standard errors are in parentheses.

Figure 1. Alabama 8-th Grade Students SAT Total Scores, 1992, 1996-2004

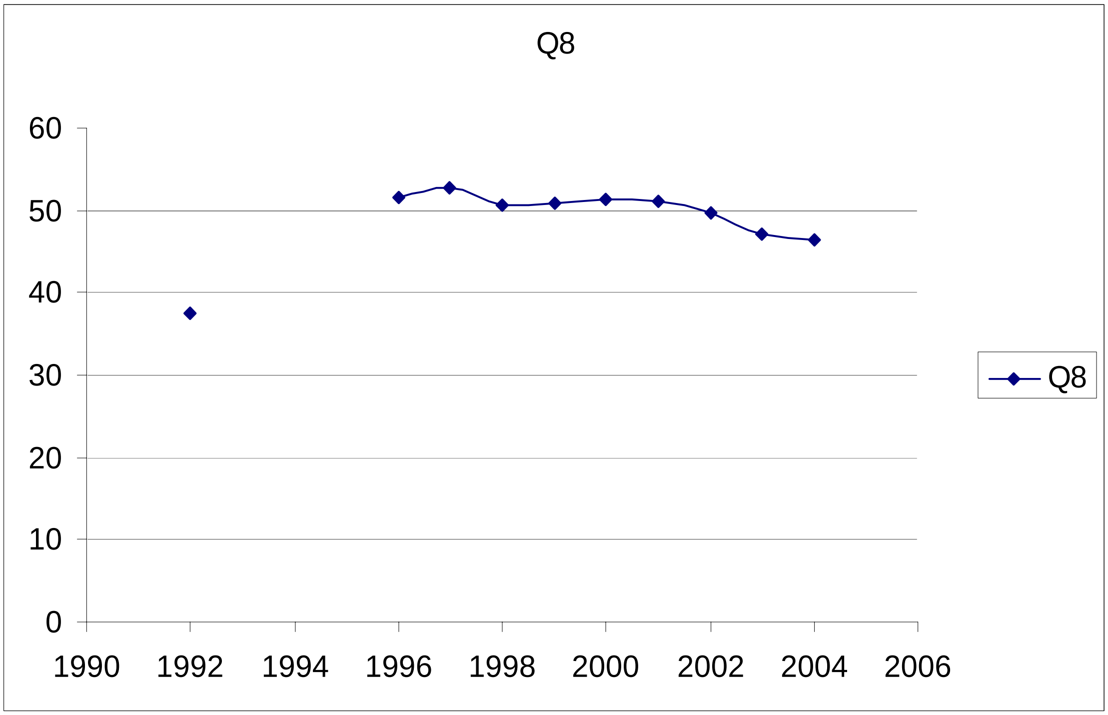
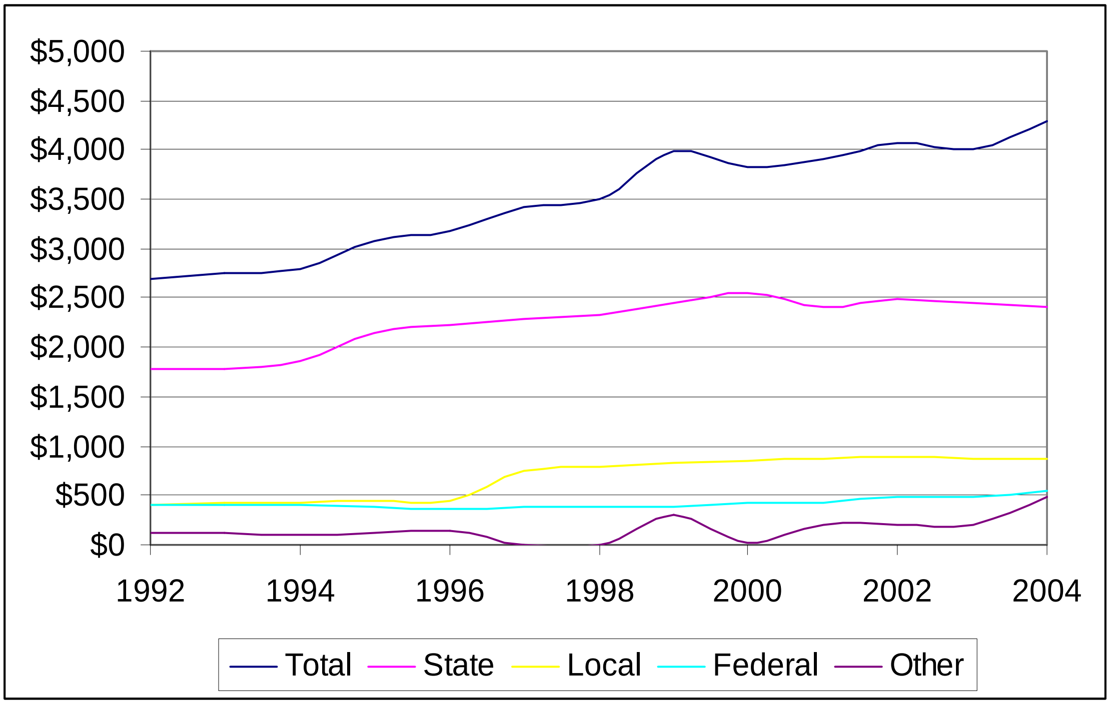
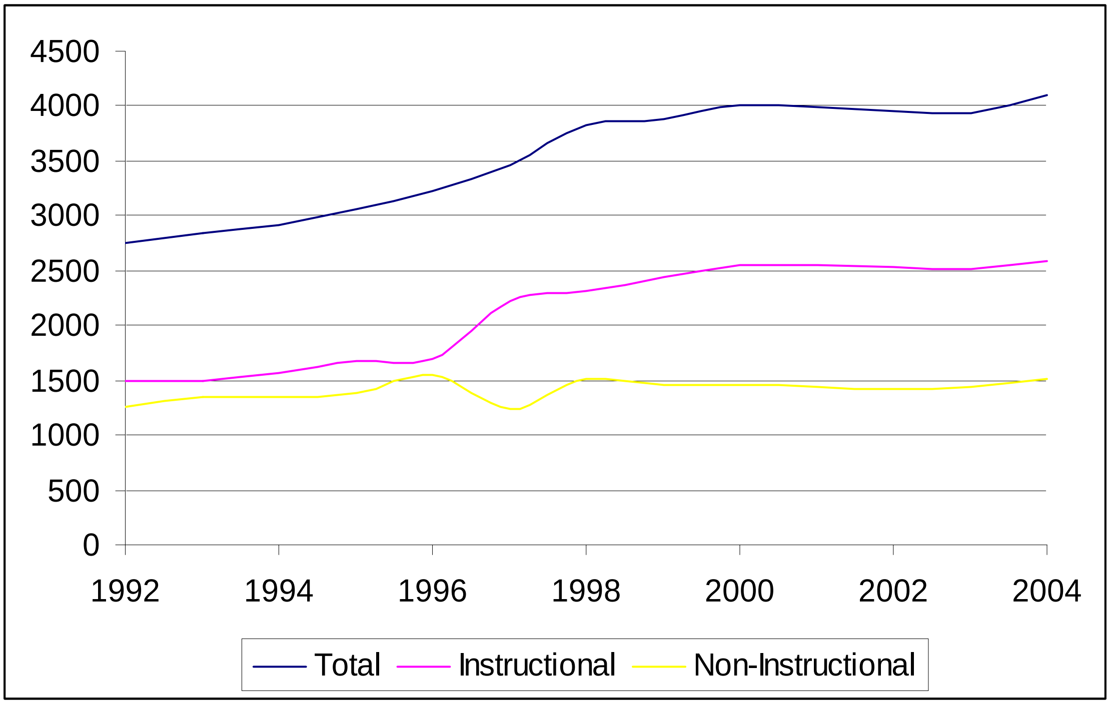


Figure 2. Real Per Pupil Funding by Source, Alabama, 1992 - 2004



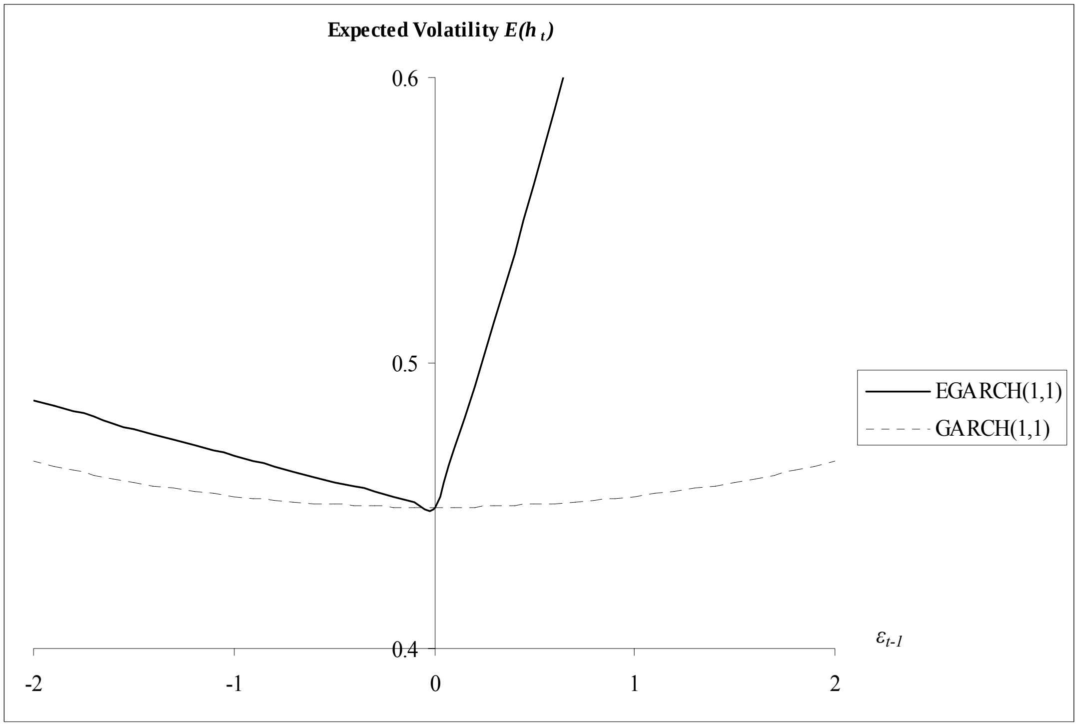
Note: Numbers are CPI deflated.

Figure 3. Real Per Pupil Expenditures by Source, Alabama, 1992 – 2004



Note: Numbers are CPI deflated.

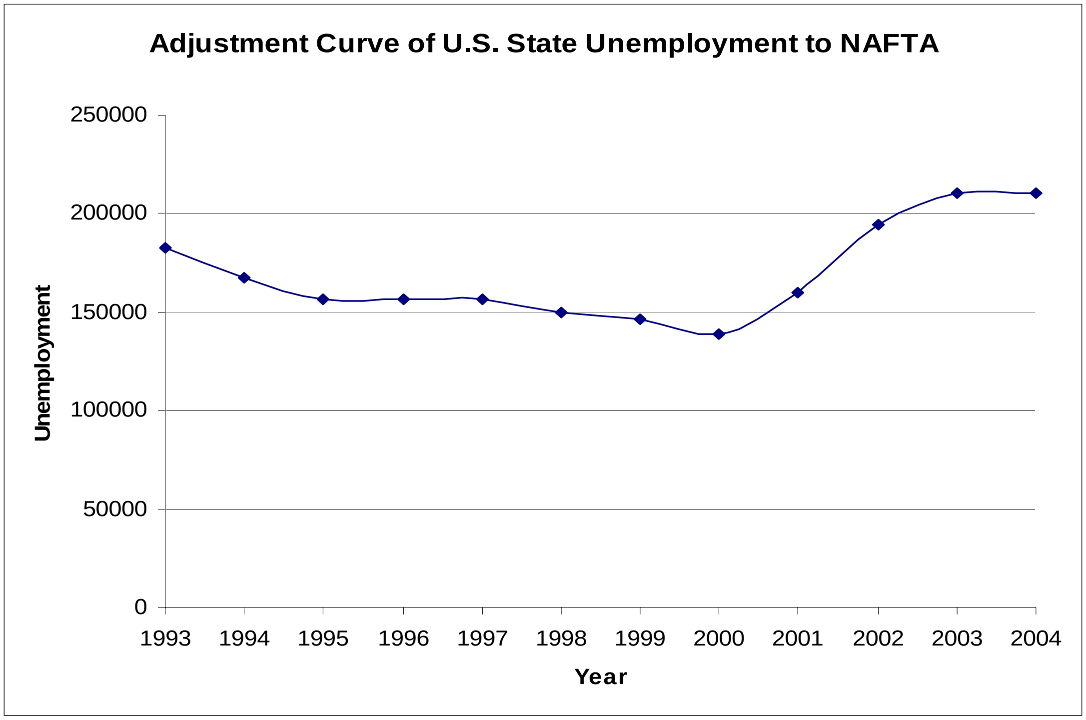
Figure 4. The News Impact Curves of the GARCH(1, 1) Model and EGARCH(1, 1) Model



EGARCH(1,1) curve corresponds to equation:
$\ln(h_t) = -.8 + \ln(h_{t-1}) + .45(\varepsilon_{t-1}/h_{t-1}^{1/2})$, $h_{t-1}=1$, when $\varepsilon_{t-1} > 0$
$\ln(h_t) = -.8 + \ln(h_{t-1}) + .04(\varepsilon_{t-1}/h_{t-1}^{1/2})$, $h_{t-1}=1$, when $\varepsilon_{t-1} < 0$

GARCH(1,1) curve corresponds to equation:
$h_t = -.55 + h_{t-1} + .004(\varepsilon_{t-1}^2)$, $h_{t-1}=1$

Figure 5. Adjustment of US Unemployment with Respect to NAFTA



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APPENDIX: DATA SOURCES FOR THE FIRST ESSAY

Q8 and *Q4* are the eighth and fourth grade *Stanford* Achievement Test total scores, which are abstracted from various years of Alabama county school report cards. The total stands for the total battery score of Reading, Mathematics, Language, Science and Social Science during 1992 - 2002 and total battery score of Reading, Language and Mathematics during 2003 – 2004. Alabama students in grades 3-11 are given the *Stanford Test* each year to measure their academic performance. The national average for the *Stanford* Achievement Test, 9^{th} and 10^{th} Edition, is 50. However, caution should be used when comparing *Stanford 9* and *Stanford 10* scores since the *Stanford 9* (96 – 2002) is based on 1995 norms and the *Stanford 10* (2003 – 2004), a different test, is based on 2002 norms. The *Stanford Test* provider Harcourt Assessment, Inc. provided the Harcourt Assessment Percentile Rank Conversion Tables *Stanford 9* - *Stanford 10* that makes subject test scores (not total scores) comparable for the two editions. Therefore, the scores in NCLB section (section VII) were all converted to *Stanford 10* percentiles while scores in previous sections were not since they are total scores.

P_G, P_N, *SF, FF* and *OF* are total, local, state, federal and other revenues per student from the various yearly issues of *Annual Report: Statistical and Financial Data* published by Alabama Department of Education (ALSDE henceforth) for the period of 1992-1998. For 1996, the revenues data appear on page 70 in the report. The publication of *Annual Report: Statistical and Financial Data* was discontinued after 1998 thereafter the revenues data are from the *SDE Annual Report* by ALSDE for the period of 1999 to 2003. The revenues data of 2004 are from various issues of Alabama county school report cards on ALSDE's website, since the *SDE Annual Report* 2004 is not available at this time. ALSDE reported the revenues per student on ADA (Average Daily Attendance) basis before 1997 and on ADM (Average Daily Membership) by law since 1997. Average daily attendance is the aggregate attendance days of a school during a reporting period (normally a school year) divided by the number of days school is in session during this period. Average daily membership contains average daily membership reported for each school based on the number of days that each student was on roll during the first 40 days of school. Average daily membership total pupil days in first forty days divided by 40. ADA is roughly 95% of ADM in the data. In section I-VI, we convert all the revenues starting from 1997 to ADA basis to maintain consistence for comparison. So do such adjustment for other similar variables that were reported on ADA before 1997 and on ADM thereafter. School funding and expenditures in section VII are ADM based to make it easier for future update. Other funding includes interest, earnings on investment, food service income, fees and donations. *PI* and *PNI* are the instructional expenditure and non-instructional expenditure per student. They are from the same sources in which the revenues data are abstracted. For instance, the expenditure data are on page 74 in the *Annual Report: Statistical and Financial Data* for 1996.

TSR is the teacher-student ratio, a measure of class size. It is from the *Common Core of Data (CCD)*, National Center for Education Statistics, US Department of

Education except for year of 2004. CCD covers data up to 2003 therefore, we calculate the *TSR* of 2004 by dividing the number of regular program teachers (from ALSDE county school report cards) by the total enrollment. *TSR* in 2004 was available in early 2006 from CCD and it is updated for estimation in section VII.

TED is the percentage of teachers with a Ph.D. or equivalent degree. The population of teachers is the certified FTE (full time equivalents). The various issues of Alabama county school annual report cards provide the teacher education data for the period of 1997 – 2004. The teacher education data of 1996 are from page 52 in the *Annual Report: Statistical and Financial Data for 1996* by ALSDE. Note that Rank AA teachers represented teachers with a Ph.D. or equivalent degree before 1996. *MS* is the percentage of teachers with a Master's degree. *MS* data are from the same sources as *TED* data are.

TPAY means the average salaries of teachers and principals. Ethan Taylor, a Programmer Analyst in the ALSDE, provided *TPAY* data for all the years (contact: etaylor@alsde.edu).

ED denotes the percentage of persons aged 25 and over with a bachelor degree or over, which indicates the adult educational attainment. Sources are in the Table *County-level Education Data for AL,* Economic Research Service (ERS), US Department of Agriculture. ERS compiled the Table based on the results of US Census 2000 and 1990. Since only two years of *ED* data are available from 1990 to 2004, we calculated the rest of the *ED* data by simple interpolation. The *ED* in year 199x and 200x is interpolated by *ED*_199x=*ED*_1990+x*(*ED*_2000 - *ED*_1990, and *ED*_200x=*ED*_2000+x*(*ED*_2000 -

*ED*_1990. Caution should be exerted when interpreting the coefficients of *ED* in the paper.

The source of *INC* (median family income) and *POV* (poverty rate) is from *Small Area Income & Poverty Estimates,* Annual Estimates for States, Counties & School District, 1996-2002, US Census Bureau. Since the source only contains county level data for 1997 – 2002, the income and poverty rate for 1996, 2003 and 2004 are interpolated from data of their adjacent years in the same way as we did for *ED. INC* in 2003 is available in early 2006 and updated for estimation in section VII. In section VII, percent of all ages in families in poverty is replaced by percent of age 5-17 in families in poverty to be consistent for state and Alabama county level studies.

As for the *RURAL* dummy variable, the source is *Center for Business and Economic Research,* the University of Alabama. Counties that have more than 50% of their population living in rural areas are assigned the value of one for the *RURAL* dummy. According to the source, Alabama has 46 rural and 21 urban counties in 1990 and 51 rural and 16 urban counties in 2000. Therefore, we use one set of dummies for the 90's and another set of dummies for the 00's. In dynamic panel data, there must be some degrees of variation in the explanatory variable for its effect to be distinguished from the constant term (Wooldridge, 2002). The difference in the *RURAL* dummy variables satisfied such requirement.

RACE is the percentage of non-white students. The *RACE* data of 1996 is from page 34 in the *Annual Report: Statistical and Financial Data for 1996* by ALSDE. The *RACE* data during 1999 – 2003 are from the yearly *SDE Annual Report* by ALSDE. Data in 1997, 1998 and 2004 are missing and we interpolated them as we did for *ED*. *RACE* in 2004 was available in early 2006 and is updated for estimation in section VII.

UNEMP is the unemployment rate. The source is *The Local Area Unemployment Statistics (LAUS) Program,* Bureau of Labor Statistics, US Department of Labor.

ENROL is the ninth month enrollment. The *ENROL* data of 1996 is from page 28 in the *Annual Report: Statistical and Financial Data for 1996* by ALSDE. The *ENROL* data during 1999 – 2003 is from the yearly *SDE Annual Report* by ALSDE. *ENROL* in 2004 is missing, we use Average Daily Membership (ADM) in 2004 as a proxy as they are very close numbers in the past. *ENROL* in 2004 is updated for estimation in section VII.

BLACKBELT indicates whether the county is one of the following 19 Black Belt counties in Alabama: Barbour, Bullock, Butler, Choctaw, Clarke, Conecuh, Dallas, Escambia, Greene, Hale, Lowndes, Macon, Marengo, Monroe, Perry, Pickens, Sumter, Washington, and Wilcox. The source is the *Black Belt Fact Book,* Institute for Rural Health Research, the University of Alabama.

PV is the appraised property valuation divided by enrollment, which is a measure of wealth per student. The data of appraised property valuation is in the Table titled Comparative Figures for Appraised Valuation, Revenues and Receipts and Expenditures from *Financial Statement of State of Alabama*, All counties, compiled by Department of Examiners of Public Accounts, Montgomery, AL. Sandy Shirley (Sandy.Shirley@examiners.state.al.us) in the Alabama State Department of Examiners of Public Accounts provided the yearly statements, which covers 1996 - 2004.

SCHOOL is the number of public schools in the county. It is from the *Common Core of Data (CCD)*, National Center for Education Statistics, US Department of Education except 2004. The data for 2004 are interpolated as they are not available in the CCD database. *SCHOOL* in 2004 is updated for estimation in section VII.

The Consumer Price Index (CPI) deflates all the monetary variables in the panel data study (1996 – 2004). The CPI denotes All Urban Consumers (CPI-U) on US city average for all items with 1982-84=100.

NOTES

[1] Source: Economic Time Bomb: US Teens Are Among the Worst at Math. The Wall Street Journal, December 7, 2004.

[2] See Eric Hanushek and Richard Murnane's comments in the source cited in footnote 1.

[3] See appendix for definitions of average daily attendance and average daily membership.

[4] Each study represents a separate estimate of one of the key resource parameters on measured student performance (Hanushek, 1996, p. 55)

[5] By standardizing, it means test scores are converted to a standard score (or z-score) by subtracting the population mean from an individual (raw) score and then dividing the difference by the population standard deviation. A z-score has a zero mean and unit standard deviation.

[6] Teacher test scores are also standardized to have zero mean and unit standard deviation. The only two standardized variables in FL's study are student and teacher test scores. The only standardized variable in our replication study is student test score.

[7] See page 277 in FL's study for a more detailed explanation.

[8] Even when we use per capita income in our model, the huge disparity remains.

[9] States may switch from the use of *Stanford 9* to *Stanford 10* in different years. For example, Florida introduced *Stanford 10* in Spring 2005.

[10] Source: *The New FCAT NRT: Stanford Achievement Test Series, Tenth Edition*, Florida Department of Education and Harcourt Assessment, Inc., 2005.

[11] Other funding includes interest, earnings on investment, food service income, fees and donations.

[12] The revenues and spending do not deviate too much for most of the last 13 years.

[13] When also using percent of teachers with a master's degree instead of a Ph.D. degree in the W3SLS estimation, the result for the teacher's education variable is not promising either.

[14] If $lnQ8 = \beta P_N$, then we have $Q8 = \text{Exp}(\beta P_N)$. It follows that $\partial Q8/\partial P_N = \beta\ \text{Exp}(\beta P_N) = \beta Q$. Rearranging above equation leads to $(\partial Q8/Q8)/(\partial P_N/P_N) = \beta P_N$.

[15] Source: US Department of Education.

[16] To avoid perfect multicollinerity between the time dummies and NCLB dummy, four instead of five time dummies are used in the two-way fixed effects model. The four time dummies are for 2000-2003.

[17] Another measure of highly qualified teachers is the percent of teachers that are teaching in a core subject for which the teacher is highly qualified by the State of Alabama as required by NCLB.

[18] See Galchus (1994) for a similar study on Arkansas.

[19] Coauthors professors Henry Kinnucan and Henry Thompson.

[20] Coauthor John Francis, assistant professor at Auburn University Montgomery.

[21] For example see Krugman (1993A, 1993B) and Mussa (1993).

[22] Both of these quotes come from: Fletcher, Michael A, "Bush Says CAFTA Will Save Jobs", Washington Post, 16 July 2005: A04.

[23] Additional examples of trade models that explicitly model unemployment include Davidson et al (1988), Hoon (2001), and Sener (2001).

[24] Unemployment is difference stationary indicated by a Dickey-Fuller stationarity test.

[25] Model B with N5 is the default model for policy discussion unless noted.

[26] This elasticity is simulated with its counterpart on the supply side (ε_R) fixed at a best-bet level of -0.05.

[27] This elasticity is simulated with its counterpart on the demand side (η_R) fixed at a best-bet level of -0.05.

[28] See Levinsohn (1999) for discussion on the issue why data disaggregation matters to detect labor movement. Focusing on a set of 25 trade liberalization episodes, Wacziarg and Wallack (2004) uncover increased sectoral labor shifts due to trade liberalization only within data with higher level of disaggregation.