Home Computer Use and Child Development

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What would happen to the developmental domains such as cognitive skills and non-cognitive traits if a home computer became available when it had not been? Would there be dose-response function of home computer usage and is there identifiable impact of the newly acquired internet access? Conversely, what would happen if once available home computer became no more available? To provide answers to those questions, we have analyzed ECLS-K fielded in the spring third grade (2002) and fifth grade (2004) using the inverse-probability-of-treatment weight estimator utilizing the generalized propensity score and OLS regression framework. We find that 1) newly available home computer tends to increase favorable outcomes in all domains of development but loss of home computer availability is likely to decrease favorable outcomes in reading test scores and externalizing behavior problem, 2) those children who used the newly available home computer "3-6 times a week" are likely to benefit more than those children who used it "every day" while the most affected children by the loss of home computer are those who had used the home computer most frequently, and 3) newly obtained internet access appears to lower behavior problem and discontinuation of the internet access seems to invite unfavorable effects.

1 Research Interest

Research on relationships between home computer use and child's development has actively investigated possible causal effects of home computer use on academic achievement. However, empirical evidence for the relationship is at best mixed. For instance, after reviewing several descriptive papers, Subrahmanyam et al. conclude that the current evidence tends to agree on the positive effects of home computer use on cognitive development (Subrahmanyam et al. 2001). Interestingly, Clotfelter et al. find that different conclusions may be supported by the preference of statistical models (Clotfelter et al. 2008). More precisely, the authors find that estimates from ordinary least square (OLS) indicate that those students who have a home computer available perform better on standardized math and reading tests compared to those without home computer while fixed effect model suggests "modest but statistically significant negative impacts of home computer access, and little impact of use conditional on access."

Using HomeNetToo project whose sample were drawn from socio-economically disadvantaged children, Jackson et al. tries to infer the causal effects of the internet use from the dose-response function of the internet use (Jackson et al. 2006). Underlying idea is that if children who use the internet more frequently tend to score better on math and reading tests, it may be acceptable to believe existence of a causal effect of the internet use. Using very descriptive statistical techniques, the authors conclude that those students with the internet access performed better in standardized reading tests and grade point averages than those without the internet access while no trend were detected as to standardized mathematics tests.

Also empirical research on the relationship between the internet use and subjective well-being has reported conflicting evidence. Most notably, Kraut and colleagues initially reported that the internet use tends to induce negative outcomes in psychological well-being such as feeling lonely and depressive symptoms in the sample of HomeNet study (Kraut et al. 1998). In a subsequent report, Kraut and associates found that those negative relationships disappeared (Kraut et al. 2002). In a separate study, Gross surveyed 261 students in 7^{th} to 10^{th} grade on their home internet use. Regression analyses adjusting for online tenure, gender, age, and connection speed revealed no association between average time spent online a day and several measures of subjective well-being enumerating loneliness, social anxiety, depression, and daily life satisfaction (Gross 2004).

Bearing these findings in mind, we try to contribute to the literature in several aspects. First, we examine effects of home computer usage on extended domains of child development beyond traditional areas of cognitive skills measured by mathematics and reading test scores. More specifically, self-assessed externalizing as well as internalizing behavior problem will be given equal amount of attention as primary outcome areas. Second, we not only evaluate binary treatment effects of home computer but also assess dose-response function of computer utilization using the measure of home computer use frequency. In addition, differential outcomes by the internet access are also subsumed under our research area.

What distinguishes most conspicuously this paper from the extant literature linking child development to technology access and usage lies in introduction of a rigorous statistical method: a class of the propensity score methods. Especially, together with the traditional OLS estimator, we implement the inverse-probability-of-treatment weight (IPTW) estimator to get causal effects of each treatment after estimating the propensity score. Since our treatment variables involve multi-valued treatment alternatives, we extensively rely on methods developed in the generalized propensity scores literature. Finally, our research interest divide and estimate separately two possible treatment regimes: providing computer access and discontinuing computer access. Namely, we ask on the one hand: what would happen to the specific domain of child development if a child was allowed for home computer access when he/she had not enjoyed? On the other, what would happen to the specific domain of child development if his/her home computer was taken away?

To achieve these goals, we analyze the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (hereafter ECLS-K) data sets collected at the spring of third grade and fifth grade. We use data from those survey rounds in consideration of availability and comparability of treatment variables across survey waves even though there is greater risk of introducing sample selection bias, i.e. sample attrition problem of the initial representative sample, inherent to longitudinal surveys compared to the case when earlier survey rounds are in use. To attenuate the sample selection problem, we also implement OLS weighted by the weight variable provided by the data collector, the National Center for Education Statistics (NCES).

2 Data and Measurement

To attain our research goals outlined above, we analyze responses in two survey rounds from ECLS-K which is a series of longitudinal surveys following nationally representative kindergarteners from the fall semester in 1998. Original sample of ECLS-K consisted of 21,260 children attending kindergarten in the 1998-99 academic year. With geographical areas being the primary sampling units, the National Center for Education Statistics (NCES) chose schools as the second-stage units from which students were sampled (Tourangeau et al. 2006). Among 7 waves of data collection efforts including the baseline survey, we choose two specific survey rounds: the spring of third grade (2002) and the spring of fifth grade (2004) which will be denoted by $t \in \{1,2\}$ (or time 1 and time 2) respectively. Note that among several data sets available for public access, we use the longitudinal kindergarten-fifth grade public-use data file.

The most important reason to select the third and fifth grade surveys is the availability of self-assessed externalizing and internalizing behavior problem measures. Even though measures on externalizing and internalizing behavior problems are available in earlier surveys, those are all reported from either teachers or parents. Because we believe that self-reported measures are more valid as well as more reliable even for children especially for those ages in this study, we prefer self-assessed measures. Another reason to opt for those two survey rounds includes the fact that ECLS-K questionnaire started featuring measures on the internet access in home from the third grade wave. Current stage in development of statistical literature also plays a role in the choice. Even though there is rich body of research results and statistical recommendations to investigate causal treatment effects for two-time-period longitudinal study, extension into multi-time-period data is only emerging in the current stream of research (especially Robins' marginal structural model).

At this point, we also note that we create two different sample data sets depending on research questions. Bestowal data set contains treatment variables and observational points suited to answer the question "what if a child obtained home computer availability when he/she had not enjoyed?" In contrast, Withdrawal data set carries treatment variables and sample points appropriate to answer the question "what if a child experienced loss of once-enjoyed home computer availability?"

1) Treatment variables

Bestowal data set. To draw approximate answers for the question "what if home computer became available when there had been no computer available", two questions from parents' questionnaires are exploited in each survey. One question asked: "do you have a home computer that child uses?" The other question in use asked: "in an average week, how often does child use the computer?" There were four valid response alternatives: never, once or twice a week, three to six times a week, and every day.

We construct the home computer availability variable ("combtl") as follows: zero if no computer available or never use of home computer at both time periods and unity if no computer available or never use of home computer at time 1 but either computer available or never use at time 2. From the perspective of examining relationships between computer usage and multi-faceted outcomes, it is reasonable to expect no disparate treatment effects for the category "computer available but no use" distinguished from the category "just computer unavailable", which is the main rationale for the current operationalization. Also note that this measure of the home computer availability variable compares the treatment group of those children who were inaccessible to at time 1 but were provided a home computer at time 2 to the control group of those children who were continuously inaccessible to home computer in two-time period.

To construct the dose-response variable ("frebtl") of home computer usage, we divide those students whose value of the home computer availability variable is unity into subpopulations according to the latter question on frequency of home computer usage mentioned above. More precisely, we assign zero to a child if the home computer availability variable ("combtl") is zero, unity if the child used home computer "once or twice a week" at time 2 conditioned on unavailability of home computer at time 1, two if the child used home computer "three to six times a week" at time 2 conditioned on unavailability of home computer at time 1, if the child used home computer "every day" at time 2 conditioned on unavailability of home computer at time 1.

We introduce another question to create the internet access treatment variable: "does child use a computer at home to get on the internet?" which is an indicator variable. The recoded internet accessibility variable ("intbtl") is a treatment variable with three values: zero if the home computer availability variable ("combtl") is zero, unity if a child was assigned to unity for the home computer availability variable ("combtl") and at the same time did not use the internet at time 2, and two if the child was assigned to unity for the home computer availability variable ("combtl") and used the internet at time 2.

Withdrawal data set. Those three questions in both waves advanced above are utilized to make the other sets of treatment variables in opposite direction of treatment.

The home computer availability variable ("comwdl") is a dichotomous variable: zero if a home computer was available and was in use at least once or twice a week at both times and unity if a home computer was available and was in use at least once or twice a week at time 1 but home computer was unavailable or was never in use at time 2. It should be readily noticeable that this measure of the home computer availability variable contrasts the treatment group of those children who were accessible to at time 1 but whose home computers were taken away at time 2 to the control group of those children who did continuously enjoy home computer availability in two-time period. Also note that definition of a control group differs between the bestowal data set and the withdrawal data set.

We operationalize the dose-response variable (“frewdl”) of home computer usage by subpopulations of the home computer availability variable (“comwdl”). The home computer usage variable has the value zero if the home computer availability variable (“comwdl”) is zero, the value unity if the child used home computer “once or twice a week” at time 1 but either no home computer was available or home computer was never used at time 2, the value two if the child used home computer “three to six times a week” at time 1 but either no home computer was available or home computer was never used at time 2, the value three if the child used home computer “every day” at time 1 but either no home computer was available or home computer was never used at time 2.

Finally, we explain how to create the internet accessibility treatment variable (“intwdl”) which has three possible values. The internet accessibility variable maps a child into zero if the home computer availability variable (“comwdl”) is zero, into unity if the child has the value unity for the home computer availability variable (“comwdl”) and did not use the internet at time 1, and into two if the child has the value unity for the home computer availability variable (“comwdl”) and used the internet at time 1.

2) Outcome variables.

Two domains of child development are areas of our primary interest as outcomes of treatment variables: cognitive skills and non-cognitive traits. For the measures of cognitive skills, mathematical test scores and reading test scores are extracted from the data file. Among three types of test score metrics of interest, namely Item Response Theory Scale Score (IRT scale scores), Standardized Score (T-scores), and Proficiency probability scores, we exploit IRT scale scores which are criterion-referenced measure, that is, achievement scores with respect to a criterion set of items and, therefore, make it possible to measure gains in longitudinal fashion. IRT scale scores can be interpreted as probabilistic scores with respect to the number of correct answers a student would have made if she/he were given all the 153 questions in mathematics and 186 questions in reading.

To measure non-cognitive traits, externalizing and internalizing behavior problem reports are put to use from the Self-Description Questionnaire (SDQ). For construction of six subscales (competency/interest in reading, competency/interest in mathematics, competency/interest in overall school, peer relationship, externalizing problem, and internalizing problem), children were asked 42 individual questions each of which had 4 response choices (1: not at all true, 2: a little bit true, 3: mostly true, or 4: very true). NCES provides average of subscales only if at least two-thirds of individual items in a certain subscale had been measured. Because there has been relatively lower rate of missingness in individual items, missingness does not pose a problem according to the manuals.

The externalizing subscale consists of six items regarding externalizing problems. More specifically, the subscale asked about fighting and arguing with other kids, talking and disturbing others, and problems with distractibility. Alpha coefficient of reliability is 0.77 and 0.78 for the spring of third grade and fifth grade respectively. Eight items on feeling sad a lot of the time, feeling lonely, feeling ashamed of mistakes, feeling frustrated, and worrying about school and friendships constitute the internalizing behavior problem measure. Alpha reliability is reported to be 0.81 and 0.79 for the survey period consecutively. Because all ECLS-K data sets release only average estimate of those submeasures whether public-use or restricted, we have no option but to use those averages for the point estimates of the externalizing and internalizing behavior problems. We recode original scale spanning from unity to four point into a range of zero and three point to obtain more smooth interpretation: zero point represents no problem behaviors at all while three point implies very frequent encounter of specified behavior problems.

3) Confounding variables

From the literature specifying causal relationship between two variables using a directed acyclic graph (DAG), statistical association arises in three ways: 1) when there is causal relationship between two variables regardless of direction of causality, 2) when the two variables share a common cause, and 3) when a collider is conditioned on that can be roughly understood as a third variable affected by the two variables at the same time (Pearl 2000; VanderWeele & Robins 2007). Because our treatment variables can be safely assumed to be generated at some point between two time points and outcome variables to be generated at time 2, it is reasonable to assume that causal direction would flow from the treatment variables into the outcome variables. Then, it is critical to condition on a group of variables influencing the treatment variables and the outcome variables at the same time. Two sets of confounding variables are selected: individual-level variables including demographic and socio-economic variables and school-level variables.

Individual-level confounding variables. Individual-level confounding variables include exhaustively age, gender, race/ethnicity, family composition contrasting two biologically related parents with other parents type, continuous measure on socio-economic status provided by NCES, disability status, parents expectation on how far their child would receive education, and computer skills evaluated by teachers.

School-level confounding variables. School-level confounding variables are location types with three values on rural versus urban areas, census region with typical four values, school types such as catholic school or public school, a report from a principal as to adequacy of computer facility in school, and a variable purporting whether a child transferred between two time points. More rich description, original variable labels in the raw data file and their univariate frequency or descriptive statistics on the confounding variables in the analytical data sets can be found in Table 1 below and Appendix 1.

It should be noted that our confounding variables are all measured at time 1, for which two strings of consideration are attached. First, we would like to minimize risk of reverse causality in the direction of confoundedness and by doing so minimize potential bias in the estimates of interest. A good example on this point can be a variable on child’s computer skills. If we use computer skill measure collected at time 2, it is more likely that a child’ computer skills are influenced by the newly available home computer compared to the case that the child’ computer skill confound the causal direction from the treatment variables to the outcome variables. Under the former scenario, adjusting for the computer skill variable is most likely to bias downward the causal estimates on test score outcomes because we anticipate positive direction of causality from the home computer availability to computer skill and also positive causal relationship from the computer skill to test scores. More generally, it is widely accepted in the causality literature that adjusting for intermediate variables generated by the treatment variable but influencing the outcome variable generally bias causal estimates of the treatment effects (Rosenbaum 2002; VanderWeele and Robins 2007).

Mitigating a collider problem or, sometimes called, endogenous selection problem is the other reason for the lagged measure on confounding variables. For instance, let us assume that there is no causal effect from the home computer availability to test score measures. In the mean time, suppose further that the home computer availability increase parents' expectation on child's education measured at time 2 while the test scores enhance the parents' expectation as well. Under this set of assumptions all of which are quite plausible, conditioning on the parents' expectation will generate positive correlation between the treatment variable and the outcome variables giving biased estimates of the causal effects. However, using the lagged variables substantially decrease possibility of those potential bias.

3 Descriptive Statistics

Table 1 spanning two pages from the next page shows descriptive statistics in the two analytical samples. In the table, mean and standard deviation are provided for continuous measures as well as minimum and maximum values whereas frequency and percentage of each category are shown for the discrete variables. Bestowal data set consists of 1,062 observations among which about 52% of children are assigned to the treatment of the home computer availability while the remaining 48% of children act as the control group. There is a detectable trend of decrease in frequency as the intensity of home computer usage steps up. Also it is more likely to institute the internet access as well once a home computer is available.

Withdrawal data set features 4,549 children among whom dominant proportion of 0.939 constitutes the control group whereas small fraction of children in the data set were treated for the home computer availability variable. Those two trends observed in Bestowal data set regarding frequencies of the other two treatment variables also appear to penetrate Withdrawal data set.

Those descriptive statistics on univariate distribution indicates that by time 1, most children had access to a home computer. When those two data sets are considered, our estimates are that approximately four in five children (4,549 among 1,062+4,549=5,611) had a home computer available at time 1 and additional one in twenty children (273 among 5,611) joined the group by time 2.

Table 1 Descriptive statistics

	Var. name	Values	Bestowal data set				Withdrawal data set			
			Mean/Freq.	Std./Pct.	Min.	Max.	Mean/Freq.	Std./Pct.	Min.	Max.
Treatment variables[1)]	Combtl	0: no home computer	510	48.0						
		1: home computer	552	52.0						
	Frebtl	0: no home computer	510	48.0						
		1: once or twice a week	255	24.0						
		2: 3-6 times a week	171	16.1						
		3: every day	126	11.9						
	Intbtl	0: no home computer	510	48.0						
		1: no	153	14.4						
		2: yes	399	37.6						
	Comwdl	0: home computer available at time 2					4,270	93.9		
		1: no home computer					279	6.1		
	Frewdl	0: home computer available at time 2					4,270	93.9		
		1: once or twice a week					151	3.3		
		2: 3-6 times a week					85	1.9		
		3: every day					43	1.0		
	Intwdl	0: home computer available					4,270	93.9		
		1: no					97	2.1		
		2: yes					182	4.0		
Outcome variables with lagged one	math2		105.2	22.4	47.0	148.6	119.0	18.7	47.3	150.9
	math1		84.0	21.0	33.2	135.9	97.8	19.7	36.2	146.6
	read2		130.0	23.0	58.6	178.5	145.5	20.4	60.8	181.2
	read1		108.0	24.3	46.5	165.7	125.0	22.8	45.7	178.9
	sdqext2		1.0	0.7	0	3	0.7	0.6	0	3
	sdqext1		1.1	0.7	0	3	0.9	0.6	0	3
	sdqint2		1.2	0.6	0	3	0.9	0.6	0	3
	sdqint1		1.4	0.7	0	3	1.0	0.7	0	3
Demographic and socio-economic covariates	Age		132.8	4.5	123	147	132.9	4.3	123	148
	Gender	0: male	522	49.2			2,308	50.7		
		1: female	540	50.9			2,241	49.3		
	Race	0: white	445	41.9			3,253	71.5		
		1: black	181	17.0			316	7.0		
		2: Hispanic	281	26.5			535	11.8		
		3: others	155	14.6			445	9.8		

Note. 1) See text for how to construct treatment variables.

Table 1 continued.

	Var. name	Values	Bestowal data set				withdrawal data set			
			Mean/Freq.	Std./Pct.	Min.	Max.	Mean/Freq.	Std./Pct.	Min.	Max.
	Bioparents	0: yes	514	48.4			1,130	24.8		
		1: no	548	51.6			3,419	75.2		
	Ses		-0.5	0.7	-2.5	2.3	0.2	0.7	-2.5	2.6
	Disable	0: no disability	796	75.0			3,338	73.4		
		1: disability	266	25.1			1,211	26.6		
	Expect	0: receive less than a high school diploma 1: to graduate from high school 2: to attend two or more years of college 3: to finish a four- or five- year college degree 4: to earn a master's degree or equivalent 5: to finish a ph.D, MD, or other advanced degree	2.7	1.2	0	5	3.1	0.9	0	5
	Computer Skill	0: not yet 1: beginning 2: in progress 3: intermediate 4: proficient	1.5	1.1	0	4	2.0	1.2	0	4
School related covariates	Urban	0: large and mid-size city	364	34.3			1,453	31.9		
		1: large and mid-size suburb	325	30.6			1,932	42.5		
		2: small town and rural	373	35.1			1,164	25.6		
	Region	0: northeast	116	10.9			798	17.5		
		1: Midwest	237	22.3			1,505	33.1		
		2: south	441	41.5			1,343	29.5		
		3: west	268	25.2			903	19.9		
	School Type	0: public	968	91.2			3,525	77.5		
		1: catholic	57	5.4			691	15.2		
		2: other religious	29	2.7			262	5.8		
		3: other private	8	0.8			71	1.6		
	Computer Facility	0: do not have 1: never adequate 2: often not adequate 3: sometimes not adequate 4: always adequate	3.1	1.3	0	4	3.2	1.3	0	4
	School Change	0: did not change	855	80.5			3,799	83.5		
		1: transferred	207	19.5			750	16.5		
N of obser.			1,062				4,549			

Even cursory look at descriptive statistics reveals a sample selection problem in the sense that Withdrawal data set contains children from more socially advantageous backgrounds while those in Bestowal data set are more likely to be drawn from socially adverse backgrounds. For example, all the mean estimates on the outcome measures as well as their lagged variables show preferable statistics in Withdrawal data set. These estimates are just a repetition of major findings in the "digital divide" literature given that no one in Bestowal data set had access to home computer at time 1 but only half of them obtained it at time 2 while all of those in Withdrawal data set had access to a home computer and 93.9% of them continued to have home computer available at both times. Even distribution of school sectors children attended reflects the trend by making greater proportion of observations in Withdrawal data set register non-public schools.

4 Statistical Analyses

1) OLS regression

In this subsection, we build up two OLS estimands to evaluate treatment effects on outcome variables. This exercise is intended to provide an assay against which one can appraise how large biases are introduced in the usual multivariate approach as opposed to the inverse-probability-of-treatment weight method. To implement a multivariate approach, two functional forms are tested. A regressor variable framework formulates the production of outcome variables at time 2 as

$$O_i = \beta_0 + \sum_{j=1}^{c} \beta_j 1[T_i = j] + \beta_{c+1} LO_i + \sum_{j=1}^{p} \gamma_j X_{ij} + \varepsilon_i \qquad 1$$

where i denotes each child, O represents an outcome variable measured at time 2 and LO a lagged outcome variable measured at time 1. X means a confounding variable and there are p number of confounding variables. We include all the lagged outcome variables into confound variables. In other words, reading test score, externalizing, and internalizing behavior problem variables measured at time 1 are included in the set X when the outcome variable is mathematics test scores at time 2. Traditional assumptions on ε_i are applied, namely, $\varepsilon_i \sim i.i.d \; N(0, \sigma^2)$ where i.i.d abbreviates "independent and identically distributed" and N refers to normal distribution.

T is a treatment variable whose range is 0 to c. As usual, 1 represents indicator function evaluating zero if a condition within bracket is false and unity otherwise. Note that all the treatment variables considered in this paper are discrete variables and the value zero of the treatment variables plays a role of control or baseline contrast so that we omit the zero category for the indicator function related to the treatment variable. Under this general formulation, parameters of primary interest are $\beta_j : j \in \{1, \ldots, c\}$ embodying the treatment effect of a specific category in a treatment variable compared to the control group.

We also consider a change score model as specified by

$$O_i - LO_i = \beta_0 + \sum_{j=1}^{c} \beta_j 1[T_i = j] + \sum_{j=1}^{p} \gamma_j X_{ij} + \varepsilon_i \qquad 2$$

Notice that the same notation and assumptions hold as Equation 1. The change score model is most conspicuous in treating the difference between outcome variables in two adjacent time points as a response variable as compared to the regressor variable model. The natures of these two competing models have received extensive investigation in several articles (for example, Allison 1990; Yang & Tsiatis 2001) so that it suffices to mention that the regressor variable model assumes that the lagged outcome variable has a causal effect on the subsequent outcome variable, while the change score model is built on the stipulation that without assumption with respect to the causal effect of previous test scores, the increment or decrement between test scores between two time points is modeled.

As acknowledged in previous discussion, we are concerned about the potential bias due to sample selection inherent in longitudinal surveys when we analyze only complete data sets with all the observations deleted that have at least one missing point. To extenuate the potential bias, we also provide weighted OLS estimates together with non-weighted estimates from list-wise deleted data sets. We use the longitudinal weight ("c56pw0") supplied by NCES and the confidence intervals are constructed by linearization variance estimates when the longitudinal weight is in use in the model (Lohr 1999).

2) IPTW estimator

Recent development in statistical literature has emphasized identification of "effects of causes" rather than "causes of effects" (Holland 1986). Regression framework can be seen as a method to materialize the latter approach while propensity score methods underscoring counterfactuals or potential outcomes are widely accepted as appropriate for the former approach. In this subsection, we discuss how to estimate the causal effects of the treatment variables under the framework of IPTW estimator using the estimated propensity score.

To advance formal discussion, let us denote by $Y_i(t)$ the potential outcome of a child i when he/she is treated with $t \in \{0,\ldots,c\}$ where t refers to a specific category of a treatment variable if the variable is discrete or refers to an interval if the treatment variable is continuous. In this paper, we are interested in the population average treatment effect of a category t compared to the control as specified by

$$\beta_t \equiv E[Y(t) - Y(0)] : t \in \{1,\ldots,c\} \qquad 3$$

The fundamental problem of identification of the parameters of interest is that for a child i, we observe only one potential outcome, never more than one. Rosenbaum and Rubin showed that for binary treatment variable case, one can recover the average treatment effect by conditioning on the propensity score under the unconfounded treatment assignment assumption conditional on a set of the confounding variables X stating that

$$T \perp Y(t) \mid X : t \in \{0,1\} \qquad 4$$

because

$$E[Y(1)-Y(0) \mid X=x] = E[Y(1) \mid T=1, X=x] - E[Y(0) \mid T=0, X=x]$$
$$= E[Y \mid T=1, X=x] - E[Y \mid T=0, X=x] \qquad 5$$

and $T \perp Y(t) \mid p(X)$ if Equation 4 holds and $p(X)$ is strictly between zero and unity, where $p(x) = \Pr(T=1 \mid X=x)$ is the propensity score, namely, the conditional probability of getting the treatment given the confounding variables (Rosenbaum & Rubin 1983; Heckman & Navarro-Lozano 2004; Hirano et al. 2003). Under this setting, the average treatment effect can be obtained by the rule of iterated expectations, namely,

$$E[Y(1)-Y(0)] = E[E[Y(1)-Y(0) \mid p(X)]]. \qquad 6$$

Four classes of methods have been suggested regarding how to use the propensity score: 1) propensity score matching, 2) stratification based on the propensity score, 3) regression with the propensity score as a covariate, and 4) IPTW using the propensity score. In this paper, we experiment IPTW approach due to its simplicity in implementation and desirable properties (Austin 2009). In a nutshell, IPTW estimate can be obtained by the equation

$$E[Y(1)-Y(0)] = E\left[\frac{Y(1)*1[T=1]}{p(1,X)}\right] - E\left[\frac{Y(0)*1[T=0]}{p(0,X)}\right] \qquad 7$$

where $p(0,X)$ refers to the conditional probability of receiving the treatment 0 given the confounding variables X.

Imbens (2000) and Hirano and Imbens (2004) generalize the binary treatment variable case into multi-valued treatment variable case. More specifically, under a relaxed assumption of weak unconfoundedness instead of Equation 4 above, namely,

$$1[T=t] \perp Y(t) \mid X : t \in \{0,\ldots,c\} \qquad 8$$

it can be shown that

$$E[Y(t)-Y(0)] = E\left[\frac{Y(t)*1[T=t]}{r(t,X)}\right] - E\left[\frac{Y(0)*1[T=0]}{r(0,X)}\right] \qquad 9$$

where $r(t,X)$ denotes the generalized propensity score, namely, the conditional probability of receiving the treatment value t given the confounding variables.

For the binary treatment variables, we estimate the propensity score using logit regression and for the multi-valued treatment cases, we estimate the propensity score using multinomial logistic regression ("logit" and "mlogit" function respectively in STATA) with all the confounding variables and the lagged outcome variable included as covariates. Since how to compute standard error of a parameter is not developed to recommendable extent, we bootstrap to construct 95% confidence interval (Imbens 2000; Chernick 1999). In addition, we are not sure how to incorporate the longitudinal weight so that we just provide estimates from complete data set approach.

3) Results

Table 2 and Table 3 display estimates of causal effects of treatment variables from estimators specified above in Bestowal data set and Withdrawal data set respectively. For clear presentation, we provide only the estimated parameters of interest omitting all the coefficients associated with confounding variables.

Bestowal data set

The first observation from Table 2 is that regression estimates are scarcely likely to attain the conventional p-value 0.05 while 95% of IPTW estimates tend to stay away from zero meaning that the null hypothesis of zero effect is likely to be rejected. Also readily noticeable is the difference in magnitude of estimates between those from regression framework and those from IPTW estimator. In general, estimates of IPTW estimator tend to show greater coefficients of treatment effects compared to those of regression framework.

Beyond statistical significance, some interesting patterns can be found. 1) Generally, children in the treatment group appear to exhibit favorable outcome (Subrahmanyam et al. 2001). For instance, those children who got access to the home computer at time 2 are more likely to achieve higher points in mathematics test and reading test while reporting decreased level of externalizing and internalizing behavior problems compared to those children who continuously stayed out of access to the home computer at two time points. 2) However, more interestingly, the effects of the home computer availability differ depending on the frequency of home computer usage: those children tend to benefit more who use a home computer "3-6 times a week" rather those children who use it "every day". This observation suggests that dose-response function of home computer usage may follow quadratic relationship inducing harm rather than good beyond some point of usage. One possible explanation of this results is crowding-out effects stating that too much involvement in home computer use would crowd out other opportunity to develop a favorable outcome, for instance, time to exercise critical thinking (Shields & Behrman 2000).

3) There is no clear trend as to the effects of the internet access in enhancing test scores when the regression estimates are considered. However, the internet access seems to lower externalizing and internalizing behavior problems even when we look at regression estimates for judgment though all the coefficients fail to reject the null hypothesis of zero effect. Conversely, IPTW estimates show that internet access leads to more desirable outcomes in test scores as well as behavior problems. Interestingly, IPTW estimates reveal that those children not allowed to the internet access are not statistically different in their outcomes from those in the control group in all domain of child development.

Withdrawal data set

We find that relatively large set of coefficients from the regression framework are statistically significant in Withdrawal data set. However, as before, estimates of IPTW estimator are more likely to attain statistical significant at the conventional level of p-value 0.05. Another comparable pattern in estimates includes larger magnitude of estimates from IPTW estimator in contrast with those from regression framework. Another observation is that estimates from the regressor variable approach are more prone to statistically significant than those from the change

Table 2 Estimation results for Bestowal data

		Reg.Var.		Reg.Var.Weight.		Change.		Change.Weight.		IPTW		
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Est.	Lower	Upper
Math	combtl.1	0.592	0.704	1.254	1.221	0.153	0.725	0.877	1.236	5.803	3.928	7.638
	frebtl.1	0.072	0.864	1.234	1.419	-0.368	0.891	0.621	1.429	6.027	3.724	8.249
	frebtl.2	1.584	0.989	1.324	2.106	1.167	1.021	1.289	2.170	7.763	5.003	10.459
	frebtl.3	0.370	1.084	1.185	1.282	-0.090	1.118	0.762	1.371	3.924	1.021	6.621
	intbtl.1	0.567	0.990	0.630	1.785	0.249	1.022	0.372	1.758	2.170	-0.679	4.912
	intbtl.2	0.604	0.789	1.555	1.379	0.104	0.813	1.121	1.411	7.425	5.432	9.507
Read	combtl.1	0.639	0.795	1.720	1.215	0.855	0.883	2.523 †	1.363	5.724	3.809	7.629
	frebtl.1	0.771	0.976	1.155	1.413	0.787	1.085	2.519	1.629	6.446	4.097	9.172
	frebtl.2	0.900	1.118	1.533	2.030	0.995	1.242	1.418	2.254	6.805	3.923	9.860
	frebtl.3	0.085	1.224	3.087 †	1.693	0.814	1.360	4.172 *	2.037	3.531	0.692	6.423
	intbtl.1	0.836	1.118	0.698	1.810	1.568	1.241	2.335	2.286	1.416	-1.559	4.034
	intbtl.2	0.539	0.891	2.215	1.373	0.490	0.989	2.614 †	1.485	7.566	5.465	9.943
Exter.	combtl.1	-0.039	0.040	-0.014	0.064	-0.023	0.047	0.000	0.079	-0.132	-0.215	-0.052
	frebtl.1	-0.035	0.049	0.040	0.071	0.018	0.058	0.148	0.093	-0.133	-0.236	-0.032
	frebtl.2	-0.079	0.056	-0.104	0.100	-0.049	0.066	-0.141	0.127	-0.188	-0.309	-0.074
	frebtl.3	0.002	0.062	0.019	0.086	-0.070	0.073	-0.073	0.093	-0.062	-0.193	0.053
	intbtl.1	0.017	0.056	0.066	0.078	0.064	0.066	0.155	0.112	-0.016	-0.131	0.106
	intbtl.2	-0.067	0.045	-0.052	0.076	-0.068	0.053	-0.075	0.090	-0.173	-0.265	-0.086
Inter.	combtl.1	-0.004	0.037	-0.070	0.053	-0.002	0.046	-0.066	0.077	-0.087	-0.163	-0.020
	frebtl.1	0.016	0.046	-0.035	0.059	-0.005	0.056	-0.078	0.096	-0.068	-0.162	0.016
	frebtl.2	-0.058	0.052	-0.106	0.081	-0.058	0.064	-0.063	0.105	-0.148	-0.249	-0.045
	frebtl.3	0.024	0.057	-0.082	0.078	0.069	0.070	-0.046	0.102	-0.043	-0.157	0.068
	intbtl.1	0.019	0.052	0.005	0.075	0.020	0.064	-0.011	0.107	0.002	-0.106	0.114
	intbtl.2	-0.015	0.042	-0.106 †	0.058	-0.014	0.051	-0.092	0.082	-0.126	-0.204	-0.056

Note. $^{\dagger:}$<=0.1, *<=0.05, **<=0.01, ***<=0.001.

Table 3 Estimation results for Withdrawal data

		Reg.Var.		Reg.Var.Weight.		Change.		Change.Weight.		IPTW		
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Est.	Lower	Upper
Math	comwdl.1	-1.372 *	0.584	0.388	0.892	-0.507	0.629	0.966	0.974	-6.691	-8.604	-4.991
	frewdl.1	-0.574	0.770	-0.574	0.770	0.122	0.831	1.568	1.207	-5.569	-7.976	-3.432
	frewdl.2	-1.585	1.015	-1.585	1.015	-0.633	1.096	0.379	1.790	-7.649	-10.748	-5.171
	frewdl.3	-3.857 **	1.422	-3.857 **	1.422	-2.542 †	1.534	0.259	2.165	-8.136	-20.047	-1.215
	intwdl.1	-1.340	0.960	1.503	1.623	-0.366	1.036	2.170	1.811	-9.015	-12.619	-5.716
	intwdl.2	-1.389 *	0.705	-0.215	0.950	-0.580	0.761	0.313	1.028	-6.299	-8.530	-4.410
Read	comwdl.1	-1.675 *	0.673	-1.122	0.921	-1.167	0.775	-0.434	1.026	-7.456	-9.704	-5.452
	frewdl.1	-1.203	0.887	-0.706	1.170	-0.765	1.021	0.596	1.296	-6.557	-9.649	-4.012
	frewdl.2	-0.926	1.170	-1.159	1.472	-0.194	1.347	-1.267	1.647	-8.325	-11.950	-5.114
	frewdl.3	-4.928 **	1.639	-2.570	2.503	-4.619 *	1.886	-2.099	2.928	-7.511	-20.746	0.906
	intwdl.1	-1.299	1.107	-0.654	1.504	-0.738	1.273	-0.027	1.504	-8.956	-13.109	-5.082
	intwdl.2	-1.870 *	0.813	-1.375	1.079	-1.389	0.935	-0.654	1.283	-7.168	-10.111	-4.896
Exter.	comwdl.1	0.039	0.032	0.051	0.053	0.047	0.038	0.072	0.063	0.099	0.033	0.165
	frewdl.1	0.004	0.042	0.017	0.073	0.022	0.050	0.068	0.085	0.050	-0.040	0.144
	frewdl.2	0.057	0.055	0.079	0.088	0.064	0.066	0.066	0.107	0.149	0.053	0.259
	frewdl.3	0.130 †	0.077	0.108	0.113	0.103	0.093	0.102	0.133	0.148	-0.033	0.406
	intwdl.1	0.092 †	0.052	0.135	0.091	0.108 †	0.063	0.090	0.104	0.174	0.062	0.287
	intwdl.2	0.011	0.038	0.007	0.061	0.015	0.046	0.062	0.075	0.077	-0.003	0.160
Inter.	comwdl.1	-0.009	0.032	0.053	0.049	0.006	0.039	0.044	0.062	0.067	-0.003	0.127
	frewdl.1	-0.068	0.042	-0.025	0.066	-0.056	0.052	-0.027	0.092	0.000	-0.085	0.085
	frewdl.2	0.018	0.056	0.109	0.084	0.016	0.068	0.062	0.096	0.153	0.035	0.272
	frewdl.3	0.148 †	0.078	0.201 **	0.078	0.209 *	0.096	0.264 **	0.100	0.032	-0.125	0.269
	intwdl.1	-0.066	0.053	-0.015	0.083	-0.023	0.065	0.009	0.090	0.024	-0.088	0.126
	intwdl.2	0.020	0.039	0.091	0.057	0.020	0.048	0.063	0.079	0.079	0.000	0.157

Note. †:<=0.1, *<=0.05, **<=0.01, ***<=0.001.

score models. Also noticeable is an observation that estimates from unweighted regression are more likely to show statistical significance as opposed to estimates from weighted regression.

1) Are children whose home computer was taken away at time 2 more likely to reveal some indication of unfavorable outcomes than those children who kept having the home computer available for two time points? We fail to detect any clear pattern for mathematics test scores and internalizing behavior problem but there is some tendency suggesting somewhat negative outcomes in reading test scores and externalizing behavior problem for the treatment group. For instance, all the regression coefficients in reading test scores are negative for the home computer availability variable while those in externalizing behavior problem are positive even though only one estimate passed statistical test at the conventional p-value. However, estimates from IPTW show the same direction in their causal effects and, moreover, those estimates are statistically significant.

2) Maybe most consistent estimates across statistical models in Withdrawal data set is adverse effects of loss of home computer availability when a child used a home computer "every day" (estimates of "frewdl.3"). Not only coefficients for test scores are negative except one case of weighted change score model and coefficients for behavior problem are unfailingly positive but also those estimates tend to approach statistical significance. Indeed, closer look at Table 3 bring to light the observation that most statistically significant coefficients are concentrated on the rows registering the treatment effects of a home computer loss when a child was previously a daily user of the home computer.

As to the effects of deprivation of the internet access, direction of coefficients indicates some damaging effects even though no estimates are statistically significant except two cases of the regressor variable model for mathematics and reading test scores. However, all causal estimates except those for externalizing behavior problem in IPTW approach suggests more or less negative effects of discontinuation of the internet access.

5 Conclusions and Discussion

What would happen to the developmental domains such as cognitive skills as well as non-cognitive traits if a home computer became available when it had not been? What about dose-response function of the home computer usage on the child's development? Does the newly acquired internet access also have meaningful impact on those domains of development? Conversely, what would happen if once available home computer was taken away? Is a child who was a more frequent user of a home computer more likely to be affected by the loss of the home computer availability compared to those children who used a home computer less often? Is there also distinguishable pattern by the status of the internet access?

To provide a reasonable answer to those questions, we have analyzed survey responses fielded in the spring third grade (2002) and fifth grade (2004) of ECLS-K study using IPTW estimator utilizing the propensity score and OLS regression framework materializing regressor variable approach and change score model. Our findings can be summarized as follows:

1) Newly available home computer tends to increase favorable outcomes in all domains of development. 2) Those children who used the newly available home computer “3-6 times a week” are likely to benefit more than those children who used it “every day,” which suggests emergence of negative effects after a certain level of computer usage. 3) The internet access appears to lower behavior problem outcomes even though we failed to detect a clear pattern on the causal effects of the internet access on test score metrics.

4) When a child was deprived of a home computer availability, the child are estimated to show some indication of more or less negative outcomes only in reading test scores and externalizing behavior problem. 5) Interestingly, the most affected children by the loss of home computer availability are those who had used the home computer most frequently, an asymmetric result compared with estimates from Bestowal data set. 6) Finally, we find some evidence pointing toward unfavorable effects of withdrawal of the internet access even though estimates from regression framework fail to attain statistical significance.

However, we find that generally OLS regression gave statistically insignificant estimates while IPTW estimator produced statistically significant estimates. Indeed, it is quite surprising to notice that there is no causal estimate of a specific treatment effect that all the five statistical models agree in its statistical significance at the conventional level of 0.05 p-value. Not only in the level of statistical significance but also in the magnitude of estimates do we find a large difference between two sets of estimators. Our current explanations on these observations are very limited: 1) there may be a problem in the assumption of strict overlap of support for the generalized propensity score (Flores & Mitnik 2009) and 2) strong correlation between outcome variables and their lagged variables may suppress estimates in regression framework. To find more sophisticated answers and come up with refined solutions will be our future task.

In this paper, we just tried IPTW estimator using the generalized propensity score. However, it will increase reliability and robustness of estimates for causal effects of treatment variables to experiment other propensity score methods such as subclassification and matching. Therefore, we also reserve extension to other propensity score methods for our future task. More elaborate improvement on adjustment of missing data including attrition of longitudinal data is in our future agenda as well.

Appendix 1 Variable description and original variable labels.

Var. name	Description	Orig. variables
math2	IRT scale mathematics test scores at time 2	c6r3mscl
math1	IRT scale mathematics test scores at time 1	c5r3mscl
read2	IRT scale mathematics test scores at time 2	c6r3rscl
read1	IRT scale mathematics test scores at time 1	c5r3rscl
sdqext2	self-assessed externalizing problem behaviors at time 2	c6sdqext
sdqext1	self-assessed externalizing problem behaviors at time 1	c5sdqext
sdqint2	self-assessed internalizing problem behaviors at time 2	c6sdqint
sdqint1	self-assessed internalizing problem behaviors at time 1	c5sdqint
combtl	Conditioned on unavailability of home computer at time 1, do you have a home computer that child uses at time 2 ?	p5homecm,p5compwk,p6homecm,p6compwk
frebtl	Conditioned on unavailability of home computer at time 1, in a typical week, how often does child use the computer at time 2 ?	p6compwk
intbtl	Conditioned on unavailability of home computer at time 1, does child use a computer at home to get on the internet at time 2?	p6cmpint
comwdl	Conditioned on availability of home computer at time 1, do you have a home computer that child uses at time 2?	p5homecm,p5compwk,p6homecm,p6compwk
frewdl	In a typical week, how often does child use the computer at time 1?	p5compwk
intwdl	Does child use a computer at home to get on the internet at time 1?	p5cmpint
age	age in month at time 1	dobmm,dobyy,c5asmtmm, c5asmtyy
Gender	Gender	Gender
Race	race/ethnicity	Race
biopar	whether child lived together with two bio-parents at time 1	p5hparnt
ses	Socio-economic composite index	w3sesl
disabl	status of disability	p5disabl
expect	how far in school do you expect child to go?	p5expect
comskill	This child uses the computer for a variety of purposes-for example, for example, to write reports or stories formatting them correctly, or to use a database to retrieve information	t5comptr
urban	location of school	r5urban
region	census region of school	r5region
sctyp	school type from the school administrator question	s5sctyp
comfac	In general, how adequate is each of the following school facilities for meeting the needs of the children in your school: computer lab	s5compok
schchg	did child change school between time 1 and time 2?	r6r5schg

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