## Comment on M.G. Sciffer, L.B. Perry, & A.M. McConney, "Critiques of socio-economic school compositional effects: are they valid?"

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## ARTICLE HISTORY

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Sciffer, Perry, and McConney (2020) identify a number of potentially serious methodological flaws in several recent studies of school socioeconomic composition (school SES hereafter) and academic achievement, including one by Armor, Marks, and Malatinszky (2018). Most of the studies criticized by Sciffer et al. themselves challenged an older literature that relied heavily on cross-sectional data (such as the PISA studies) to find large school SES effects on test scores. Some of the newer papers, including Armor et al., are particularly critical of cross-sectional methodologies for claiming to demonstrate causality in the school effectiveness literature. The reason is because aggregate characteristics like school SES can create "artifactual" effects not unlike the ecological fallacy when cross-sectional methods are used.<sup>1</sup>

While Sciffer et al. raise several major methodological issues in a host of recent studies, this comment responds to their critique of the student fixed effects (student FE) analysis for identifying school SES effects. Armor et al. made extensive use of this methodology due to the known necessity of controlling for stable, unobservable differences between students in estimating the effects of school composition.

The Sciffer et al. criticism of Armor et al. is straightforward. They assert that changes in school SES are likely to be very small or even negligible from year to year within the same student cohorts. Further, although they acknowledge that the elementary-to-middle school transition in the U.S. generally involves a change of schools, they said that effect would be attenuated by the lack of change in the other (four) grades.<sup>2</sup> They also believe that the high proportion of public-school attendance in the U.S. suggests minimal school SES changes even between elementary and middle schools. Accordingly, there is insufficient within-student variation in school SES to reliably estimate the effect of school SES on academic achievement. Additionally, they argue that student mobility within elementary and middle school grades may indicate student characteristics that are confounded with school SES effects. In sum, the Armor et al. study's use of a student fixed effect design made it unlikely they would detect an effect of changes in school SES on academic achievement growth.

 $<sup>^{1}</sup>$ Sciffer et al. abbreviated school socioeconomic composition as SEC, which we change to "school SES" throughout this comment.

 $<sup>^{2}</sup>$ Sciffer et al. refer to "the 5 occasions without cohort changes," but for grades 3 to 8, there are only four other cohort changes in addition to the elementary to middle school change.

At the outset, and to be fair, in theory these are not unreasonable criticisms. By controlling for all time invariant differences between students, the student FE models used by Armor et al. rely entirely on within-student variation over time to estimate the effects of school composition on student achievement. If students' corresponding school compositions are, indeed, relatively static both within the elementary and the middle school years and even between the elementary to middle school transition, there may well be insufficient within-student variation to obtain reliable estimates for school SES effects. Moreover, if the students who do experience changes in school composition over time do so for reasons related to their performance (e.g. changing schools due to behavior problems), then their school SES levels could be confounded with their achievement.

It is equally important to note that Sciffer et al. did not present any data or analyses to substantiate these claims; without data, their arguments remain hypothetical rather than definitive. Fortunately, we can take a second look at our three statewide databases to see if these assertions have empirical support in the data. If their assertions are correct, we should find very small within-student variation in school SES, and even the elementary to middle school variation should be negligible.

In order to address these questions, we carry out several additional analyses using the same data that was used in Armor et al. (2018). The short answer: there is substantial within-student variation in school SES, in all three statewide datasets, so one of their main arguments—lack of significant within-student variation—is not supported by the data.

First, to examine the claim that the variance of school SES within students is insufficient for generating reliable estimated effects in our fixed effects models, we decompose school SES variances in each of our three statewide datasets to withinstudent and between-student components. The results of this analysis, in terms of overall and within-student standard deviations, are shown in Table 1. Student SES was measured by free or reduced lunch status in Arkansas and South Carolina. In North Carolina, student SES was measured by an index combining free/reduced lunch and parents' highest education level; both measures were standardized before averaging.<sup>3</sup> The overall standard deviation of school SES in each of the three states ranged from .39 to .46.

		Standard Deviation by Component for Students in:				
		Arkansas	North Carolina	South Carolina		
All Grades	Overall:	0.45	0.39	0.46		
	Within-Student:	0.18	0.16	0.12		
	Observations:	1,503,601	2,269,914	736,393		
	Unique Students:	$385,\!849$	454,250	210,862		
Grades 3-5	Overall:	0.47	0.40	0.48		
	Within-Student:	0.14	0.11	0.09		
Grades 6-8	Overall:	0.43	0.37	0.44		
	Within-Student:	0.13	0.10	0.08		

Table 1. Variation in School SES by State: Overall and Within-Student Standard Deviations

Notably, by repeating this analysis on subsets of observations within grades 3-5 and grades 6-8, we show that a substantial amount of the within-student variation

<sup>&</sup>lt;sup>3</sup>Free/reduced lunch was coded by 0, 1, or 2 for free, reduced, and paid, respectively; parent education was years of attainment (10 for did not finish HS; 12 for HS grad; 13 and 14 for some college; 16 for college grad; 19 for post-grad).

occurs independently of the elementary-to-middle school transition, particularly for Arkansas. We conclude it is not the case that most variation in school SES is due to the change of schools between the elementary and middle school grades, which is a near-universal standard in American school systems.

It should be noted, also, that these are very large samples. To improve comparisons and accuracy across differing analyses, all "singletons"—students who contributed test scores in only a single year—were dropped (Correia 2015). Even with these omissions, total observations were approximately 1.5 million for Arkansas, 2.3 million for North Carolina, and three-fourths of a million for South Carolina. The numbers of unique students with two or more observations were approximately 385,000 for Arkansas, 450,000 for North Carolina, and 210,000 for South Carolina.

Second, if the within-student variation in school SES is very small, regression errors would be large and coefficient estimates would be unreliable. As a further check on the degree to which school SES varies within students, we examine that possibility in Table 2, which compares coefficients and standard errors between pooled cross-sectional models and student FE models. If there is insufficient variation in within-student school SES, we might expect to see standard errors for the school SES coefficients "blow up" in our student FE model, reflecting an unreliable basis for estimating the effects in question. In fact, we do not see that; indeed, in every case the standard error for the student FE model is smaller than the pooled cross-sectional model. For example, the standard error for the Arkansas cross-sectional model is 2.03, compared to .81 for the student FE model. The North Carolina and South Carolina comparisons are .14 to .08 and .17 to .12, respectively.

	Ark	ansas	North Carolina		South Carolina		
	Coef. Effect Size	Coef. Size	Coef. Size	Effect Coef. Size	Coef. Size	Effect Coef. Size	
Student SES	24.93  0.22 (0.37)	-0.66 -0.01 (0.11)	$5.18  0.44 \\ (0.04)$	0.00  0.00  (0.01)	$\overline{\begin{array}{ccc} 3.01 & 0.30 \\ (0.04) \end{array}}$	-0.01 0.00 (0.02)	
School SES	$\begin{array}{c} 29.74 \\ (2.03) \end{array} 0.12$	(0.81) -0.01		-0.34 -0.01 (0.08)	3.42  0.16 (0.17)	-0.19 -0.01 (0.12)	
Grade-by-Year FE Student FE	Yes No	Yes Yes	Yes No	Yes Yes	Yes No	Yes Yes	

Table 2. Comparing School SES Effects and Standard Errors, with and without Student FE

Cluster-robust standard errors for all coefficient estimates are shown in parantheses.

Another way to explore the amount of within-student variation in school SES in our sample is to examine the distribution of within-student school SES values (Mummolo and Peterson 2018). In order to help interpret within-student variation, we have converted the standardized school SES values to percentages of students in the federal free lunch program. During the years when these data were collected, eligibility was limited to low income families. Figure 1 shows the distribution of the within-student ranges in percentage of free lunch students for Arkansas. The median of this distribution is 9 percent and the 75th percentile is 18 percent, which means that more than 90,000 students experience changes of nearly 20 percentage points or more in the percentage of low income students in their schools as they progress from one grade to another. The histogram makes clear there is ample variation in the levels of school SES experienced by students over time, with many thousands of students experiencing very substantial changes in school SES over their school career.

Finally, we have executed sensitivity tests to address additional concerns raised



**Figure 1.** The distribution of within-student ranges of treatment: the difference between each student's highest recorded percentage of peers receiving free lunch and their lowest recorded percentage of peers receiving free lunch throughout our sample period.

by Sciffer et al. Their first concern we address is whether student mobility might have negative effects and might reduce school SES effects. To test this possibility, we repeated our student FE analyses on subsamples excluding any student who switched schools other than the elementary to middle school transition (almost always between grade 5 and 6) or who repeated a grade; these results are shown in columns labeled (1) corresponding to each state in Table 3. We see that while eliminating these students does reduce the within-student standard deviation of school SES, the reduction is only by a small fraction for Arkansas (from .18 to .15, or about 15 percent), and the estimated school SES effects are left largely unchanged. The reductions in withinstudent standard deviations of school SES are about 20% and 25% for NC and SC, respectively.

Table 3.	Sensitivity	Tests: $(1)$	Removing g	grade repeaters	/movers; (2)	Keeping c	only observ	vations fro	om students	remain-
ing in the	same elemen	ntary scho	ol or middl	e school						

	Ark	ansas	North Carolina		South Carolina		
	(1)	(2)	(1)	(2)	(1)	(2)	
	Effect Coef. Size	Effect Coef. Size	Effect Coef. Size	Effect Coef. Size	Effect Coef. Size	Effect Coef. Size	
Student SES	-0.33 0.00 (0.19)	$-0.38  0.00 \\ (0.21)$	$   \begin{array}{ccc}     0.01 & 0.00 \\     (0.01) & & \\     \end{array}   $	0.03  0.00  (0.01)	-0.03 0.00 (0.03)	-0.01 0.00 (0.04)	
School SES	-0.58  0.00  (0.88)	-0.38 0.00 (0.99)	-0.40 $-0.02(0.10)$	-0.38 $-0.01(0.11)$	-0.21 $-0.01(0.17)$	-0.36 -0.02 (0.29)	
Within-Student SD Unique Students	$0.15 \\ 253,281$	$   0.14 \\   202,481 $	$0.13 \\ 390,272$	$0.13 \\ 360,559$	$0.09 \\ 185,246$	$0.07 \\ 149,633$	

Cluster-robust standard errors for all coefficient estimates are shown in parantheses.

We fashion a second, very strict sensitivity test that keeps only those students who advanced exactly one grade each year and remained in the same school throughout our sample periods, even dropping those observations for the elementary-middle school transition—which admittedly represents the largest potential school SES change. Even here the estimates appear to be robust; coefficient standard errors increase only slightly for Arkansas and North Carolina.

The standard error changes more substantially for South Carolina, increasing from .12 in Table 1 to .29 in the corresponding column (2) of Table 3, which is larger than the standard error for the cross-sectional model. That suggests the elementary-to-middle school composition change is more critical for South Carolina than the other states, and without it, there may be insufficient variation of the within-student school SES.

## Discussion

The analyses presented here are in response to criticisms raised by Sciffer, Perry, and McConney (2020), which suggested that there is insufficient variation in school composition as U.S. students move from 3rd grade to 8th grade to reliably estimate school SES effects using student FE methods. The further analyses of the achievement data from the original article demonstrate, generally, that in the three states studied here from the late 1990s to 2012, there is, indeed, sufficient variation in school SES composition as students progress from 3rd to 8th grade to reliably estimate school compositional effects.

Although not discussed in the original article, during these time frames all three states continued to discuss and debate the pros and cons of school desegregation, and two of the three were involved in court actions of various types to promote further racial or economic integration policies. Even though court-ordered desegregation plans have ended in the great majority of U.S. school districts, the racial and economic composition of schools continues to be a topic of intense debate among school policy advocates of various types. Hence it is not surprising to us that the racial and economic composition of schools continues to be a moving target in the U.S., a policy issue that may not arise in other English speaking countries, at least not to this extent.

In this regard, we point out that there are active movements in several states to increase socioeconomic integration, including large urban school districts in New York City, Maryland, and Minnesota. These movements inevitably invoke improved achievement for low-income and minority students. The student fixed effect methodology used in recent U.S. studies strongly suggest that improved academic achievement is not a likely outcome of such policies, and if so that fact needs to be understood by those responsible for deciding on whether or not to expand mandatory integration policies.

## References

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