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In utero shocks and health at birth: the distorting effect of fetal losses

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ABSTRACT
Research on the effect of in utero shocks on health at birth may be influenced by in utero selection. This study outlines a conceptual framework and shows that the results of the standard empirical approach are biased if (i) the exposure changes the probability of fetal death and (ii) health differences exist between deceased and surviving fetuses. Furthermore, an empirical example is provided to illustrate, the potential importance of fetal selection. Examining the impact of heat on birth weight, I find that accounting for fetal selection substantially increases the heat effect compared to the standard approach. These results suggest that incorporating the distorting effect of fetal losses into the estimations may be critical in some cases to provide more informed guidance for public policy.

JEL codes: I12, J13, Q54
Keywords: in utero selection, health at birth, birth weight, temperature, climate change

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Terhesség alatti sokkok és születéskori egészség: a magzati veszteségek torzító hatása

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ÖSSZEFOGLALÓ

A terhesség alatti sokkok születéskori egészségre gyakorolt hatásával kapcsolatos kutatások eredményeit befolyásolhatja a terhesség alatti szelekció. Ez a tanulmány egy koncepcionális keretet felvázolva megmutatja, hogy a szokásos empirikus megközelítés eredményei torzítottak, ha (i) a sokk megváltoztatja a magzati halálozás valószínűségét, és (ii) az elhunyt és a túlélő magzatok potenciális születéskori egészsége eltér. A magzati szelekció potenciális jelentőségét egy empirikus példával illusztrálom. A magas hőmérséklet születési súlyra gyakorolt hatását vizsgálva azt találom, hogy a magzati szelekció figyelembevétele jelentősen megnöveli a magas hőmérséklet hatására vonatkozó becslést a standard megközelítéssel kapott eredményhez képest. Ez az eredmény azt sugallja, hogy a magzati veszteségek torzító hatásának becslésekbe történő beépítése bizonyos esetekben elengedhetetlen ahhoz, hogy megalapozottabb iránymutatást lehessen nyújtani a közpolitikai döntéshozók számára.

JEL: I12, J13, Q54

Kulcsszavak: méhen belüli szelekció, születéskori egészség, születési súly, hőmérséklet, klímaváltozás

In utero shocks and health at birth: the distorting effect of fetal losses

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Abstract

Research on the effect of in utero shocks on health at birth may be influenced by in utero selection. This study outlines a conceptual framework and shows that the results of the standard empirical approach are biased if (i) the exposure changes the probability of fetal death and (ii) health differences exist between deceased and surviving fetuses. Furthermore, an empirical example is provided to illustrate, the potential importance of fetal selection. Examining the impact of heat on birth weight, I find that accounting for fetal selection substantially increases the heat effect compared to the standard approach. These results suggest that incorporating the distorting effect of fetal losses into the estimations may be critical in some cases to provide more informed guidance for public policy.

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1. Introduction

There is a vast literature on the effect of various shocks, exposures, and interventions during pregnancy on birth outcomes. This includes studies on the effect of various environmental and other factors, e.g. exposure to air pollution (Coneus and Spiess, 2012; Currie et al., 2009; Gehrsitz, 2017; Liu et al., 2022; Mouganie et al., 2023; Rangel and Vogl, 2019), toxic chemicals and pesticides (Calzada et al., 2023; Currie et al., 2011; Currie and Schmieder, 2009), storms and hurricanes (Currie and Rossin-Slater, 2013; Jones, 2020), water contamination (Currie et al., 2013; Wang et al., 2022), introduction of smoking bans (Bharadwaj et al., 2014; Hajdu and Hajdu, 2018), exposure to violence and crime (Currie et al., 2022; Grossman and Khalil, 2022; Koppensteiner and Manacorda, 2016; Le and Nguyen, 2020), prenatal nutrition programs (Bitler and Currie, 2005; Currie and Rajani, 2015; Haeck and Lefebvre, 2016; Hoynes et al., 2011), cash transfers (Amarante et al., 2016; Chung et al., 2016; Hoynes et al., 2015), and so on.

These studies are interested in the effect of an event (which may be a shock, exposure, or intervention) on health at birth: how the health of an average newborn changes when is exposed to the event while in utero (compared to when not exposed). The conventional empirical approach uses live birth data and compares the health of two groups of newborns: (i) those who were exposed to the event and (ii) those who were not exposed to the event. However, even if the “treatment status” (exposure to the event) is randomly assigned, the event can affect not only the outcome of interest but may also change the group of newborns for whom the outcome is observed. Therefore, the estimated effect may incorporate not only the actual effect on health at birth, but also the effect of different forms of selection that induce changes in the number of fetuses that survive to live birth. First, the exposure can change the survival probability of some fetuses (in utero selection). Second, the anticipation of the event may induce behavioral changes that affect the timing of conceptions (selection into pregnancy). Some women (and their partners) may delay, bring forward or cancel pregnancy, or decide to have a child, as a result of information about an upcoming event. Third, if the exposure to the event is prolonged and affects the pre-conception period as well, it may also influence reproductive health, leading to changes in the number of conceptions.[1] It means that uncovering the causal effect of the event

[1] Further difficulties might arise due to the fact that in most administrative and survey databases it is the place of residence at birth that is known and not the history of residence during pregnancy. Adverse events during pregnancy may induce migration processes, which can lead to a difference between where women live during pregnancy and at the childbirth. Although this type of selection does not affect the number of newborns, it makes it difficult to correctly assign the exposure to the event to individuals.

by simply comparing the exposed and non-exposed birth cohorts is often not straightforward (even in experimental settings).

Since none of these selections is likely to be random, their effect cannot be ignored. Fetal losses due to exposure to an adverse event are likely to remove fetuses with below-average health, while a positive event may help the "marginal" fetuses to survive to live birth. Facing the possibility of being exposed to an adverse event, some more cautious, more educated, and forward-thinking women may delay pregnancy, reducing the number of babies exposed to the event. Assuming that these women are also more careful during pregnancy and better informed about factors affecting the outcome of pregnancy, the „missing" newborns would probably have been of above-average health. In sum, the different exposure-induced selection processes (in utero selection, selection into pregnancy) have similar impacts on the number of newborns, but their compositional effect on health at birth may be opposite to each other.

This paper examines a special case: exposure to an event where only in utero selection (a change in the probability of fetal death) is present, while selection into pregnancy is very unlikely to play a role. The potential importance of in utero selection cannot be overlooked, as the mortality of human embryos between fertilization and live birth is very high: between 40% and 70%, and most of these losses remain clinically unobserved (Jarvis, 2016; Wilcox et al., 2020). Although many early embryo losses are caused by chromosomal abnormalities due to random errors in embryo development, environmental and behavioral factors may also play an important role (Larsen et al., 2013; Regan and Rai, 2000; Simpson, 2007; van den Berg et al., 2012).

In this paper, I first formalize the problem by applying the principal stratification approach (Frangakis and Rubin, 2002; Rubin, 2006) and show that in utero selection distorts the effect estimated by the standard empirical approach using live birth data if (i) the exposure to an event changes the chance of fetal death and (ii) the potential health at birth of the deceased fetuses (which would have been observed if they had survived in a counterfactual situation) is different from that of the surviving fetuses.

Next, I present an empirical example. The aim of this exercise is to highlight the potential importance of selection bias. I also show a simple way of obtaining a corrected estimate that accounts for the distorting effect of fetal mortality. The assumptions applied for this exercise are common in the literature: (i) a negative (positive) event does not decrease (increase) the chance of fetal mortality, (ii) the potential health at birth of fetuses whose survival depends on the exposure to the event is lower than that of fetuses that survive anyway. Specifically, I examine the effect of in utero exposure to hot temperatures on birth weight. The number of hot days during the whole pregnancy cannot be accurately predicted before pregnancy and can be considered random (after conditioning on time-trend and seasonality), therefore behavioral changes affecting the number of births are unlikely to happen. The deviation of the weather from the long-term trend and seasonality can only be forecasted with a high degree of accuracy one or two weeks in advance (Bauer et al., 2015), thus, it is unlikely to change many pregnancy decisions made several weeks or months earlier. In addition, heat exposure in the pre-conception and post-conception periods can be distinguished, and although they may be correlated, their effects can be estimated separately.[2] Consequently, the most important heat-induced selection process that affects the number of conceptions that survive to live birth is the spontaneous death of the fetus.

Examining exposure to in utero temperature is important in itself. As the Earth's climate is projected to warm rapidly in the next decades (IPCC, 2018, 2014), understanding the effects of heat is a particularly interesting public policy issue. Health at birth plays an important role in shaping later life outcomes (Behrman and Rosenzweig, 2004; Bharadwaj et al., 2018; Black et al., 2007; Currie, 2009; Figlio et al., 2014; Helgertz and Nilsson, 2019; Lambiris et al., 2022), so several previous studies have analyzed the effect of in utero exposure to heat on birth weight and other pregnancy outcomes (for a review see Hajdu and Hajdu, 2022a). Most of them concluded that hot temperatures reduce birth weight and increase the chance of low birth weight (Andalón et al., 2016; Chen et al., 2020; Cil and Kim, 2022; Conte Keivabu and Cozzani, 2022; Davenport et al., 2020; Deschênes et al., 2009; Hajdu and Hajdu, 2021a; Molina and Saldarriaga, 2017; Ngo and Horton, 2016). At the same time, other papers have shown that heat causes a substantial increase in the risk of pregnancy loss (Davenport et al., 2020; Hajdu and Hajdu, 2023, 2021b; Sexton et al., 2021), which suggests that the effect of hot temperatures on birth weight is likely to be underestimated in the literature since a non-negligible proportion of pregnancies do not reach the stage of live birth if exposed to heat.

In this paper, I use Hungarian administrative data on more than 5 million live births conceived between 1975 and 2019. First, applying the standard approach of the literature, I show that exposure to heat during pregnancy leads to lower birth weight. Exposure to one additional day with an average wet bulb temperature >20°C in utero, relative to a day with an average wet bulb temperature ≤20°C, reduces birth weight by 0.38 grams. But the number of conceptions that survive to live birth is also reduced due to exposure to hot temperatures. In the second step of the analysis, I show that each additional >20°C day during the pregnancy causes

[2] In addition, exposure to an above-average number of heat days during pregnancy can be considered a relatively mild shock – at least in continental climates –, so heat-induced migration can be rightly considered insignificant.

a reduction of 0.16 percent in the number of conceptions that survive to live birth. In the final part of the paper, I show that even a slightly unbalanced selection process can result in a large birth weight difference between the deceased and surviving fetuses. The potential birth weight of the deceased fetuses may be at least a couple of hundred grams lower than that of the surviving fetuses. It means that even under a very conservative assumption of the difference in the potential birth weight of deceased and surviving fetuses, the bias caused by in utero selection is severe. Consequently, the corrected estimate of the effect of a >20°C day, which accounts for the effect of in utero selection, is at least twice the estimate based on the usual empirical approach.

This paper contributes to the economics literature on the impact of shocks during pregnancy on health at birth. Although it is well understood in this literature that endogenous selection can be a problem (see e.g., Almond and Currie, 2011), it is still not a standard practice in empirical studies to test whether the results are affected by selection bias or to estimate the approximate magnitude of the bias. It is usually assumed that in utero selection reduces the strength of the effect to be estimated and is therefore considered less important to quantify it.[3] This approach has negative consequences from both a scientific and a public policy perspective. In cases where the fetal selection is particularly dominant and the estimated effects may be statistically insignificant, the papers can remain in the "file drawer" (Dickersin, 1990; Franco et al., 2014). From a policy perspective, the main drawback of not quantifying the distorting effects of endogenous selection is that it may lead to potentially misleading guidance for public policy and provides inaccurate input for cost-benefit analysis. In related literature that examines the effect of early life shocks on adult outcomes, selection bias due to childhood mortality is also a frequently discussed issue, however, its extent is also usually not quantified (Currie and Vogl, 2013). The main issue is similar to the problem of in utero selection, and Bozzoli et al. (2009) show in an illustrative model that under certain circumstances the effect of selection (removal of the least healthy) can outweigh the effect of scarring (the effect on adult outcomes). Other fields, like epidemiology and population health, are also well aware of the problem of in utero selection (Bruckner and Catalano, 2018; Raz et al., 2018), but only simulation studies have addressed the issue (e.g., Nobles and Hamoudi, 2019), and the literature lacks quantification of the bias in real-world data. I add to the literature by showing that the effect of in utero selection can be substantial, but a corrected estimate of the effect of interest can be calculated in a simple way, without the need to rely on additional data sources.

[3] Note, however, that in the presence of different forms of selection, as discussed above, the sign of net bias is not clear.

The paper is also related to the literature that examines the issue of sample selection which is relevant to many fields of applied microeconomics. Previous papers constructed a bound on a “treatment” effect assuming that selection affects observations at the top or the bottom of the distribution of the outcome variable (Horowitz and Manski, 2000; Lee, 2009; Zhang and Rubin, 2003), but these bounds are often too wide to be useful for public policy, and their implementation is not evident in non-experimental settings with continuous treatment (e.g. exposure to air pollution or heat). In the case of fetal selection, plausible assumptions (supported by observational and simulation results) can be made about the exposure-induced selection process. Such assumptions are used in this paper to provide more useful guidance for public policy.

The rest of the paper proceeds as follows. Section 2 outlines a conceptual framework to formalize the problem, describe the bias arising from in utero selection, and help in understanding the steps of the empirical analysis. The next sections provide an empirical example to illustrate the potential importance of fetal selection when considering the effect of an event on health at birth. Section 3 describes the data used in the analysis and outlines the empirical models. Section 4 presents the results. Section 5 discusses the implications of the findings and concludes.

2. Conceptual framework

This section outlines a simple conceptual framework, based on the principal stratification approach (Frangakis and Rubin, 2002; Rubin, 2006), that formalizes the bias that arises from in utero selection in the standard estimation of the effect of an event on the health of newborns. Selection into pregnancy and other forms of selection are ignored within this framework. That is, it is assumed that exposure to an event influences the number of births only through changes in the number of fetal deaths. I start by presenting the estimate obtained using the standard empirical approach of the literature and show how the actual effect of interest can be derived from it.

Let A_i be a binary variable representing the exposure to an event. This event can have a positive or negative effect on health. A_i takes the value 1 if fetus *i* was exposed to the event while in utero and 0 otherwise. Let S_i be a binary variable with value 1 if fetus *i* survives to live birth and 0 otherwise. Let the pair S_{i0} and S_{i1} denote the survival to live birth of fetus *i* for A_i=0 and A_i=1, respectively. Depending on A_i and S_i there are four types of fetuses (Table 1). Fetuses with S_{i0}=1 and S_{i1}=1 survive to birth regardless of exposure to the event (Type 1). Fetuses with S_{i0}=1 and S_{i1}=0 survive to birth only if they have not been exposed to the event (Type 2). Fetuses with S_{i0}=0 and S_{i1}=1 survive to birth if they have been exposed to the event, but not otherwise (Type 3). Finally, fetuses with S_{i0}=0 and S_{i1}=0 cannot survive to birth under any conditions (Type 4). Let H_i denote the health at birth of fetus *i*. Let the pair H_{i0} and H_{i1} denote the potential health of fetus *i* for A_i=0 and A_i=1, respectively.

Table 1: Typology of fetuses by exposure and survival to live birth

		exposed to the event (A_i=1)	
		survive (S_i=1)	do not survive (S_i=0)
not exposed to the event (A_i=0)	survive (S_i=1)	<u>Type 1</u> S_{i0}=1 and S_{i1}=1	<u>Type 2</u> S_{i0}=1 and S_{i1}=0
	do not survive (S_i=0)	<u>Type 3</u> S_{i0}=0 and S_{i1}=1	<u>Type 4</u> S_{i1}=0 and S_{i0}=0

Since health at birth is observable only for those fetuses that survive to live birth, the causal effect of the event can only be determined for Type 1 fetuses. This is the real question for many studies, and can be labeled the “actual” effect of the event on health at birth:

$$\Delta\widehat{H} = E\left[H_{i1}|S_{i0}=1,S_{i1}=1\right] - E\left[H_{i0}|S_{i0}=1,S_{i1}=1\right]. \tag{1}$$

However, when the effect of an event is assessed, usually live birth data are used and the health of two groups of newborns are compared: (i) newborns who were exposed to the event and (ii) newborns who were not exposed to the event. This comparison is, by definition, looking at those fetuses that survive until live birth:

$$\Delta H = E[H_{i1}|S_{i1}=1] - E[H_{i0}|S_{i0}=1]. \tag{2}$$

The problem with this estimate is that the cohorts of exposed and non-exposed newborns are not fully comparable, and is different from (1), the effect of interest. We can use the four types of fetuses in Table 1, and express $E[H_{i0}|S_{i0}=1]$ and $E[H_{i1}|S_{i1}=1]$ in (2) as the weighted average of health at birth of Type 1 and Type 2 fetuses, and Type 1 and Type 3 fetuses, respectively, where the weights are the conditional probabilities of survival and fetal death:

$$E[H_{i0}|S_{i0}=1] = P[S_{i1}=1|S_{i0}=1]\times E[H_{i0}|S_{i0}=1,S_{i1}=1] + P[S_{i1}=0|S_{i0}=1]\times E[H_{i0}|S_{i0}=1,S_{i1}=0]. \quad (3)$$

$$E[H_{i1}|S_{i1}=1] = P[S_{i0}=1|S_{i1}=1]\times E[H_{i1}|S_{i0}=1,S_{i1}=1] + P[S_{i0}=0|S_{i1}=1]\times E[H_{i1}|S_{i0}=0,S_{i1}=1]. \quad (4)$$

Substituting (3) and (4) into (2), and given that $P[S_{i1}=1|S_{i0}=1] + P[S_{i1}=0|S_{i0}=1] = 1$, and $P[S_{i0}=1|S_{i1}=1] + P[S_{i0}=0|S_{i1}=1] = 1$, we can obtain:

$$\begin{aligned}\Delta H = {} & E\left[H_{i1}|S_{i0}=1,S_{i1}=1\right] - E\left[H_{i0}|S_{i0}=1,S_{i1}=1\right] \\ & + P[S_{i1}=0|S_{i0}=1]\times(E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]) \\ & - P[S_{i0}=0|S_{i1}=1]\times(E[H_{i1}|S_{i0}=1,S_{i1}=1] - E[H_{i1}|S_{i0}=0,S_{i1}=1]). \quad (5)\end{aligned}$$

On the right-hand-side of (5), we first see the effect of the event on health at birth of Type 1 fetuses ($\Delta\widehat{H}$). The other two terms represent the effects of selections caused by the exposure. Compared to a baseline population of newborns, some newborns may “disappear” as a result of fetal mortality, while other fetuses that have previously deceased may survive due to exposure to the event. If these fetuses are not randomly selected, then they distort the estimate of the effect of the event. The impact of the selections depends on (i) the extent of the in utero selection and (ii) the difference in potential health at birth between fetuses that survive to birth in any case and fetuses whose survival depends on the exposure.

Taking into account the characteristics of the event, (5) can be further simplified. It is reasonable to assume that an adverse event during pregnancy would not change the outcome of pregnancy from death to survival. In other words, fetuses that survived the exposure to the adverse event, would not have died in a counterfactual situation in which they were not exposed. This is called monotonicity (Rubin, 2006; Zhang and Rubin, 2003). Formally, $P[S_{i0}=0|S_{i1}=1] = 0$. Therefore, for a negative event:

$$\Delta H = \Delta\widehat{H} + P[S_{i1}=0|S_{i0}=1]\times(E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]). \quad (6)$$

The bias in the estimate of the standard approach is the product of (i) the chance of fetal death due to exposure among fetuses that survive to live birth in the absence of the exposure and (ii) the difference in the potential health between fetuses that survive to live birth and those that do not survive to live birth if exposed to the adverse event, conditionally that they survive to live birth without the exposure. Potential health in this case refers to the health of the fetuses which would have been observed if they had survived to live birth in the absence of the exposure. Simply stated, the value of this difference reveals which part of the health distribution the deceased fetuses are selected from.

Even if $P[S_{i0}=0|S_{i1}=1] > 0$, (6) can still be valid if $E\big[H_{i1}|S_{i0}=1,S_{i1}=1\big] - E\big[H_{i1}|S_{i0}=0,S_{i1}=1\big] = 0$. This would mean that fetuses that survived the exposure to the adverse event but would have died without the exposure are randomly selected from the health distribution.

In contrast, monotonicity in the case of a beneficial event during pregnancy means that the event is unlikely to cause the death of a fetus that would otherwise have survived to live birth. Therefore, $P[S_{i1}=0|S_{i0}=1] = 0$. Thus, estimating the effect of a positive event gives:

$$\Delta H = \Delta\widehat{H} - P[S_{i0}=0|S_{i1}=1] \times (E[H_{i1}|S_{i0}=1,S_{i1}=1] - E[H_{i1}|S_{i0}=0,S_{i1}=1]). \qquad (7)$$

In this case, the bias is the product of (i) the share of "new" births caused by the positive event and (ii) the difference in the health at birth between the "regular" and "new" newborns.

In the usual cases, the effect of an adverse event on health at birth is negative, whereas the effect of a beneficial event is positive. If the exposure changes the survival probability of some fetuses and these fetuses have below-average potential health, then (6) and (7) provide a lower bound of that the effect of the event on Type 1 fetuses. In an extreme case, when the magnitude of the bias is particularly large (selection dominates the estimation), the sign of the estimated effect may differ from the sign of the actual effect. On the other hand, if the exposure does not influence the survival of the fetuses or the selection is independent of the potential health, (6) and (7) give a good (unbiased) estimate of the effect of the exposure.

How can we test whether selection bias exists and, if so, how can we estimate its magnitude and correct for it? The "actual" effect of the exposure on health at birth ($\Delta\widehat{H}$) can be estimated in three steps. First, ΔH has to be estimated, as it is usually done in the literature, using data on live births. Second, after creating a dataset aggregated at a geographical or temporal level (depending on the nature of the exposure) containing the number of conceptions that survive to live birth, the probability of death from exposure to the adverse event ($P[S_{i1}=0|S_{i0}=1]$) – conditional on survival without exposure – can be estimated using the log number of conceptions as the dependent variable in a regression. Similarly, in the case of a positive event, $P[S_{i0}=0|S_{i1}=1]$ can be estimated. This can serve as a direct test of whether or not in utero selection distorts the estimate of the effect of the event in question. Finally, the $E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]$ or the $E[H_{i1}|S_{i0}=1,S_{i1}=1] - E[H_{i1}|S_{i0}=0,S_{i1}=1]$ term from (6) and (7) should be estimated. Again, these are the differences in the potential health between fetuses that survive to live birth irrespective of the exposure and those whose survival depends on the exposure. Unfortunately, these are not observable, as it cannot be identified which fetuses would have died in a counterfactual situation in which they were or were not exposed to the event in question. However, because fetal mortality tends to remove those fetuses that are in poor potential health at birth, these health differences are unlikely to be negative. In short, although it is not possible to give an exact value for the actual effect of the exposure on the health of the newborns, it can be calculated under different assumptions about the difference in the potential birth weights.

3. Data and methods

3.1. Data

The primary dataset of the empirical analysis is the live birth registry of the Hungarian Central Statistical Office (Hungarian Central Statistical Office, 2022a). It covers all live births in Hungary, and, among others, it contains information on the date of birth, pregnancy length, birth weight, and the mother's municipality of residence for each newborn. The newborns' conception date (C) was estimated from their date of birth (B) and gestational age (G) that is reported in completed weeks and calculated from the first day of the last menses:

$$C = B - 7\times G + 15. \tag{8}$$

In (8) it is assumed that conceptions occur on the 15th day of the menstrual cycle. The estimated conception date and the mother's county of residence allowed the creation of a county-by-year-by-week-level dataset containing the two outcome variables of this study: (i) the number of conceptions that survive to live birth per week in the twenty Hungarian counties (NUTS3 regions) and (ii) the average birth weight of these conceptions (newborns).[4]

The analysis sample consists of live births conceived between 1975 and 2019, and is limited to births with non-missing information on birth date, pregnancy length, birth weight, and county of residence of the mother. These restrictions result in the exclusion of less than 1% of all conceptions. The final sample covers more than 5 million conceptions that survive to live birth (N=5,070,222) incorporated into 46,800 county-by-conception-year-by- conception-week cells.

Information on ambient temperature is drawn from the European Climate Assessment & Dataset project (Cornes et al., 2018). The E–OBS 27.0e dataset (The ECA&D Project Team., 2023) provides information, among others, on daily mean temperatures, humidity, and precipitation for Europe with a spacing of 0.1° × 0.1° in regular latitude/longitude coordinates starting from 1950. The gridded weather data were aggregated to the county-by-day level by

[4] Each year is divided into fifty-two weeks, therefore the 52nd calendar week is eight days long (except in leap years, when it lasts nine days).

averaging the temperatures and precipitation measures. Next, I calculated the wet-bulb temperature from the daily mean temperature and daily relative humidity data of the counties using the method of Stull (2011). I focus on daily mean temperature, which is a better indicator of the overall temperature exposure for a given day than the minimum or maximum temperature. Wet-bulb temperature is one of the most commonly used measures of heat stress. The main advantage of this measure is that it captures much better the thermal stress that people experience under different humidity conditions than dry-bulb temperature.

For the analysis, I created a week-level dataset that shows the number of days when the daily average wet-bulb temperature is over 20°C. For simplicity, and since many previous studies found that the effects of mild and cold temperatures on birth weight are very similar and much weaker than the effect of hot temperatures (Deschênes et al., 2009; Hajdu and Hajdu, 2021a; Molina and Saldarriaga, 2017), I focus on only extreme heat stress. Specifically, the effect of a >20°C day is compared to the effect of a ≤20°C day. Days with an average wet-bulb temperature >20°C are extremely heat-stressful. On these days the mean of the daily average dry-blub temperature is 26°C. In Hungary, the daily average dry-blub temperature of 25°C is the threshold for a first-level warning of extreme heat.

In the final dataset, exposures to different weather conditions are calculated for the whole gestation period, assuming a 39-week-long pregnancy starting with the week of conception. Table 2 summarizes the dependent variables and the main right-hand-side variable: birth weight, number of conceptions, and wet-bulb temperature >20°C. The mean number of conceptions that survive to live birth is 108 (per week, per county), and they have an average birth weight of slightly more than 3200 grams. The number of days with an average wet-bulb temperature >20°C during the gestation period ranges between 0 and 50 days, with a mean of 6 days.

Table 2: Descriptive statistics

Variable	Mean	SD	Min	Max	N
Birth weight	3215.7	95.3	2588.4	3569.1	46,800
N of conceptions that survive to live birth	108.3	79.1	16.0	788.0	46,800
Exposure to wet-bulb temperature >20°C during pregnancy	6.0	7.6	0.0	50.0	46,800

Notes: Units of observations: county-by-year-by-calendar-week. The in utero exposure period is defined as a 39-week-long period starting with the week of conception.

3.2. Methods

First, the effect of heat exposure on birth weight is estimated by the standard empirical approach of the literature:

$$BW_{cyw} = \beta^{BW} \cdot TW20_{cyw} + \sum_k \gamma^k \cdot P^k_{cyw} + \delta \cdot TW20^{pre}_{cyw} + \sum_k \mu^k \cdot P^{k,pre}_{cyw}$$

$$+ \rho_{cy} + \lambda_w + \pi'_w \cdot t_{yw} + \pi''_w \cdot t^2_{yw} + \varepsilon_{cyw}, \qquad (9)$$

where BW is the average birth weight of newborns conceived in year y, calendar week w, and county c. TW20 is the variable of interest that shows the number of days with a daily average wet-bulb temperature >20°C during the entire pregnancy. β^{BW} shows the effect of exposure to one additional >20°C day during pregnancy on newborns' birth weight (relative to a day with an average wet-bulb temperature of ≤20°C). This corresponds to ΔH in (6).

P is a vector of precipitation controls, which shows the number of days when the amount of daily precipitation falls in precipitation bin k (0 mm, 0−2 mm, 2−5 mm, 5−10 mm, over 10 mm). Wet-bulb temperature and precipitation in the pre-conception period (five weeks) are entered as control variables ($TW20^{pre}$ and P^{pre}), as conceptions are affected by pre-conception weather (Barreca et al., 2018; Hajdu and Hajdu, 2022b), most likely via changes in reproductive health (Ahmad et al., 2012; Brown-Woodman et al., 1984; Hansen, 2009; Xiao et al., 2022; Zhou et al., 2020), and post-conception weather may be correlated with pre-conception weather.

County-by-year fixed effects (ρ) absorb county-specific shocks to average birth weight at the year level. Calendar week fixed effects (λ) account for seasonal differences in birth weight. In addition, the seasonality of birth weight is allowed to change over time by the inclusion of calendar-week-specific quadratic time trends (π).[5] Standard errors are clustered at county and year-by-calendar-week levels.

The effect of heat on the number of conceptions (that survive to live birth) is analyzed with a similar equation:

$$\ln(NC^B_{cyw}) = \beta^{NC} \cdot TW20_{cyw} + \sum_k \gamma^k \cdot P^k_{cyw} + \delta \cdot TW20^{pre}_{cyw} + \sum_k \mu^k \cdot P^{k,pre}_{cyw}$$

$$+ \rho_{cy} + \lambda_w + \pi'_w \cdot t_{yw} + \pi''_w \cdot t^2_{yw} + \varepsilon_{cyw}, \qquad (10)$$

where NC^B is the number of conceptions that survive to live birth in year y, calendar week w, and county c. Otherwise, the right-hand-side variables in (10) are the same as in (9). In this case, β^{NC} shows the effect of a >20°C day on the log number of conceptions. Or in other words,

[5] Since the last calendar week of the year is eight or nine days long, while the other calendar weeks are seven days long, additional two variables are included in the regression, measuring the number of days in the 39-week-long gestation period and the 5-week-long pre-conception period.

$100\times \beta^{NC}$ shows the percentage effect of a >20°C day on the number of conceptions.[6] More importantly, $-\beta^{NC}$ is equivalent to the probability of fetal mortality due to heat exposure, under the condition that only those conceptions are considered that survive to live birth without the exposure. And this is what we are looking for from (6): $P[S_{i1}=0|S_{i0}=1]$ (for proof, see Online Appendix B).

4. Results

4.1. Exposure to heat and birth weight

The effect of exposure to heat during pregnancy on birth weight (β^{BW}), estimated using the standard empirical approach, is reported in Column 1 of Table 3. I find that heat exposure has a significant influence on birth weight. Exposure to one additional day with an average wet-bulb temperature >20°C while in utero reduces birth weight by 0.38 grams. The size of this effect is comparable to the results of previous studies using similar data and method (Chen et al., 2020; Deschênes et al., 2009; Hajdu and Hajdu, 2021a).[7]

Table 3: The effect of exposure to heat on birth weight and number of conceptions

	(1)	(2)
	Birth weight	ln(N of conceptions)
Avg. wet-bulb temperature >20°C	-0.384^{**} (0.091)	-0.157^{**} (0.022)
N	46,800	46,800

Notes: In Column 2, the coefficient and SE are multiplied by 100. The models have county-by-year fixed effects, calendar-week fixed effects, and calendar-week-specific quadratic time trends. Precipitation and pre-conception exposure to heat and precipitation are controlled for. The in utero exposure period is defined as a 39-week-long period starting with the week of conception. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

The sensitivity of this result is tested in several ways. First, a falsification test is performed (Table A1, Online Appendix A). In this exercise, temperature and precipitation are replaced by weather data that were measured exactly one year later. The idea is that the birth weight of newborns could not have been affected by future temperature, consequently, zero coefficients are expected to be estimated in this regression. A large and statistically significant temperature coefficient would imply that unmeasured seasonality drives the baseline result. The result of

[6] More precisely: $(e^{\beta^{NC}}-1)\times 100$ shows the percentage effect, but for small β they are indistinguishable.
[7] Taking into consideration the different reference temperature, temperature categories, and climatic conditions.

the falsification test strengthens the credibility of the baseline estimate: the estimated coefficient of exposure to days with an average wet-bulb temperature >20°C is not only statistically insignificant but practically zero.

As further sensitivity tests, I experiment with alternative sets of fixed effects and time trends (Table A2, Online Appendix A), exclude some of the control variables, include lags of the dependent variable, treat exposure in the conception week as a control variable, and change the weights (Table A3, Online Appendix A). In general, I find that these alternative specifications lead to similar conclusions: heat stress during pregnancy reduces birth weight. The results also robust when using different measures of heat exposure: (i) N of days with an average wet-bulb temperature >19°C, (ii) N of days with an average wet-bulb temperature >21°C, (iii) N of days with an average dry-bulb temperature >25°C, (iv) N of days with an average dry-bulb temperature >27°C (Table A4, Online Appendix A). These results show that more extreme heat has stronger effects on health at birth and the survival chance of the fetus.

4.2. In utero selection due to exposure to heat

However, exposure to extreme heat while in utero can not only influence the health at birth but can also lead to the death of the fetus. When I estimate the effect of high wet-bulb temperature on the number of conceptions that survive to live birth (β^{NC}), this is exactly what I find (Table 3, Column 2). Exposure to one additional day with an average wet-bulb temperature >20°C during the pregnancy reduces the number of conceptions by 0.16%.[8] In other words, the chance of fetal mortality is increased by 0.0016 for every heat day (among fetuses that survive to live birth in the absence of heat exposure). This result indicates that the estimated effect on birth weight is distorted by in utero selection.

Similar to the birth weight analysis, I perform several robustness checks. Replacing the temperature and precipitation variables with weather data that were measured exactly one year later results in a close to zero coefficient of wet-bulb temperature >20°C (Table A1, Online Appendix A). The conclusion remains the same for alternative measures of heat exposure (Table A4, Online Appendix A). Using different fixed effects (Table A5, Online Appendix A) or control variables (Table A6, Online Appendix A) does not change the baseline conclusion. However, it is clear that failing to account for the pre-conception weather leads to a lower temperature coefficient. But it is not surprising; pre-conception exposure to heat has a strong effect on the conception rate (Barreca et al., 2018; Hajdu and Hajdu, 2022b) and is (negatively)

[8] Note that in Column 2 of Table 3, the coefficient and the SE are multiplied by 100.

correlated with post-conception exposure to heat. Therefore, excluding pre-conception weather from the control variables causes an omitted variable bias.

4.3 The actual effect of exposure to heat

It is clear from these results that the effect of heat on birth weight is underestimated by the usual empirical approach. The only question is exactly to what extent, and how to obtain the actual effect of heat (the effect on fetuses that survive to live birth irrespective of the exposure, $\Delta\widehat{H}$) from the results of the previous sections. This is given by rearranging (6):

$$\Delta\widehat{H} = \Delta H - P[S_{i1}=0|S_{i0}=1]\times(E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]). \qquad (11)$$

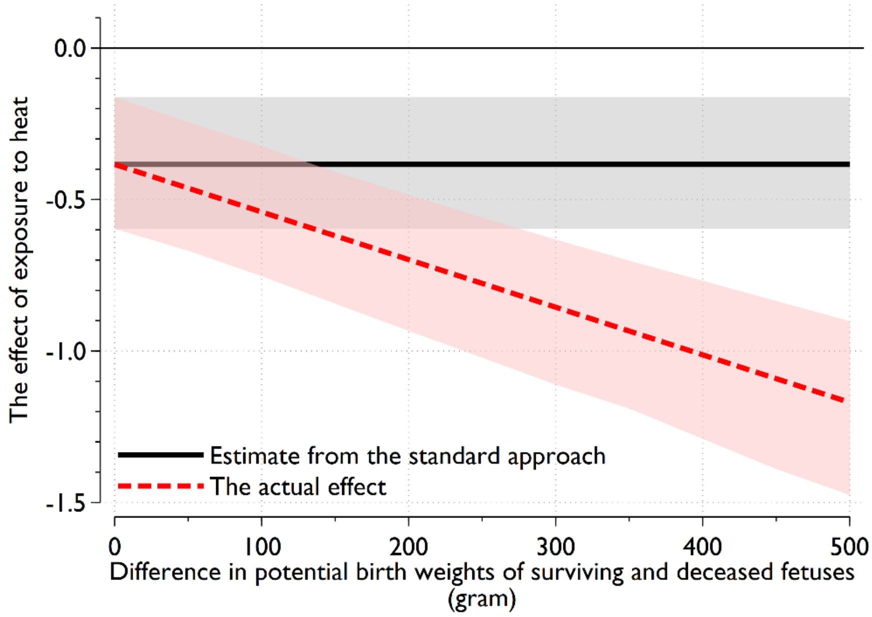
Or using the regression coefficients from (9) and (10):

$$\Delta\widehat{H} = \beta^{BW} + \beta^{NC}\times(E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]). \qquad (12)$$

The latter equation shows that the effect of interest can be calculated using the estimate of the standard approach and the effect of the in utero selection. It is also obvious that there is only one unknown term left on the right-hand side of (12), which prevents us from obtaining the actual effect of heat on birth weight. This is the birth weight difference between the deceased and surviving fetuses ($E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]$). It is perhaps worth emphasizing that potential birth weight means their birth weight if they had not been exposed to warm temperatures. In other words, this birth weight difference indicates which part of the counterfactual health distribution the fetuses that deceased (due to heat exposure) are selected from. Unfortunately, this difference cannot be observed, but $\Delta\widehat{H}$ can be calculated for different hypothetical values of the birth weight difference.

Figure 1 does exactly that. It depicts the actual effect of heat ($\Delta\widehat{H}$) and the estimate from the standard approach (β^{BW}) as a function of the difference in the potential birth weight between surviving and deceased fetuses ($E[H_{i0}|S_{i0}=1,S_{i1}=1] - E[H_{i0}|S_{i0}=1,S_{i1}=0]$). Obviously, the standard estimate is independent of the difference between potential birth weights, therefore it is constant in the figure: −0.38 grams. It is also evident from (12) that if the birth weight difference is zero, then the estimated effect from the standard approach and the actual effect are identical. However, if the potential birth weight of the deceased fetuses is lower than that of fetuses that survive anyway, the actual effect of heat is stronger than the estimate obtained with the standard approach. Under the assumption that the potential birth weight of the surviving fetuses is 200 grams higher than that of the deceased fetuses, the actual effect is −0.70 grams, which is almost twice the baseline estimate. For a potential birth weight difference of 500 grams, the actual effect is more than three times the result of the standard approach (−1.17 grams vs. −0.38 grams).

Figure 1: The effect of heat on birth weight estimated by the standard approach and the actual effect of heat

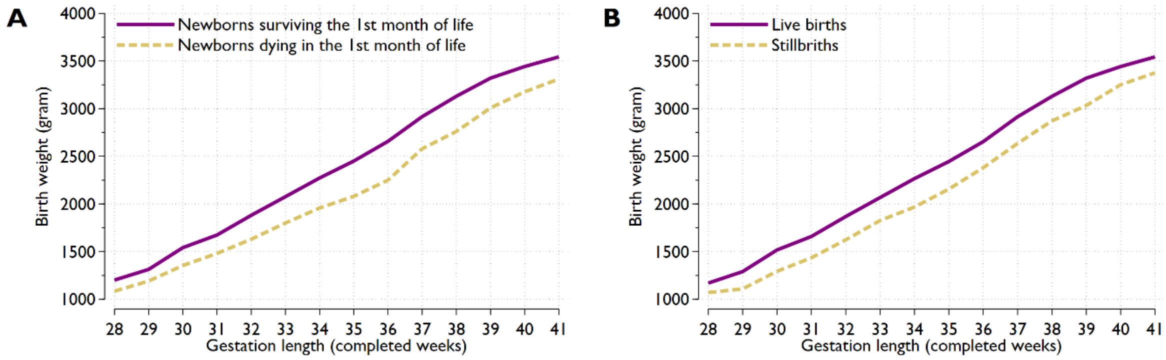


Notes: Shaded areas represent 95% confidence intervals calculated from 500 bootstrap samples. The estimate from the standard approach (solid line) are from Table 3. The actual effect of heat is calculated using (12) for different values of the last term (the difference in the potential birth weight between surviving and deceased fetuses).

In general, Figure 1 shows that if heat-induced fetal mortality is more likely to affect lower birth weight fetuses, then the actual effect of heat on birth weight is larger than the estimated effect of the standard approach. Furthermore, this difference is larger the more selective the fetal mortality. Now only one question remains: how large is the potential birth weight difference between surviving and deceased fetuses? Although the actual difference cannot be observed in any way, there are some indications that it may be at least a few hundred grams.

On panel A of Figure 2, I plot the average birth weight of newborns who survived the first month of life and those who died during this period by pregnancy length. Panel B of Figure 2 shows similar values for live-born and stillborn infants. Both panels are based on individual-level Hungarian administrative data between 1985 and 2019 (Hungarian Central Statistical Office, 2022b, 2022a, 2022c). Two important observations can be made by looking at these figures. First, although all these children reached an advanced stage of pregnancy, there is a big difference between the average birth weight of those who died soon after and those who survived, even after controlling for pregnancy length. Second, this difference seems to be quite stable. In both figures, the birth weight difference is around 200-300 grams at most pregnancy weeks.

Figure 2: Average birth weights of surviving and deceased infants



Notes: Panel A is created using the registries of live birth and infant mortality of the Hungarian Central Statistical Office between 1985-2019. The average birth weight of the newborns surviving the first month of life is calculated using the average birth weight and the number of newborns who died in the first month of life and the total number of newborns. Panel B is created using the registries of live birth and stillbirths of the Hungarian Central Statistical Office between 1985-2019. Data with less than 28 weeks or more than 41 weeks of gestation are excluded.

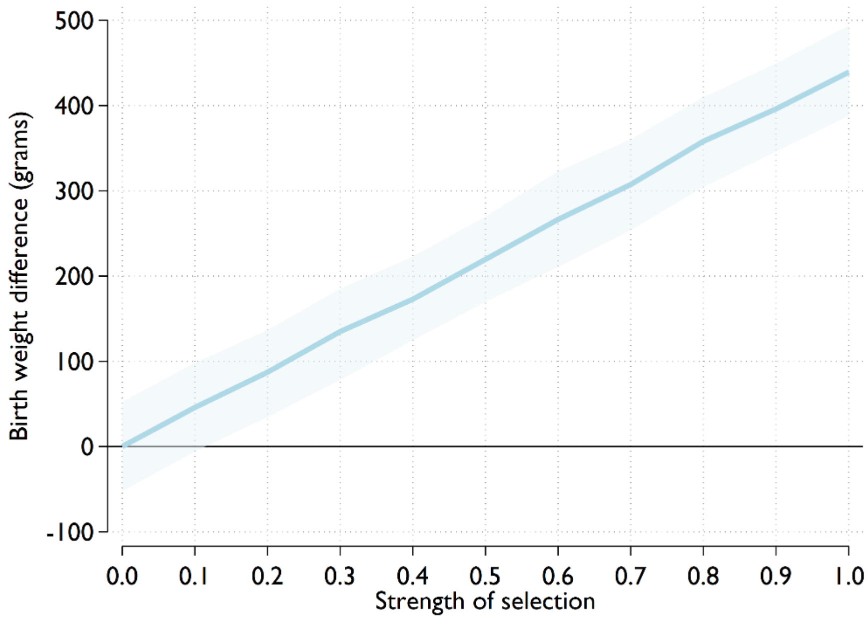
A simple simulation exercise also suggests that the birth weight difference in question is likely to be significant. Consider a hypothetical birth cohort of 100,000 fetuses, where the potential birth weight of each fetus is randomly selected from a normal distribution with a mean of 3200 and a standard deviation of 550.[9] In this example, the potential birth weight of each fetus is that weight that would be observed if they were born. Next, assume that this fetal cohort is exposed to a hot day during its time in the womb. As a result, in line with the empirical estimate presented in Table 3, 0.16 percent of the cohort dies in the womb, while the other 99.84 percent survive to live birth. Assume also that the deceased fetuses are randomly selected either from the bottom or top 50 percent of the potential birth weight distribution. Let s denote the share of the deceased fetuses that are selected from the bottom 50 percent. Consequently, the share of the deceased fetuses that are selected from the top 50 percent is $(1-s)$. Define a measure of the strength of selection as $2s-1$. Take two extreme scenarios. In the first one, the selection of the deceased fetuses is completely random (that is s is equal to 0.5): half of the deceased fetuses are randomly selected from the bottom 50 percent of the potential birth weight

[9] These values roughly correspond to the mean and standard deviation of the birth weights of the 5 million newborns in the sample of this paper.

distribution, while the other half are randomly selected from the top 50 percent. In this case, the strength of selection is 0. In the second scenario, the selection tends to remove those with low potential birth weight. In this case, all of the deceased fetuses are randomly selected from the bottom 50 percent of the potential birth weight distribution (that is *s* is equal to 1), and the strength of selection is 1.

In this simulation the potential birth weight of all fetuses is known, therefore the counterfactual difference in the birth weights of the surviving and deceased fetuses can be calculated under different *s* (or in other words, under different values of strength of selection). Figure 3 shows this counterfactual difference as a function of the strength of selection. Not surprisingly when the deceased fetuses are selected completely randomly (the strength of selection is 0) the difference in the birth weights of the surviving and deceased fetuses is zero. When the strength of selection is 1 (all deceased fetuses are selected from the bottom 50 percent of the potential birth weight distribution), the birth weight difference is almost 450 grams. In an in-between scenario in which a quarter of the deceased fetuses are selected from the top half of the potential birth weight distribution and three-quarters from the bottom half (selection strength is 0.5), the deceased fetuses weigh 220 grams less than the surviving fetuses.

Figure 3: Simulated difference in the potential birth weights of the surviving and deceased fetuses as a function of the strength of the in utero selection



Notes: The shaded area represents 95% confidence intervals calculated from 500 replications. The solid line is the mean of the 500 replications.

Similar conclusions can be drawn from a slightly different simulation exercise using the same cohort of fetuses (Figure A1, Online Appendix A). In this simulation, the 0.16 percent of fetuses that do not survive to live birth are randomly selected from the bottom *d* percent of the birth weight distribution (where *d* runs from 100 to 50). When *d* is equal to 100, the selection is completely random and unconstrained, consequently, the difference in the birth weights of the surviving and deceased fetuses is zero. When the deceased fetuses are selected from the bottom 80 percent of the potential birth weight distribution (so only the heaviest 20 percent are "protected" from the selection), the birth weight difference is almost 200 grams.

These results clearly show that even a slightly unbalanced selection process, which tends to remove fetuses with a lower potential birth weight, can result in a large birth weight difference between the deceased and surviving fetuses. Consequently, the potential birth weight of fetuses that die as a result of exposure to hot temperatures may be at least a couple of hundred grams lower than that of the surviving fetuses. Such a birth weight difference implies that the actual effect of heat exposure during pregnancy, which accounts for the effect of in utero selection, is substantially larger than the estimate from the usual empirical approach.

5. Conclusions

This paper focuses on the issue of fetal selection, which arises when the effect of in utero exposure to an event on health at birth is estimated. This issue is important because the presence of in utero selection may lead to biased results if the conventional approach in the literature is applied. By formalizing the problem, I show that a bias arises if (i) the exposure changes the chance of fetal death of the affected fetuses and (ii) there is a difference in the potential health at birth of the deceased and surviving fetuses (which would have been observed if they had survived in the counterfactual situation).

Next, the paper presents an empirical example that highlights the potential significance of the selection bias. Using administrative data on conceptions that survive to live births in Hungary between 1975-2019, I show that the standard approach yields a small negative estimate of the effect of in utero exposure to heat on birth weight. Exposure to one additional day with an average wet-bulb temperature >20°C reduces birth weight by 0.38 grams. However, in utero exposure to heat also affects the survival probability of the exposed fetuses. Each >20°C day reduces the number of conceptions that survive to live birth by 0.16%. This means that the standard empirical approach gives a biased estimate of the effect of heat. The extent of this bias depends on the difference in the average potential birth weight between surviving and deceased fetuses. I show that even if we assume that this birth weight difference is moderate, the bias is large. The corrected estimate of the effect of a >20°C day, which accounts for the impact of in utero selection, is at least twice the estimate from the conventional empirical approach. Although incorporating the distorting effect of fetal mortality into the estimate of the effect of heat may lead to a less certain answer about the impacts of the exposure, it increases the credibility of the results, or at least it should do so, and these corrected estimates may provide more useful and reliable guidance for public policy.

From a narrower perspective, the empirical results of this paper mean that the projected impact of climate change on birth weight (Deschênes et al., 2009; Hajdu and Hajdu, 2021a; Ngo and Horton, 2016) is likely to be underestimated. According to the corrected estimate of the effect of heat, the impacts of climate change on newborns' health may be considerably stronger than previously thought.

The findings of this study are of course not only of interest for studies on the effect of heat exposure but are also relevant for all studies on the effect of various shocks, exposures, and interventions during pregnancy on birth outcomes. One of the main implications of this study is that future papers exploring the effects of different shocks should pay more attention to selection processes (that induce changes in the number of fetuses that survive to live birth) and how their effects can be incorporated into the estimates. Running a regression using the number of conceptions that survive to live birth as a dependent variable is a simple way to identify the potential problem of selection bias. Although the distorting effect of fetal selection may be negligible in some cases, it should be standard practice to test for the presence of selection biases and to obtain the approximate magnitude of the bias.

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Online Appendix

Appendix A

Table A1: Falsification test using weather one year later

	(1)	(2)
	Birth weight	ln(N of conceptions)
Avg. wet-bulb temperature >20°C	−0.034 (0.108)	0.055 (0.029)
N	46,800	46,800

Notes: Exposure to high wet-bulb temperature during pregnancy is replaced by weather data measured exactly one year later. In Column 2, the coefficient and SE are multiplied by 100. The models have county-by-year fixed effects, calendar-week fixed effects, and calendar-week-specific quadratic time trends. Precipitation and pre-conception exposure to heat and precipitation are controlled for. The in utero exposure period is defined as a 39-week-long period starting with the week of conception. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Table A2: Sensitivity tests: experimenting with fixed effects (birth weight)

	(1)	(2)	(3)	(4)	(5)	(6)
Avg. wet-bulb temperature >20°C	−0.479** (0.083)	−0.353** (0.093)	−0.326** (0.113)	−0.326* (0.130)	−0.391** (0.110)	−0.583** (0.134)
Fixed effects	C-Y, W	C-Y, W	C, Y, W	Y, C-W	C-Y, C-W	C-Y-S, W
Time trends	W-spec. linear	W-spec. cubic	C-spec. quadratic, W-spec. quadratic	C-W-spec. quadratic	C-W-spec. quadratic	W-spec. quadratic
N	46,800	46,800	46,800	46,800	46,800	46,800

Notes: Dependent variable: birth weight. C=county, Y=year, W=calendar week, S=season. Precipitation, and pre-conception exposure to heat and precipitation are controlled for. The in utero exposure period is defined as a 39-week-long period starting with the week of conception. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Table A3: Sensitivity tests: controls and weighting (birth weight)

	(1)	(2)	(3)	(4)	(5)
Avg. wet-bulb temperature >20°C	-0.378^{**} (0.101)	-0.378^{**} (0.091)	-0.358^{**} (0.081)	-0.407^{**} (0.098)	-0.371^{**} (0.095)
Specification	Excl. pre-conception weather	Excl. precipitation	Weighted by the N of conceptions	Incl. lagged dep. var.	Conc. week as control
N	46,800	46,800	46,800	46,700	46,800

Notes: Dependent variable: birth weight. The models have county-by-year fixed effects, calendar-week fixed effects, and calendar-week-specific quadratic time trends. Precipitation and pre-conception exposure to heat and precipitation are controlled for (unless otherwise indicated). The in utero exposure period is defined as a 39-week-long period starting with the week of conception (unless otherwise indicated). In Column 4, five lags of the dependent variable are included. In Column 5, the conception week is treated as a control variable, and the main exposure variables cover weeks 2-38 of the pregnancy. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Table A4: Alternative measures of heat exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Birth weight	ln(N of conceptions)	Birth weight	ln(N of conceptions)	Birth weight	ln(N of conceptions)	Birth weight	ln(N of conceptions)
Avg. wet-bulb temperature >19°C	−0.262** (0.088)	−0.084** (0.016)						
Avg. wet-bulb temperature >21°C			−0.490** (0.161)	−0.301** (0.045)				
Avg. dry-bulb temperature >25°C					−0.247** (0.081)	−0.118** (0.020)		
Avg. dry-bulb temperature >27°C							−0.335* (0.128)	−0.234** (0.033)
N	46,800	46,800	46,800	46,800	46,800	46,800	46,800	46,800

Notes: In Column 2, Column 4, Column 6, and Column 8, the coefficient and SE are multiplied by 100. The models have county-by-year fixed effects, calendar-week fixed effects, and calendar-week-specific quadratic time trends. Precipitation and pre-conception exposure to heat and precipitation are controlled for. In Columns 5-8, humidity controls are also included. The in utero exposure period is defined as a 39-week-long period starting with the week of conception. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Table A5: Sensitivity tests: experimenting with fixed effects (number of conceptions)

	(1)	(2)	(3)	(4)	(5)	(6)
Avg. wet-bulb temperature >20°C	-0.174^{**} (0.021)	-0.154^{**} (0.021)	-0.184^{**} (0.044)	-0.206^{**} (0.043)	-0.184^{**} (0.024)	-0.145^{**} (0.028)
Fixed effects	C-Y, W	C-Y, W	C, Y, W	Y, C-W	C-Y, C-W	C-Y-S, W
Time trends	W-spec. linear	W-spec. cubic	C-spec. quadratic, W-spec. quadratic	C-W-spec. quadratic	C-W-spec. quadratic	W-spec. quadratic
N	46,800	46,800	46,800	46,800	46,800	46,800

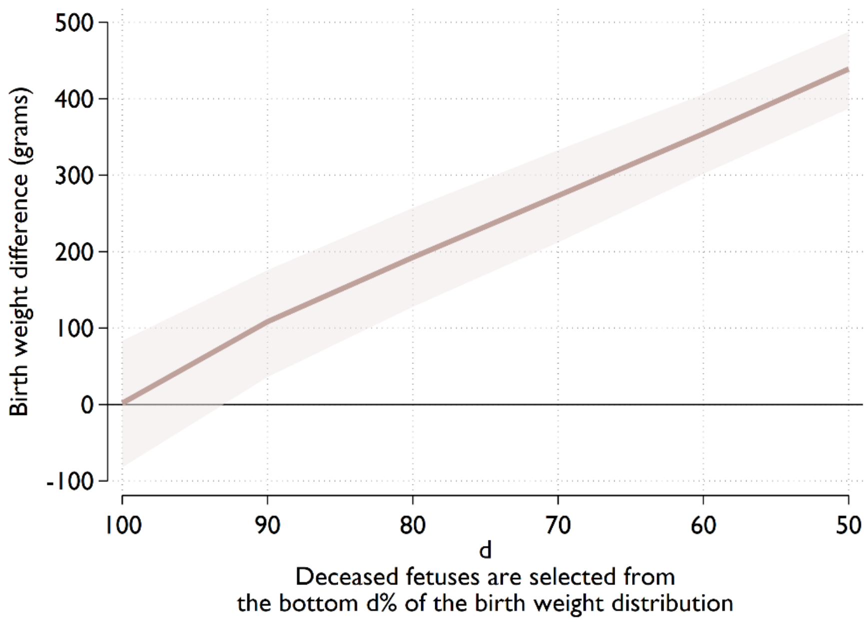
Notes: Dependent variable: ln(N of conceptions). Coefficients and SEs are multiplied by 100. C=county, Y=year, W=calendar week. Precipitation and pre-conception exposure to heat and precipitation are controlled for. The in utero exposure period is defined as a 39-week-long period starting with the week of conception. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Table A6: Sensitivity tests: controls (number of conceptions)

	(1)	(2)	(3)	(4)
Avg. wet-bulb temperature >20°C	−0.061* (0.023)	−0.162** (0.021)	−0.155** (0.021)	−0.157** (0.022)
Specification	Excl. pre-conception weather	Excl. precipitation	Incl. lagged dep. var.	Conc. week as control
N	46,800	46,800	46,700	46,800

Notes: Dependent variable: ln(N of conceptions). Coefficients and SEs are multiplied by 100. The models have county-by-year fixed effects, calendar-week fixed effects, and calendar-week-specific quadratic time trends. Precipitation and pre-conception exposure to heat and precipitation are controlled for (unless otherwise indicated). The in utero exposure period is defined as a 39-week-long period starting with the week of conception (unless otherwise indicated). In Column 3, five lags of the dependent variable are included. In Column 4, the conception week is treated as a control variable, and the main exposure variables cover weeks 2-38 of the pregnancy. Standard errors clustered at the county and year-by-week levels are in parentheses. *p<0.05, **p<0.01.

Figure A1: Simulated difference in the potential birth weights of the surviving and deceased fetuses



Notes: In this simulation, a cohort of 100,000 fetuses is used, where the potential birth weight of each fetus is randomly selected from a normal distribution with a mean of 3200 and a standard deviation of 550. The potential birth weight of each fetus is the weight that would be observed if they were born. It is assumed that 0.16 percent of the fetuses die in the womb, while the other 99.84 percent survive to live birth. The 0.16 percent of the deceased fetuses are randomly selected from the bottom *d* percent of the potential birth weight distribution (where *d* runs from 100 to 50). The counterfactual difference in the (potential) birth weights of the surviving and deceased fetuses is calculated under different *d*. The shaded area represents 95% confidence intervals calculated from 500 replications. The solid line is the mean of the 500 replications.

Appendix B

In addition to the notation introduced in Section 2 of the main text, let $N[S_{i0},S_{i1}]$ denote the number of different types of fetuses in our hypothetical cohort that are shown in Table 1. Thus, $N[S_{i0}=1,S_{i1}=1]$ is the number of fetuses that survive to birth regardless of the exposure to the event in question. $N[S_{i0}=1,S_{i1}=0]$ is the number of fetuses that survive to birth only if they have not been exposed to the event, and so on. With a similar notation $N[S_{i1}=1]$ and $N[S_{i0}=1]$ is the number of fetuses that survive to birth if they were exposed and unexposed to the event in question, respectively.

Using these notations, β^{NC} from (10) can be written as:

$$\beta^{NC} = \ln(N[S_{i1}=1]) - \ln(N[S_{i0}=1]) \approx \frac{N[S_{i1}=1] - N[S_{i0}=1]}{N[S_{i0}=1]}$$

$$= \frac{N[S_{i0}=1,S_{i1}=1] + N[S_{i0}=0,S_{i1}=1] - N[S_{i0}=1,S_{i1}=1] - N[S_{i0}=1,S_{i1}=0]}{N[S_{i0}=1]}$$

$$= \frac{N[S_{i0}=0,S_{i1}=1] - N[S_{i0}=1,S_{i1}=0]}{N[S_{i0}=1]}. \tag{B1}$$

Under the assumption that fetuses that survived the exposure to an adverse event, would not have died in a counterfactual situation in which they were not exposed ($P[S_{i0}=0|S_{i1}=1] = 0$, and therefore ($N[S_{i0}=0,S_{i1}=1] = 0$), (B1) can be simplified to:

$$\beta^{NC} \approx -\frac{N[S_{i0}=1,S_{i1}=0]}{N[S_{i0}=1]}. \tag{B2}$$

Since by definition:

$$P[S_{i1}=0|S_{i0}=1] = \frac{N[S_{i0}=1,S_{i1}=0]}{N[S_{i0}=1]}, \tag{B3}$$

it is easy to see that:

$$P[S_{i1}=0|S_{i0}=1] \approx -\beta^{NC}. \tag{B4}$$