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The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit: Comment[†]

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In a recent article in the American Economic Review, *Dahl and Lochner (2012) use changes in the Earned Income Tax Credit to estimate the causal effect of family income on child achievement. Their instrumental variable (IV) estimates imply that a $1,000 increase in income raises combined math and reading test scores by about 6 percent of a standard deviation. I document a variable coding error. Correcting this error reduces the IV estimates by 32 percent; correcting this error does not change the qualitative conclusions of the study.* (*JEL* H24, H31, I21, I38, J13)

The endogeneity of income has long prevented researchers from forming a consensus regarding the causal effect of income on child achievement (Haveman and Wolfe 1995; Duncan and Brooks-Gunn 1997; Mayer 1997). In particular, children in poor families are likely to have adverse home environments which might also affect their achievement levels. Moreover, changes in family circumstances over time such as moving, illness, or parental job loss or promotion may affect both family income and parenting behavior.

Dahl and Lochner (2012)—henceforth, DL—outline an instrumental variables (IV) strategy to estimate the causal effect of family income on child achievement that intends to eliminate bias due to the omission of permanent and transitory achievement determinants that are correlated with income, as well as bias due to measurement error. Their strategy uses the expansions of the Earned Income Tax Credit (EITC) in the late 1980s and 1990s as an exogenous source of income variation for American families. To the extent that income affects child achievement, DL expect to observe relative improvement in the test scores of children from families benefitting the most from the EITC expansions. Their analysis uses panel data on nearly 4,500 children matched to their mothers in the Children of the NLSY (National Longitudinal Survey of Youth). DL's instrumental variables (IV) estimates suggest that current income has a significant effect on a child's math and reading achievement—a $1,000 increase in family income raises math and reading test scores by about 6 percent of a standard deviation.

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While replicating DL's study, I discovered several coding errors which, when corrected, reduce the IV estimates by 32 percent. The most important of these errors relates to DL's construction of family income. In their construction of family income DL fail to add federal tax credits, and they include state tax credits twice. Since the EITC is a federal credit, this means that DL's measure of family income does not include the EITC. This is a critical omission considering that the correlation between EITC income and changes in the EITC schedule is, presumably, a primary source of income variation in their strategy. When these mistakes are corrected, the IV estimates fall by 32 percent. Correcting these errors does not change the statistical significance of the estimates, or the qualitative conclusions of the study.

This paper proceeds as follows. In Section I, I describe DL's study and I replicate the results. I show how the magnitude of the results are changed once family income is correctly measured. Section II concludes.

I. Description of Dahl and Lochner's (2012) Study

In this section, I provide a detailed description of DL's study. I begin by describing the data and the estimation strategy. Next, I replicate their results and document the coding errors. I conclude this section by showing how correcting the coding errors affects the scaling of the IV estimates.

A. *Data*

Data are drawn from the Children of the NLSY matched to their mothers in the main NLSY. The NLSY is a panel survey that originally included a nationally representative sample of 12,686 men and women who were all 14 to 21 years of age on December 31, 1978. Beginning in 1986, the children born to NLSY female respondents have been assessed every two years. The estimation sample consists of child observations merged to their mothers for the survey years 1988–2000.

The NLSY provides many components of family income which are aggregated into three categories of pretax income: earned income, unearned income, and nontaxable income. While the NLSY contains a broad array of income questions, it does not ask an individual how much they received in EITC payments or paid in taxes. DL impute each family's state and federal EITC payment and tax burden using the TAXSIM program (version 9) maintained by Daniel Feenberg and the National Bureau of Economic Research (see Feenberg and Coutts 1993).

Cognitive achievement is measured using standardized math and reading scores from the Peabody Individual Achievement Tests (PIAT). The tests measure a child's ability in math, reading recognition (word recognition), and reading comprehension (the ability to derive meaning from printed words). To make PIAT tests more easily interpretable, DL create normalized test scores with a mean of zero and a standard deviation of one based on the random sample of test takers (i.e., excluding the poor, military, and minority oversamples). They also create a combined math-reading score by taking the average of the normalized math and reading scores. This is then renormalized to have a mean of zero and standard deviation of one in the random sample.

The main sample is restricted to children who are observed in at least two consecutive sample years between 1988 and 2000 and who have valid PIAT scores, family background characteristics, and family income measures. The sample is limited to children whose mothers did not change marital status during two-year intervals when tests are measured, and observations are excluded if family income levels exceed \$100,000 or if there are very large changes in income. NLSY oversamples of poor white families and military families are excluded from the sample.

B. *Methods*

In this section, I reproduce DL's child achievement model. The model intends to capture how changes in family income affect child achievement. Let x_i reflect observable permanent characteristics, μ_i reflect unobserved permanent ability (i.e., a child fixed effect), w_{ia} reflect time-varying characteristics, and I_{ia} reflect total family income for child i at age a. Using this notation, DL present a simple model for child outcome y_{ia} as follows:[1]

$$y_{ia} = x_i'\alpha_a + w_{ia}'\beta + I_{ia}\delta_0 + \mu_i + \varepsilon_{ia}. \tag{1}$$

Least squares estimation of this model faces three major challenges: omitted variable bias due to unobserved permanent child characteristics, omitted variable bias due to unobserved transitory shocks (e.g., illness, moves, job loss, or promotion), and bias due to measurement error in income. DL propose an estimation strategy that intends to eliminate bias from all three sources. They eliminate the threat of bias due to unobserved child fixed effects by taking first differences, yielding the following equation:

$$\Delta y_{ia} = x_i'\alpha + \Delta w_{ia}'\beta + \Delta I_{ia}'\delta_0 + \Delta\varepsilon_{ia}, \tag{2}$$

where permanent characteristics are allowed to affect the growth of child achievement (i.e., $\alpha \equiv \alpha_a - \alpha_{a-1}$). For I_{ia} DL intend to use total net family income (inclusive of EITC payments and net of other federal and state taxes and transfers). EITC income, $\chi_a^{s_{ia}}(P_{ia})$, is a function of pretax income,(P_{ia}), where the superscript s_{ia} denotes which schedule a child's family is on (the EITC schedules differ based on the number of children in the household). They also net out other taxes, $\tau_a^{s_{ia}}(P_{ia})$. Therefore, total net family income is given by

$$I_{ia} = P_{ia} + \chi_a^{s_{ia}}(P_{ia}) - \tau_a^{s_{ia}}(P_{ia}).$$

The main impediments to least squares estimation of equation (2) are bias due to measurement error in income, and omitted variable bias due to unobserved transitory shocks. To address these issues, DL employ an IV strategy that builds on

[1] In the most general model, DL allow income to have long-run effects by incorporating lags into the model. However, the model that forms the basis for their main results excludes income lags. Since the effects of lagged income are not important for their main results, and in order to simplify the discussion, I exclude the lags in this model.

Gruber and Saez (2002) and is loosely based on Feldstein (1995) and Currie and Gruber (1996). This IV strategy takes advantage of major changes in the EITC. As an instrument for ΔI_{ia} they use

$$\Delta \chi_a^{IV}(P_{i,a-1}) \equiv \chi_a^{s_{i,a-1}}\left(\hat{E}[P_{i,a} \,|\, P_{i,a-1}]\right) - \chi_{a-1}^{s_{i,a-1}}(P_{i,a-1}),$$

where $\hat{E}[P_{i,a} \,|\, P_{i,a-1}]$ is an estimate of pretax income given lagged pretax income. In practice, they regress pretax income on an indicator for positive lagged pretax income and a fifth-order polynomial in lagged pretax income in the calculation of $\hat{E}[P_{i,a} \,|\, P_{i,a-1}]$. This yields predicted changes in EITC income as a function of lagged pretax income, taking into account the fact that income evolves over time in a predictable way and the EITC schedule changes in some years. By holding fixed the type of EITC schedule (one versus two+ children) $s_{i,a-1}$ in generating the instrument, DL only exploit variation in predicted EITC income due to government changes in EITC schedules over time, and not due to changes in family structure.

Finally, they note that simply estimating equation (2) using $\Delta \chi_a^{IV}$ as an instrument for ΔI_{ia} will likely yield biased estimates for δ_o since the changes in families' simulated EITC payments are a function of lagged pretax income, which is likely endogenous. Therefore, they augment equation (2) with a flexible function of lagged pretax income when instrumenting. Letting $\Phi(P_{i,a-1})$ reflect a flexible function of lagged pretax income, they estimate

$$\Delta y_{ia} = x_i'\alpha + \Delta w_{ia}'\beta + \Delta I_{ia}'\delta_o + \Phi(P_{i,a-1}) + \eta_{ia}, \tag{3}$$

using $\Delta \chi_a^{IV}$ as an instrument for ΔI_{ia}. Empirically, DL use the same functional form for $\Phi(P_{i,a-1})$ as is used in calculating $\hat{E}[P_{i,a} \,|\, P_{i,a-1}]$ (i.e., an indicator for positive lagged pretax income and a fifth-order polynomial in lagged pretax income). With the inclusion of a fully flexible, but time-invariant control function, all identifying variation comes from differential changes in the EITC schedule over time, and not from differences in lagged income levels.

C. *Replication Results*

In Table 1, column 1, I present DL's published estimates of the contemporaneous effects model, where child achievement is measured using the combined math and reading test score.[2] In panel A, I present results for the model estimated in levels (equation (1)); in panel B I present results for the model estimated in differences (equation (2)); in panel C I present results for the model estimated using the IV (equation (3)). Income is measured in \$1,000s and test scores are standardized, so the estimates represent the percent of one standard deviation that the test score changes given a \$1,000 increase in family income.

In column 2, I present results from my replication. Dahl and Lochner graciously provided me with copies of their programs and data which allowed me to replicate their results almost perfectly.

[2] In order to simplify the discussion, I focus exclusively on the combined math and reading test score. My replication results for the individual tests also matched DL's published results nearly perfectly.

TABLE 1—ESTIMATES OF THE CONTEMPORANEOUS EFFECTS MODEL

	Dahl and Lochner published results (1)	Replication (2)	Type of EITC schedule fixed[a] (3)	Type of EITC schedule fixed + correctly measured income (4)
Panel A. Estimated in levels				
Combined math and reading	0.0047	0.0047	0.0047	0.0048
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	8,609	8,609	8,609	8,609
Panel B. Estimated in differences				
Combined math and reading	0.0011	0.0011	0.0011	0.0012
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	8,609	8,609	8,609	8,609
Panel C. IV estimates				
Combined math and reading	0.0610	0.0607	0.0575	0.0413
	(0.023)	(0.023)	(0.022)	(0.013)
First stage	1.270	1.2712	1.2584	1.7548
	(0.381)	(0.379)	(0.362)	(0.362)
Reduced form	Unreported	0.0772	0.0724	0.0724
	—	(0.019)	(0.018)	(0.018)
Observations	8,609	8,609	8,609	8,609

Notes: Child achievement is a normalized average of math and reading scores. Income is measured in thousands of 2000 US$. Panel A "levels" regressions (equation (1)) control for all variables listed in DL, Appendix Table A1. Panel B "difference" regressions (equation (2)) use two-period differences and control for baseline variables in DL, panel A of Table A1. Panel C "instrumental variables" regressions (equation (3)) use two-period differences and control for baseline variables in panel A of Table A1, an indicator for positive lagged pretax income, and a fifth-order polynomial in lagged pretax income. Samples include children taking a math or reading PIAT test in the survey years 1988 through 2000. Standard errors are reported in parentheses and are clustered at the family level.

[a] Across two-year differences, the type of EITC schedule (i.e., one versus two+ kids) is fixed to the lagged year type.

D. *Coding Errors*

In the course of replicating DL's results, I discovered two coding errors. First, contrary to DL's description, they do not hold the type of EITC schedule fixed (i.e., one versus two+ children) in generating the instrument. Failing to do so implies that instrument variation arises due to changes in family structure in addition to government changes in the EITC schedule. I correct this mistake and re-estimate the model. The new estimates are presented in Table 1, column 3. This correction reduces the magnitude of the IV estimate, though the change is very slight.

The second coding error is less benign. In their construction of family income, DL fail to add federal tax credits and state tax credits are added twice. Since the EITC is a federal credit, this means that DL's measure of family income does not include the EITC. This is a critical omission since, presumably, the correlation between the instrument and changes in EITC income is a primary source of income variation in their identification strategy. Correcting this error does not affect the instrument, but it does strengthen the first stage since EITC income is highly correlated with the instrument. Results using the corrected measure of family income are presented in column 4 of Table 1. In total, the IV estimate falls by 32 percent after correcting the two errors. The statistical significance of the IV estimate is unchanged.

II. Conclusion

Dahl and Lochner (2012) employ an IV strategy to estimate the causal effect of family income on child achievement. Their strategy takes advantage of the large changes in the EITC schedule during the late 1980s and early 1990s. They find that a $1,000 increase in family income raises combined math and reading test scores by 6 percent of a standard deviation. In this comment I document several coding errors. The most important error relates to DL's construction of the family income variable, wherein they fail to add EITC income. Correcting this error does not affect the instrument, but it does increase the magnitude of the first stage and, therefore, the scaling of the IV estimates. When the mistakes are corrected, the IV estimate falls by 32 percent. The qualitative conclusions of DL's study are unaffected by the correction of these errors.

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