Environmental Research 144 (2016) 158–164

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Climate change and fetal health: The impacts of exposure to extreme temperatures in New York City

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ARTICLE INFO

Article history:
Received 30 July 2015
Received in revised form
3 November 2015
Accepted 13 November 2015
Available online 21 November 2015

Keywords:
Climate change
Fetal health
Urban sustainability

ABSTRACT

Background: Climate change is projected to increase the frequency, intensity, and duration of heat waves while reducing cold extremes, yet few studies have examined the relationship between temperature and fetal health.
Objectives: We estimate the impacts of extreme temperatures on birth weight and gestational age in Manhattan, a borough in New York City, and explore differences by socioeconomic status (SES).
Methods: We combine average daily temperature from 1985 to 2010 with birth certificate data in Manhattan for the same time period. We then generate 33 downscaled climate model time series to project impacts on fetal health.
Results: We find exposure to an extra day where average temperature $<25\,°F$ and $>85\,°F$ during pregnancy is associated with a 1.8 and 1.7 g (respectively) reduction in birth weight, but the impact varies by SES, particularly for extreme heat, where teen mothers seem most vulnerable. We find no meaningful, significant effect on gestational age. Using projections of temperature from these climate models, we project average net reductions in birth weight in the 2070–2099 period of 4.6 g in the business-as-usual scenario.
Conclusions: Results suggest that increasing heat events from climate change could adversely impact birth weight and vary by SES.

1. Introduction

Numerous studies have investigated the short- and long-run problems associated with climate change, such as damages to agriculture or reduced labor productivity (Intergovernmental Panel on Climate Change (IPCC), 2014; Graff Zivin and Neidell, 2013; McMichael et al., 2006; Easterling et al., 2000). The impacts on public health are also great, with a large literature associating heat and cold waves with higher mortality rates (Lee et al., 2006; Barreca, 2012; Barreca et al., 2012; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Deschenes, 2012; Gosling et al., 2009; Li et al., 2013; Gasparrini et al. 2015) and spontaneous fetal death rates (Fukuda et al., 2014). However, a handful of studies have begun to observe other possible climate-driven health outcomes, such as poor fetal health, which previous work shows affects later-life outcomes like educational attainment and income (Almond, 2006; Black et al., 2007; Deschenes et al., 2009a; Van Zutphen et al., 2012; Kent et al., 2014; Simenova, 2011). In fact, low birth weight and short gestation was responsible for 20% of deaths for infants <1 year old in 2011 in New York City (NYC) (NYC Dept. of Health and Mental Hygiene, 2013). Consequently, NYC provides a valuable setting for examining the relationship between temperature and fetal health, not only due to its large urban population of 8.4 million, but because temperatures in NYC increased by approximately 1.5 °C between 1901 and 2011, which is greater than global and US national trends (Horton et al., 2010; Intergovernmental Panel on Climate Change (IPCC), 2014; U.S. Global Change Research Program, 2013). Further, it is critical we understand the public health implications of extreme heat events in cities since they may be worsened by the urban heat island effect. These vulnerabilities are recognized by the NYC government, which has made climate change and public health related issues a priority (NYC Office of the Mayor, 2014; Rosenzweig et al., 2011).

In this study, we investigate two timely and critical research questions regarding climate change and public health. First, what is the impact of maternal exposure to extreme temperatures on fetal health and how might it vary by socioeconomic status (SES)? Second, what are the projected impacts of climate change, via higher temperatures, on fetal health? To address the former, we

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http://dx.doi.org/10.1016/j.envres.2015.11.016
0013-9351/

exploit the variation in maternal exposure to extreme temperatures across years between 1985 and 2010 using micro-level data with ample, detailed information on maternal characteristics for the universe of births in Manhattan, a borough of NYC (Supplementary material, Figs. A1–A2). We observe the effects of temperature on important predictors of infant health: birth weight and gestational age. We also explore differences among socioeconomic groups to determine the possibility of mitigating factors (e.g., air conditioners (ACs)).

In examining the second question, we contribute to the growing understanding of the health impacts of climate change, which is expected to increase the frequency and duration of heat waves and reduce the occurrence of cold waves. A few studies have begun to use a range of climate models to assess public health risks, but to our knowledge, prior research has not applied this approach to future birth outcomes (Li et al., 2013; Petkova et al., 2013). In our study, we generated downscaled daily temperature outputs for Manhattan using 33 climate models and two Representative Concentration Pathways (RCPs): RCP4.5 (an emission scenario consistent with transition to cleaner technologies) and RCP8.5 (a business-as-usual (BAU) emission scenario). Using a suite of models specifically for Manhattan, we can sample the climate-driven range or uncertainty in future birth outcomes, which will inform and motivate public health and climate change related policies.

2. Methods

2.1. Data and measures

2.1.1. Birth certificate data

We used restricted birth certificate data from the New York City Department of Health and Mental Hygiene (NYCDHMH) New York City Vital Statistics (NYCVS) from 1985 to 2010. We obtained the appropriate institutional review board approvals to access New York City birth certificate data from the Bureau of Vital Statistics of New York City's Department of Health and Mental Hygiene Vital Statistics. This dataset includes the universe of births in Manhattan and has information on the month and year of birth, detailed data on infant health such as the dependent variables of interest which are birth weight (g) and gestational age (weeks). It also has ample information on maternal characteristics, including mother's age, education, ethnicity, marital status, smoking status, and if she participated in Aid to Families with Dependent Children (AFDC), which is often used as a measure of income on birth certificate data.

2.1.2. Weather data

We obtained data from the National Climatic Data Center using the Global Historical Climatology Network (GHCN)-Daily database which has information on minimum and maximum temperature in Central Park, Manhattan. Taking the average of these two values, we find average daily temperature.

2.1.3. Pollution data

We also collected daily ambient pollution data from the Environmental Protection Agency since we include pollution as a control variable in one of our sensitivity checks. Data were averaged across all pollution monitors in NYC. Pollutants of interest were SO_2, CO, NO_2, and PM_{10} between 1988 and 2005. We chose this time period for consistency since PM_{10} at pollution monitors in NYC were not measured prior to 1988 and after 2005.

2.2. Statistical analysis and climate models

2.2.1. Regression analysis

To address our first research question, we estimate impacts of maternal exposure to extreme and moderate temperatures on fetal health and, for consistency, use a similar approach to a study by Deschenes et al. (2009). The explanatory variable of interest is the number of days of maternal exposure during different trimesters of pregnancy to the following temperature bins: <25 °F, 25–45 °F, 45–65 °F, 65–85 °F, >85 °F. Since we only have information on birth month and birth year, we define the first trimester as the 8th, 7th, and 6th months prior to birth, the second trimester as the 5th, 4th, and 3rd months prior to birth, and the third trimester as the 2nd and 1st month prior to birth and the birth month. For example, to determine maternal exposure to extreme heat ($T>85$ °F) in the third trimester for a baby born July 12, 1990, we sum the number of days in Manhattan where average $T>85$ °F for May, June, and July 1990 (discussion of possible measurement error is discussed later in Section 4.1). We use a regression framework to observe the relationship between fetal health and temperature in Manhattan, where ample daily weather data are available. We combine these weather data with information on the universe of births in Manhattan from 1985 to 2010, which includes more than 500,000 births. On average in Manhattan between 1985 and 2010, mothers were exposed to 10 days where average $T<25$ °F and 3 days where average $T>85$ °F during their pregnancy. For more information on exposure to various temperature bins, see Table A5 in the Supplementary material.

We exploit the variation in extreme temperature from year to year which is plausibly exogenous to confounding variables common in observational studies, such as if the mother smokes, since we assume it is difficult for mothers to predict years when extreme temperatures will occur. Additionally, we control for detailed maternal characteristics, seasonality of birth, and annual trends. Our regression also addresses potential nonlinearities between temperature and fetal health by estimating impacts within different temperature bins. We use the following baseline regression:

$$health_{imy} = \varphi_0 + \sum_{j=1}^{4} \beta_j^{Tr1} Tavg_{jmy} + \sum_{j=1}^{4} \beta_j^{Tr2} Tavg_{jmy} + \sum_{j=1}^{4} \beta_j^{Tr3} Tavg_{jmy} + \Gamma \boldsymbol{X}_{imy} + month_{\boldsymbol{m}} + year_y + \epsilon_{imy} \quad (1)$$

where $health_{imy}$ is birth weight (g) or gestational age (weeks) for mother i who gives birth in month m and year y. The variable, $Tavg_{jmy}$, is the number of days a mother is exposed to average daily temperature bin j (<25 °F, 25–45 °F, 65–85 °F, >85 °F and 45–65 °F is the omitted category) in trimester 1 ($Tr1$), trimester 2 ($Tr2$), and trimester 3 ($Tr3$). To account for important covariates, $\boldsymbol{X}_{imy}$ includes a dummy variable for infant's sex and dummy variables for mother's age (categorized by year), education (categorized as ≤ 8 years, 9–11, 12, 13–14, 15, ≥ 16, or unknown years completed), ethnicity (categorized as Puerto Rican, Other Hispanic, Asian and Pacific Islander, White Non-Hispanic, Black Non-Hispanic, Other, or unknown), marital status, if the mother smoked, number of cigarettes smoked each week, number of previous deliveries, and if the mother participated in AFDC. The variable $month_m$ includes dummy variables for each birth month to control for seasonality. Studies also suggest birth month is correlated to maternal characteristics, so by including $month_m$, we compare mothers who give birth in the same month and mitigate omitted variable bias (Strand et al., 2011a; Buckles and Hungerman, 2013). Birth year trends, $year_y$, are also included to account for annual factors that change monotonically and ε_{imy} is the error term. Standard errors are clustered at the birth month-birth year level to account for serial correlation within each birth month-birth year.

The coefficient of interest is β_j, which represents the change in birth weight due to an extra day of exposure to temperature bin j relative to the baseline category, 45–65 °F, in a given trimester. We assume that the effects of temperature within each temperature bin are the same (e.g., the impact on birth weight at 30 °F is equivalent to the impact at 40 °F) and we expect at very high temperatures, the impact of temperature on fetal health will be negative, while the effect from colder temperatures is less clear in the current literature. We then calculate the *cumulative impact* of exposure to different temperature bins during the entire pregnancy by taking a linear combination of coefficients for each trimester using the "lincom" command, which adjusts the standard errors appropriately, in Stata version 13 (StataCorp, College Station, Tex).

Missing observations of the dependent variables (birth weight and gestational age) were dropped from the sample, which included 0.2% and 0.7% (resp.) of observations. Observations with missing temperature data during any part of the 9 months of pregnancy were also dropped (2.4% of the observations). The final sample size for analyses where birth weight or gestational age is the outcome variable is 514,104 or 510,781 observations (resp.). The sample sizes are different due to missing data for each variable.

2.2.2. Downscaled climate models for Manhattan

To project impacts on birth outcomes in the future from exposure to extreme temperatures, we use monthly bias-corrected and spatially disaggregated (BCSD) climate projections at 1/8° resolution derived from the WCRP CMIP5 multi-model data set. The BCSD projections were obtained online (Maurer et al., 2007). The output from the land-based grid box corresponding to New York City (Central Park), was used to create change factors at 1/8° resolution for each calendar month based on the difference between each 30-year future time slice and the same GCM's 30-year baseline time slice. These change factors are then applied to the respective observed daily weather data to create a future projection with the same statistical characteristics and sequence as the observations.

The approach described here does not explore how intra-annual and inter-annual temperature variability may change. By not considering sub-monthly changes in variability, we were able to use fine-spatial-resolution projections (as the 1/8°BCSD product is monthly, not daily). By applying the delta method separately for each calendar month, we do capture one component of possible changes in intra-annual variance, changes in the annual temperature cycle. Previous studies have found changes in the annual cycle to be important (Ballester et al., 2010). The BCSD methodology yielded a set of 66 synthetic future temperature projections for daily T mean from 2010 to 2100 based on the three 30-year time slices, and for a baseline period 1971–2000.

The projections for future temperatures using downscaled outputs from 33 global-scale general circulation models (GCMs) and used in the Intergovernmental Panel on Climate Change Fifth Assessment report, were developed in conjunction with two RCPs (Taylor et al., 2012; Moss et al., 2010). RCPs are a set of climate forcings (in Watts per meter) each consistent with different trajectories of greenhouse gas and aerosol emissions, and land use changes developed for the climate modeling community as a basis for long-term and near-term climate modeling experiments. For this analysis, we selected the two RCPs most used by the climate modeling community, RCP 4.5 and RCP 8.5, which represent relatively low and high greenhouse gas projections (resp.). RCP 4.5 is a scenario where greenhouse gas concentrations are eventually stabilized this century, consistent with sharp emissions reductions. RCP 8.5 is consistent with increasing emissions over the century or a BAU scenario. Increasing emissions are associated with a high-energy intensity, high population growth, and slow development of green technologies (such as renewable energy sources and energy efficiency) pathway (Van Vuuren et al., 2011). To the authors' knowledge, only two studies by Li et al. (2013) and Petkova et al. (2013) used a suite of climate models for public health purposes in New York City (NYC).

3. Results

3.1. Main regression analysis

Fig. 1 plots the coefficients (circles) and their standard errors (bars) using Eq. (1) for birth weight, where the horizontal line is 0. Results in the first two trimesters follow an inverted U-shape, where the impacts on birth weight are negative at the extreme temperatures relative to more comfortable temperatures ($R^2 = 0.033$). Specifically, we find a negative, significant effect for mothers exposed to an extra day where average $T < 25$ °F in trimester 1, where birth weight reduces by 0.8 g ($p < 0.05$) relative to more comfortable temperatures. We then calculate the cumulative impact during the entire pregnancy and find that exposure to an extra very cold day reduces birth weight by 1.8 g ($p < 0.01$). We also find that exposure to an extra day of average $T > 85$ °F in trimesters 1 and 2 reduces birth weight by 1.1 g ($p < 0.10$), where the cumulative impact during the entire pregnancy is associated with a reduction in birth weight of 1.7 g ($p < 0.10$) (mean birth weight is 3233 g with a standard deviation of 601 g). Finally, we find a very small, significant reduction from exposure to an extra day of extreme heat in trimester 1 on gestational age of 0.004 weeks or 46 min, but no significant cumulative impact (mean gestational age is 39 weeks with a standard deviation of 2.4 weeks).

We focus the remainder of our analysis on birth weight since the impact on gestational age is minor. For more information, detailed tables and further discussion of the main results are available in the Supplementary material, Table A1. In another regression, we use Eq. (1) as a linear probability model (LPM), where the dependent variable is a dummy variable if an infant is born with low birth weight (i.e., birth weight < 2500 g). In the LPM, the coefficient of interest, β_j, represents the change in probability of having a low birth weight baby due to an extra day of exposure to temperature bin j relative to the baseline category. Results are in Table A1 column 3. We find that exposure to an extra day of average temperature < 25 °F or > 85 °F is associated with increases in the probability of having an infant with low birth weight by 0.0003 or 0.0005 (resp.). Finally, in another model, we allow for more flexibility in Eq. (1) by adding squared and cubed terms of birth year and results are in Table A1, column 5. Results are similar to the main results in column 1, reinforcing the robustness of results.

3.2. Projected impacts of climate change

Based on the downscaled CMIP5 climate models, both RCPs project a reduction in the number of cold days and an increase in the number of hot days, implying that the net impact of climate change on birth weight could be small since the effect from cold waves may offset the impacts from heat waves (Supplementary material, Fig. A3). To project impacts of climate change on birth weight, we sum the number of days of exposure to average daily $T < 25$ °F and > 85 °F for a 9 month pregnancy period for each month-year for our baseline and projected study periods: 2010–2039, 2040–2069, and 2070–2099. We then take the mean of the total exposure within each study period, so we have average exposure to very hot and cold temperatures during a 9 month

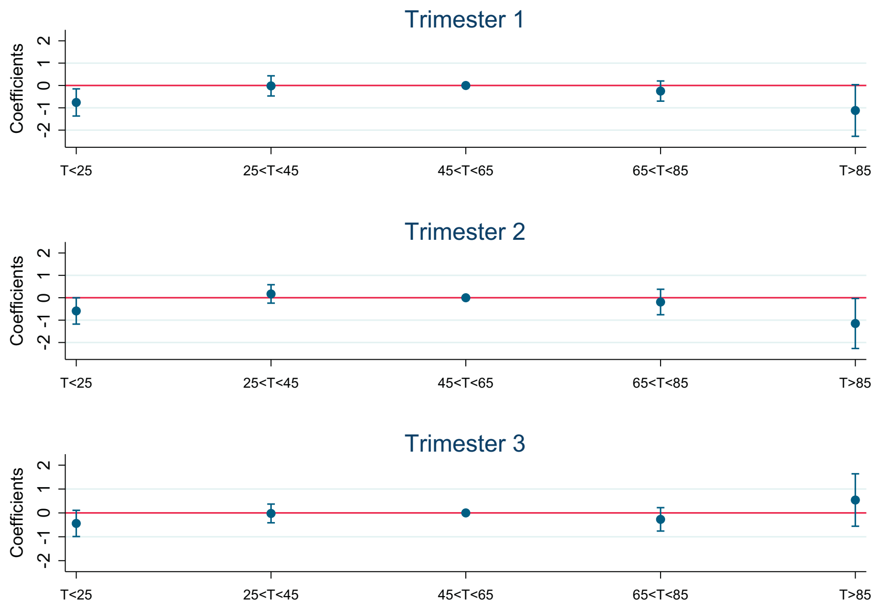

Fig. 1. The impact of temperature on birth weight in Manhattan between 1985 and 2010. The reference category is 45 °F $< T < 65$ °F. The circle represents the coefficient and the bars are the standard errors and the horizontal line is 0.

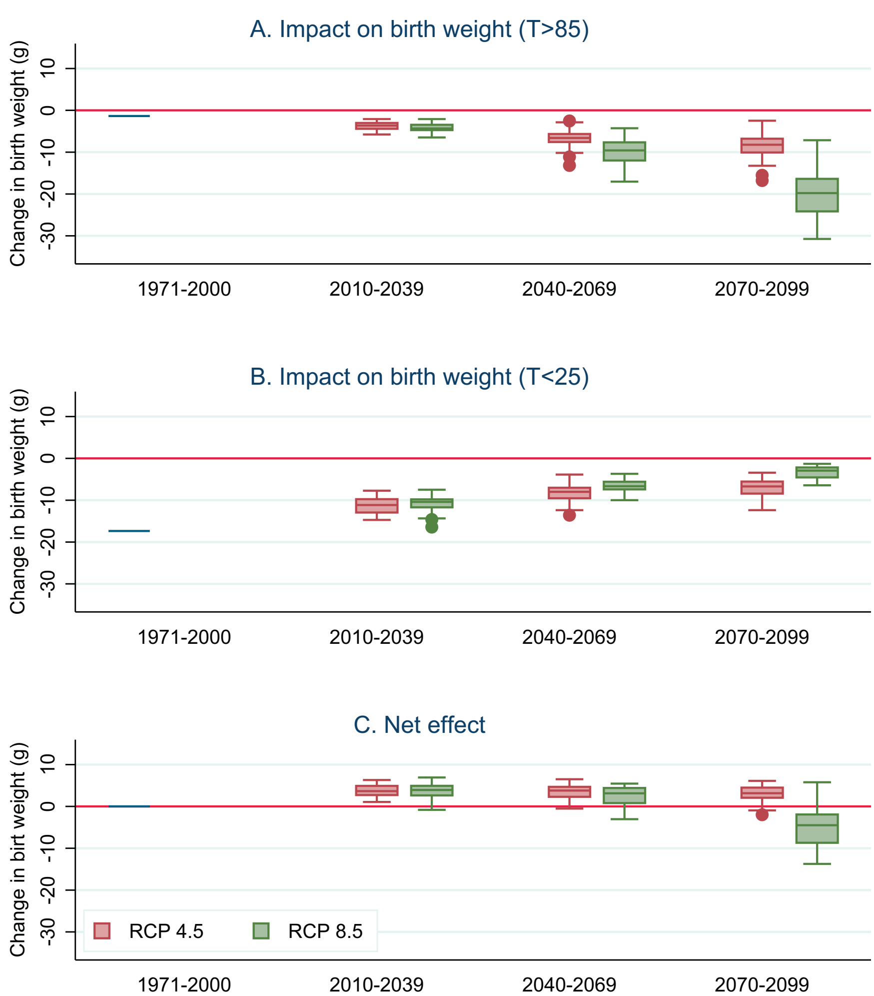

Fig. 2. Changes in birth weight over the different projection periods for the 33 downscaled climate models for each scenario and study period from exposure to very hot (Panel A) and cold (Panel B) temperatures. Panel C shows net changes in birth weight relative to the baseline period. The box symbols represent, from bottom to top, the lower adjacent value, 25th percentile, median, 75th percentile, upper adjacent value and the dots are outside values. The horizontal line is 0.

pregnancy for the baseline and projected study periods for each model and climate scenario.

Next, to calculate the total projected change in birth weight resulting from exposure to very hot or cold temperatures, we multiply the average number of days when $T > 85$ °F or $T < 25$ °F during a 9 month pregnancy for each climate model, scenario and period by -1.7 g or -1.8 g (resp.), which is the cumulative impact on birth weight from exposure to an extra day of extreme heat or cold found in our main results. We then determine the projected net impact on birth weight for each model, scenario, and study period by taking the difference between the projected change in birth weight and the change in birth weight in the baseline period.

Fig. 2 is a box plot of the distribution of changes in birth weight over the 33 downscaled climate models for each scenario and study period from exposure to very hot and cold temperatures in Panels A and B (resp.), and Panel C shows net changes in birth weight relative to the baseline period. The box shows the 25th and 75th percentiles and median (the middle line in the box). Initially in the 2010–2039 period, the mean net effect across models is 3.8 g and 3.7 g in the RCP4.5 and RCP8.5 scenario (resp.). The positive net effects are due to the reduction in the average number of cold days and smaller number of very hot days. In the following 2040–2069 period, the mean net projection for the RCP4.5 scenario remains the same, but the BAU scenario decreases to 2.5 g, where both RCP4.5 and RCP8.5 scenarios include some models that predict a negative impact. Finally, in the last 2070–2099 period, the number of very hot days increases dramatically and shows a mean net *reduction* in birthweight of 4.6 g in the BAU scenario, though a positive net effect remains in the RCP4.5 scenario.

3.3. Other tests and sensitivity checks

We perform additional tests and sensitivity checks to further explore our main results using Eq. (1) and address possible concerns about our regression analysis. For more information, detailed tables and further discussion of other tests and sensitivity checks are in the Supplementary material, Tables A2–A4.

3.3.1. Differences by SES

Since our model exploits year-to-year variation in extreme temperatures, we assume that the timing of birth is unlikely correlated to exposure since mothers are unable to predict years of extreme heat or cold. In the baseline model in Eq. (1) we include control variables (e.g., maternal characteristics) to reduce the standard errors on coefficients since these variables are important in predicting birth outcomes. We test the exogeneity of variation in exposure to extreme temperatures by running the baseline regression without maternal characteristics and expect similar coefficients to our main results (Strand et al., 2011) (Table A1, column 4). Using these models, we find statistically similar coefficients to our main results ($R^2 = 0.009$). However, we find a spurious relationship between exposure to mild heat (i.e., 65 °F $< T <$ 85 °F) and reduction in birth weight.

We explore this relationship further using Eq. (1) and observe impacts by SES, specifically mothers less than 18 years of age, have less than 12 years of education, have at least a Bachelor's Degree, are Hispanic, Black (non-Hispanic), or White (non-Hispanic). Again, if annual variation to different temperatures is random, then we expect comparable results across varying socioeconomic groups. Results from these models show a consistently significant, negative cumulative impact from exposure to extreme cold between -5 and -1.3 g. With respect to extreme heat, we find statistically significant, negative impacts in trimester 2 between -5.4 and -2 g for all categories except for Black and White mothers and mothers with at least a Bachelor's degree.

3.3.2. Ambient pollution as a possibly confounding variable

Ambient pollution is a possibly confounding variable since the literature suggests it is correlated to temperature and birth weight. We include average ambient levels of SO_2, CO, PM_{10}, and NO_2 from 1988 to 2005 in Manhattan during the entire 9 months of pregnancy using Eq. (1). This dramatically reduces our sample size since pollution data are missing for many months and years ($N = 249{,}035$). Consequently, results may be less precisely estimated due to the smaller sample size, however by adding relevant covariates, standard errors may be smaller. After controlling for pollution, results show a negative, but insignificant cumulative impact similar to the main results from exposure to extremely hot and cold temperatures during pregnancy. The insignificance of the coefficient could be due to the smaller sample size noted earlier.

3.3.3. Smaller temperature bins

Third, results and methodologies in the related epidemiological literature are often inconsistent due to difficulties in representing exposure using a continuous variable since pregnancies occur throughout different seasons (Strand et al., 2011). To circumvent this, we use categorical variables in Eq. (1) to determine exposure to different temperatures, however, the optimal temperature thresholds or bins are currently unclear. We test different thresholds and run Eq. (1), but use smaller temperature bins of a size of 10 °F (i.e., $T < 20$ °F, 20–30 °F… 80–90 °F, $T > 90$ °F), where 50–60 °F is the reference category, and compare effects to the main results. Similar to the main results, we find negative, significant impacts from exposure between 80 and 90 °F in trimester 2 and where $T < 20$ °F in the first two trimesters. However, we also find a positive, significant impact from exposure to an extra day where $T > 90$ °F, which is surprising. It is important to note that maximum exposure to $T > 90$ °F during pregnancy for this study period was 2 days and average exposure was 0.2 day, making these events very rare. Whereas average exposure to days where average temperature was between 80 and 90 °F was 13 days. This suggests the positive results for women exposed to $T > 90$ °F are driven by a very small sample of anomalous events.

4. Discussion

The main results using Eq. (1) show statistically significant decreases in birth weight resulting from exposure to extreme heat and cold. The effects are modest, but to put these results in perspective, a study by Almond et al. (2005) shows that smoking during pregnancy reduced birth weight by 200 g while another study by Wahabi et al. (2013) associated maternal exposure to secondhand smoke with a reduction in birthweight of 35 g. In which case, exposure to an extra *week* of extreme cold or heat is approximately 4 or 5% (resp.) of the effect of smoking during pregnancy on birth weight and 24% or 28% (resp.) of exposure to secondhand smoke.

We also observed impacts by SES since some socioeconomic groups could reduce their exposure to extreme temperatures by indoor heating or cooling systems. We found similar impacts from exposure to extreme cold across different SESs, but this is unsurprising since exposure to very cold weather is easier to mitigate in NYC, where the NYC Dept. of Housing Preservation and Development's City Housing Maintenance Code requires building owners to provide heat and hot water to all tenants year around; otherwise tenants can file violations or complaints with the city (NYC Dept. of Housing Preservation and Development, 2014). This result suggests that despite access to heated buildings, the effect from cold weather may be difficult to overcome.

However, we found differences by SES when examining impacts of exposure to extreme heat. These findings may reflect the fact that building owners are not required to provide any cooling mechanism for tenants. Additionally, the effect is exacerbated for teen mothers, who experience the greatest reductions in birth weight from exposure to extreme heat. A possible explanation is that teen mothers are more likely to be outdoors and in school relative to older, working mothers who may have more access to ACs or fans to mitigate their exposure. Also, three groups did not experience any impact from exposure to extreme heat. Two of these groups, specifically White or college-educated mothers, are typically considered of a higher SES, in which case they could possibly afford to mitigate their risk of exposure by purchasing an AC, for example. However, using these datasets we cannot directly test for these mitigating factors, nor do we have information regarding occupation, so the evidence is speculative at best.

Deschenes et al. (2009) find statistically significant modest reductions in birth weight from exposure to extreme temperatures between 0.003 and 0.009% per day, especially in the second and third trimesters. Our results show statistically significant impacts from exposure to extreme heat during Trimester 2 only, though the cumulative impact throughout pregnancy is also significant. Overall, our results show modest decreases in birth weight from exposure to extreme heat, which are in line with the findings in the Deschenes et al. (2009) study.

We then address our second research question regarding projected changes in birth weight resulting from climate change using results from several climate model simulations for NYC specifically. Mean net projected impacts in the 2070–2099 period scenario suggest a *net reduction* in birth weight for the RCP8.5 or BAU scenario, while the effect in the RCP4.5 (lower emissions) scenario remains positive and similar to the previous periods' predictions. This suggests that if action is taken early enough to decrease emissions of long-lived greenhouse gases, the impact on fetal health could be minimized.

4.1. Limitation: measurement error

One of the primary limitations to this study is not having exact birth dates, but only birth months and years. Consequently, we measure exposure to temperature during pregnancy with some measurement error. We determine exposure to extreme temperatures by summing the number of days of exposure for the month and year of birth and the 8 months prior. For example, if a mother gave birth July 3, 1990 and another mother gives birth July 20, 1990, in the data it only appears as July 1990. However, the mother who gave birth earlier in the month may have experienced different exposure to extreme heat or cold. Although we have information on gestational age, we can only estimate maternal exposure within 4 weeks since we do not know the exact birth week. We consider which direction this measurement error could bias our results. First, if the measurement error is systematic, we could possibly overestimate impacts. For example, mothers who give birth later in the month and perhaps experience more exposure to extreme heat may be systematically different from mothers who give birth earlier in the month. Second, if the measurement error is random or noise, then it is a “classical measurement error,” which standard models show bias estimates toward zero or the null hypothesis and potentially underestimate the true effect (Wooldridge, 2002).

Regarding the former, there is a large literature on the relationship between birth month and later-life out comes, such as income, health, and education. A study by Buckles and Hungerman (2013) suggests birth month, which we control for, is correlated to maternal characteristics and that weather at the expected time of birth was a driving factor. To the authors' knowledge, the correlation between birth week and maternal characteristics is less clear, though since the long-term average temperature differences between two calendar weeks in the same month are generally smaller than the average temperature differences from one month to the next, this bias, if any, is likely small. This suggests the measurement of exposure is estimated with classical measurement error and would bias results to zero.

5. Conclusion

Our research shows that exposure to extreme heat and cold affects birth weight, though we find no meaningful, significant impact on gestational age. We explore the relationship further and find impacts on birth weight from maternal exposure to extreme heat differ across SES, while the effect from exposure to extreme cold is persistent across different socioeconomic groups. Using detailed information from downscaled climate models, we find that early action to limit climate change by reducing greenhouse gas emissions could minimize adverse effects. This work demonstrates the potential for further incorporation of climate projections into public health and policy research.

Further understandings of the biological mechanisms linking birth outcomes and climate change, as well as the utility of mitigating factors, like ACs, remain areas of future research since we are unable to directly test for these in our study. However, this information would be highly valuable for climate change adaptation. Future work includes merging climate and health data with information on possibly mitigating factors to extreme temperatures or climate change, such as household information on AC use or time spent working outside during pregnancy, overall health, and long-term physiological adaptation to higher temperatures. We would expect households with ACs or pregnant mothers who worked indoors all day to experience a smaller effect on birth weight.

Additionally, we base these estimates on a few assumptions. We assume that the size of a birth cohort in 2009 will be the same as in 2070, however, it is likely population will increase in the next few decades, suggesting this is a conservative estimate. However, individuals may also adapt to climate change via ACs, so the total number of mothers affected could decrease over time, assuming no major changes in energy expenses. Other factors, like changes in healthcare or access to healthcare or possible educational campaigns may also alter these economic estimates.

Funding sources

Appropriate institutional review board approvals were granted to access New York City birth certificate data from the Bureau of Vital Statistics of New York City's Department of Health and Mental Hygiene Vital Statistics and the University of Oregon. Any errors are my own.

Acknowledgments

The authors would like to thank Daniel Bader, Patrick Kinney, Matthew Neidell, Douglas Almond, Jean Stockard, Chandra Kiran B Krishnamurthy, John, Mutter, Tony del Genio, Regina Zimmerman, Noreen Sandy, and Berton Freedman for their input and help on this project. We also want to thank three anonymous referees for their helpful comments on improving the paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2015.11.016.

References

Almond, D., Chay, K., Lee, D., 2005. The costs of low birth weight. Q. J. Econ., 1031–1083.

Almond, D., 2006. Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 U.S. Population. J. Polit. Econ. 109, 191–210.

Ballester, J., Giorgi, F., Rodo, X., 2010. Changes in European temperature extremes can be predicted from changes in PDF central statistics. Clim. Change 98, 277–284.

Barreca, A., 2012. Climate change, humidity, and mortality in the United States. J. Environ. Econ. Manag. 63, 19–34.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., Shapiro, J.S., 2012. Adapting to Climate Change: The Remarkable Decline in the U.S. Temperature–Mortality Relationship over the 20th Century. MIT Dept. of Economics Working Paper Series, pp. 12–29.

Black, S.E., Devereux, P., Salvanes, K., 2007. From the cradle to the labor market? The effect of birth weight on adult outcomes. Q. J. Econ. 122, 409–439.

Buckles, K., Hungerman, D.M., 2013. Season of birth and later outcomes: old questions, new answers. Rev. Econ. Stat.

Deschenes, O., Greenstone, M., Guryna, J., 2009a. Climate change and birth weight. Am. Econ. Rev.: Pap. Proc. 99, 211–217.

Deschenes, O., Moretti, E., 2009. Extreme weather events, mortality, and migration. Rev. Econ. Stat. 4, 659–681.

Deschenes, O., Greenstone, M., 2011. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. Am. Econ. J.: Appl. Econ., 152–185.

Deschenes, O., 2012. Temperature, Human Health, and Adaptation: a Review of the Empirical Literature. NBER Working Paper Series 18345.

Easterling, D.R., Meehl, G.A., Parmesan, C., Changon, S.A., Karl, T.R., Mearns, L.O., 2000. Climate extremes: observations, modeling, and impacts. Science, 2068–2074.

Fukuda, M., Fukuda, K., Shimizu, T., Nobunaga, M., Mamsen, L.S., Andersen, C.Y., 2014. Climate change is associated with male:female ratios of fetal deaths and newborn infants in Japan. Fertil. Steril. 102 (5), 1364–1370.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., et al., 2015. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375.

Graff Zivin, J., Neidell, M., 2013. Temperature and the Allocation of Time: Implications for Climate Change. National Bureau of Economic Research (NBER) Working Paper Series 15717.

Gosling, S.N., Lowe, J.A., McGregor, G.R., Pelling, M., Malamud, B.D., 2009. Associations between elevated atmospheric temperature and human mortality: a critical review of the literature. Climactic Change 92, 299–341.

Horton, R., Gornitz, V., Bowman, M., Blake, R., 2010. Climate observations and projections. Ann. N. Y. Acad. Sci. 1196, 41–62.

Intergovernmental Panel on Climate Change (IPCC), 2014. Fifth Assessment Report.

Kent, S.T., McClure, L.A., Zaitchik, B.F., Smith, T.T., Gohlke, J.M., 2014. Heat waves and health outcomes in Alabama (USA): The importance of heat wave definition. Environmental Health Perspectives 122 (2), 151–158.

Lee, S.J., Steer, P.J., Filippi, V., 2006. Seasonal patterns and preterm birth: a systematic review of the literature and an analysis in a London-based cohort. Fetal Med. 113, 1280–1288.

Li, T., Horton, R.M., Kinney, P.L., 2013. Projections of seasonal patterns in temperature-related deaths for Manhattan, New York. Nat. Clim. Change 3, 717–721.

Maurer, E.P., Brekke, L., Pruitt, T., Duffy, P.B., 2007. Fine-resolution climate projections enhance regional climate change impact studies. Eos Trans. AGU 88; p. 504.

McMichael, A.J., Woodruff, R.E., Hales, S., 2006. Climate change and human health: present and future risks. Lancet 367, 859–869.

Moss, R.H., et al., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756.

NYC Dept. of Health and Mental Hygiene Bureau of Vital Statistics, 2013. Appendix A: supplemental population, mortality, and pregnancy outcome data tables. Summary of Vital Statistics 2011 The City of New York.

NYC Dept. of Housing Preservation and Development (2014) "Heat and Hot Water." *HPD*. N.p., n.d. Web.

NYC Office of the Mayor (2014): PlaNYC: A Greener, Greater New York.

Petkova, E.P., Horton, R.M., Bader, D.A., Kinney, P.L., 2013. Projected heat-related mortality in the U.S. urban northeast. Int. J. Environ. Res. Public Health 10, 6734–6747.

Rosenzweig, C., et al., 2011. Responding to climate change in New York state: The ClimAID integrated assessment for effective climate change adaptation in New York State. Ann. Ny. Acad. Sci. 1244, 2–649.

Simenova, E., 2011. Out of sight, out of mind? Natural disasters and pregnancy outcomes in the USA. CESifo Econ. Stud. 57, 403–431.

Strand, L.B., Barnett, A.G., Tong, S., 2011. The influence of season and ambient temperature on birth outcomes: a review of the epidemiological literature. Environ. Res. 111, 451–462.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93, 485–498.

U.S. Global Change Research Program, 2013. 2013 U.S. National Climate Assessment.

Van Vuuren, D., et al., 2011. The representative concentration pathways: an overview. Clim. Change 109, 5–31.

Van Zutphen, A.R., Lin, S., Fletcher, B.A., Hwang, S.A., 2012. A population-based case-control study of extreme summer temperature and birth defects. Environmental Health Perspectives 120, 1443–1449.

Wahabi, H.A., Alzeidan, R.A., Fayed, A.A., Mandil, A., Al-Shaikh, G., Esmaeil, S.A., 2013. Effects of secondhand smoke on the birth weight of term infants and the demographic profile of Saudi exposed women. BMC Public Health 13, 341.

Wooldridge, Jeffrey M. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT, 2002.