Supplemental Information

DD Analysis

The DD analysis we use in this study involves the estimation of a multivariate linear regression model of the form shown below.

$$(1)\ Y_{ist} = \beta_0 + \beta_1 MedicaidExpansion_{st} + \alpha_i + \ \gamma_t + \delta_s + \lambda' X_i + \eta Z_{st} + \varepsilon_{ist}$$

Where Y_{ist} is the child or parent health outcome measured at each wave *t*. $MedicaidExpansion_{st}$ is a binary variable equal to 1 if child *i* lives in state *s* that expanded Medicaid during wave *t*, and zero otherwise; α_i refers to child fixed effects that captures all time-invariant factors related to health, such as constant family characteristics and unobserved features; γ_t refers to wave fixed effects that captures secular trends affecting all children over time; Z_{st} includes a vector of time-varying state-level covariates described earlier in the manuscript; and ε_{ist} is the error term. The parameter of interest is β_1, which represents the effect of the ACA Medicaid expansion. Because the analytic sample only included children who did not move across states during the study period, state fixed effects (δ_s) and all time-invariant child- and family-characteristics (X_i) were subsumed by the child fixed effects (α_i) in these models. Because child fixed effects are included and expansion status is time-varying at the state-level, only within-child variation, post-expansion in outcomes is captured by β_1. All statistical analyses were weighted to adjust for sampling procedures, nonresponse, differential attrition, and standard errors were clustered at the state level as is standard in DD analysis because treatment status varies at the state level.

State-level Medicaid Expansion Status

As described in the main manuscript, although the ACA was originally a federal mandate, the Supreme Court allowed states to opt out of this requirement in 2012. As a result, some states opted to expand Medicaid to all adults with household incomes less than 138 percent FPL, while some states did not. In our study, children (and parents) who reside in twenty-five states are coded as 1 (in the waves post-expansion) to denote expansion and those in the remaining sixteen states are coded as 0 (in all waves). Table S1 shows details of states' expansion decisions. Most states expanded in 2014 and are coded as 1 in waves 5 (Spring 2014), 6 (Spring 2015) and 7 (Spring 2016), as is standard in DD analyses, for the baseline Table 2 results. States that expanded after 2014 are coded as 1 only in those relevant waves. For example, Pennsylvania expanded only in 2015, so is coded as 1 only in waves 6 (Spring 2015) and 7 (Spring 2016) as is standard in DD analyses, for the baseline results presented in Table 2. Due to ECLS-K:2011's clustered sampling framework, there were no children sampled from 10 states; nevertheless, ECLS-K:2011 is nationally-representative. See more details about ECLS-K:2011 here: https://nces.ed.gov/ecls/kindergarten2011.asp.

Testing Pre-trends Assumption

Linear Pre-trends

A key assumption of the DD analysis is that trends in health outcomes of children and parents residing in states that expanded Medicaid versus not would be similar prior to the expansion. The summarized graphs in Figure 1 of the manuscript show these trends. In Table S2, we provide results from regression-adjusted models that show that linear pre-trends in our models are not statistically different between the two groups of states prior to the expansion providing confidence in the DD identification strategy. Essentially, in this analysis, we restrict the sample to the pre-expansion time period only and report the results of the coefficient—*Expansion x Wave*, which is an interaction between a binary variable representing whether a child resided in a state that expanded its Medicaid program (as shown in Table S1) and a linear wave term. The rest of the model specification is similar to (1), which also includes wave, child fixed effects, state-level covariates, and are weighted by sampling weights.

Heterogeneity Analysis

Benefits of parental health insurance expansions might not be equally shared across all populations given significant pre-existing health disparities across key sociodemographic subgroups. We examine heterogeneity in treatment effects by conducting three sets of subsample analyses (1) by race/ethnicity; (2) sex; and (3) high/low income within the sample of low-income households for primary outcomes of interest in which we observed significant main effects (see Appendix Table S3). We find that the effect on children's BMI is primarily driven by white children, specifically girls. This might be consequential given that white girls experience more weight-related stigma in middle school. [1,2] We also observe a larger improvement in parental health among Black and below-median income households in our analytical sample. These results suggest that the benefits of health insurance expansions might be reaching the most vulnerable families even within the low-income sample. However, it is important to interpret these results with caution due to small sample sizes.

Additional Robustness Checks

Differential Parental Eligibility Thresholds

In our main models, we define our primary treatment status to include states that expanded Medicaid to low-income adults through the ACA (in 2014 and beyond). Prior to the ACA, however, states had different income thresholds for low-income *parents*, meaning that the generosity of the ACA Medicaid expansions varied across states that expanded. For example, in Colorado, parents whose household income was less than 106% of the FPL were eligible for Medicaid in 2011. In Pennsylvania, only parents whose household income was less than 46% of the FPL were eligible for Medicaid in 2011. Both states expanded through the ACA and all adults whose household income was less than 138% of the FPL became newly eligible in 2014. The expansion was likely more impactful in Pennsylvania than it was in Colorado because a larger sample of low-income parents in Pennsylvania became newly eligible. On the other hand, some states that had income eligibility thresholds for parents above 138% FPL in 2011 actually lowered their thresholds to meet the federal 138% level (e.g., Wisconsin).

We examine these differences in parental eligibility in this robustness check by redefining the analytical sample. Specifically, we estimate equation 1 using an analytical sample that only includes those children whose parents would have been newly eligible. In other words, we drop children whose parents were eligible for Medicaid based on pre-ACA income thresholds, from both expansion and non-expansion states. We calculate this measure using parental income eligibility limits in 2011 combined with whether they resided in a state that expanded or not. Appendix Table S4 shows each expansion state's parental income eligibility threshold in 2011. In this model, parents and children in low-income households (<138% FPL) that reside in states that did not expand Medicaid through the ACA consist of the control group. However, children and parents who were already eligible for Medicaid based on pre-ACA income thresholds in the expansion and non-expansion states are dropped from the analysis as the new ACA expansions likely changes their public health insurance eligibility less,[1] if at all. Essentially, this analysis aims to isolate treatment effects on parent and child outcomes by focusing on parents who were *most* likely to be newly eligible under ACA, and on whom we would expect the effects to be the largest.

[1] Dropping this sample of children/parents who were likely eligible for Medicaid expansions prior to the ACA is a more conservative approach because past research shows "welcome mat" effects for that sample (Hudson & Moriya, 2017). Nevertheless, this alternative model specification teases the causal effects on the most appropriate "targeted" population of the ACA expansions.

In other words, in this robustness check, we estimate a DD model on a more precise analytical sample that includes children from low-income households that were most likely to be newly eligible for Medicaid under the ACA in expansion states and those who would have been newly eligible in non-expansion states had the states they reside in expanded under the ACA, making that comparison group a valid counterfactual. These results are described in the main manuscript as well.

Alternative Coding for Primary Outcomes

As described in the main text, driven by past theory and research on health insurance expansions,[3] we re-coded the self-rated overall health status for parents and children. Specifically, overall health status was reported on a continuous 5-point scale *(1= Excellent, 2=Very Good, 3=Good, 4=Fair, and 5 = Poor)* for both parents and children in the ECLS-K:2011 data. Similarly, we use the composite child BMI values provided in the data for our main results. However, children's BMI is often converted to percentiles or standardized scores (Z-scores) based on age- and sex-specific growth charts provided by the CDC in the U.S. In Table S6, we present comparable DD results on the continuous, 5-point measure of health status (for both parents and children), BMI Z-scores, and BMI Z-score-based overweight, obese, and underweight indicators for completeness.

First, the parental health effects are fairly robust. Post-ACA expansion, parents are less likely to report worse health. Child health results are also similar—again, we do not observe any significant changes in this measure. Results on BMI-Z Scores and BMI-Z Score-based overweight indicator are also not statistically significant. Because BMI Z-Scores are calculated using age- and sex-specific CDC growth charts based on cross-sectional data, they are not wellsuited [4,5] for use in longitudinal models, such as those in the present study that tease out fairly small, within-child changes across states in BMI trajectories post-ACA.

Alternative Sample Selection and Fixed Effects Specification

Second, we also explored if our baseline results are robust to alternative sample selections (such as households with less than 100% FPL, households where parents do not have a college-degree) or the exclusion of individual fixed effects (see Table S7). We find that the results are qualitatively similar to our baseline results.

Staggered Treatment Timing

Finally, we briefly examine if the staggered timing of the Medicaid expansions across states affects the robustness of our baseline results. In our analytical sample, we have three different expansion timings—most states (20) expanded in January 2014 or earlier, 1 state (Michigan) expanded late in April 2014 (coded as expanded in 2014 onwards in our baseline analysis), 3 states (Indiana, New Hampshire, and Pennsylvania) expanded in 2015, and 1 state (Montana) expanding in 2016 (see Table S1). First, following past ACA literature,[6] we re-run our DD analysis by excluding the late expanders and report results in Table S8. The coefficients are qualitatively similar to the baseline results despite lower precision for parent health.

Second, we also carried out the Goodman-Bacon decomposition[7] for the main outcomes of interest for which we report significant results—child BMI and parent health. Again, similar to earlier studies,[6] we do not expect earlier treatment cohorts to influence heavily in comparisons (by acting as controls) to later treatment cohorts due to a low number of late treatment states in our analytical sample. Also, because we have a large sample of "never treated" cohorts, we do not expect this to be issue. Nevertheless, following past ACA literature on this topic,[6] we include the results from the Goodman-Bacon decomposition that essentially examines all 2x2 DD analysis independently.[7] Specifically, the decomposition provides weights and coefficients to isolate the effect from treatment timing variation ("Earlier Group Treatment" vs. "Later Group Control" and "Later Group Treatment" vs. "Earlier Group Control") and from comparisons of "Treatment" vs. "Never Treated" (see Figure 2). We find that 92 percent of our DD estimate of parent health and 93.5 percent of our DD estimate on child BMI comes from comparisons of treated and never treated (i.e., weight attributed to closed triangles in the figure). In other words, only 7-8 percent is attributable to comparisons with states with differential treatment timing (summing weights across the x's). Together, these additional robustness checks increases our confidence that staggered treatment timing does not play a strong role in our analysis.

Supplemental References

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Tables and Graphs

Table S1. Timing of ACA Medicaid Expansion States

	Early* Expansion States	Expansion States (January 2014)	Late* Expansion States	Non-Expansion States	No ECLS-K Data±
1	California	Arizona	Indiana	Alabama	Alaska
2	Connecticut	Arkansas	Michigan	Florida	Delaware
3	Hawaii	Colorado	Montana	Georgia	Idaho
4	Massachusetts	Illinois	New Hampshire	Kansas	Kentucky
5	Minnesota	Iowa	Pennsylvania	Louisiana***	Maine
6	New Jersey	Maryland		Mississippi	North Dakota
7	New York	Nevada		Missouri	Rhode Island
8	Vermont	New Mexico		Nebraska	South Dakota
9	Washington	Ohio		North Carolina	Washington, D.C.
10		Oregon		Oklahoma	Wyoming
11		West Virginia		South Carolina	
12		Wisconsin**		Tennessee	
13				Texas	
14				Utah	
15				Virginia	

* Early expanders are treated as if they expanded in 2014, meaning all time points prior to 2014 (waves 1-4) are coded as not yet expanded for these states as well because the expansions/enrollment to Medicaid was effective beginning in 2014 for these states. Late expanders are treated as expanded only in the years after their expansion.
** Although Wisconsin did not technically expand its Medicaid program under the ACA, it covers adults up to 100% FPL.
***Louisiana expanded in July 2016, but this timing is beyond the study period. Therefore, we consider it a non-expansion state in this study.
± Of these, in our study period, the following would have been considered as (1) non-expansion states: Idaho, Maine, South Dakota, and Wyoming; and (2) expansion states: Alaska (2015), Delaware, Kentucky, North Dakota, Rhode Island, and Washington, D.C.

Table S2. Linear Pre-trends Test Among Low-Income Households (< 138% FPL)

A. Parent Health	Overall Health	
	(1)	
Expansion x Wave	-0.012	
	(0.009)	
Observations [a]	6,160	
B. Child Health Utilization	Doctor Visits	
	(1)	
Expansion x Wave	-0.003	
	(0.010)	
Observations [a]	9,420	
C. Child Health	Overall Health	BMI
	(1)	(2)
Expansion x Wave	-0.001	-0.04
	(0.003)	(0.042)
Observations [a]	12,220	13,800

Notes: Sample is restricted to the pre-expansion time period only in this table. Each cell corresponds to a different OLS regression. Expansion x Wave is an interaction between a binary variable representing whether a child resided in a state that expanded its Medicaid program and a linear wave term. The regressions also include wave, child fixed effects, state-level covariates, and are weighted by sampling weights. Heteroscedasticity-robust standard errors in parentheses, clustered at the state-level.

[a] Sample size (in child-years) rounded to the nearest 10 as per dataset guidelines;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S3. Heterogenous Effects on Primary Outcomes Among Low-Income Households (< 138% FPL)

	A. Parent Health			B. Child BMI		
A. By Race/Ethnicity	White	Black	Hispanic	White	Black	Hispanic
	(1)	(2)	(3)	(1)	(2)	(3)
Expansion	0.042	0.080*	0.013	-0.447*	-0.209	-0.277
	(0.022)	(0.033)	(0.031)	(0.191)	(0.312)	(0.192)
Mean DV	0.864	0.823	0.792	16.96	24.06	16.98
Observations [a]	2,880	1,390	5,290	4,330	2,310	8,310
B. By Sex	Parents of Boys	Parents of Girls		Boys	Girls	
	(1)	(2)		(1)	(2)	
Expansion	0.047**	0.022		-0.207	-0.467**	
	(0.014)	(0.021)		(0.168)	(0.171)	
Mean DV	0.815	0.844		16.99	16.76	
Observations [a]	5,550	5,210		8,670	8,170	
C. By Income	Below Median Income	Above Median Income		Below Median Income	Above Median Income	
	(1)	(2)		(1)	(2)	
Expansion	0.076***	-0.010		-0.361*	-0.244	
	(0.020)	(0.021)		(0.169)	(0.204)	
Mean DV	0.790	0.868		16.98	16.77	
Observations [a]	5,370	5,380		8,450	8,340	

Notes: Each column of each panel corresponds to a different OLS regression model. Each model includes wave and child fixed effects and sampling weights. Expansion represents β_1 from equation (1), and measures the average effect of the Medicaid expansions after it took place. Heteroscedasticity-robust standard errors, in parentheses, are clustered at the state level.
[a] Sample sizes (in child-years) are rounded to the nearest 10 as per dataset guidelines.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S4. Heterogenous Effects on Primary Outcomes Among Low-Income Households (< 138% FPL)

	C. Child Health			**D. Child Health Utilization**		
A. By Race/Ethnicity	White	Black	Hispanic	White	Black	Hispanic
	(1)	(2)	(3)	(1)	(2)	(3)
Expansion	0.001	0.006	-0.0138	0.022	-0.035	0.031
	(0.012)	(0.014)	(0.0229)	(0.025)	(0.033)	(0.025)
Mean DV	0.974	0.930	0.919	0.940	0.956	0.919
Observations [a]	4130	2,030	7,450	2,970	1,470	5,580
B. By Sex	Boys	Girls		Boys	Girls	
	(1)	(2)		(1)	(2)	
Expansion	-0.017	0.011		-0.012	0.036	
	(0.013)	(0.014)		(0.022)	(0.026)	
Mean DV	0.925	0.959		0.931	0.931	
Observations [a]	7,890	7,410		5,780	5,390	
C. By Income	Below Median Income	Above Median Income		Below Median Income	Above Median Income	
	(1)	(2)		(1)	(2)	
Expansion	-0.017	0.006		0.037	-0.014	
	(0.014)	(0.012)		(0.022)	(0.028)	
Mean DV	0.926	0.958		0.920	0.941	
Observations [a]	7,650	7,640		5,600	5,600	

Notes: Each column of each panel corresponds to a different OLS regression model. Each model includes wave and child fixed effects and sampling weights. Expansion represents β_1 from equation (1), and measures the average effect of the Medicaid expansions after it took place. Heteroscedasticity-robust standard errors, in parentheses, are clustered at the state level.
[a] Sample sizes (in child-years) are rounded to the nearest 10 as per dataset guidelines.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S5. Pre-ACA Parental Income Eligibility Thresholds (as of 2011) for Expansion States included in ECLS-K Data, % of FPL

ARIZONA	106	NEW JERSEY	200
ARKANSAS	17	NEW MEXICO	67
CALIFORNIA	106	NEW YORK	150
COLORADO	106	OHIO	90
CONNECTICUT	191	OREGON	40
HAWAII	100	PENNSYLVANIA	46
ILLINOIS	191	VERMONT	191
INDIANA	36	WASHINGTON	74
IOWA	83	WEST VIRGINIA	33
MARYLAND	116	WISCONSIN	200
MASSACHUSETTS	133		
MICHIGAN	64		
MINNESOTA	215		
MONTANA	56		
NEVADA	88		
NEW HAMPSHIRE	49		

Source: Data come from Kaiser Family Foundation, "Medicaid Income Eligibility Limits for Parents, 2002-2020." https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-parents/

Table S6. Alternative Outcome Coding Among Low-Income Households (< 138% FPL)

A. Parent Health	Overall Health (Continuous 1-5)	Overall Health (Very Good/Excellent = 1)				
	(1)	(2)				
Expansion	-0.0742*	0.017				
	(0.0344)	(0.018)				
Mean DV	2.494	0.77				
Observations [a]	10,760	10,760				
C. Child Health	Overall Health (Continuous 1-5)	Overall Health (Very Good/Excellent = 1)	BMI Z-Score (Using Age-Sex-Specific CDC Growth Charts)	BMI Z-Score Based Overweight Indicator (Using Age-Sex-Specific CDC Growth Charts)	BMI Z-Score Based Obesity Indicator (Using Age-Sex-Specific CDC Growth Charts)	BMI Z-Score Based Underweight Indicator (Using Age-Sex-Specific CDC Growth Charts)
	(1)	(2)	(3)	(4)	(5)	(6)
Expansion	0.050	-0.017	0.024	0.008	-0.010	-0.012
	(0.029)	(0.016)	(0.034)	(0.018)	(0.011)	(0.007)
Mean DV	1.858	0.782	0.641	0.551	0.194	0.023
Observations [a]	15,300	15,300	16,780	16,780	16,780	16,780

Notes: Each column of each panel corresponds to a different OLS regression model. Each model includes wave and child fixed effects and sampling weights. Expansion represents β_1 from equation (1), as shown in appendix, and measures the average effect of the Medicaid expansions after it took place. Mean of each dependent variable (DV) provides the within-child average of the DV after controlling for just wave fixed effects. Heteroscedasticity-robust standard errors, in parentheses, are clustered at the state level. [a] Sample sizes (in child-years) are rounded to the nearest 10 as per dataset guidelines. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S7. Additional Robustness Checks

A. Parent Health	**Overall Health**		
	Less than 100% FPL	Parents with less-than college education	No Individual Fixed Effects (Less than 138% FPL)
Expansion	0.030*	0.026**	0.043***
	(0.0113)	(0.008)	(0.010)
Mean of DV	0.806	0.882	0.835
Time Varying State Covariates	No	No	No
Observations [a]	7,860	20,770	10,760
R-squared (within-child)	0.006	0.003	0.024

B. Child Health Utilization	**Doctor Visits**		
	Less than 100% FPL	Parents with less-than college education	No Individual Fixed Effects (Less than 138% FPL)
Expansion	0.013	0.003	-0.002
	(0.014)	(0.012)	(0.013)
Mean of DV	0.93	0.92	0.934
Time Varying State Covariates	No	No	No
Observations [a]	8,190	21,670	11,160
R-squared (within-child)	0.010	0.010	0.035

C. Child Health	**Overall Health**			**Child BMI**		
	Less than 100% FPL	Parents with less-than college education	No Individual Fixed Effects (Less than 138% FPL)	Less than 100% FPL	Parents with less-than college education	No Individual Fixed Effects (Less than 138% FPL)
Expansion	-0.014	-0.003	-0.003	-0.501***	-0.341**	-0.443**
	(0.008)	(0.004)	(0.009)	(0.140)	(0.113)	(0.131)
Mean of DV	0.93	0.96	0.875	16.94	16.76	16.23
Time Varying State Covariates	No	No	No	No	No	No
Observations [a]	11,210	29,780	15,300	12,410	31,940	16,840
R-squared (within-child)	0.003	0.001	0.010	0.465	0.475	0.160

Notes: Each column of each panel corresponds to a different OLS regression model. Each model includes wave and child fixed effects and sampling weights. Expansion represents β from equation (2), as shown in appendix, and measures the average effect of the Medicaid expansions after it took place. Mean of each dependent variable (DV) provides the within-child average of the DV after controlling for just wave fixed effects. Heteroscedasticity-robust standard errors, in parentheses, are clustered at the state level. a Sample sizes (in child-years) are rounded to the nearest 10 as per dataset guidelines. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S8. Impact of the ACA Medicaid Expansion on Health Outcomes Excluding Late Expansion States

A. Parent Health	Overall Health	
	(1)	
Expansion	0.020	
	(0.018)	
Mean of DV	0.72	
Time Varying State Covariates	Yes	
Observations [a]	7,710	
R-squared (within-child)	0.005	
B. Child Health Utilization	Doctor Visits	
	(1)	
Expansion	0.002	
	(0.019)	
Mean of DV	0.92	
Time Varying State Covariates	Yes	
Observations [a]	8,000	
R-squared (within-child)	0.013	
C. Child Health	Overall Health	BMI
	(1)	(2)
Expansion	0.0002	-0.337*
	(0.011)	(0.146)
Mean of DV	0.81	0.47
Time Varying State Covariates	Yes	Yes
Observations [a]	11,370	15,600
R-squared (within-child)	0.013	0.002

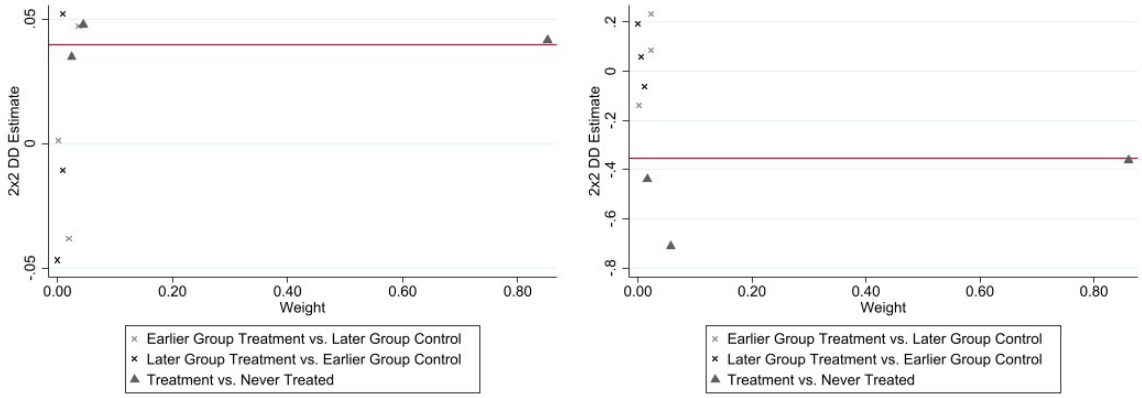
Notes: Each column of each panel corresponds to a different OLS regression model. Each model includes wave and child fixed effects, state-level covariates, and sampling weights. Expansion represents β_1 from equation (1) as shown in appendix, estimated for sub-sample of lower-income (< 138% FPL) households after the exclusion of the late expansion states. As before, the coefficient measures the average effect of the Medicaid expansions after it took place. Mean of each dependent variable (DV) provides the within-child average of the DV after controlling for just wave fixed effects. Heteroscedasticity-robust standard errors, in parentheses, are clustered at the state level.

[a] Sample sizes (in child-years) are rounded to the nearest 10 as per dataset guidelines.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure S1. Goodman-Bacon Decomposition

Parent Health **Child Health (BMI)**



Notes: Figure displays estimates and weights from the Goodman-Bacon decomposition[7] implemented with the aid of the user-written Stata command "bacondecomp".[8] Red horizontal line shows the combined DD estimate, and x's and triangles represent the various of 2 x 2 DD estimates scattered with weights for each of those comparisons shown on the X-axis. Because the decomposition implementation in STATA does not allow sampling weights or time-varying covariates, the combined DD estimates (0.04 for parent health and -0.35 for child BMI shown in the figure) are slightly different from our preferred specification in Table 2. Also, we imputed the median values for parent health when values were missing and for both parent health and child BMI we create fully balanced panels to allow decomposition to execute the full comparisons. Finally, summing the weights on the timing terms (x's) show that only 8 (7) percent of the DD estimate on parent health (child BMI) comes from timing variation.