**ONLINE SUPPLEMENTARY MATERIAL**

**Supplemental File 1**

Initialization of the Environment and Population

We sought to develop a synthetic but realistic population with characteristics similar to Philadelphia’s children and adolescents. We used data regarding Philadelphia schools from the Elementary and Secondary Information System (ELSI) of the National Center for Education Statistics, as well as tract-level data from the 2010 to 2014 American Community Survey (ACS). Specifically, ELSI contains data regarding the distribution of grade, race/ethnicity, and gender of the student population within all public and private schools in Philadelphia. Based on these distributions, the ABM creates a population of children within each of Philadelphia’s schools with the total number of children equivalent to 20% of the full student enrollment of the school. Each child is assigned a grade, age (12th graders are 17, 11th graders are 16, etc.), gender, and race/ethnicity based on distributions in ELSI. Next, the ABM assigns each child to a household generated within a randomly-selected location inside of their school’s catchment area. Finally, the ABM assigns relevant household socio-demographic characteristics based on census tract-level data from the 2010-2014 American Community Survey. These characteristics include parents’ age, education, and work status, as well as household income.

As each simulation runs, individual agents age and advance through school. Specifically, every 365 model time steps all children advance to the next age and grade level. Children ‘age out’ of the model once they advance past 12th grade and are replaced by a child of pre-kindergarten age (i.e., four years old). The result of this process is that at any given point, the model only includes school-aged children, however after the first 365 time steps there are at least some agents in the population that were not present upon initialization of the model.

Preschool Attendance

*Quality Pre-Kindergarten Landscape in Philadelphia*

Pre-kindergarten quality has a large impact on children’s later educational achievement (1). In the ABM we differentiate between different types of pre-kindergarten programs. We assign each child to either attend or not attend a ‘quality’ pre-kindergarten program based on their household income and the availability of publicly-funded quality preschool slots in Philadelphia. In brief, pre-kindergarten quality in Pennsylvania is assessed via the Quality Rating and Improvement System (QRIS), Keystone STARS. STARS is a ‘continuous quality improvement program that rates early childhood education programs’ (2). Quality programs are those who achieve a level three or four certification in the STARS program.

In Philadelphia, 76% of the 42,514 three- and four-year-olds live in households with income ≤300% FPL, and are thus eligible for at least one publicly-funded pre-kindergarten program (2). However, there are not enough publicly-funded quality pre-kindergarten slots to meet this demand and, as a result, only 47% of those eligible are actually enrolled in publicly-funded pre-kindergarten. Public spots are divided between federally- and state-funded Head Start programs (54% of public slots), Pennsylvania’s Pre-K Counts program (25%), and the Child Care Works program (21%). Head Start and Pre-K Counts provide funding on a per-child basis to pre-kindergarten providers. All Head Start and Pre-K Counts providers are considered to be quality programs. In contrast, Child Care Works is a federal-state partnership that provides a subsidy for families to choose their own pre-kindergarten provider, with no restrictions on quality (2). In Philadelphia, it is estimated that 20% of Child Care Works slots are in quality programs. Each program has income eligibility requirements: Head Start is available to children in households with income ≤100% FPL, Pre-K Counts is for those with income ≤300% FPL, and Child Care Works is available for those ≤200% FPL.

*Pre-Kindergarten Assignment*

In the ABM, we implement a process that assigns children to one of six quality pre-kindergarten statuses: 1) does not attend quality pre-kindergarten, 2) attends a quality private pre-kindergarten program, 3) attends Head Start, 4) attends Pre-K Counts, 5) attends quality pre-kindergarten via the Child Care Works program, 6) attends a quality pre-kindergarten as part of the ‘universal’ program implemented with Sugary Drink Tax revenue. First, we assign children in households with income >300% FPL to attend a quality private program with probability of 0.7; the remainder of these children do not attend a quality program. These children are treated differently than those with income ≤300% FPL because they are not income-eligible for any public programs. Children with income ≤300% FPL are eligible for at least one publicly-funded pre-kindergarten program. In brief, we ‘fill up’ the number of slots for each program by randomly selecting participants from the population of children who meet each program’s eligibility criteria. For instance, there are 8,209 Head Start slots in Philadelphia, which can be allocated to 19.3% of the 42,514 three- and four-year olds in Philadelphia. The ABM calculates the ‘target’ number of slots for each program based on each program’s coverage and the size of the population in the model. Next, the model fills slots by randomly selecting children who meet income eligibility thresholds. For example, to assign Head Start slots, children are selected randomly from households ≤100% FPL until all slots are full. This process repeats for Pre-K Counts and children from households ≤300% FPL, then for Child Care Works and children from households ≤200% FPL. Children with income ≤300% FPL who are not assigned to one of the pre-kindergarten programs are assigned a status of ‘no quality pre-kindergarten.’ As described below, in scenarios that include the universal pre-kindergarten program, we assign children from households ≤300% FPL to additional slots to be created with revenue from the SBT.

Educational Achievement

The ABM simulates children’s educational achievement based on their pre-kindergarten attendance and socio-demographic characteristics including gender, age, race/ethnicity, household income, and parents’ educational attainment. The equation takes the following form:

where is the educational achievement of a given child, is a dummy-coded variable indicating whether the child is male, is a vector of dummy variables indicating race/ethnicity (white, black, Latino), is logged household income, is the educational attainment of the highest-educated parent, is a vector of variables indicating the type of pre-kindergarten program the child attended (none, private high-quality, Head Start, Pre-K Counts, Child Care Works, or Universal SBT) and is a random component. The s represent an intercept and the magnitude of association between a given variable and achievement, respectively.

*Parameter Estimation*

We estimated the relationship between socio-demographic characteristics and achievement directly, using multiple linear regression models and data from the Panel Study of Income Dynamics-Child Development Supplement (PSID-CDS). We used generalized estimating equations (GEE) models with robust standard errors to account for correlations between sibling pairs in the PSID-CDS and incorporated weights developed by the PSID to account for both sampling design and attrition. Since PSID-CDS lacked data on pre-kindergarten program type and quality, we used published estimates from Barnett (2011) to quantify the impact of participation in pre-kindergarten programs of varying quality on children’s educational achievement. Specifically, in the ABM, achievement levels increase by 0.0 SD among children who participate in Head Start, 0.25 among participants in Pre-K Counts or Child Care Works, and 0.50 SD among those who participate in the quality slots recommended as part of the SBT. We also conduct sensitivity analyses to understand how model outcomes are impacted by the value of the parameter related to the effect of attending a quality slot funded by the SBT (see ‘Sensitivity Analyses’ section below). Parameter values used for the main analyses in the manuscript, and their sources, are given in Supplemental Table 1.

Sugar Sweetened Beverage Consumption

We simulate children’s SSB weekly consumption using a two-step process. First, we estimate a ‘target’ SSB consumption level for each child based on their preschool attendance, educational achievement, socio-demographic characteristics, and a random component representing between-person variation in SSB consumption:

where is average weekly SSB consumption of a given child or adolescent and is a between-person residual.

Second, each seven model time steps (i.e., equivalent of one week) the ABM simulates each child’s actual SSB consumption in the previous week based on their target SSB consumption plus a random component that represents within-person ‘week-to-week’ variation in SSB consumption:

Eq. (3)

where is predicted SSB consumption of a given child or adolescent in a specific week, and is the within-person residual that represents week-to-week variation in SSB consumption of that child or adolescent.

In simulation scenarios with the SBT, we adjust the ‘target’ SSB consumption level based on own-price elasticities of sugar-sweetened beverages. In effect, each child or adolescent in the model has a ‘baseline’ SSB consumption level that is calculated before the SBT is implemented. Once the SBT is implemented, this consumption level is adjusted based on the effect associated with the (dichotomous) presence or absence of *any* SBT tax, as well as own-price elasticities of SBT and the excise tax rate (which, depending on the scenario, is either 25% or 50%) (3). Notably, we use strata-specific elasticities based on children’s poverty status, based on Sturm (2010). This process is given by the following:

Eq. (4)

where is average soda consumption in the presence of a tax, is the pre-determined average soda consumption before the tax is implemented, is the SBT tax rate, is the poverty strata-specific SSB effect of a one percentage point increase in the amount of the SSB tax rate, and is the strata-specific effect of any tax (i.e., the intercept).

*Parameter Estimation*

To estimate most parameters predicting average soda consumption, we again use data from the PSID-CDS. In brief, the 2007 PSID-CDS asks participants “During the past 7 days, how many times did you drink Soda pop (for example, Coke, Pepsi, or Mountain Dew), sports drinks (for example, Gatorade), or fruit drinks that are not 100% fruit juice (for example, Kool-Aid, Sunny Delight, Hi-C, Fruitopia, or Fruitworks)?” Participants responded using 7 categories, which we convert into a continuous measure of number of drinks per week. We tested models using Poisson, negative binomial, linear, and gamma regression using the Aikake Information criterion (AIC). Based on these results, we use negative binomial regression for final models. As with the models of academic achievement, models of soda consumption accounted for correlated observations between siblings and incorporated weights accounting for sample design and attrition.

We used PSID-CDS for this analysis, rather than other sources of dietary data (e.g., the National Health and Nutrition Examination Survey) because we were specifically interested in the associations between pre-kindergarten attendance and educational achievement, respectively, and SSB consumption. Other data sources of which we are aware lack data regarding these measures of early childhood education. Since the PSID-CDS lacks data regarding pre-kindergarten program quality, in the ABM we estimate the effect of pre-kindergarten attendance on SSB consumption using a dichotomous indicator of pre-kindergarten attendance. Since PSID-CDS lacks data regarding soda taxes in the communities in which participants reside, we use parameters from the published literature.

While several studies have estimated own-price elasticities of demand for sugar sweetened beverages, we use estimates from Sturm et al (2010) regarding the effect of having any differential tax on SSB, as well as the amount of the tax (i.e., percentage point difference between tax on SSB vs other foodstuffs). Our use of estimates from Sturm and colleagues (2010) have several advantages. In contrast to many studies of the own-price elasticity of demand of SSB (4; 5; 6), Sturm and colleagues estimate the effect of taxes from a longitudinal study of children and adolescents combined with state-level data on differential tax rates on SSB. They also estimated SSB elasticities separately among poor children, which aligns with our interest in examining differences in SSB consumption across racial/ethnic and income-based strata. To understand the extent to which our choice of parameters regarding the effect of the tax may drive model outcomes, we employ parameter variation experiments (see ‘Sensitivity Analyses’ section below) using a range of parameters from the literature.

Parameter estimates for calculating SSB consumption, as well as their sources, are given in Supplemental Table 2.

Intervention Scenarios

We use the ABM to implement a 2x3 factorial design to examine SSB consumption under a total of six scenarios representing all combinations of the following: 1) no excise tax on SSB, a tax of 25%, or a tax of 50%, and 2) pre-kindergarten intervention or not. The 2x3 factorial design allows us to compare outcomes associated with each intervention scenario against the ‘control’ scenario (i.e., no SBT, no pre-kindergarten intervention).

The 25% tax is the equivalent of the 1.5-cent-per-ounce tax passed in Philadelphia, based on average SSB prices (7; 8). The 50% tax is the equivalent of the originally-proposed three-cent-per-ounce tax. We use own-price elasticity estimates from Sturm et al (2010) to quantify the effect of SSB price changes on weekly SSB consumption among children (3). Notably, we use separate elasticity estimates for children in households with annual income >100% FPL and those with income ≤100% FPL. As reported in Sturm et al (2010), the elasticity estimates suggest that children and adolescents in poor households are more sensitive to price changes in SSB than those in non-poor households.

The pre-kindergarten intervention is based on the recommendations issued by the Philadelphia Commission on Universal Pre-Kindergarten. Specifically, the Commission recommended creation of an additional 10,000 quality pre-kindergarten slots for children from households ≤300% FPL. Of these, 6,500 slots would be funded with SBT revenue and 3,500 with funding from other public sources. In the ABM, we create an additional number of slots proportionate to the 10,000 recommended by the Commission. Specifically, 10,000 slots can cover 22.3% of all 3- and 4-year olds in Philadelphia. Thus, in the ABM, we create an additional number of slots in the same proportion relative to the size of the 3- and 4-year old population.

As previously described, we assume that participation in a pre-kindergarten program subsidized via the SBT will improve children’s educational achievement scores by 0.50 SD. We consider this a realistically-optimistic scenario based on effect sizes in the literature (1; 9). If the program is implemented as recommended, there is reason to believe that the pre-kindergarten program implemented as part of the SBT will exceed the quality of existing, publicly-funded pre-kindergarten programs in Philadelphia. Specifically, the Commission issued the following recommendations for the program: 1) all additional slots should include providers that are certified as 3- and 4-STAR programs, 2) the program should enable children to participate all day (≥8 hours/day) throughout the year (≥260 days/year), 3) programs should use curricula approved by the Pennsylvania Office of Child Development and Early Learning and that align with the state early learning standards, 4) programs should participate in ongoing assessments and receive other resources to promote quality improvement, 5) receipt of City (i.e., SBT) funding should be contingent on compliance with salary scales that greatly increase the wages of teachers at different levels (e.g., average compensation for a lead teach would increase from $27,000/year currently to $50,000/year), and 6) teachers should be supported to obtain additional education and certification in support of implementing quality pre-kindergarten.

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| **Supplemental Table 1: Parameters and sources for predicting children's educational achievement (in standard deviations)** | | |
|  | **b** | **Source** |
|  |  |  |
| **Male** | 0.02 | PSID-CDS |
| **Age (yr)** | -0.06 | PSID-CDS |
| **Race/Ethnicity** |  | PSID-CDS |
| White | Ref. |  |
| Latino | 0.02 |  |
| Black | -0.79 |  |
| Other | 0.05 |  |
| **Parental Education (yr)** | 0.14 | PSID-CDS |
| **Log Income** | 0.05 | PSID-CDS |
| **Pre-Kindergarten** |  | Barnett (2011) |
| None | Ref. |  |
| Private Quality | 0.50 |  |
| Head Start | 0.00 |  |
| Pre-K Counts | 0.25 |  |
| Soda Tax | 0.50 |  |
| **Intercept** | 7.04 | PSID-CDS |
| **SD of Residuals** | 0.82 |  |

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| **Supplemental Table 2: Parameters and sources for predicting children's sugar-sweetened beverage consumption** | | |
|  | **b** | **Source** | |
| *Negative Binomial Model* |  |  | |
| **Male** | 0.16 | PSID-CDS | |
| **Age (yr)** | 0.01 | PSID-CDS | |
| **Race/Ethnicity** |  | PSID-CDS | |
| White | Ref. |  | |
| Latino | -0.06 |  | |
| Black | 0.05 |  | |
| Other | -0.43 |  | |
| **Parental Education (yr)** | -0.05 | PSID-CDS | |
| **Log Income** | 0.04 | PSID-CDS | |
| **Pre-Kindergarten** | -0.04 | PSID-CDS | |
| **Achievement (SD)** | -0.10 |  | |
| **Intercept** | 3.36 | PSID-CDS | |
| *Residuals* |  |  | |
|  | 8.52 | PSID-CDS | |
|  | 2.50 | Arbitrary | |
| *Presence and Amount of SSB Tax* |  | Sturm et al (2010) | |
| | child = poor | -.142 |  | |
| | child = poor | -.811 |  | |
| | child = non-poor | -.004 |  | |
| | child = non-poor | -.006 |  | |

**Supplemental Table 3: Studies reporting standardized effect sizes of participation in pre-kindergarten programs**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Study | Program | Description | Duration | Effect Size |
| Schweinhart (2005) | Perry Preschool | Small-scale intervention among low-income African American children in Michigan | 2.5 hours per day, 5 days per week, 30 weeks per year | 0.33 SD on reading and math at age 14 |
| Ramey (2010) | Abecedarian | Small-scale intervention among at-risk children from families in Orange County, North Carolina | Full day, year round | 0.50 SD on reading and math from ages 8 to 21 |
| Camilli et al. (2010) | Meta-analysis of 123 center-based ECE programs in the U.S. | Varied | Varied | 0.23 SD on cognitive achievement for all programs; projected effect size of 0.63 SD at child age 5-10 years with more direct and individualized instruction and fewer other services |
| Puma et al. (2010) | Head Start | Locally-administered federal ECE program for low-income households | Varies from 4 hours per day to full day, 9-months or full year | No significant effects on cognitive achievement at first grade (i.e., 0 SD) |

**Supplemental Table 4: Studies reporting own-price elasticities and effects of taxation on sugar sweetened beverage consumption**

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| --- | --- | --- | --- |
| Study | Description | Elasticity Estimate Based on Tax Rate or SSB Price | Findings |
| Sturm et al. (2010) | Examined associations between existence and rate of SSB tax and SSB consumption among a national sample of fifth graders. Separately estimated effects for all children and low-income children | Tax rate | All children  Soda tax amount: -.004;  Soda tax indicator: -.006  Low-income children  Soda tax amount: -.142;  Soda tax indicator: -.811 |
| Fletcher et al (2010) | Examined associations between existence and rate of SSB tax and SSB consumption among a national sample of children and adolescents | Tax rate | Change in probability of any consumption of SSB: -.005 per one percentage point increase in tax rate  Change in calories from soft drinks: -5.92 kCal (-5.1%) per one percentage point increase in tax rate |
| Andreyeva et al. (2010) | Pooled effect size estimates from 14 U.S.-based studies of price elasticity of soft drinks, conducted primarily among adults. | SSB price | Own-price elasticity: -0.79 (95% CI: 0.33-1.24) |
| Smith et al (2010) | Assessed household-level own-price and cross-price elasticities of demand based on beverage budget share of SSBs and beverage prices reported in a national longitudinal survey of household food purchases | SSB price | Own-price elasticity: -1.2 |