Urban Afforestation and Infant Health: Evidence from MillionTreesNYC

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Abstract

This paper examines the impact of urban afforestation on infant health outcomes by exploiting a quasi-experimental setting where one million new trees were planted in New York City (NYC), but not in counties surrounding NYC over the same time period. Using a complete natality record of NYC and surrounding counties over 2004-2015 and employing both the synthetic control method and difference-in-differences, we find that an approximately 10% increase in urban forest cover decreased prematurity and low birth weight among mothers in NYC by 2.1% and 0.24%, respectively, relative to similar mothers outside of NYC. The low birth weight finding is equivalent to getting a mother smoking two cigarettes a day during pregnancy to quit. An internal validity test suggests that changes in the composition of NYC mothers cannot explain the observed effects. Additionally, we find evidence that declines in $PM_{2.5}$ concentrations are a potential causal mechanism. Results suggest that urban afforestation may be able to complement existing policies aimed at improving infant health.

Keywords: infant health; urban afforestation; synthetic control method; difference-in-differences; New York City; trees

JEL Codes: H23; I18; J13; Q51; Q53; Q58

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1. Introduction

Forests and trees provide beneficial ecosystem services. For example, trees remove pollutants from the air. It is estimated that urban trees in the US reduce air pollution by more than 711,000 metric tons per year, valued at $3.8 billion in avoided damages (Nowak et al., 2006). Trees also lower ambient outside temperatures and create shade, acting like natural cooling mechanisms, reducing the urban “heat island effect” and decreasing summertime electricity use by 1.5-5.2% (Donovan & Butry, 2009). Trees are also an important source of recreation value and can stimulate people to be physically active. Correlational evidence suggests that people living in areas with more greenspace and tree cover tend to be more active outdoors (Hansmann et al., 2007) and exercise more (Coombes et al., 2010). Property values are also higher in urban areas with nearby trees (Sander et al., 2010). However, despite an extensive literature on the many benefits of tree cover, their human health externalities are largely unknown, particularly the empirical health benefits of afforestation.

The existing literature on trees and human health, nascent as it is, has tended to study correlations between proximal forest canopy, greenspace, and health outcomes (e.g., Dadvand et al., 2014; Lovasi et al., 2013; Donovan et al., 2011), or has exploited instances of forest destruction to study the tree-human health relationship (e.g., Berazneva & Byker, 2017; Jones & McDermott, 2017; Garg, 2016). Less understood are the health impacts of afforestation, particularly in urban areas where more than half the world’s population resides. This is problematic for at least two reasons. First, many urban areas, predominantly in developed countries, are implementing significant afforestation programs to plant millions of new trees (e.g., New York City, Los Angeles, Denver, London, Copenhagen, Auckland). Part of the impetus for such programs are the supposed health impacts that greater urban forest cover provides through reduced air pollution and enhanced outdoor recreation opportunities, among other things. For example, a US Forest Service report on the 2007 Los Angeles afforestation program states that "expanding the urban forest is … integral to enhancing public health programs" and that "the presence of trees in cities provides public health benefits and improves the well-being of those who live, work, and play in cities" (McPherson et al., 2008, pgs. 1 & 41). Similarly, the 2007 New York City afforestation program contained a "Trees for Public Health" component that focused on planting new trees in neighborhoods with high asthma hospitalization rates for children (Campbell et al., 2014). Despite such well-meaning statements and initiatives, there is a lack of credible evidence that planting urban trees do meaningfully improve health, precluding rigorous assessments of many of the public health claims being made. Second, there is a growing body of literature finding that infant and prenatal health is particularly sensitive to changes in environmental quality (e.g., Knittel et al., 2016; Currie & Walker, 2011; Currie, 2009 and see Graff Zivin & Neidell, 2013 for more detail), which in-turn impacts human capital outcomes, long-term earnings potential, and health later in life (Isen et al., 2017; Currie et al., 2014). If urban afforestation (an improvement to environmental quality) has a meaningful effect on infant health, then investments in tree cover could generate positive, long-term spillover effects on schooling attainment, test scores, use of disability programs, and wages. Thus, in this regard, investigating afforestation health externalities has the potential to be highly impactful.

In this paper, we study the infant health externalities of urban afforestation by exploiting a quasi-experiment provided by the MillionTreesNYC program in New York City (NYC) where one million new trees were added to the urban forest canopy from 2007 to 2015. MillionTreesNYC increased the NYC forest canopy by approximately 10% (Grove et al., 2006). We study the effect of the MillionTreesNYC program, and thus sharp increases in urban environmental quality, on the health of infants born to mothers living in NYC relative to similar mothers living in the areas surrounding NYC, but where no large-scale afforestation program occurred over the same period. To develop a credible counterfactual of infant outcomes in the absence of the afforestation program, we employ the synthetic control method of Abadie and Gardeazabal (2003) and Abadie et al. (2010). We additionally use a more traditional difference-in-differences model in order to augment the synthetic control results. A rich, restricted use US CDC National Center for Health Statistics dataset containing millions of individual birth observations in NYC and the surrounding counties is used in the analysis.

Four conclusions arise. First, using the synthetic control method we find that prematurity and low birth weight among mothers in NYC fell by 2.1% and 0.24%, respectively, in the aftermath of the afforestation program. The low birth weight effect is equivalent to getting a mother smoking two cigarettes a day during pregnancy to quit (Currie et al., 2009). This result is robust to several alternative specifications of the model and constructions of the counterfactual. Second, we find no significant effects of the MillionTreesNYC program on the demographic characteristics of mothers in NYC. This suggests that the estimated infant health effects are not due to changes in the composition of NYC mothers. Third, improvements in prematurity and low birth weight are larger among African American mothers relative to other races. Since African American mothers are more likely than other groups to have low birth weight and/or premature babies (Meyer et al., 2010), this result suggests that afforestation may have broader racial health disparities consequences. Finally, we show that decreases in $PM_{2.5}$ pollution concentrations in NYC after the afforestation program may be a potential causal mechanism for the infant health effects observed.

2. Background and Related Literature

To the best of our knowledge, there are no studies that have specifically looked at afforestation and infant health. However, a broader literature has empirically measured the public health impacts of trees. This broader literature can be broken down into: (i) studies using observational data to investigate correlations between status quo tree coverage and health outcomes of interest (e.g., Ulmer et al., 2016; Dadvand et al., 2014; Lovasi et al., 2013; Donovan et al., 2011; Lovasi et al., 2011; Nilsson et al., 2011), and (ii) studies that use data from areas experiencing deforestation or forest loss, sometimes using quasi-experimental techniques (e.g., Berazneva & Byker, 2017; Jones & McDermott, 2017; Garg, 2016; Donovan et al., 2015; Donovan et al., 2013). Results from observational studies suggest that urban tree cover is associated with improved health. For example, Ulmer et al. (2016) found that neighborhood tree cover was related to better overall health status, lower obesity rates, fewer cases of Type 2 diabetes, lower blood pressure, and fewer asthma cases. Though it is unclear if findings from such observational studies are simply the result of healthier individuals sorting themselves into areas with greater tree densities. Economists have tended to study the health impacts of forest loss using more sophisticated models and more credible identification strategies. They have found, for example, that forest loss in developing countries has significantly increased the incidence of malaria (Berazneva & Byker, 2017; Garg, 2016). In the US, Jones and McDermott (2017) found that ash tree loss due to an invasive species was associated with higher cardiovascular and respiratory mortality in affected areas.

While the preponderance of evidence suggests that trees and human health are connected, it is not clear from the extant literature if the act of planting new trees (i.e., afforestation) leads to improvements in health. Moreover, even if afforestation can improve health, are the health effects economically significant? An obvious place to look for evidence is among infants, where previous research has demonstrated that they are especially sensitive to changes in environmental conditions (Currie et al., 2014). There are several possible causal mechanisms that might explain how urban afforestation could influence infant and prenatal health, including through air pollution exposure, extreme temperatures, stress, and exercise/outdoor recreation. We will briefly discuss each potential pathway in-turn. First, urban trees may remove significant amounts of pollutants from the air, lowering air pollution concentrations, and thusly reducing mothers' exposure. Previous research has shown a strong causal connection between trees and air pollution removal (Nowak et al., 2014; Nowak et al., 2006) and a separate relationship between urban air pollution and infant health (Currie & Walker, 2011; Currie et al., 2009). Second, trees can moderate extreme temperature fluctuations by creating shade and altering microclimates. Since extreme temperatures are known to negatively affect health (Deschenes, 2014), afforestation may be able to mitigate negative health impacts to mothers, especially in urban areas where the heat island effect is more pronounced. Third, exposure to trees and greenspace can help reduce stress and improve mental health (Bowler et al., 2010). It has been known for decades that mothers' stress levels and mental health are determinants of low birth weight and infant prematurity (Kramer, 1987). Planting trees in cities may therefore reduce a mother's stress and improve her mental health, thereby affecting birth outcomes. Lastly, tree cover can stimulate people to be more physically active and/or engage in more exercise (Jones, 2016; Hansmann et al., 2007). Moderate exercise during pregnancy is recommended by the American College of Obstetrics and Gynecologists because of its beneficial effects on the mother, fetus, and newborn (Prather et al., 2012). Therefore, it is possible that urban afforestation can lead to improved infant health outcomes by motivating mothers to be more physically active.

To our knowledge, there is only one previous study of infant health and urban tree cover. In it, Donovan et al. (2011) investigated whether greater tree canopy cover (due to existing variations in canopy cover and not as a result of an afforestation program) in Portland, OR was associated with reduced risk of poor birth outcomes. The authors found that areas with 10% higher tree cover within 50m of a house reduced the incidence of low birth weight by a statistically significant 1.42 per 1,000 births, after controlling for mother demographics (Donovan et al., 2011). While the Donovan et al. (2011) study provides the first empirical evidence that trees and infant health are connected, a useful contribution in its own right, there are several advancements made to it in the present paper, which we believe can increase the causal interpretation of results. First, we exploit a natural experiment where urban tree cover in NYC, but not in the surrounding areas, was dramatically increased within a short period of time.[1] Second, we study the health externalities of afforestation and not correlations of unchanging (or marginally changing) tree cover and health. That is, this work can answer, for the first time, "What are the infant health externalities associated with a large urban afforestation program?" Third, great care is taken to construct a credible, data-driven counterfactual of infant health outcomes in NYC. This is a notable improvement in this literature because past studies of birth outcomes and tree cover tend to assume, often without verification, that mothers living in areas with fewer trees have similar characteristics as mothers living in more forested areas. Since tree cover is not randomly assigned, mothers or mothers-to-be with higher incomes or preferences for greater tree cover may sort themselves into areas with larger forest canopies, which, if not

[1] Limited levels of tree plantings in areas surrounding NYC cannot be completely ruled out. Businesses, homeowners, and municipalities will often engage in some tree planting for idiosyncratic reasons. However, there were no large-scale afforestation programs like MillionTreesNYC in areas surrounding NYC and over the same period of time. Furthermore, even if afforestation occurred in areas comprising the counterfactual, it would have the effect of biasing our results against finding an association between trees and infant health, rather than biasing us in favor of finding of an effect.

accounted for, would bias estimates of the infant health effects of tree cover. Lastly, we account for unobservable time trends in birth outcomes in our models to eliminate potential confounders that are unrelated to afforestation. Prior studies in this area will often ignore time trends altogether, which could bias results. For example, improvements in infant health over time might be mistakenly attributed to changes in tree cover, when factors such as increased access to healthcare, reductions in poverty, rising education levels, etc. are driving the observed effect.

3. The MillionTreesNYC Afforestation Program

Announced in October 2007 by then Mayor Michael Bloomberg, actress Bette Midler, and US Forest Service Chief Abigail Kimbell, MillionTreesNYC was a campaign to plant one million new trees across all five NYC boroughs (i.e., all of NYC) over a decade. Implemented by the City of New York Department of Parks and Recreation and the New York Restoration Project, the program was under the umbrella of the city's larger sustainability plan, PlaNYC2030, which was designed to make NYC "greener and greater" (Campbell et al., 2014). The afforestation program was completed two years ahead of schedule in late-2015. A majority of the trees planted were on public streets and in city parks, but approximately 3% were planted on housing authority properties, private yards, and at K-12 schools (Campbell et al., 2014).

Planting locations were not randomly assigned and there are noticeable concentrations in upper-Manhattan and the lower-Bronx, though with wide distribution across the five boroughs (Figure 1). There are several reasons why placement was not random. First, the city prioritized afforestation in areas with low existing street tree stocks and those lacking greenspaces. Second, as part of the "Trees for Public Health" component of the program, the city focused on six neighborhoods with few street trees and high asthma hospitalization rates for children.[2] Lastly,

[2] These were: Hunts Point, Bronx; Morrisania, Bronx; East New York, Brooklyn; East Harlem, Manhattan; Rockaways, Queens; and Stapleton, Staten Island.

residents could ask to have a tree planted near where they lived by either requesting that a street tree be planted on their block or by entering a tree giveaway contest, where winners would receive a free tree to be planted at a location of their choosing (e.g., private property, school, community garden).

[Figure 1]

To some degree then, afforestation was targeted in locales where we might expect the marginal benefits of trees to be highest (e.g., areas with fewer existing trees, higher health risks, more public housing, etc.). For purposes of identification, this would tend to have the effect of increasing the likelihood of observing a significant improvement in health outcomes in the aftermath of the program, if in fact a tree-health connection exists. While we do not believe that this invalidates the empirical design or the usefulness of this exercise (we are still exploiting a policy change that created meaningful changes in urban environmental quality), we do believe that in the absence of a randomized trial, our results have to be interpreted carefully. In particular, any observed impacts of the MillionTreesNYC program on infant health could be reasonably driven by strategic, targeted afforestation in select portions of the city, and not by a simple increase in the NYC forest canopy in any random area. In other words, the results should not be widely interpreted as evidence for or against infant health externalities of a generic afforestation program, but should be interpreted as causally-consistent evidence of birth outcome externalities associated with afforestation focused on areas where the marginal benefits of tree cover may be greatest. For this reason, our findings may not necessarily be generalizable to other urban areas or afforestation contexts, especially if tree planting locations in these other contexts were selected by convenience and not by their potential marginal benefits. However, given recommendations by US Forest Service researchers and others to select planting locations that maximize social benefits of trees (e.g., Morani et al., 2011), coupled with evidence that so-called "priority planting" is becoming more common (e.g., Bodnaruk et al., 2017), our results may be more generalizable than they first appear. To the extent that more and more cities follow New York City's lead in setting priority planting areas as part of afforestation projects, then the findings from the present research become more consequential.

4. Data

The primary source of data are US CDC National Center for Health Statistics (NCHS) Vital Statistics Natality records from New York, Connecticut, New Jersey, and Pennsylvania for 2004-2015, the most recent year available at the time of data collection. Natality records provide a rich source of data on every birth occurring in these four states over this time period, including information on both mother and child characteristics. We use the restricted access files that provide county of residence and county of birth information. Following previous research on infant health and environmental quality (e.g., Currie & Walker, 2011; Donovan et al., 2011), we focus on prematurity (defined as a birth that occurs before the 37th week of pregnancy) and low birth weight (defined as infants weighing less than 2500 grams at birth).

Mothers living in one of five counties that comprise NYC (Manhattan County, Bronx County, Queens County, Kings County, and Richmond County), and hence are in areas where trees were planted as part of the MillionTreesNYC program, are considered to be in the treatment group. Given that individual CDC natality records are geocoded at the county level, we are unable to spatially match individual outcomes to individual tree plantings. However, because NYC is densely populated and highly urbanized, and because afforestation occurred throughout every NYC borough, it is reasonable to assume that a given mother would not be living far from a newly planted tree(s) or from a city park or greenspace where trees were added as part of the program. Moreover, while some of the effects of tree cover are highly local (e.g., recreation, stress), others are less so and can span larger distances, such as across the entire city (e.g., air pollution changes, extreme temperatures) – and see Jones and McDermott (2017) for an empirical example of tree canopy impacts on county level air quality. Hence, there is a high likelihood, especially based on our conversations with urban foresters in NYC, that most New Yorkers (including mothers and mothers-to-be) have the potential to experience some health altering benefit of the forest canopy increase.[3]

The counterfactual or control group is constructed using the synthetic control method (Abadie & Gardeazabal, 2003) as described in the next section. The feasible pool or "donor pool" of mothers from which the synthetic control is constructed consists of the universe of mothers living in non-NYC counties with a population centroid within 200km of the NYC population centroid. There are 54 counties that are within this distance and they have a combined 2010 US Census population of 20,849,196. In the robustness checks, we consider alternative specifications of the feasible pool, including using a 100km cutoff, dropping NYC border counties, and keeping only the 20 highest population counties in New York, New Jersey, Connecticut, and Pennsylvania. We exclude from the feasible pool the two counties in Long Island, NY because prevailing west-to-east wind patterns may lead to air quality changes in these counties if the afforestation program lowered air pollution concentrations.[4] We note that no other urban areas in the feasible pool and over the same time period experienced a large-scale afforestation program.

[3] We would actually expect that assigning treatment status at the county level would reduce the likelihood of observing a significant association between afforestation and infant health. This is because we are capturing health outcomes from a mix of mothers living very near newly planted trees in the county (where effects would be expected to be largest) and mothers living further away from the new tree cover (where the effects may be less significant). If in fact effects are largely spatially driven, then, if anything, our results would be downward biased by assigning treatment at the county level compared to matching individual tree plantings to individual mothers.
[4] In one of the robustness checks, the Long Island counties are included in the feasible pool.

Summary statistics of the infant health outcome variables of interest and the mother and child characteristics that we include in all models are shown in Table 1, categorized by distance from NYC. Panel A shows the means and standard deviations for the synthetic control sample, where a county level average of all individual observations has been taken. Here, NYC mothers are more likely than mothers residing in counties 0-200km or 0-100km away to experience low birth weight and prematurity. 8.6% of births in NYC were low birth weight and 11.9% of NYC births were premature. NYC mothers are also more likely to be Hispanic or African American compared to mothers in the feasible pool. We also observe lower educational attainment and higher rates of high school dropouts among NYC mothers relative to the feasible pools. However, average rates of smoking during pregnancy, probability of being a teenage mother, and likelihood of having multiple births are either similar or slightly lower in NYC relative to proximal counties. Panel B reports means and standard deviations of the individual observations when the data are not averaged at the county level. The means are nearly identical to these in Panel A, demonstrating that aggregating the data does not alter the averages in a significant way. However, in the empirical section, we consider models of county averaged natality data (i.e., the synthetic control method) and models using individual outcome data (i.e., a difference-in-differences model). Results will be shown to be similar across data specifications.

[Table 1]

5. Econometric Design

To estimate the impact of the MillionTreesNYC program on infant health outcomes, we need to identify the counterfactual path of birth outcomes in NYC in the absence of the afforestation program. To satisfy the common trends assumption necessary for a difference-in-differences (DID) design, the counterfactual must credibly mimic NYC growth rates and trends in the years before MillionTreesNYC. Several approaches exist for constructing such a counterfactual. One approach would be to select mothers living in counties proximally located to NYC that are similar in terms of birth outcomes and demographic characteristics. There are several concerns that we have with this approach in the current context. First, it is inherently subjective on the part of the researcher. NYC is a rather unlike other urban areas in the US and has unique economic and socio-demographic characteristics. It would be challenging to find mothers in another county or group of counties that, unweighted, resembled mothers in NYC. Additionally, it would be difficult, in our opinion, to defensibly justify one selection of control counties over another given NYC's uniqueness. Second, and perhaps more importantly, infant health outcomes and characteristics of mothers living in counties surrounding NYC are trending differently than NYC in the years leading up to the program. Prematurity and low birth weight are declining in NYC during the pre-treatment period, but in several of the surrounding counties, these outcomes are either increasing or relatively fixed over this period, leading to overall differences in pre-treatment trends (see Appendix A). Hence, a simple selection of mothers in adjacent-to-NYC counties would not produce a credible counterfactual because the control would not only reflect the impact of MillionTreesNYC, but also other pre-treatment differences which affected subsequent birth outcomes.

The synthetic control method of Abadie & Gardeazabal (2003) and Abadie et al. (2010) provides an alternative, more sophisticated, data-driven approach for constructing the counterfactual. Rather than arbitrarily selecting which mothers are in the control (and which are not), the synthetic control method uses an algorithm to rigorously select combinations of control units from a feasible pool of observations such that the treated and "synthetic" control have common trends on observable characteristics during the pre-treatment period. This approach builds on "difference-in-differences estimation, but use[s] systematically more attractive comparisons" by moving "away from using a single control unit or simple average of control units" to using "a weighted average of the set of controls" (Athey & Imbens, 2017, p.9). In the present context, this is an improvement on traditional approaches that rely on arbitrary selections of control units because the synthetic control is not just any weighted combination of control units, but is a precise, data-driven weighting of control units such that pre-treatment differences in observable characteristics between the treated and the synthetic control are minimized, thus satisfying the common trends assumption that is key to a DID design. Indeed, in their recent review of the causal inference literature in the *Journal of Economic Perspectives*, Athey and Imbens (2017) called the synthetic control method "arguably the most important innovation in the policy evaluation literature in the last 15 years." Not surprisingly, the method has been employed widely by economists (e.g., Adhikari et al., 2016; Kreif et al., 2016; Bohn et al., 2014; Billmeier & Nannicini, 2013; Cavallo et al., 2013).

We use the synthetic control method to construct "synthetic NYC", a counterfactual of infant health outcomes based on weighting county level averaged natality records from a feasible pool of the 54 counties located within 200km of NYC. Hence, for each variable, the feasible pool consists of 54 observations per year, or one observation per county-year. Synthetic NYC is weighted to resemble NYC infant health trends and other observable characteristics of NYC prior to the afforestation program (as described below).

Let J be the number of available control counties and define the $J \times 1$ weighting vector $W = (w_1, \dots, w_J)'$ such that $\sum_{j=1}^{J} w_j = 1$ and $w_j \geq 0$ for $j = (1, \dots, J)$. Each scalar w_j represents the nonnegative weight placed on the j^{th} county in synthetic NYC. Let H_0 be a $K \times 1$ vector of K birth outcomes and mother characteristics covariates for NYC prior to the start of the afforestation program. Let H_1 be a $K \times J$ matrix of comparable data vectors for each of the J counties in the feasible pool. Following Abadie and Gardeazabal (2003), the vector of weights W^* is chosen to minimize,

$$W^* = \arg\min_{W} \ (H_0 - H_1 W)' V (H_0 - H_1 W)$$

$$s.t. \tag{1}$$

$$w_j \geq 0, \quad \sum_{j=1}^{J} w_j = 1 \quad for \quad j = (1, \dots, J)$$

where V is a positive-definite matrix whose diagonal elements reflect the relative importance of the variables in H_0 and H_1.[5] Variables in H_0 and H_1 include pre-treatment infant health outcomes, Hispanic mother, African American mother, mother's educational attainment, mother is a high school dropout, mother smoked during pregnancy, teenage mother, birth order, whether the birth was a multiple birth, and sex of the child. Minimizations are performed separately for low birth weight and prematurity and the resulting weighting vectors are provided in Appendix B.

To compare NYC and synthetic NYC using a DID design, we calculate the following DID estimator following Bohn et al. (2014),

$$DID_{NYC} = \left(Health_{post}^{NYC} - Health_{post}^{synthNYC}\right) - \left(Health_{pre}^{NYC} - Health_{pre}^{synthNYC}\right) \tag{2}$$

where $Health_{post}$ is the mean infant health outcome after MillionTreesNYC and $Health_{pre}$ is the mean outcome during the pre-treatment period. A finding of $DID_{NYC} > 0$ ($DID_{NYC} < 0$) would be evidence that low birth weight and prematurity increased (decreased) after the afforestation program.

[5] Abadie and Gardeazabal (2003) also suggest an alternative approach where the synthetic control is constructed based solely on pre-treatment trends in the outcome variable(s) of interest, thus ignoring all socio-demographic covariates. Our results from this approach are very similar to results when the covariates are included, consistent with the findings in Bohn et al. (2014).

To estimate uncertainty around DID_{NYC}, placebo or falsification tests are used (Abadie et al., 2010). In the falsification tests, the synthetic control method is applied to every single unit in the feasible pool as if it had undergone an urban afforestation program. DID_{NYC} is then compared to the distribution of the placebo DID estimates (DID_{PL}) obtained from each falsification test. A two-sided *p*-value can be obtained as (Galiani & Quistorff, 2016),

$$p\text{-value} = \Pr(|DID^{PL}| \geq |DID^{NYC}|) = \frac{\sum 1\left(\left|DID_j^{PL}\right| \geq \left|DID^{NYC}\right|\right)}{J} \tag{3}$$

where DID^{PL} is the distribution of placebo DID estimates averaged over the post-treatment period, DID^{NYC} is the estimated average DID effect for NYC from equation (2), and DID_j^{PL} is the j^{th} placebo county average DID estimate for $j = (1, \ldots, J)$. Following Abadie et al. (2010), we weight each DID_j^{PL} by the pre-treatment root mean squared prediction error.[6]

The previously described synthetic control method is used to construct a data-driven counterfactual to NYC using county level averages of birth outcomes and mother characteristics. Using equations (2) and (3), we can empirically assess the impact of MillionTreesNYC on NYC infant health using a DID design, and we will show the findings from this method in the results section below. However, we also wish to take advantage of the rich, individual-level data we have available to us using a more traditional DID approach. Therefore, we additionally estimate a fixed effects regression model that employs the weights generated by the synthetic control method to re-weight the contribution of each individual observation such that the cumulative weight associated with the observations from a county matches the synthetic weights, following a similar approach in Bohn et al. (2014). This will result in a weighted counterfactual of

[6] This has the effect of giving more weight to placebo units with good pre-treatment match to NYC. Placebo units with poor fit prior to treatment do not provide credible information to measure the relative rarity of estimating a large post-treatment effect for a unit that was well-fitted prior to treatment (Abadie et al., 2010).

individual outcomes to be compared to observed individual birth outcomes in NYC. The model takes the following form,

$$Outcome_{ict} = \alpha + \beta_1 Tree_c + \beta_2 After_t + \beta_3 (Tree \times After)_{ct} + X'_{it}\beta_4 + Year_t + \varepsilon_{ict} \qquad (4)$$

where $Outcome_{ict}$ is the birth outcome (low birth weight or prematurity) for mother i living in county c at year t, $Tree_c$ is an indicator equal to one if the county implemented an urban afforestation program, $After_t$ is an indicator equal to one in the years after the program was implemented, X'_{it} is the same set of mother and birth characteristics previously described, $Year_t$ is the year fixed effect, and ε_{ict} is the idiosyncratic error term. The year fixed effects will control for unobservable time heterogeneity, such as annual shocks in infant health outcomes. The DID estimator, β_3, is the coefficient on the interaction between $Tree$ and $After$. Standard errors will be clustered by county and year. Results from estimating equation (4) will be presented in addition to DID results from the synthetic control method and associated falsification tests.

Before moving to the results, a note needs to be made regarding the definition of the treatment time period. As previously stated, MillionTreesNYC was announced in late-2007 and ended in late-2015 after the one-millionth tree had been planted. The fact that the afforestation project was rolled-out over several years slightly complicates the assignment of the treatment period. Setting the treatment period as starting in 2007 or 2008, for example, would not be ideal because few trees were planted during the early stages of the program. Conversely, saying that the treatment year was 2014 or 2015, for example, would be too late since most of the trees associated with the program would have already been planted. Therefore, we use the midpoint of the program rollout, 2011, as the treatment year in the baseline specification. In the robustness checks, alternative treatment years are explored.

6. Results

6.1. Internal Validity Test

For the DID estimator to be internally valid, trends in the synthetically weighted observable characteristics of mothers must be the same across the treatment and control groups, before and after treatment. That is, we seek to demonstrate that MillionTreesNYC has no effect on mother socio-demographic characteristics. This follows the spirit of the DID internal validity test in Currie and Walker (2011). As a test of the validity of the research design, we estimated the effects of MillionTreesNYC on each mother characteristic using the weights obtained for synthetic NYC. The results of doing this are presented in Table 2. The mother characteristic listed in each column in Table 2 is the outcome variable and the estimate presented is the DID estimate of the effect of MillionTreesNYC on that characteristic, calculated using a variation of equation (2). Each estimate is from a separate run of the synthetic control method in equation (1), but with different dependent variables. P-values are reported in brackets underneath each estimate. Notice that none of the DID estimates are significantly different from zero at conventional levels. In other words, NYC mothers are not statistically different from synthetic NYC mothers before and after the afforestation program. This suggests that any estimated infant health effects of MillionTreesNYC are not due to changes in the composition of NYC mothers over time. Hence, we can proceed with our investigation of infant health outcomes with some confidence that the research design is internally valid.

[Table 2]

6.2. Synthetic Control Results

The results of using the synthetic control method to construct synthetic NYC are illustrated in Figure 2. Specifically, Figure 2 plots the differences or “gaps” in infant health outcomes between NYC and synthetic NYC in the years before and after the afforestation program. Panel A is for low birth weight and panel B is for prematurity. During the pre-treatment period, we are looking for the common trends assumption to be met, which we see evidence of in both panels by the nearly zero gaps and no apparent trending in health outcomes in years -5 to -1. This indicates that the synthetic control method has produced a credible counterfactual of birth outcomes.

[Figure 2]

In the years after the program's rollout, there are clear improvements in both low birth weight and prematurity in NYC relative to the synthetic control. The gaps are trending negative, indicating that mothers in NYC had a lower probability of low birth weight and prematurity compared to the control. Moreover, the gaps generally become more negative (i.e., a growing negative gap) in the years after the program. This is consistent with a growing urban forest canopy. Note that saplings were planted in NYC rather than fully grown mature trees. Over time, saplings grow, and as trees grow they generally provide greater benefits (e.g., by removing more air pollutants, generating more shade, etc.). Assuming a causal connection exists, then the infant health benefits of a given tree would also tend to be growing over time. This factor may explain the growing negative gaps observed in Figure 2 and is consistent not only with tree ecology, but prior work on tree cover and health (Jones & McDermott, 2017).

Are these results significant, however? That is, are the improvements in low birth weight and prematurity outcomes observed in Figure 2 different than what we would expect by random chance? The synthetic control falsification tests can be used to answer these questions. Figure 3 presents the results from these tests. The black line in each panel is the standardized gap in infant outcomes low birth weight and prematurity, respectively, between NYC and synthetic NYC and the light gray lines are the standardized gaps for each of the 54 feasible control counties and their unique synthetic controls. We first observe during the pre-treatment period that the NYC gap is not an outlier relative to the placebo controls. This is important because if the NYC gap was an outlier, there would be cause for concern that any post-treatment gaps might be due to lack of fit during the pre-treatment period rather than an effect of the program. Next, in the years after the program was implemented, we do observe that the NYC gap is generally an outlier compared to the placebo controls; it is generally below the placebo gaps in both panels. This means that the magnitude of decreases in low birth weight and prematurity in NYC cannot be replicated by applying the synthetic control method to counties that did not implement MillionTreesNYC over the same period. Since the negative low birth weight and prematurity gaps for NYC are unusually large relative to the gaps for counties that did not implement afforestation programs, then our interpretation, following Abadie et al. (2010), is that these results provide evidence of an infant health externality associated with MillionTreesNYC.

[Figure 3]

To quantify the results presented in the graphical analysis, we use equations (2) and (3) to calculate the DID estimators and associated p-values (Table 3). Consistent with the graphical results, we observe that instances of both prematurity and low birth weight in NYC fell by 2.1% and 0.24%, respectively, in the aftermath of the afforestation program, compared to similar mothers living in counties less than 200km away (panel A). Both of these DID estimates are significant at the 5% level or better. In terms of numbers of infants affected, MillionTreesNYC had the effect of lowering incidence of prematurity by approximately 250 per 100,000 live annual births, and incidence of low birth weight by roughly 21 per 100,000 live annual births. To put this into perspective, smoking one cigarette per day during pregnancy increases low birth weight by 0.12% (Currie et al., 2009). Hence, our estimates of the effect of NYC urban afforestation on low birth weight are roughly equivalent to getting a mother smoking two cigarettes a day during pregnancy to quit. Restricting the feasible pool to mothers within 100km of NYC (panel B) cuts the sample size by more than half (which is why it is not our preferred specification), but the results tell a similar story.

[Table 3]

6.3. Synthetic Control Robustness Checks

Several robustness checks were performed on these results (Table 4). In panel A, the treatment year is set at 2008 (the first full year after MillionTreesNYC was announced), rather than 2011 as used in the baseline results. As expected, this has the effect of attenuating the DID estimates for both low birth weight and prematurity because now we are including the early years of the program when fewer trees had been planted and hence the benefits provided by additional tree cover were low (i.e., fewer trees, fewer benefits to mothers). The estimate on prematurity remains negative and significant despite the large attenuation, though low birth weight, while still negative, becomes insignificant. Not to belittle the point, but these results are consistent with a causal story because we would in fact expect there to be little or no effect of MillionTreesNYC on infant health outcomes during the first year or two of the program's rollout, which, since the DID estimator is calculated as an average over the post-treatment period, and because the impacts are near zero for the first couple of years, would have the effect of attenuating this average, exactly as observed in panel A.

[Table 4]

In panel B, we generate the pre-policy dynamic effect estimate by showing no effect of MillionTreesNYC in the years before the program was actually implemented. Specifically, we used the synthetic control method over the period 1999-2006, where 1999-2002 is the "pre-treatment period” and 2003-2006 is the “treatment period”, but of course no afforestation program was in fact implemented over this time period. NYC and synthetic NYC were matched on the same observable mother and infant characteristics as before and separate runs of the synthetic method were performed for low birth weight and prematurity. As shown in panel B, we find no effect of the afforestation program before it actually began; the DID estimators on birth outcomes are close to zero and highly insignificant. This finding helps with the causal interpretation of the results.

In panels C, D, and E, checks are made on the construction of the feasible pool of counties to see if the results are being driven by which counties were included in the donor pool. In panel C, rather than using a distance-based inclusion criteria (like that used in the baseline results), we used a population-based criteria. The feasible pool now includes the 20 highest population counties in New York (outside of NYC), New Jersey, Pennsylvania, and Connecticut. The synthetic control method was again employed to create a synthetic NYC using this feasible pool. The results from this check are similar in magnitude and significance to those in the baseline. In panel D, the two previously dropped Long Island, NY counties are now included in the feasible pool. As a reminder, these counties were originally dropped because prevailing west-to-east wind patterns might bring air quality improvements to Long Island if MillionTreesNYC in fact lead to reductions in air pollution, which would mean that Long Island may not be a credible control candidate. We can see from the results in Table 4 that including these counties in the feasible pool has a fairly small effect on the magnitude of the DID estimates, though low birth weight is now only marginally significant. Finally, we may be concerned that there are some mothers who work and play in NYC, but who live in one of the counties bordering NYC (e.g., work in NYC, but live across the river in New Jersey). These mothers may benefit in some way from the afforestation program, but because they do not reside in NYC, would be potentially included in synthetic NYC. This is problematic because it means that synthetic NYC could potentially contain natality data from a subset of mothers who may have experienced some of the benefits of MillionTreesNYC. Therefore, as a robustness check, in panel E we dropped all counties that border NYC from the feasible pool (excluding Long Island counties, which were previously dropped) and produced a new synthetic NYC. The magnitudes of the DID estimates for low birth weight and prematurity are relatively unchanged by this process, and both estimates remain at least marginally significant. Overall, the results from these robustness checks suggest that alternative constructions of the feasible pool does not meaningfully change the qualitative findings from the baseline results of an association between infant health and MillionTreesNYC.

6.4. Fixed Effects Model Results

Applying the synthetic weights to individual level birth outcomes and mother characteristics allows us to take advantage of the richness of the natality data by investigating the impacts of MillionTreesNYC on individual rather than county-averaged health outcomes. The results of using this data to estimate equation (4) are presented in Table 5. We begin with a discussion of panel A where OLS is used. The first and third columns include year of birth fixed effects only. The DID estimator for low birth weight is double the value of Table 3 and is more statistically significant. The estimate on prematurity is slightly lower than the value in Table 3, but is more significant now. The second and fourth columns add maternal characteristics as in equation (4). Adding these characteristics has little effect on the estimated coefficients. These results suggest that MillionTreesNYC significantly reduced instances of prematurity by 1.8% and instances of low birth weight by 0.35%. These findings are comparable to those found using county averages and the synthetic control method. The main difference here is that we employ a more traditional DID model of individual observations that includes time fixed effects.

[Table 5]

In panel B of Table 5, a discrete choice logit model is used in place of OLS in light of the binary nature of the dependent variables. As before, columns one and three included time fixed effects, while columns two and four additionally include covariates for mother characteristics. The reported marginal effects in panel B are all smaller compared to the OLS results in panel A. However, the signs remain unchanged across panels and the significance of the results are all at the 5% level or better in panel B, providing continued evidence in support of an infant health externality story.

6.4.1. Impacts by Mother Characteristics

A stated goal of the MillionTreesNYC program was to improve public health outcomes in several key areas across the city where rates of childhood asthma were particularly elevated. Upon investigation, we found that these neighborhoods are predominantly composed of racial and ethnic minorities, particularly Hispanics and African Americans (e.g., Hunts Point, Bronx: 74.6% Hispanic and 22.2% African American; East New York, Brooklyn: 63.6% African American and 29.6% Hispanic; East Harlem, Manhattan: 52.1% Hispanic). More generally, there was a social and environmental justice component of the program that sought to improve health and environmental outcomes is less advantaged parts of the city that were predominantly made up of people of color (Campbell et al., 2014).

Two questions that our data can shed some light on are: (i) “Did MillionTreesNYC lead to improved infant health outcomes for mothers of color?”, and; (ii) “Is there evidence of disproportionate impacts of the program on these mothers compared to mothers from other racial and ethnic backgrounds?" Using the synthetically weighted individual level mother data and the fixed effects DID specification described in the last section, we estimated the impacts of MillionTreesNYC on birth outcomes, separately by race (Table 6, panels A-D). For African American mothers (panel A), we find that the afforestation program lead to larger improvements in both low birth weight and prematurity compared to non-African American mothers (panel B); 0.62% larger for low birth weight and 0.52% larger for prematurity. Among Hispanic mothers (panel C), the evidence is mixed. Instances of low birth weight were slightly less likely for Hispanic mothers in the aftermath of the program relative to non-Hispanic mothers (by 0.04%), but it appears that non-Hispanic mothers (panel D) have fewer instances of prematurity than Hispanic moms (by 0.06%).

Overall, there are two important takeaways from these results. First, in response to the first question posed at the beginning of the last paragraph, we find empirical evidence suggesting that MillionTreesNYC was associated with significant reductions in low birth weight and premature births among African American and Hispanic mothers. Not only is this consistent with one of the general goals of the program, but is also important on its own since mothers from these two racial and ethnic groups tend to suffer from above-average rates of low birth and prematurity (Meyer et al., 2010). If targeted urban afforestation programs, such as MillionTreesNYC, can be used to bring rates of these outcomes below the threshold for concern, then the consequentiality of urban tree planting may be greater than previously thought. Given that these results are only suggestive of an effect, this may be a worthwhile area for future research, especially because it is not clear why mothers of color might tend to benefit more from afforestation. Is it simply because NYC planted a disproportionate number of trees in less advantaged neighborhoods? Or, could it be that mothers of color are at a different point on the production possibility frontier, as suggested by Currie and Walker (2011)?[7] In response to the second question posed earlier, there is some evidence (though mixed for Hispanic mothers) that the infant health outcome improvements associated with the program were in fact *larger* for African American, and perhaps Hispanic mothers, compared to mothers from different race and ethnicity backgrounds. This suggests that the greatest benefits of the program, at least in terms of reductions in small or premature births, went to these mothers of color.

[Table 6]

7. Air Pollution as a Potential Causal Mechanism

As previously discussed, prior research has suggested a causal link between urban trees, air pollution, and health (e.g., Jones & McDermott, 2017; Nowak et al., 2013). To explore air pollution as a potential causal mechanism for the infant health effects we observe, we collected annual pollution concentration data from the US EPA AirData monitoring network for five criterion pollutants: $PM_{2.5}$, O_3, CO, SO_2, and NO_2. Data were collected for the same set of counties previously considered. To determine the annual pollution level for a given county, we constructed a 25-mile (40.2km) circle around the population-weighted centroid of each county and proceeded to take a weighted average of all the air quality monitored data within the circle for a given year and pollutant type, where the weights are equal to the inverse of the square root of their distance to the population-weighted centroid. Only monitors reporting at least 60% of their scheduled data drops were included in the analysis. Similar approaches have been used in

[7] Another possibility is that because Hispanic and African American mothers, relative to white mothers, had higher rates of low birth weight and prematurity before the afforestation program, there was more room for improvement in natality outcomes among these groups. It's possible that targeted afforestation might have led to even larger improvements than non-targeted afforestation, but because pre-existing natality outcomes among Hispanic and African American mothers were higher, we should not necessarily be surprised to observe a larger effect for these two groups since their potential improvements were greatest.

Levinson (2012) and in Currie and Neidell (2005). As before, the treatment year is set at 2011 and the years 2004-2015 are investigated. The unit of analysis is a county-year.

Since pollution is correlated with weather, we additionally collected annual county level data on minimum temperature, maximum temperature, and precipitation from the NOAA National Centers for Environmental Information. The 25-mile population-weighted centroid approach was also used for weather monitoring stations.

Using the pollution and weather data, we employed the synthetic control method to investigate the impact of MillionTreesNYC on air pollution concentrations. DID results obtained from separate synthetic control runs are provided in Table 7 by pollutant type. With the exception of $PM_{2.5}$, we find no evidence suggesting that air pollution concentrations for SO_2, NO_2, O_3, or NO_2 significantly changed in the years after the tree program was initiated compared to the synthetic control, though we note that all but one (for O_3) of the DID estimates are negative as might be expected if urban trees improved air quality. However, for $PM_{2.5}$, we observe a highly significant fall in particulate concentrations in NYC that was not observed in the synthetic control. On average, annual $PM_{2.5}$ levels in NYC are 0.010 $\mu g m^{-3}$ *lower* over 2011-2015 relative to the control and this estimate is significant at the 1% level. This result is comparable to Nowak et al. (2013) who found that urban trees in the US reduce annual average $PM_{2.5}$ by 0.05% to 0.24%, which would correspond to a reduction in NYC ranging 0.005-0.026 $\mu g m^{-3}$. Our estimate falls within this range and therefore seem reasonable.[8]

[Table 7]

[8] As a robustness check, we also calculated the county level pollution concentration using a 50-mile population-weighted centroid and also a simple average of all monitors within a county. The results were largely unchanged by these modifications, though the sample sizes differed widely due to fewer or greater missing observations.

In light of these results, we were prompted by a reviewer to “reverse engineer” the models to ask: Given the infant health outcomes observed, what change in $PM_{2.5}$ would be expected, if air pollution was the only causal mechanism driving the effect, and how does the expected $PM_{2.5}$ change compare to the actual 0.010 $\mu g m^{-3}$ drop found? Using dose-response functions from Harris et al. (2014) and Stieb et al. (2012), for low birth weight and prematurity, respectively, we calculated (assuming a proportional relationship) that $PM_{2.5}$ would need to decline by 0.04 $\mu g m^{-3}$ to fully explain the observed 0.24% low birth weight improvement and by 4.2 $\mu g m^{-3}$ to fully explain the observed 2.1% prematurity improvement. Put differently, the 0.10 $\mu g m^{-3}$ fall in $PM_{2.5}$ that we can associate with MillionTreesNYC explains approximately 23.3% and 0.24% of the observed low birth weight and prematurity improvements, respectively, from the synthetic control results. Hence, if air pollution was the only causal mechanism by which afforestation affected infant health (which is unlikely), then these results suggest that observed $PM_{2.5}$ changes are only explaining a small portion of the total effect. Future work might investigate other potential causal mechanisms in order to augment this analysis (e.g., temperature and tree shade, behavioral modifications, mental health, etc.)

It is also worth noting that it is not immediately clear why we observe a significant effect on $PM_{2.5}$, but not on other criteria air pollutants. Prior literature suggests that urban trees can affect concentrations of $PM_{2.5}$, O_3, CO, SO_2, and NO_2 (Nowak et al., 2006). Perhaps the magnitude of the effects on non-PM pollutants in this setting are simply too small to detect using monitored data, or perhaps more sophisticated deposition models are required to tease out the nuanced empirical relationship between trees and air pollutants.

There is also at least one policy implication of these results. Urban air pollution reductions from afforestation are an ancillary benefit of tree plantings, potentially improving the net costs of such programs and allowing for programs with more tree planting in more areas. There is also the possibility that afforestation may allow for increased emissions by reducing the human exposure per unit of emissions. If afforestation reduces pollution concentrations, the constraint in urban areas may be relaxed allowing for additional emissions while remaining below the regulatory standards. A potential consequence if emissions were to increase is downwind populations that did not implement an afforestation program would be subjected to greater pollution exposures. For this increased emission effect to be realized, however, substantially larger concentration reductions from afforestation would be required than we found here.

8. Conclusions

In this paper, we exploited a quasi-experiment provided by a large urban afforestation program in New York City, MillionTreesNYC, to investigate the association between urban tree canopy and infant health. The synthetic control method was used to produce synthetic NYC, a counterfactual that credibly mimicked infant health trends in NYC in the years before MillionTreesNYC. Differences in prematurity and low birth weight between NYC and synthetic NYC were investigated by calculating DID estimators and p-values. In a second, alternative model, we took advantage of the rich, individual level natality data available to us by employing a more traditional DID regression model using the individual weighted data. Across both models, there is consistent empirical evidence for an infant health externality. A more than 10% increase in the NYC urban forest canopy produced by MillionTreesNYC is associated with a 2.1% decrease in premature infant births and a 0.24% decrease in low birth weights. The low birth weight finding is roughly equivalent to getting a mother smoking two cigarettes a day during pregnancy to quit. There is also evidence suggesting that African American and Hispanic mothers benefited more from the program than other racial and ethnic groups. Lastly, we find evidence that decreases in $PM_{2.5}$ concentrations in NYC during the post-treatment period is a potential causal mechanism that might explain the observed improvements in natality outcomes.

The results from this study can be compared to the only other investigation of infant health and urban tree cover in Donovan et al. (2011), where it was found that a 10% increase in tree canopy cover near a mother's home reduced incidence of low birth weight by 1.42 per 1000 births. Here, we find that MillionTreesNYC is associated with a 0.24% decrease in low birth weight, which is equivalent to an average annual reduction of 0.21 per 1000 births.[9] Our estimate on low birth weight is about one-seventh the size of the Donovan et al. (2011) result. In addition, Donovan et al. (2011) did not observe a significant effect of urban trees on prematurity, while we do: MillionTreesNYC is associated with an average annual reduction in prematurity by 2.5 per 1000 births. It is worth mentioning again that the present study and Donovan et al. (2011) are similar in that they both examine infant health outcomes and urban trees, but differ in that the present work examines the impact of a large-scale afforestation program, whereas Donovan et al. (2011) use natural cross-sectional variability in tree cover across a city to compare health outcomes in areas with more tree cover to outcomes in areas with less tree cover. It could be the case that exogenous additions of urban trees produces a different effect on infant health compared to living in an area with greater existing forest cover. We also cannot rule out the fact that investigations not employing quasi-experimental designs could be picking up the effects of residential sorting behavior (e.g., higher income mothers sorting into areas with more trees), thereby biasing results. Lastly, the underlying relationship between trees and health may simply differ between NYC and Portland, OR (where the Donovan et al. study was conducted). NYC is

[9] Calculated on the basis of 119,632 average annual live births in NYC over the study period.

more urbanized, densely populated, and has fewer greenspaces than Portland, leading, perhaps, to the case where an urban tree in NYC may have a higher marginal benefit than the same tree in Portland. Forests are situated within a short drive from Portland, whereas longer drives are required from NYC to reach a similar level of wilderness. Hence, trees may be more beneficial in NYC, consistent with the theoretical model in Jones and McDermott (2015). This could explain why we observe a significant effect of MillionTreesNYC on prematurity, whereas prior literature, using data in an area with many proximal forests, has not. Regardless, our work complements Donovan et al. (2011) by providing additional empirical evidence, using a stronger identification strategy, supporting the existence of an infant health externality.

More broadly, this work contributes to the nascent literature on trees and human health, and in particular, the literature on the health benefits of urban afforestation. In light of continued interest in urban tree planting in cities across the US and the globe, there is a need for credible empirical investigations into the externalities of these programs. If, as suggested in this work, infant health outcomes are meaningfully improved by urban afforestation targeted in areas with little or no existing tree cover, then there is the potential for long-term benefits of these programs on adult human capital and health outcomes that have been tied to infant health in previous research (see Currie, 2009). In particular, outcomes such as schooling attainment, test scores, use of disability programs, residence in high income areas, and wages are influenced by infant health outcomes such as low birth weight (Currie et al., 2011). As urban planners seek to continue to improve the welfare of their residents, then urban afforestation might be considered within the broader portfolio of improvements to the natural environment. At a minimum, urban afforestation can complement existing policies aimed at addressing low birth weight and prematurity.

There are several limitations and caveats of this work. Due to data limitations, we were unable to match individual birth outcomes to individual tree plantings. If the largest benefits of newly planted trees are among mothers living closest to them, then our results are likely an underestimate of the effect of MillionTreesNYC because we are capturing effects from a mix of mothers both close and far away from planted trees. Second, since the NYC tree program was targeted to areas with few or no existing trees in addition to areas with above-average rates of childhood asthma, the generalizability of the results is reduced. That is, unless, of course, more urban areas follow NYC and implement similar "priority planting" afforestation programs rather than planting trees in areas selected on the basis of convenience and/or space availability only. Third, while we know the mother's county of residence and the county of birth, we do not have information on mother residential histories. Mothers who are new to NYC or who moved there midway into their pregnancy may experience different impacts of the afforestation program compared to longtime residents who have been habituated to the pre-MillionTreesNYC canopy cover size. Fourth, we are not able to construct a panel of mothers such that mother fixed effects could be used as done in other work on infant health (e.g., Currie & Walker, 2011; Currie et al., 2009). This is because while we know if a given mother has had multiple births, we do not know the dates of every birth. Lastly, the specific causal mechanisms by which trees influence infant health remain elusive and is a relevant topic for future work.

In conclusion, targeted urban afforestation programs such as MillionTreesNYC may affect prematurity and low birth weight among infants in NYC. Since we have focused on only one of the possible health effects of urban trees, albeit an important one, it is likely that the total health benefits of urban afforestation are larger than those estimated here. Hence, future research in this area has the potential to be highly impactful.

Appendix A: Pre-Treatment Trends in Infant Health Outcomes without Weighting

This appendix presents results that demonstrate differences in pre-treatment trends for low birth weight and prematurity between mothers residing in NYC (treatment) and mothers residing in counties within 200km of NYC (control) when the synthetic control method has not been employed. Locally weighted regression (lowess) smoothed plots with a bandwidth of 1 are presented for low birth weight (Figure A1) and prematurity (Figure A2).

Figure A1: Low Birth Weight Before and After MillionTreesNYC (unweighted)

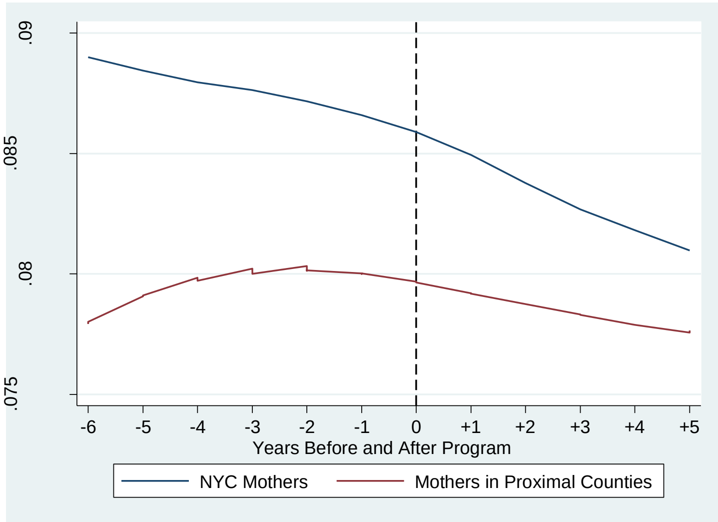
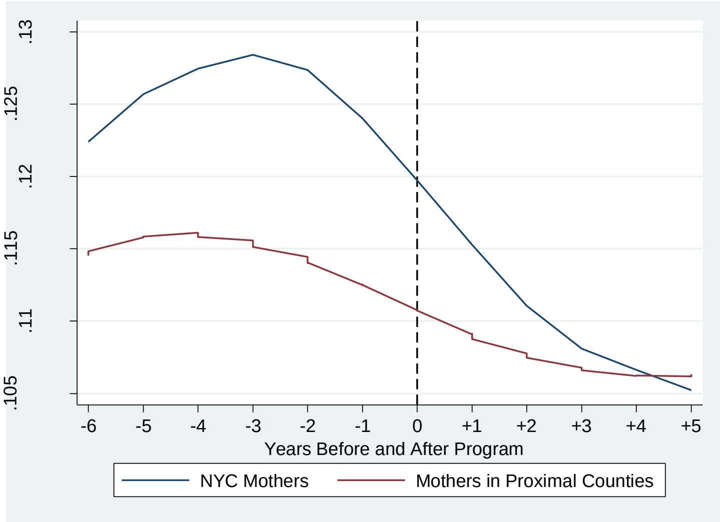


Figure A2: Prematurity Before and After MillionTreesNYC (unweighted)



Appendix B: Synthetic Control Weighting Vector

This appendix contains the weighting vector, W, obtained from using the synthetic control method, separately for low birth weight and prematurity (Table B1). Weights are obtained by performing the minimization procedure in Equation (1) in the main text.

Table B1: Weights Used to Construct Synthetic NYC

FIPS	Low Birth Weight	Prematurity	FIPS	Low Birth Weight	Prematurity
9001	0.01	0	36071	0.013	0
9003	0.012	0	36079	0.055	0
9005	0.003	0	36087	0.005	0
9007	0.003	0	36105	0.012	0
9009	0.01	0	36111	0.106	0
9011	0.006	0	36119	0.011	0.259
9013	0.013	0	42011	0.008	0
34001	0.009	0	42017	0.007	0
34003	0.007	0	42025	0.066	0
34005	0.007	0	42029	0.003	0
34007	0.016	0	42045	0.01	0
34009	0.004	0	42069	0.008	0
34011	0.007	0	42077	0.009	0
34013	0.02	0.362	42079	0.011	0
34015	0.017	0	42089	0.067	0
34017	0.009	0	42091	0.006	0
34019	0.003	0	42095	0.018	0
34021	0.038	0	42101	0.196	0
34023	0.01	0	42103	0.002	0
34025	0.008	0	42107	0.007	0
34027	0.006	0	42127	0.005	0.027
34029	0.003	0	42131	0.002	0.043
34031	0.009	0			
34033	0.01	0			
34035	0.021	0			
34037	0.003	0			
34039	0.067	0			
34041	0.005	0			
36021	0.016	0.169			
36025	0.01	0.139			
36027	0.006	0			
36039	0.007	0			

Notes: list of US counties within 200km of NYC (based on population centroid distance) and corresponding synthetic weights assigned by the synthetic control method. Per health outcome weights may not sum to one due to rounding error. FIPS=Federal Information Processing Standard codes.

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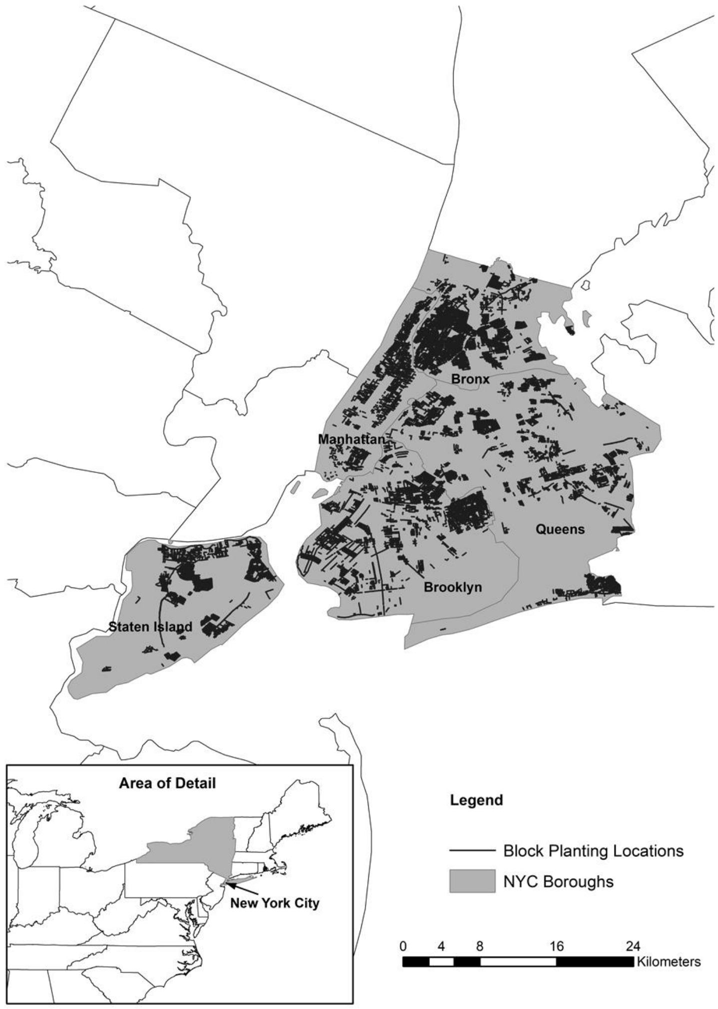
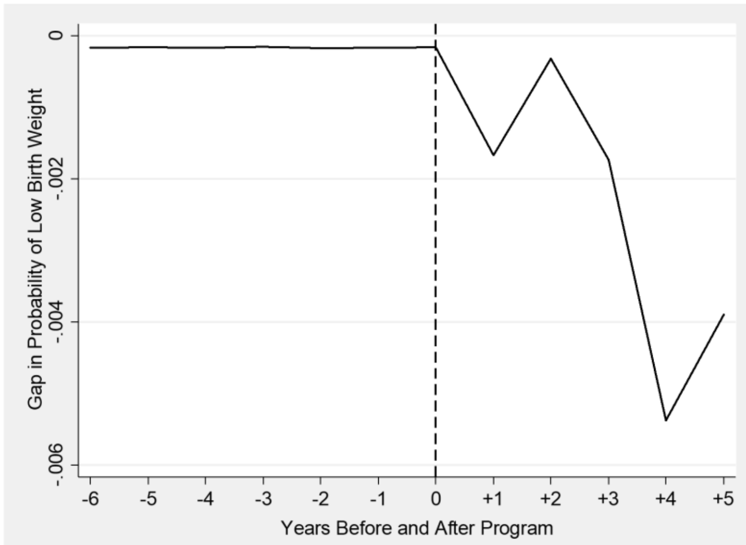
Figure 1: MillionTreesNYC Street Tree Planting Locations (City Blocks)



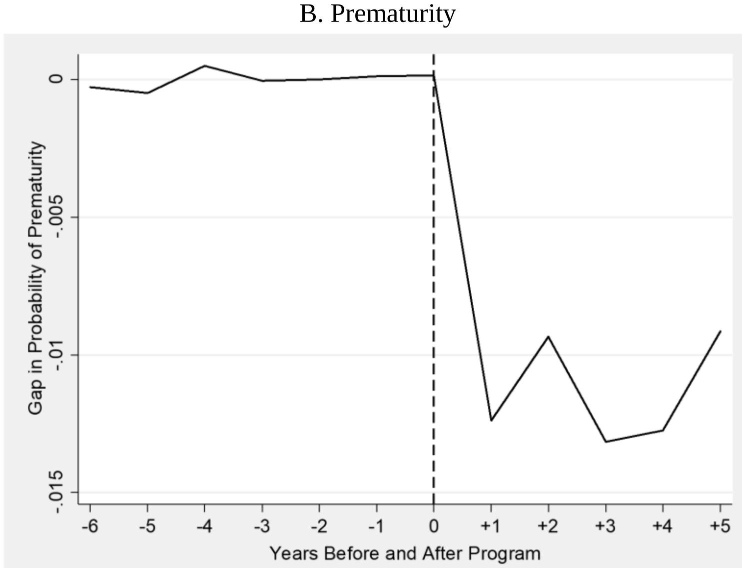
Source: New York City Department of Parks and Recreation.

Figure 2: Gaps in Natality Outcomes between NYC and Synthetic NYC Before and After Tree Program

A. Low Birth Weight



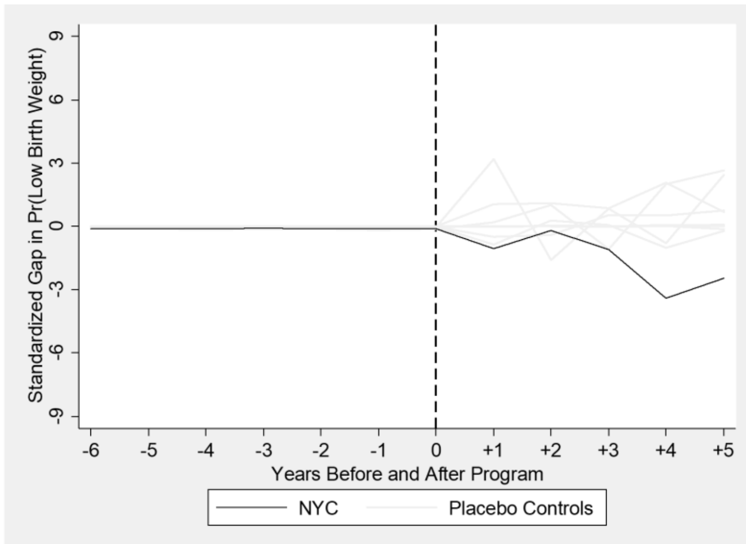
B. Prematurity



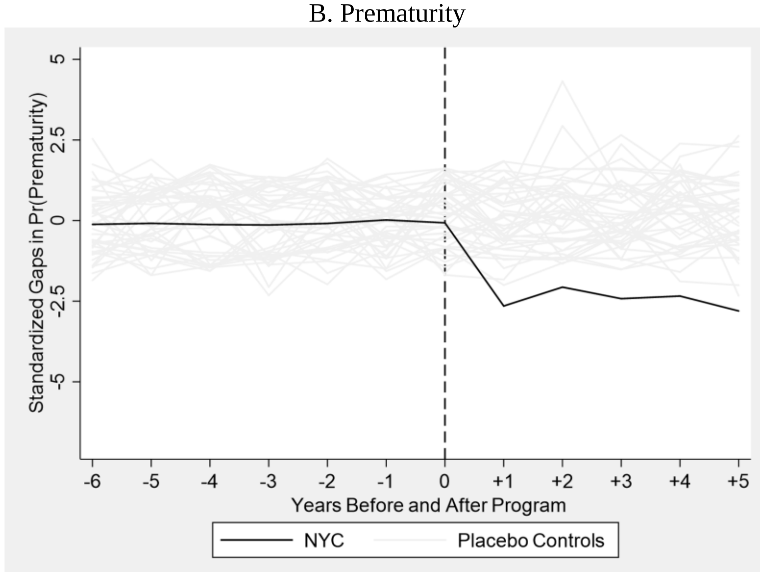
Notes: Gaps in natality outcomes between NYC and synthetic NYC in the years before and after the midpoint of the tree program rollout are plotted for probability that the child is low birth weight or premature. NYC and synthetic NYC are matched on pre-treatment natality outcomes, mother Hispanic, mother black, mother education, HS dropout, mother smoked, teen mother, birth order, multiple birth, and child gender.

Figure 3: Results from Falsification Tests between NYC and Feasible Pool

A. Low Birth Weight



B. Prematurity



Notes: Standardized gaps in natality outcomes between NYC and synthetic NYC (black line) and standardized gaps between each county in the feasible pool and its unique synthetic control for 54 placebo permutations (gray lines) plotted for low birth weight and prematurity in the years before and after the midpoint of the tree program rollout. Gaps standardized by pre-treatment RMSPE. Treatment and synthetic controls are matched on pre-treatment natality outcomes, mother Hispanic, mother black, mother education, HS dropout, mother smoked, teen mother, birth order, multiple birth, and child gender.

Table 1: Sample Summary Statistics

	NYC		Counties ≤200km		Counties ≤100km	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Synthetic Control Sample						
Low birth weight	0.086	0.003	0.079	0.012	0.078	0.011
Prematurity	0.119	0.010	0.111	0.017	0.112	0.016
Mother Hispanic	0.325	0.011	0.173	0.111	0.240	0.108
Mother black	0.285	0.028	0.122	0.105	0.133	0.109
Mother education	4.049	0.187	4.632	0.699	4.941	0.727
Mother HS dropout	0.224	0.021	0.112	0.076	0.097	0.070
Mother smoked	0.014	0.004	0.100	0.090	0.037	0.044
Teen mother	0.058	0.014	0.060	0.030	0.042	0.021
Birth order	2.004	0.023	2.028	0.182	2.051	0.275
Multiple birth	0.036	0.001	0.042	0.010	0.048	0.009
Child male	0.512	0.001	0.512	0.013	0.511	0.010
Sample size	12		648		228	
Panel B: Individual Outcomes						
Low birth weight	0.084	0.278	0.084	0.277	0.077	0.267
Prematurity	0.115	0.319	0.113	0.317	0.112	0.316
Mother Hispanic	0.319	0.466	0.178	0.382	0.285	0.451
Mother black	0.268	0.443	0.199	0.399	0.142	0.349
Mother education	4.133	1.926	4.428	1.833	4.523	1.977
Mother HS dropout	0.224	0.417	0.148	0.355	0.168	0.374
Mother smoked	0.013	0.112	0.107	0.309	0.032	0.177
Teen mother	0.051	0.221	0.068	0.251	0.040	0.197
Birth order	2.004	1.306	2.057	1.261	2.137	1.407
Multiple birth	0.036	0.186	0.041	0.198	0.043	0.203
Child male	0.512	0.500	0.511	0.500	0.512	0.500
Sample size	940,597		1,233,568		309,653	

Note: This table reports summary statistics for natality outcomes and mother characteristics for NYC, counties ≤200km from NYC, and counties ≤100km from NYC. Panel A is the synthetic control sample where individual observations have been averaged at the county level. Panel B is the individual observation sample that has not been average at the county level. Data sources: CDC NCHS.

Table 2: Research Design Validity: Impact of MillionTreesNYC on Mother's Characteristics

	Hispanic	Black	HS Dropout	Smoke	Education	Teen Mother
DID Estimate	-0.0194	-0.0078	0.0017	0.0003	-0.0316	-0.0018
	[0.48]	[0.98]	[0.98]	[0.50]	[0.13]	[0.15]
Sample size	660	660	659	655	659	660

Notes: each column contains results from separate runs of the synthetic control method, but where the same weights are used in each run and are equal to the weights used to construct synthetic NYC in the baseline analysis. Dependent variable is the mother characteristic indicated in the column. Treatment unit is NYC and the treatment period is 2011. These synthetic controls test whether the composition of mothers in NYC changed before and after the tree program. P-values reported in brackets.

Table 3: Difference-in-Differences Estimates of the Effect of MillionTreesNYC on Natality Outcomes

Natality Outcome	Average Pre-treatment Difference	Average Post-treatment Difference	DID Estimate	*p*-value
Panel A: ≤ 200km Feasible Pool				
Low Birth Weight	-0.0002	-0.0026	-0.0024	0.05
Prematurity	0.0001	-0.0210	-0.0211	0.04
Sample size	660	660	660	
Panel B: ≤ 100km Feasible Pool				
Low Birth Weight	-0.0000	-0.0018	-0.0018	<0.00
Prematurity	-0.0001	-0.0169	-0.0168	0.05
Sample size	240	250	240	

Notes: Average differences pre- and post-treatment are estimates for the difference in natality outcomes between NYC and the matched synthetic control group (synthetic NYC). In Panel A (Panel B), the feasible pool of counties have population centroids ≤ 200km (≤ 100km) from the population centroid of NYC. NYC and the synthetic control group are matched on pre-treatment natality outcomes and mother Hispanic, mother black, mother education, teen mother, HS dropout, smoking, multiple birth, birth gender, and birth order. P-value calculated from falsification tests of all possible treatment-control permutations (see text for description). Difference-in-differences (DID) calculated as $\left(Health_{post}^{NYC} - Health_{post}^{synthNYC}\right) - \left(Health_{pre}^{NYC} - Health_{pre}^{synthNYC}\right)$.

Table 4: Synthetic Control Robustness Checks

Natality Outcome	Average Pre-treatment Difference	Average Post-treatment Difference	DID Estimate	*p*-value
Panel A: Alternative Treatment Year				
Low Birth Weight	0.0002	-0.0007	-0.0009	0.48
Prematurity	0.0000	-0.0023	-0.0023	<0.00
Sample size	660	660	660	
Panel B: Pre-Policy Dynamic Effect Estimate				
Low Birth Weight	-0.0000	-0.0005	-0.0005	0.76
Prematurity	0.0000	-0.0001	-0.0001	0.69
Sample size	440	440	440	
Panel C: Highest Population Counties				
Low Birth Weight	-0.0000	-0.0030	-0.0030	0.05
Prematurity	-0.0000	-0.0154	-0.0154	<0.00
Sample size	252	252	252	
Panel D: Including Long Island Counties				
Low Birth Weight	-0.0000	-0.0025	-0.0025	0.10
Prematurity	0.0001	-0.0231	-0.0232	0.05
Sample size	684	684	684	
Panel E: Dropping NYC Border Counties				
Low Birth Weight	0.0001	-0.0023	-0.0024	0.10
Prematurity	-0.0000	-0.0226	-0.0226	0.04
Sample size	600	600	600	

Notes: see notes below Table 3 for descriptions of the estimates in each column. Panel A uses 2008 as the treatment year. Panel B uses the pre-policy period to create a dynamic effect estimate of the impact of the NYC tree program in the years prior to when it actually started. Panel C includes in the feasible pool only the 20 highest population counties in the states neighboring NYC. Panel D includes Long Island counties (Nassau and Suffolk) in the feasible pool. Panel E drops from the feasible pool the counties that border NYC (not including Long Island): Westchester County NY, Bergen County NJ, Hudson County NJ, Union County NJ, and Middlesex County NJ.

Table 5: Fixed Effects Regression Difference-in-Differences Analysis

	(1) Low Birth Weight	(2) Low Birth Weight	(3) Prematurity	(4) Prematurity
Panel A: OLS				
NYC resident × after MillionTreesNYC	-0.0050***	-0.0035**	-0.0188***	-0.0180***
	(0.0011)	(0.0016)	(0.0018)	(0.0017)
R^2	0.055	0.167	0.078	0.132
Panel B: Logit (marginal effects)				
NYC resident × after MillionTreesNYC	-0.0035***	-0.0032**	-0.0125**	-0.0100**
	(0.0006)	(0.0013)	(0.0061)	(0.0050)
Pseudo R^2	0.0001	0.060	0.137	0.167
Mother's Characteristics	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Sample size	4,422,725	2,172,154	4,429,180	2,177,194

Notes: each column is a separate regression of equation (4) in the text. DID coefficients reported. Weights generated by the synthetic control method are used to select control counties and re-weight the contribution of each individual observation such that the cumulative weight associated with the observations from a county matches the synthetic weights. All regressions include an indicator for NYC residency, an indicator for the midpoint of the afforestation program rollout, and year of birth fixed effects. Mother's characteristics include: mother Hispanic, mother black, education, HS dropout, smoked during pregnancy, teen mother, birth order, multiple birth, and gender of child. Clustered standard errors in parentheses. ***p<0.01; **p<0.05; *p<0.10.

Table 6: Heterogeneity of Impacts by Mother Race and Ethnicity (Fixed Effects DID Regressions)

	(1) Low Birth Weight	(2) Prematurity
Panel A: African Americans only		
NYC resident × after MillionTreesNYC	-0.0074***	-0.0206***
	(0.0014)	(0.0022)
R^2	0.146	0.134
Sample size	497,288	498,947
Panel B: Non-African Americans only		
NYC resident × after MillionTreesNYC	-0.0012**	-0.0154***
	(0.0005)	(0.0016)
R^2	0.172	0.128
Sample size	1,674,866	1,678,247
Panel C: Hispanics only		
NYC resident × after MillionTreesNYC	-0.0031***	-0.0166***
	(0.0007)	(0.0016)
R^2	0.132	0.104
Sample size	519,185	519,702
Panel D: Non-Hispanics only		
NYC resident × after MillionTreesNYC	-0.0027*	-0.0172***
	(0.0016)	(0.0015)
R^2	0.182	0.144
Sample size	1,652,969	1,657,492
Mother's Characteristics	Yes	Yes
Fixed Effects	Yes	Yes

Notes: see notes below Table 5 for descriptions of the regressions. Each column-panel combination is a separate regression. Panel A is restricted to African American mothers only. Panel B is restricted to Non-African American mothers only. Panel C is restricted to Hispanic mothers only. Panel D is restricted to non-Hispanic mothers only. Clustered standard errors in parentheses. ***p<0.01; **p<0.05; *p<0.10.

Table 7: Air Pollution Impacts of MillionTreesNYC (Synthetic Control Results)

	Annual PM2.5	Annual SO2	Annual NO2	Annual O3	Annual CO
DID Estimate	-0.010	-0.019	-0.016	0.0003	-0.024
p-value	<0.00	0.26	0.72	0.70	0.30
Weather Controls	Yes	Yes	Yes	Yes	Yes
Sample size	504	480	720	564	336

Notes: DID estimates and p-values obtained from separate runs of the synthetic control method for each pollutant type. DID estimates provide information on the average annual impact of MillionTreesNYC on air pollution concentrations. Weather controls include maximum temperature, minimum temperature, and precipitation.