UNIVERSITÀ DEGLI STUDI FIRENZE
Dipartimento di Statistica, Informatica, Applicazioni "Giuseppe Parenti"
Eccellenza 2023-2027

Temporal Changes in the Quantity of Conceptions Influence Preterm Births Rates at the Population Level

Marco Cozzani, Peter Fallesen, Juho Härkönen

DISIA WORKING PAPER
2025/08

Temporal Changes in the Quantity of Conceptions Influence Preterm Births Rates at the Population Level

Marco Cozzani[1], Peter Fallesen[2,3], Juho Härkönen[4]

[1]University of Florence, Italy, [2]ROCKWOOL Foundation, Denmark, [3]Stockholm University, Sweden, [4]European University Institute, Italy

Email: marco.cozzani@unifi.it

Abstract

The presence of temporalities in conceptions, births, and birth outcomes such as preterm birth are well-known. However, the link between these phenomena has received surprisingly little attention. Drawing on birth certificates data from the United States (2010–2019), we demonstrate how temporal changes in conceptions are linked with birth outcomes. First, we formalize the relationship between temporal variation in conceptions and birth outcomes and model how changes in conception rates affect birth outcomes. Second, we demonstrate the temporal relationship between changes in conception rates and birth outcomes. Third, we illustrate the impact of temporal variation in conceptions on the variation in birth outcomes across different U.S. population groups. Our results show a link between the number of conceptions and the distribution of preterm births, such that a decline in conceptions will lead to a decrease in preterm births eight months after, whereas an increase will lead to the opposite pattern. This link is stronger among groups with higher incidences of preterm birth, such as Black Americans relative to non-Hispanic White Americans. Temporal variation in conceptions accounts for about one-tenth of the temporal variation in birth outcomes, and this proportion increases among groups with higher incidence rates of preterm birth. This study offers new insights into the demographic determinants of health at birth at the population level.

Introduction

Rates of conceptions and births vary across time, exhibiting strong temporal patterns. The same holds true for rates of adverse birth outcomes, such as preterm birth (PTB). Temporal patterns and seasonality in fertility among human populations have received much attention, with explanations highlighting behavioral patterns, climate, fecundability, and preferences as possible determinants (Barreca, Deschenes, & Guldi, 2018; Becker, 1991; Bodnar & Simhan, 2008; Clarke, Oreffice, & Quintana-Domeque, 2019; Lam & Miron, 1996; Rizzi & Dalla-Zuanna, 2007; Seiver, 1985; Strand, Barnett, & Tong, 2011). For birth outcomes, research has considered maternal selection into season of conception, flu seasonality, and climate (Conte Keivabu & Cozzani, 2022; Currie & Schwandt, 2013; Deschênes, Greenstone, & Guryan, 2009; Torche & Corvalan, 2010). Despite the fact that both phenomena exhibit these temporal patterns, the link between them has received little attention (Cozzani, Fallesen, Passaretta, Härkönen, & Bernardi, 2023; Currie & Schwandt, 2013; Darrow et al., 2009; de Klerk et al., 2025; Nobles & Hamoudi, 2019).

Temporal variation in conceptions carried to term (from here, simply called conceptions) refers to the changes in the population rate of conceptions over time, which causes corresponding fluctuations in births five to ten months later depending on length of gestation. This variation can be understood as a temporal sequela of conception/fertility shocks of different intensities. Throughout the text, we use the term shock as a synonym of this variability. The variation in conceptions leading to live birth has two main components. The first is purely mechanical: the more conceptions there are, the more births will occur in the following five to nine months. The second component involves environmental and behavioral determinants, which influence *who* conceives and *which* fetuses survive to birth.

The relationship between variation in quantity of conceptions and distribution of birth outcomes arises primarily because pre-term and full-term children born in the same month are conceived at different times, with the distribution of births reflecting variations in conception rates from earlier months. As the conception rate fluctuates, so does the distribution of pre-term births over time. For example, if, across two months, there is a uniform increase in conceptions, we will observe a mechanical change in the proportion of pre-term births 5 to 8 months later. This happens as children born pre-term are conceived in the month with more conceptions, whereas their at-term counterparts (which are born in the same month) are conceived in the month(s) prior before conceptions increased. As a result, at birth time there will be more pre-term children, compared to the previous month, due to an increase in conceptions eight months earlier relative to nine months earlier.

This study addresses the relationship between conception quantities and distribution of birth outcomes in three ways. First, we formalize the link between temporal variation in conceptions and pre-term births. Second, we demonstrate how changes in conceptions directly reshape pre-term birth rates downstream. Third, we illustrate how temporal variation in conceptions affect birth outcomes across different racial groups in the US to a different degree. We draw from US birth registers for the period 2010-19 and show results for births to non-Hispanic White mothers and Black mother. In total, the study contributes new understandings of the relation between how many children are conceived and how many children are born preterm. Furthermore, we contribute to the understanding of the demographic determinants of the population-level distribution of health at birth.

Data and methods

We use administrative microdata from the CDC's National Vital Statistics System (NVSS), covering all U.S. birth certificates between 2010 and 2019. These data include detailed anthropometric information on the newborn, medical and delivery-related characteristics, and sociodemographic data on the mother and her partner. We restrict the analysis to births occurring through the end of 2019 to avoid capturing fertility shocks induced by the COVID-19 pandemic.

Because we are interested in identifying temporality in conception and its relationship to birth outcomes, we reconstruct the timing of conception using information on the month of birth and gestational age. The public NVSS data do not contain the exact date of birth but do include the day of the week and month. To estimate conception dates, we impute the birth date by randomly assigning a day within the reported month that matches the day of the week. We then count backward using reported gestational age to obtain the date and month of conception. Our analyses include only conceptions resulting in live births.

Our primary outcome is the preterm birth rate, defined as the proportion of births occurring before 37 completed weeks of gestation. In parts of the analysis, we stratify results by maternal race, distinguishing between non-Hispanic White and non-Hispanic Black mothers.

We conduct three sets of analyses. First, we use birth data from 2018 and 2019 to demonstrate how conception shocks affect birth outcomes. We model the expected preterm birth rate under different assumptions about the size of a conception shock and the extent of selection into or out of conception. We calculate the average preterm birth rate for each racial group over the 2018–2019 period and use this as the baseline rate in our model.

Second, we simulate how a conception shock is temporally related to birth outcomes. We remove a fraction of conceptions leading to live births in early 2018—uniformly across all births—in order to simulate the effects of a short-term decline in conceptions. Specifically, we eliminate conceptions occurring in January (one month), January–February (two months), and permanently, rerunning the simulation 1,000 times to obtain prediction intervals. In another simulation, also using 2019 birth data, we exclude births attributed to medically assisted reproduction (MAR) to approximate the impact of partial MAR clinic closures. Because MAR births are underreported in the NVSS (Tierney & Cai, 2019), this exercise provides a lower-bound estimate.

Third, we use different strategies to assess the degree to which temporal changes in conceptions are associated to temporal variation in birth outcomes, and how much variation they explain. In a time-series analysis using the full 2010–2019 NVSS data, we estimate the relationship between conceptions and preterm birth outcomes by computing the ratio R_{t_0}, defined as the number of conceptions occurring eight months prior to a birth relative to those nine months prior. We regress the preterm birth rate in month t on this ratio, including controls for month and year fixed effects to estimate the gradient. Further, to also estimate the elasticity, we log-transform both the dependent variable (preterm birth rate) and independent variable (R_{t_0}).

To assess the extent to which variation in conceptions accounts for variation in birth outcomes, we estimate a vector autoregressive (VAR) model with forecast error variance decomposition. We align conceptions at time $t-6$ with births at time t, as motivated by findings from our earlier simulation. We select lag length using the Bayesian Information Criterion (BIC) and evaluate model fit across specifications. We estimate separate models by race.

For Blacks, our estimation equation is:

$$
\begin{aligned}
ptb_t \;=\; & c^1 + t^1 + \sum_{j=1}^{12} \delta_j^1 S_{\mathrm{jt}} + \varphi^{11} ptb_{t-1} + \varphi^{12} ptb_{t-2} + \varphi^{13} ptb_{t-3} + \beta^{11} R_{t-7} \\
& + \beta^{12} R_{t-8} + \beta^{13} x R_{t-9} + \varepsilon_t^1 \\
R_{t-6} \;=\; & c^2 + t^2 + \sum_{j=1}^{12} \delta_j^2 S_{\mathrm{jt}} + \varphi^{21} ptb_{t-1} + \varphi^{22} ptb_{t-2} + \varphi^{23} ptb_{t-3} + \beta^{21} R_{t-7} \\
& + \beta^{22} R_{t-8} + \beta^{23} R_{t-9} + \varepsilon_t^2
\end{aligned}
$$

and for Whites it is:

$$
\begin{aligned}
ptb_t \;=\; & c^1 + \sum_{j=1}^{12} \delta_j^1 S_{\mathrm{jt}} + \varphi^{11} ptb_{t-1} + \varphi^{12} ptb_{t-2} + \beta^{11} R_{t-7} + \beta^{12} R_{t-8} + \varepsilon_t^1 \\
R_{t-6} \;=\; & c^2 + \sum_{j=1}^{12} \delta_j^2 S_{\mathrm{jt}} + \varphi^{21} ptb_{t-1} + \varphi^{22} ptb_{t-2} + \beta^{21} R_{t-7} + \beta^{22} R_{t-8} + \varepsilon_t^2
\end{aligned}
$$

where *c* is the constant, *t* is a time trend (only for blacks), δ_j are monthly parameters, φ are parameters for lagged values of ptb, β are parameters for lagged values of *R*, and ε is error terms.

Although the time series for preterm births among White mothers is nonstationary (p = 0.25), we are primarily interested in the proportion of variance in preterm births explained by conceptions and thus not overly concerned with lag of stationarity; model diagnostics suggest a good overall fit.

Finally, to isolate the explanatory power of conception variation alone, we create a counterfactual distribution of births by fixing the gestational age distribution at each month of conception to its period average. We then vary only the number of conceptions and regress the observed birth outcomes on this counterfactual. The resulting R^2 statistic indicates the share of temporal variation in birth outcomes attributable to changes in conception volume alone, following the approach of Currie and Schwandt (2013).

The functional relationship

First, we formalize the functional relationship between changes in the quantity of conceptions (ending up in live births) and birth outcomes at the time of birth. For simplicity's sake, we assume all pre-term births occur 8 months after conception and focus on a one-month-long change to conceptions. We focus on eight months as it is the modal category for the gestational length of pre-term born children (about 78% of all pre-term children according to the NVSS data). We define the size of the shock to conceptions as S_{t_0} (where -1 means a 100% decline in conceptions and 1 means a 100% increase), the baseline share of preterm births assuming no shock and no seasonality as p, a selection term δ that captures the relative risk of preterm birth among those who contribute to the change in the quantity of conception compared to the full population (ranging from 0 to infinity, with 1 indicating no selection), and the preterm birth rate eight months later as PTB_{t8}. The selection term allows the model to describe not only uniform conception shocks but also shocks driven by part of the population with distinct preterm birth risk. The relationship between conception shocks and the preterm birth rate can be expressed as:

$$f(S_{t0}) = PTB_{t_8} = \frac{p(1+S_{t_0})^{\delta}}{1-p+p(1+S_{t_0})^{\delta}} + \epsilon_{t_8} \qquad (1)$$

where ϵ_{t_8} is an error-term assumed orthogonal to S_{t_0}, p, and δ. The partial derivative with respect to the baseline preterm birth risk p is then:

$$\frac{\partial f}{\partial p} = \frac{(1+S_{t0})^{\delta}(1+p)-p(1+s_{t0})^{2\delta}}{\left(1-p+p(1+S_{t0})^{\delta}\right)^{2}} \quad (2)$$

and the selection term δ is defined as:

$$\delta = \frac{\log\left(\frac{(p-1)PTB_8}{(PTB_8-1)p}\right)}{\log(S_{t0}+1)} \; for \; x_{t0} > -1, S_{t0} \neq 0, p > 0 \quad (3)$$

Following from eq. 3, the size of selection term depends on the initial level of pre-term birth, p, and thus is not scale-independent. Further, x_{t0} may change for two reasons—either conceptions at t0 changes which affects the number of preterm, or conceptions changes at t_{-1}, which affects the number of at-terms.

From equations 1 and 2 it follows that changes in PTB rates due to a shock to conceptions depend on several factors: the size of the shock, the share of children who would be expected to be born preterm absent any shock to conception eight months prior to the observed birth month, and the selection effects on conception due to the shock.

Figure 1 demonstrates the impact of various shocks, ranging from -100% (no conceptions at all) to +100% (double the monthly conceptions), on the preterm birth rate in the U.S. This is done for births to non-Hispanic White mothers and Black mothers. The baseline risks in the figure are based on the average incidence of PTB for each racial group in 2018-2019 according to the NVSS data. Overall, a reduction in conceptions leads to a lower share of preterm births eight months later, while an increase in conceptions results in a higher share of preterm births. Further, as can be seen from Figure 1 (and follows from eq. 2), any shock to conceptions has a higher impact on PTB risk for Black mothers than for White mothers given the difference in underlying baseline risk. Relative shocks at higher baselines have a higher impact *both* in absolute and relative terms.

[FIGURE 1 ABOUT HERE]

The temporal relationship

Next, we demonstrate the temporal relationship between changes in the quantity of conceptions and birth outcomes. We simulate a scenario, which introduces a random decrease (assuming no selection, $\delta = 1$) in the number of conceptions (between 5%-20%

decrease) lasting a) one month; b) two months, or c) sustained over at least a 5-month window (permanent within the time frame). We then obtain birth outcomes changes in the following months under each scenario. For the sake of brevity, we only simulate a decline, but an increase in conceptions would play out identically but with opposite sign.

Figure 2 below shows the simulation: a one-month temporary (left panels) uniform conception shock produces first an improvement in birth outcomes at t+8 which is followed by a rebound with a worsening of birth outcomes at t+9. A two-month uniform conception shock (middle panel) produces an improvement in months t+8 and t+9, a return to normal rates in t+10, and a rebound in t+11 and t+12. When the shock persists (right panel), we observe an improvement in birth outcomes which is followed by a normalization. In total, Figure 2 demonstrates a demographic artifact: uniform changes in conceptions translate into a wave-shaped disturbance of birth outcome in the months that follows. Children born at month 8 months after a conception shock are both conceived before and after the fertility shock, with the pre-term conceived right after and the at term conceived right before. Thus, the shock manifests only among the PTB, as there was a reduction in the numerator (premature births) of the PTB rate $Pre\text{−}term\ births/All\ births$. The opposite scenario happens for the rebound.

[FIGURE 2 ABOUT HERE]

The simulations shown in Figure 2 assume no selective element to the conception shock. To simulate a scenario where only the part of the population who substantially have higher than average risk of PTB changes their conception risk, we remove all births indicated in the NVSS as being due to MAR, as such conceptions are known to have substantially higher risk of PTB (Goisis, Remes, Martikainen, Klemetti, & Myrskylä, 2019), which is equivalent to setting $\delta \gg 1$ in Eq. 1. This demonstrates a scenario where all fertility clinics close for a period, as was seen in several countries during the COVID-19 pandemic (Requena et al., 2020). We simulate three different closure scenarios: a 1-month closure of all clinics, a 2-month closure of all clinics, and a permanent closure of all clinics assuming no increase in natural conceptions following the closure. Figure 3 shows the impact on PTB rates under these scenarios. The simulated shocks all start at month 1. A similar decline as seen in Figure 2 occurs at 8 and 9 months, but we do not observe the same symmetric wave-function 9 month after the shock ends, because of the group's higher risk of experiencing preterm births.

[FIGURE 3 ABOUT HERE]

General and seasonal variation in conceptions and birth outcomes

The final aim of this article is to illustrate the size of the association between changes in conceptions and birth outcomes, as well as how much of the temporal variation in birth outcomes is explained by temporal variation in conceptions. To achieve this, we utilize three analytical strategies that, together, aim to provide a robust description of the relationship between these two phenomena. We build on our model defined in Equation 1, and we operationalize temporal variation as the change in conceptions in month t_0 relative to the month prior t_1. That is, instead of considering the impact of a short-time conception shock, we can extend Equation 1 to account for any change in conceptions between two months as represent by a ratio $R_{t_0} = \frac{No.\ of\ conceptions\ at\ t_0}{No.\ of\ conceptions\ at\ t_{-1}}$, such that:

$$f\left(R_{t_0}\right) = PTB_{t_8} = \frac{p\left(R_{t_0}\right)^{\delta}}{1-p+p\left(R_{t_0}\right)^{\delta}} + \epsilon_{t_8} \quad (4)$$

with the same assumptions as for Eq. 1.

First, using the R_{t_0} ratio as the independent variable, we regress it on the rate of pre-term births 8 months later using OLS models, including month and year fixed effects on NVSS data covering US births for the period 2010-2019. Figure 4 illustrates the relationship between R_{t_0} and the pre-term birth rates by racial groups. It also presents parameters derived from OLS regressions: the gradient (β) of preterm birth rates on R_{t_0}, as well as the elasticity obtained by log-transforming both variables. Both parameters indicate that changes in conceptions are more consequential for population-level preterm birth share of Blacks than Whites. However, while the estimates are adjusted for year and month dummies to account for seasonality and annual trends and to prevent confounding, this adjustment introduces over-control bias. This occurs because the seasonality and trend in R_{t_0} inherently influence the seasonality and trend in pre-term births. controlling for it will lead to over-control bias. Therefore, evaluating the full temporal role of R_{t_0} in pre-term births requires alternative empirical strategies.

[FIGURE 4 ABOUT HERE]

Therefore, second, we approach temporal variation in conceptions (R_{t_0}) and preterm birth rates from a time-series perspective and model it as a Vector Autoregressive Model with the conception timeseries lagged with 7 months. Results are shown in Table 1. Tests for Granger-causality, both for Black and White, show significant Granger-causal relationships from R_{t_0} to pre-term births, but not the reverse. Forecast error variance decomposition shows that variation in R_{t_0} explains 7-8% of variation in pre-term births for Whites and 13-15% for Black.

Finally, in Table 1 we also provide an alternative estimation of the impact of seasonality in conceptions by drawing from a strategy outlined in Currie and Schwandt (2013). We construct a counterfactual temporality in birth outcomes as if there was only temporality in conceptions, but not in birth outcomes, using births between 2010 and 2019. Overall, using this strategy we find that temporal variation in conceptions explains 12% of temporal variation in birth outcomes for Blacks, and 8% for Whites. Overall, all strategies yield similar results—changes in conceptions matters substantively for changes in birth outcomes, and more so for populations with higher baseline risk of preterm birth.

[TABLE 1 ABOUT HERE]

Discussion

A substantial body of research spanning several decades has demonstrated that many human phenomena exhibit temporal patterns often aligned with seasons. Among those, conceptions and birth outcomes have been shown to vary due to several factors. However, they have rarely been linked. In this study, we have formalized and demonstrated how the temporal variation in conceptions is connected to temporal variation in birth outcomes. We described a partly mechanical link, framing temporality as a series of consecutive conception shocks. These conception shocks influence birth outcomes by distributing both at-term and pre-term births throughout the year with different intensities. For example, a decline in conceptions from one month to another will lead to a decrease in preterm birth eight months later as they are born at the same time with a larger share of at-term children conceived before the conceptions decline. A mirrored pattern happens when an increase in the number of conceptions is observed. Further, differential selection based on risk for adverse birth outcomes into whom within a given groups conceives may further increase or decrease the influence of temporal variation in conceptions.

We presented two further important findings. First, when conceptions shocks are short-lived and uniformly occurring across the full population, they cause a waveform change in risk of adverse birth outcomes with the nodal point located 8.5 months following the end of the shock. Second, the higher the baseline risk for adverse birth outcomes is, the larger are the changes in those risks as a function of changes in conception rates. Groups with a higher incidence of PTB, such as those with shorter educations as well as ethnic minorities (Cozzani, 2023; Kelly et al., 2008), are more sensitive to changes in the quantity of conceptions when it comes to their variation in birth outcomes. Overall, these findings demonstrate that changes in conceptions carried to term may arise from different reasons, spanning from fertility decisions to increases in fetal losses, and the intensity of these changes influences the number of children born pre-term throughout the year. While we have not focused on the specific causes of conception changes, our model is applicable to a wide range of factors driving these variations.

We can draw at least two implications from these findings. First, for public health purposes understanding the reasons behind temporal patterns in conceptions is crucial. Consider the following two scenarios. In the first, environmental factors—such as climatic events, pollutants, or stressful occurrences—influence conception rates. This implies that harmful exposures might impact conception rates (Hajdu, 2023; Nobles & Hamoudi, 2019), and their impact is ultimately observed by abnormal PTB rates fluctuations throughout the year. In the second scenario, the temporal variation in conception is related to compositional changes. For example, the use MAR is influenced by the scheduling of medical procedures, and therefore it contributes to conception rates unequally across the year. Moreover, children conceived through MAR are associated with worse birth outcomes on average (Goisis et al., 2019). As a result, the concentration of these procedures is even more likely to reinforce the connection between conception rates and birth outcomes. Similarly, if specific socio-economic groups, such as those with socio-economic advantages, concentrate their fertility efforts during certain periods (Clarke et al., 2019), this could also affect the distribution of birth outcomes due to their group-specific PTB rates. The first scenario suggests that abnormal PTB rates fluctuations may be linked to external factors that directly influence newborn health, warranting attention to potential exposures around the time of conception. In contrast, the second scenario reflects a more mechanical relationship, where changes in poor birth outcomes across the year are driven by variations in the composition of conceptions rather than health-related factors. Finally, this mechanical relationship may help explain, at least in part, the improvements in birth outcomes observed, for example, following the onset COVID-19 pandemic (Cozzani et al., 2023; Gemmill et al., 2022). Failing to account for such changes in who conceives and carries to term may cause researcher to overinterpret changes in birth outcomes observed five to nine months later, because these changes may primarily be driven by changes in the number of conceptions induced by the pandemic (Aassve, Cavalli, Mencarini, Plach, & Sanders, 2021; Bailey, Currie, & Schwandt, 2023; Fallesen & Cozzani, 2023) rather than by substantive health-related interventions.

Second, this study highlights the importance of accounting for selective changes in who conceives when examining how exogenous stressors affect birth outcomes. This is particularly relevant for the growing body of research in the social and economic sciences inspired by the fetal origin hypothesis (Almond & Currie, 2011; Almond, Currie, & Duque, 2018; Torche & Nobles, 2024), and especially the extensions on the stratified responses to early exposures (Aquino, Brand, & Torche, 2022; Torche & Nobles, 2024), as the groups that are studied are those with the higher prevalence of poor birth outcomes. Although there is a consensus that the effect of environmental exposures should be assessed at the time of conception rather than at birth (Currie & Rossin-Slater, 2013; Currie & Schwandt, 2013), this is not always feasible. Reconstructing the precise date of conception is challenging, as it is typically estimated by counting backward from the date of birth using information on gestational length. This approach is subject to several limitations due to the inherent inaccuracies in how gestational length is calculated or recalled. We thus advise that, when assessing the impact of environmental events—such as pandemics, natural disasters or human-made violence—on birth outcomes in subsequent months, it is essential to account for potential conception shocks (i.e. selective fertility responses and fetal losses) triggered by these events. If an event causes simultaneous changes in conception rates, it could mechanically influence birth outcomes, independent of the event's direct effects. Overlooking these dynamics may lead to misinterpretation of the true impact of such events on birth outcomes. Our model can help to estimate the potential bias introduced by changes in the number of conceptions following an external stressor. Equation (1) can be adjusted by incorporating a known parameter as the prevalence of preterm births (PTB) in the population, and by providing an upper and lower bound of a possible change in the number of conceptions. The resulting calculation can offer a measure of how large the conception shock would need to be to fully account for the observed effect.

This study highlights the importance of considering not only etiological determinants of perinatal health but also stresses the importance of considering demographic determinants of birth outcomes. The model we outlined can be extended to not only the quantity of conceptions, but also to their compositions. Further studies should develop on how changes in population compositions may alter the health of the newborns due to, for example, changes in MAR usage, migration inflows, and changes in fertility behaviors across socio-economic groups.

References

Aassve, A., Cavalli, N., Mencarini, L., Plach, S., & Sanders, S. (2021). Early assessment of the relationship between the COVID-19 pandemic and births in high-income countries. *Proceedings of the National Academy of Sciences, 118*(36), e2105709118. doi:10.1073/pnas.2105709118

Almond, D., & Currie, J. (2011). Killing Me Softly: The Fetal Origins Hypothesis. *Journal of Economic Perspectives, 25*(3), 153-172. doi:10.1257/jep.25.3.153

Almond, D., Currie, J., & Duque, V. (2018). Childhood circumstances and adult outcomes: Act II. *Journal of Economic Literature, 56*(4), 1360-1446.

Aquino, T., Brand, J. E., & Torche, F. (2022). Unequal effects of disruptive events. *Sociology Compass, n/a*(n/a), e12972. doi:https://doi.org/10.1111/soc4.12972

Bailey, M. J., Currie, J., & Schwandt, H. (2023). The COVID-19 baby bump in the United States. *Proceedings of the National Academy of Sciences, 120*(34), e2222075120.

Barreca, A., Deschenes, O., & Guldi, M. (2018). Maybe Next Month? Temperature Shocks and Dynamic Adjustments in Birth Rates. *Demography, 55*(4), 1269-1293. doi:10.1007/s13524-018-0690-7

Becker, S. (1991). Seasonal patterns of births and conception throughout the world. *Temperature and environmental effects on the testis*, 59-72.

Bodnar, L. M., & Simhan, H. N. (2008). The prevalence of preterm birth and season of conception. *Paediatric and Perinatal Epidemiology, 22*(6), 538-545.

Clarke, D., Oreffice, S., & Quintana-Domeque, C. (2019). The demand for season of birth. *Journal of Applied Econometrics, 34*(5), 707-723. doi:https://doi.org/10.1002/jae.2711

Conte Keivabu, R., & Cozzani, M. (2022). Extreme heat, birth outcomes, and socioeconomic heterogeneity. *Demography, 59*(5), 1631-1654.

Cozzani, M. (2023). Inequalities at birth: stable socioeconomic differences in birth outcomes in three British cohorts. *Genus, 79*(1), 18.

Cozzani, M., Fallesen, P., Passaretta, G., Härkönen, J., & Bernardi, F. (2023). The Consequences of the COVID-19 Pandemic for Fertility and Birth Outcomes: Evidence from Spanish Birth Registers. *Population and development review*.

Currie, J., & Rossin-Slater, M. (2013). Weathering the storm: Hurricanes and birth outcomes. *Journal of Health Economics, 32*(3), 487-503.

Currie, J., & Schwandt, H. (2013). Within-mother analysis of seasonal patterns in health at birth. *Proceedings of the National Academy of Sciences, 110*(30), 12265-12270.

Darrow, L. A., Strickland, M. J., Klein, M., Waller, L. A., Flanders, W. D., Correa, A., . . . Tolbert, P. E. (2009). Seasonality of birth and implications for temporal studies of preterm birth. *Epidemiology (Cambridge, Mass.), 20*(5), 699.

de Klerk, N. D., de Vries, I. R., Berben, P. B., Fransen, A. F., van der Ven, M., Vullings, R., . . . van Laar, J. O. (2025). Seasonal pattern of preterm birth in the Netherlands: A population-based retrospective cohort study. *PLoS ONE, 20*(5), e0324873.

Deschênes, O., Greenstone, M., & Guryan, J. (2009). Climate change and birth weight. *American Economic Review, 99*(2), 211-217.

Fallesen, P., & Cozzani, M. (2023). Partial fertility recuperation in Spain two years after the onset of the COVID-19 pandemic. *Demographic research, 49*(17), 465-478. doi:https://www.demographic-research.org/volumes/vol49/17/files/demographic-research.49-17.zip

Gemmill, A., Casey, J. A., Margerison, C. E., Zeitlin, J., Catalano, R., & Bruckner, T. A. (2022). Patterned outcomes, unpatterned counterfactuals, and spurious results: perinatal health outcomes following COVID-19. *American Journal of Epidemiology*.

Goisis, A., Remes, H., Martikainen, P., Klemetti, R., & Myrskylä, M. (2019). Medically assisted reproduction and birth outcomes: a within-family analysis using Finnish population registers. *The lancet, 393*(10177), 1225-1232.

Hajdu, T. (2023). In utero shocks and health at birth: The distorting effect of fetal losses. *Oxford Bulletin of Economics and Statistics*.

Kelly, Y., Panico, L., Bartley, M., Marmot, M., Nazroo, J., & Sacker, A. (2008). Why does birthweight vary among ethnic groups in the UK? Findings from the Millennium Cohort Study. *Journal of public health, 31*(1), 131-137.

Lam, D. A., & Miron, J. A. (1996). The effects of temperature on human fertility. *Demography, 33*(3), 291-305.

Nobles, J., & Hamoudi, A. (2019). Detecting the effects of early-life exposures: why fecundity matters. *Population research and policy review, 38*, 783-809.

Requena, A., Cruz, M., Vergara, V., Prados, N., Galliano, D., & Pellicer, A. (2020). A picture of the covid-19 impact on IVIRMA fertility treatment clinics in Spain and Italy. *Reproductive BioMedicine Online, 41*(1), 1-5.

Rizzi, E. L., & Dalla-Zuanna, G. (2007). The seasonality of conception. *Demography, 44*(4), 705-728. doi:10.1353/dem.2007.0040

Seiver, D. A. (1985). Trend and variation in the seasonality of US fertility, 1947–1976. *Demography, 22*(1), 89-100.

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. *Environmental Research, 111*(3), 451-462.

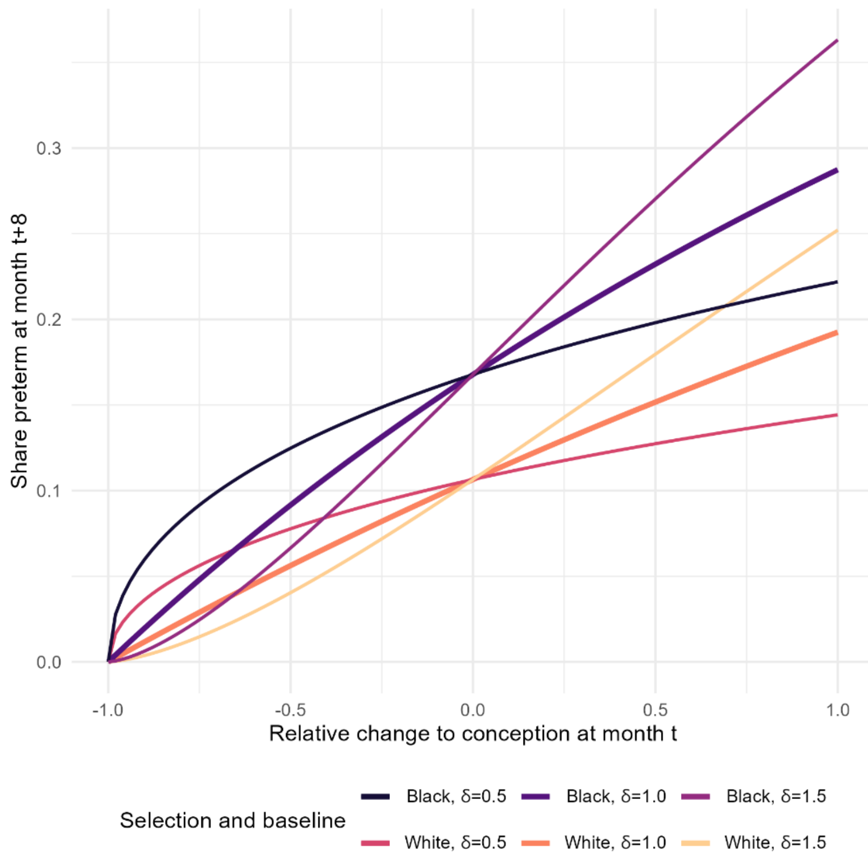
Tierney, K., & Cai, Y. (2019). Assisted reproductive technology use in the United States: a population assessment. *Fertility and Sterility, 112*(6), 1136-1143. e1134.

Torche, F., & Corvalan, A. (2010). Seasonality of birth weight in Chile: environmental and socioeconomic factors. *Annals of Epidemiology, 20*(11), 818-826.

Torche, F., & Nobles, J. (2024). Early-life exposures and social stratification. *Annual Review of Sociology, 50*.

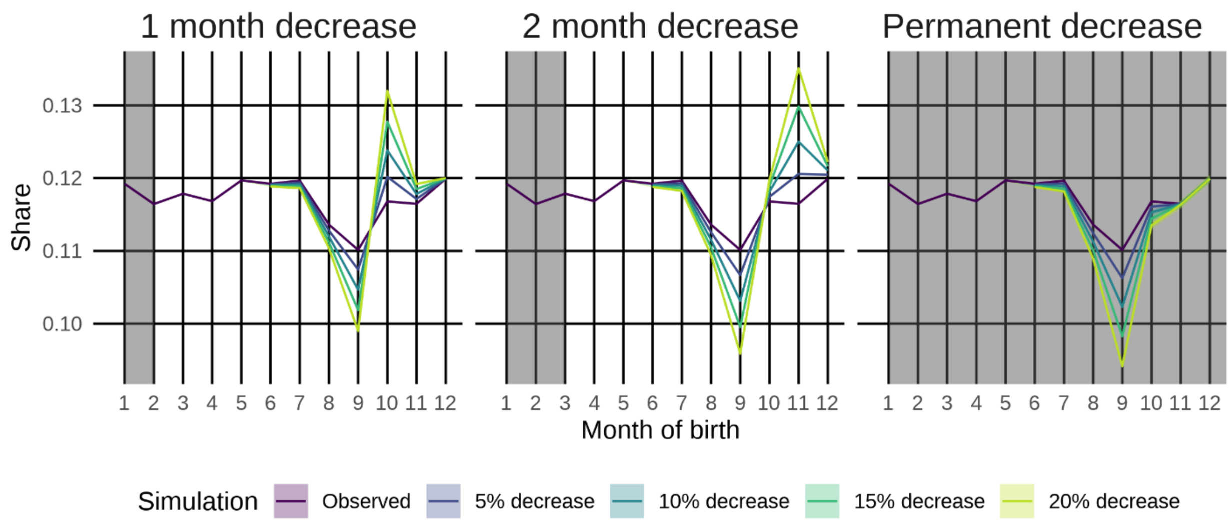
Figures and Tables

Figure 1. Demonstration of preterm birth levels at t+8 with different intensity of conception shocks at time t with different levels of selection.



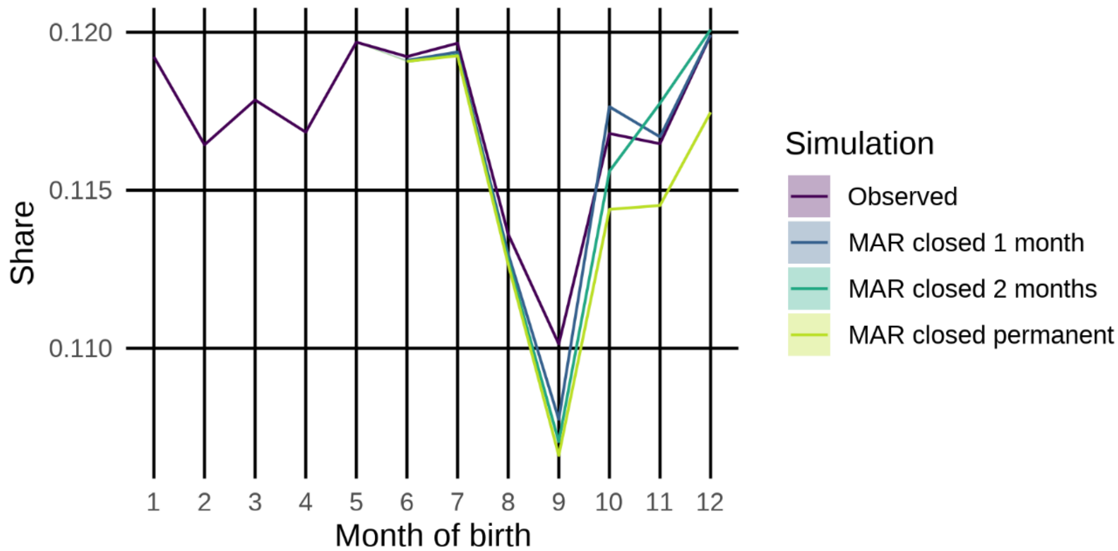
Source: US birth certificate data for 2018-19.

Figure 2. The temporal shape of the relationship of how a uniformly distributed conception shock reverberates between time 0 and time 12, simulating different intensities of conception shocks and the consequences for the share of pre-term births



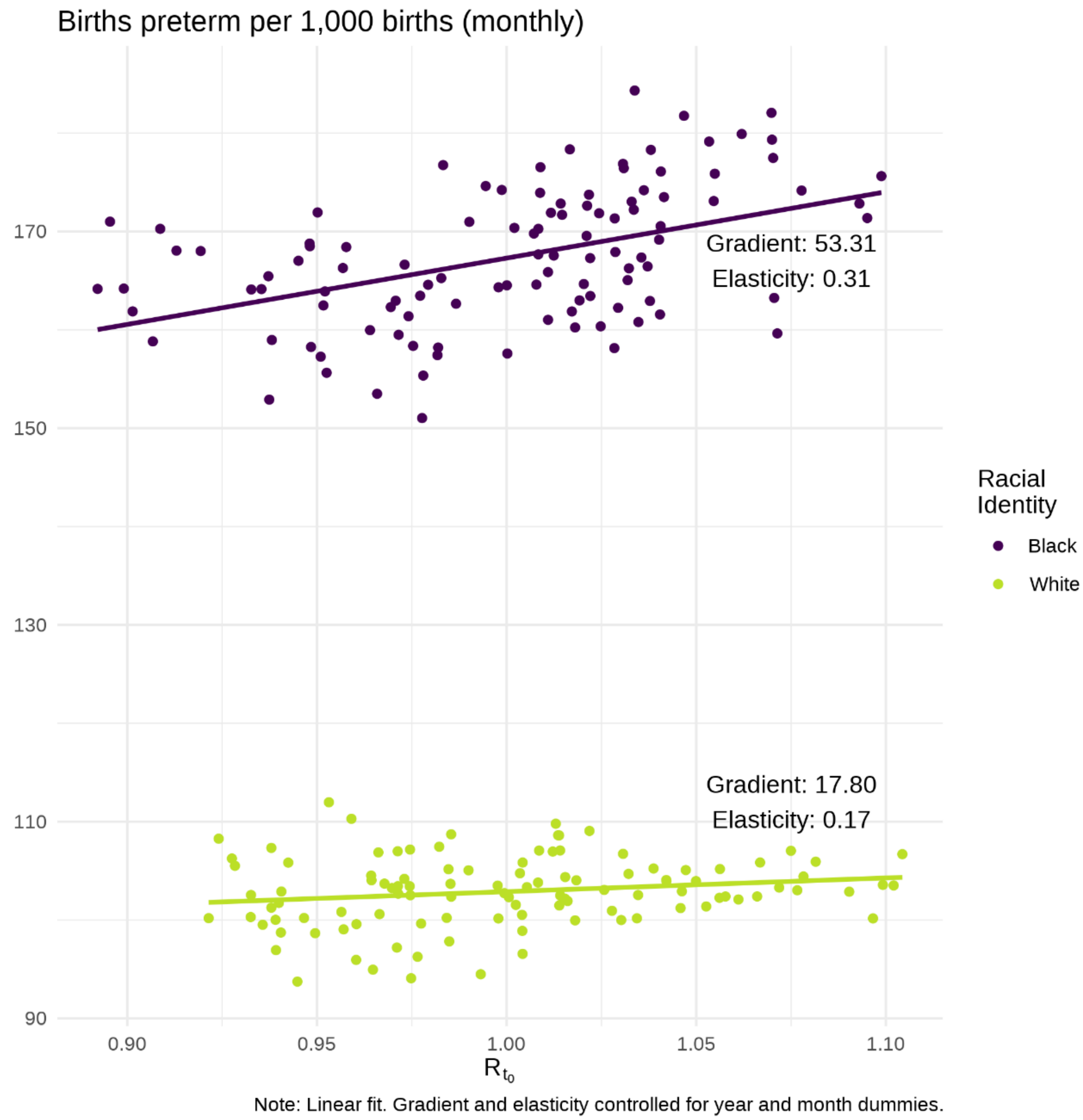
Note: Grey-shaded area delimits period at which conception shock occurs. Lines show pre-term birth risk based of birth month. Results from 1,000 simulations assigning date of birth based on day of week and month born and with a uniform assigned risk of not conceiving at varying intensity. 95% uncertainty intervals.
Source: US birth certificate data for 2018-19.

Figure 3. The temporal shape of the relationship of how a conception shock due to closure of MAR clinics between time 0 and time 12, simulating different lengths of closure and the consequences for the share of pre-term births



Note: Source: US birth certificate data for 2018-19. Results from 1,000 simulations assigning date of birth based on day of week and month born.

Figure 4. The relationship between R_{t_0} and pre-term birth rate across racial categories, 2010-19



Source: US birth certificate data for 2010-19.

Table 1: Share of pre-term births explained by changes in conceptions separately for White and Black.

	White	Black
Currie and Schwandt (2013) counterfactual approach		
Share of PTB variance explained by conceptions	$R^2 = .08$	$R^2 =.12$
VAR model		
FEVD at 3-month time horizon	.07	.13
FEVD at 6-month time horizon	.08	.15
Granger-causality: H_0: R_0 does not Granger-cause PTB	$p < .01$	$p < .01$
Granger-causality: H_0: PTB does not Granger-cause R_0	$p = .93$	$p = .92$

Notes: PTB: Pre-term birth rates. FEVD: Forecast error variance decomposition. R_0: 6-month lagged conception ratio relative to PTB. VAR: Variance Autoregressive Model. VAR models estimated with three lags for black sample and two lags for white sample. Source: NVSS birth records 2010-2019.