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The Effect of Early Childhood Programs on Third-Grade Test Scores: Evidence from Transitional Kindergarten in Michigan[†]

By Jordan Berne, Brian Jacob, Tareena Musaddiq, Anna Shapiro, and Christina Weiland*

Early childhood education (ECE) programs boost children's school readiness and can have long-run effects on participants' educational, income, and health outcomes (Phillips et al. 2017). Transitional kindergarten (TK) programs are a relatively new entrant into the early education landscape, having come about as states pushed back the dates at which children can enter traditional kindergarten (K). Unlike many public early education options, TK programs are not targeted to children from families with low income. They also differ from many public ECE options in other important ways: TK operates only in public schools, is taught by state-certified teachers who are paid at the level of other K–12 educators, and tends to use a more academic-focused curriculum than many ECE programs (Shapiro et al. 2023).

The only TK program rigorously evaluated is the statewide program in California. Manship et al. (2015) found the program increased students' early literacy, language, and math skills along with kindergarten engagement. However, a study with a larger sample followed via administrative records found no benefits of California TK on students' third- and fourth-grade test scores (Lafortune, Hill, and Severance 2023).

We extend this literature by estimating the impacts of Michigan's TK program. In Michigan, TK funding is available for all children who turn five by the state's kindergarten birthday cutoff (September 1) or within three months after (September 2–December 1). Therefore, funding is available for all five-year-olds but only the oldest four-year-olds. The state also funds early entrance into traditional kindergarten (via a waiver process) for children born between September 2 and December 1. Hence, families of children who turn five after the state's September 1 kindergarten cutoff but on or before December 1 have three options: (i) enroll in TK (in districts that offer it and in which there is space); (ii) waive into traditional kindergarten early (EK) (in all districts); or (iii) choose an alternative public or private care setting, including staying home.

Leveraging the December 1 age-eligibility cutoff in a regression discontinuity (RD) framework, we find positive impacts of attending TK on third-grade math scores and suggestive evidence of benefits for English Language Arts (ELA).

I. Data

This study uses longitudinal administrative data on the universe of Michigan public school students. Unfortunately, not every school district in Michigan has reliable data on TK enrollment. Therefore, we restrict our sample to districts that do not offer TK and districts with TK that reliably report student-level enrollment. For more information on how we identify districts with reliable data and how these districts compare to those with unreliable data, see online Appendix A.

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Table 1—Summary Statistics

	Non-TK districts		TK districts		
	All students	EK students	All students	EK students	TK students
Female (percent)	50	56	50	57	50
White (percent)	48	33	74	63	77
Black (percent)	36	51	12	18	11
Hispanic (percent)	10	9	7	7	7
Economically disadvantaged (percent)	70	76	46	56	38
Neighborhood median household income ($)	49,666	45,951	66,494	61,976	69,120
Charter school (percent)	30	46	3	4	5
District is in city (percent)	40	49	21	35	19
District is in suburb (percent)	29	32	54	49	57
District is in rural area (percent)	23	13	13	7	13
District mean third-grade math score (SD)	−0.264	−0.339	0.249	0.191	0.231
Observations	9,902	8,410	2,043	923	1,689

Notes: EK students are those who use a waiver to enroll in regular kindergarten despite turning five after the kindergarten birthday cutoff. We use the sample of students born within 30 days of the TK cutoff to construct these statistics. All statistics are calculated at the student level. See online Appendix A for a summary statistics table with a larger set of characteristics.

We also limit our sample to students who turned five near December 1 in 2014 or 2018. (We exclude students in the intervening cohorts because their third-grade tests were disrupted by the COVID-19 pandemic.) Our other data cleaning decisions and sample restrictions are detailed in online Appendix A.

As Table 1 shows, students in TK districts were more likely to be White, less likely to be economically disadvantaged, and more likely to live in suburbs. Compared to other students in the same district, TK students tended to be slightly more economically advantaged and more likely to live in a suburb. For more information on the districts with TK programs and the students who choose to participate, see Shapiro et al. (2023).

II. Empirical Strategy

Identification in this setting is challenging because at the cutoff (December 1), children not only become eligible for TK but also gain the ability to enter kindergarten early via a waiver (we denote students who choose to enter kindergarten early as EK). With the standard RD assumptions, we can only identify the combined effect of becoming eligible for both TK and EK.[1] Decomposing this intent-to-treat (ITT) effect into separate TK and EK effects requires more structure.

As we show in online Appendix B, the ITT effect for TK districts is a weighted combination of the TK and EK local average treatment effects (LATEs),

$$(1) \quad ITT = \Omega_{TK} LATE_{TK} + \Omega_{K} LATE_{EK},$$

where each Ω_x weight is the share of students at the cutoff who are compliers for option x. Notice that the quantities ITT, Ω_{TK}, and Ω_{EK} are all identified simply using districts that offer TK.

At this point, we have one equation with two unknowns: $LATE_{TK}$ and $LATE_{EK}$. Intuitively, since the ITT effect is a combination of two unobserved LATEs, recovering one of the two would allow us to back out the other. Our strategy is to use districts that do not offer TK as a second source of information to recover the LATE for the EK treatment.

In districts without TK, the RD cutoff generates variation in EK entry but not TK enrollment, allowing us to cleanly identify $LATE_{EK}$. However, using non-TK districts to infer $LATE_{EK}$ in TK districts requires some type of restriction on treatment effect heterogeneity. In theory, $LATE_{EK}$ may differ across districts. As we showed in Table 1, EK students in TK and non-TK districts differ on observable characteristics, and they likely differ in unobservable ways too. Given this possibility, we estimate two models—one that assumes treatment effect

[1] To economize on space, we present results from the usual RD validity checks in online Appendix C. A couple results raise concerns, but overall we believe we have a valid natural experiment.

homogeneity and another that relaxes this assumption.

A. *Baseline Estimation Approach*

In our baseline approach, we assume the treatment effect of EK is the same in TK and non-TK districts and estimate $LATE_{TK}$ and $LATE_{EK}$ jointly using both TK and non-TK districts. For student i in district d from cohort c, we estimate the following system of equations via two-stage least squares (2SLS):

$$(2)\quad Y_i = \beta_0 + \beta_1 TK_i + \beta_2 EK_i + f(dob_i) + \Pi \mathbf{X}_i + \lambda_{dc} + \varepsilon_{idc},$$

$$(3)\quad TK_i = \delta_0^{TK} + \delta_1^{TK} Left_i + \delta_2^{TK} Left_i \times DistHasTK_{dc} + f^{TK}(dob_i) + \Psi^{TK}\mathbf{X}_i + \theta_{dc}^{TK} + \varepsilon_{idc}^{TK},$$

$$(4)\quad EK_i = \delta_0^{EK} + \delta_1^{EK} Left_i + \delta_2^{EK} Left_i \times DistHasTK_{dc} + f^{EK}(dob_i) + \Psi^{EK}\mathbf{X}_i + \theta_{dc}^{EK} + \varepsilon_{idc}^{EK},$$

where $\mathbf{X}_i$ is a vector that includes student sex, race, and economic disadvantage status; λ_{dc}, θ_{dc}^{TK}, and θ_{dc}^{EK} are district $\times$ cohort fixed effects; and dob_i is date of birth. The f functions allow different linear relationships between date of birth and outcomes on either side of the cutoff and across districts with and without TK. The excluded instruments, $Left_i$ and $Left_i \times DistHasTK_{dc}$, indicate being born to the left of the RD cutoff and being left of the cutoff in a district $\times$ cohort in which TK is offered. We estimate these equations using a bandwidth of ± 30 days. Our estimates for $LATE_{TK}$ and $LATE_{EK}$ are $\hat{\beta}_1$ and $\hat{\beta}_2$, respectively.[2]

B. *Relaxing Model Assumptions*

In our second approach, we relax the treatment effect homogeneity assumption by allowing $LATE_{EK}$ to differ by student demographic characteristics. To operationalize this idea, we estimate EK effects in the non-TK sample separately for eight demographic cells defined by sex $\times$ race (White or Asian versus other races) $\times$ economic disadvantage status (disadvantaged versus not). We estimate these effects using a 2SLS model analogous to equations (2) and (4).

Next, within the TK sample, we calculate the share of EK students that belong to each of the same eight demographic cells. We then use these shares as weights to aggregate the cell-specific effects from the non-TK sample. The result is a single $LATE_{EK}$ estimate that reflects the cell-specific treatment effects from the non-TK districts weighted to reflect the demographic composition of EK students in TK districts.

Once we have a demographically-adjusted estimate of $LATE_{EK}$, it is straightforward to back out $LATE_{TK}$ using equation (1) and estimates of ITT, Ω_{TK}, and Ω_{EK} from the TK sample.

We conduct inference via bootstrap because this approach contains multiple steps. For consistency, we bootstrap in the baseline approach too. See online Appendix E for more details.[3]

III. Results

Figure 1 shows we have strong first-stage impacts on TK and EK enrollment at the RD cutoff. In non-TK districts, 35 percent of students waive into EK. In TK districts, 37 percent of students enroll in TK and 17 percent enter EK.

Figure 2 presents a visual representation of our ITT effects on third-grade math scores, which also provides intuition for our estimation of the treatment effects of TK and EK. In non-TK districts, there is a large negative discontinuity at the cutoff. Because EK is the only option associated with the cutoff in these districts, the figure tells us that students who waive into EK score substantially lower on the third-grade math exam. This result is not surprising given that EK students take third-grade tests one year earlier than they otherwise would, giving

[2] As a check on the 2SLS specification, we also estimate the components of equation (1) separately and back out $LATE_{TK}$. The estimates are nearly identical.

[3] Table 2 summarizes our inference results with p-values rather than standard errors because the bootstrap distributions in our relaxed assumptions approach are nonnormal and contain extreme outliers, rendering the standard errors uninformative.

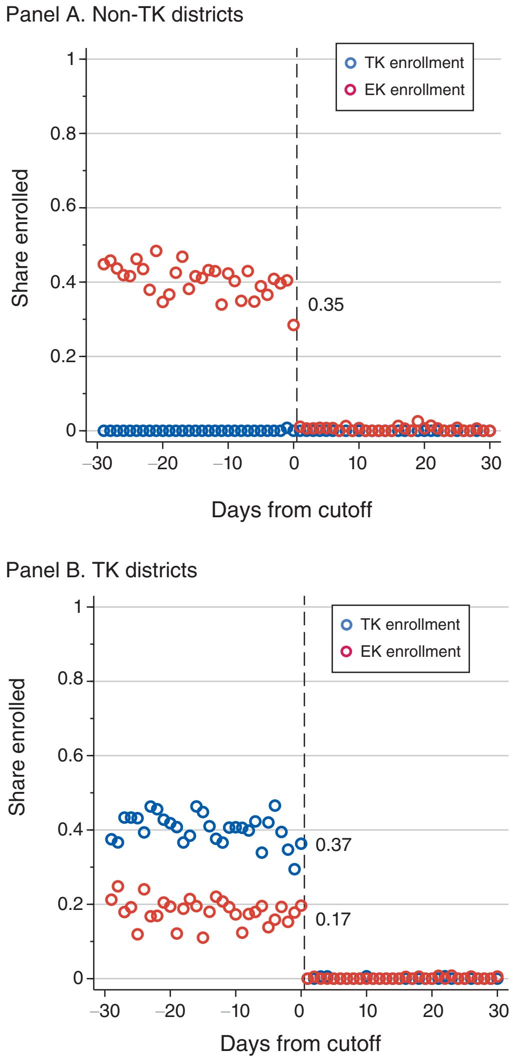

FIGURE 1. FIRST-STAGE EFFECTS ON TK AND EK ENROLLMENT IN ONE'S PRE-K YEAR

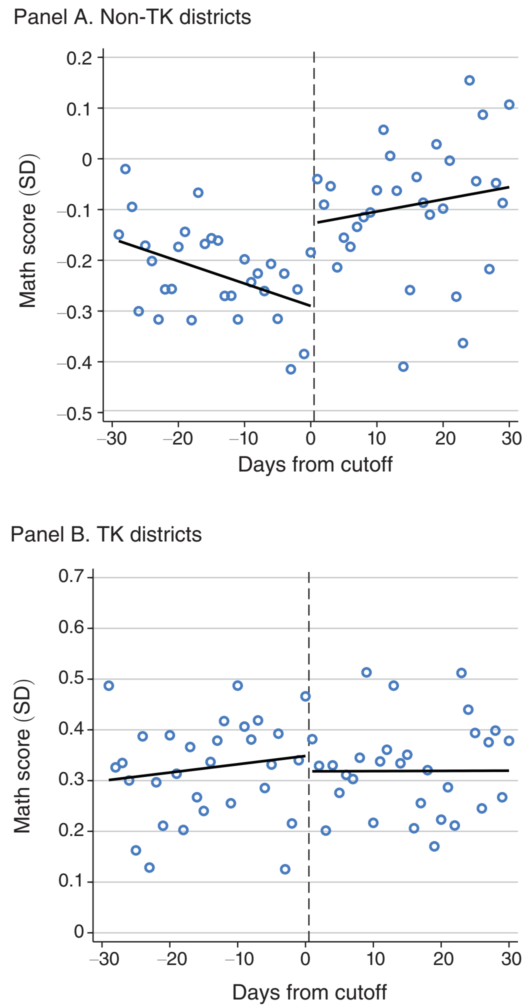

FIGURE 2. ITT EFFECTS ON THIRD-GRADE MATH SCORES

them one less year of cognitive development (Deming and Dynarski 2008). On the other hand, in TK districts—where the cutoff is associated with both kindergarten waiving and TK—there is hardly any discontinuity at the cutoff. If EK has a negative effect in TK districts as it does in non-TK districts, this implies TK must have an offsetting positive effect.

Consistent with this visual intuition, the results in Table 2 indicate that TK enrollment leads to substantial improvements in third-grade math scores. Our baseline estimate is 0.21 standard deviations ($p = 0.051$), and our relaxed assumptions estimate is 0.29 standard deviations ($p = 0.111$). The reason for the difference is that the demographic subgroups that dominate the EK compliers in TK districts (e.g., White and Asian girls regardless of economic disadvantage and White and Asian boys who are not economically disadvantaged) experience the largest negative effects from attending EK (see online Appendix D). The data-intensive nature of the relaxed assumptions approach results in less precision, but the fact that the point estimate increases gives us confidence in interpreting the math impact as positive. For ELA, we estimate

Table 2—Impacts of TK and EK on Third-Grade Test Scores

	Math				ELA			
	Baseline		Relaxed assumptions		Baseline		Relaxed assumptions	
$LATE_{TK}$	0.252	0.212	0.331	0.294	0.123	0.097	0.209	0.191
[p-value]	[0.046]	[0.051]	[0.088]	[0.111]	[0.321]	[0.401]	[0.253]	[0.293]
$LATE_{EK}$	−0.378	−0.366	−0.557	−0.557	−0.240	−0.219	−0.435	−0.435
[p-value]	[0.000]	[0.000]	[0.092]	[0.092]	[0.061]	[0.078]	[0.181]	[0.181]
Controls		X		X		X		X
Control mean	0.302				0.286			
Observations	15,680				15,669			

Notes: Inference is conducted via bootstrap, with clustering on the running variable. Online Appendix E elaborates on our inference strategy. In the relaxed assumptions approach, we always exclude controls when estimating EK LATEs because the demographic subgroups are defined by the covariates. Hence, the EK estimates in the with- and without-controls columns are identical by construction. The control mean is the average of the outcome variable for students in TK districts born one to five days after the cutoff. The first stage F-statistics in the baseline model are 336.21 (math) and 339.82 (ELA) for TK and 400.34 (math) and 340.52 (ELA) for EK.

that TK enrollment increases third-grade scores by 0.19 standard deviations ($p = 0.293$), but this estimate is not statistically distinguishable from zero.

Several points are worth noting when interpreting these estimates. First, the TK impacts are relative to a counterfactual of starting kindergarten on schedule or later, having spent one's pre-K year receiving care at home, attending Michigan's income-targeted public pre-K program, attending private pre-K, or spending the year in some other type of arrangement. Second, and related because they reflect the impact for students close to the December 1 cutoff, our estimates capture the effects of TK for children who are among the oldest in their birth cohort.

In online Appendices C and D, we conduct RD validity checks and elaborate on our identification strategies.

IV. Discussion

Research commonly finds that attending preschool has sizable impacts on kindergarten readiness, followed by partial or complete fade out in the early elementary years, and then reemergence of benefits in early adulthood (Phillips et al. 2017). Our finding that Michigan TK raises third-grade math scores stands in stark contrast to this typical pattern.

The magnitude of our estimates is large relative to the prior literature. Across all relatively rigorous evaluations of programs since the 1960s, the average impact of preschool on children's end-of-preschool cognitive skills is about 0.25 standard deviations (Duncan and Magnuson 2013). Our impact estimates are the same size for students in third grade. To give another reference point, our math estimate amounts to 61 percent of expected cognitive development between third and fourth grade.[4]

The more positive impacts of Michigan TK compared with other ECE programs could be due to a variety of factors, including (i) less formal ECE among the control group in our sample, (ii) the quality of TK teachers, and (iii) better alignment between TK and early elementary schooling. In future work, we will investigate these and other potential mechanisms as well as explore the heterogeneity of treatment effects across subgroups. We hope that our findings will inform the development and scaling of other successful ECE models in Michigan and elsewhere.

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[4] This is based on the average growth of Michigan students from third grade in 2017–2018 to fourth grade in 2018–2019 and is nearly identical to the estimates found in other literature (Hill et al. 2008).

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