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Seasonal patterns in newborns' health: Quantifying the roles of climate, communicable disease, economic and social factors

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ABSTRACT

Poor health at birth can have long-term consequences for children's development. This paper analyses an important factor associated with health at birth: the time of year that the baby is born, and hence seasonal risks they were exposed to in utero. There are multiple potential explanations for seasonality in newborns' health. Most previous research has examined these in isolation. We therefore do not know which explanations are most important – and hence which policy interventions would most effectively reduce the resulting early-life inequalities. In this paper, I use administrative data to estimate and compare the magnitudes of several seasonal risks, seeking to identify the most important drivers of seasonality in the Northern Territory of Australia, a large territory spanning tropical and arid climates and where newborn health varies dramatically with the seasons. I find that the most important explanations are heat exposure and disease prevalence. Seasonality in food prices and road accessibility have smaller effects on some outcomes. Seasonal fertility patterns, rainfall and humidity do not have statistically significant effects. I conclude that interventions that protect pregnant women from seasonal disease and heat exposure would likely improve newborn health in the Northern Territory, with potential long-term benefits for child development. It is likely that similar impacts would apply in other locations with tropical and arid climates, and that, without action, climate change will accentuate these risks.

1. Introduction

There is much evidence showing the long-term consequences of poor health at birth. Children with poor health at birth are less likely to do well at school (Bharadwaj et al., 2018), less successful in the workforce (Currie and Rossin-Slater, 2015), and more likely to face chronic disease in adulthood (Risnes et al., 2011). These findings stem from the broader 'fetal origins hypothesis' literature, which finds that conditions in utero – often proxied by health at birth – can determine childhood and adult outcomes (see Almond et al., 2018 for a review).

But what determines a newborn baby's health? The answer can help policymakers and health care workers to anticipate which pregnancies are at risk of adverse outcomes and provide appropriate preventative care. In this paper, I focus on one important factor associated with newborns' health: the time of year that the baby is born, and hence the seasonal influences they are exposed to in utero.

A large body of research shows that birth outcomes are seasonal. However, the precise patterns vary across locations, suggesting that the reasons for seasonality depend on both the climate and on other contextual factors (Strand et al., 2011b).

In this paper I analyse seasonality in a region with both tropical and arid climates. Studies from these climates tend to focus on agricultural explanations for seasonality, highlighting the effect of rainfall on the agricultural production cycle, and hence on maternal labour, income and food consumption (Chodick et al., 2009; Maccini and Yang, 2009). While agricultural cycles are an important explanation for seasonality, research from other climates finds other explanations, and these are also likely to be present in tropical and arid climates. For example, we may expect seasonality in the characteristics of parents who conceive at different times of year, in disease prevalence, and in biological responses to very hot or cold weather during pregnancy (Currie and Schwandt, 2013; Strand et al., 2012). Also, seasonal weather events such as flooding may cause maternal stress and limit access to healthcare and fresh food, impacting newborn health independently of any impact on agricultural production.

This study analyses seasonal patterns in birth outcomes in the Northern Territory (NT) of Australia. Birth outcomes in the NT exhibit very substantial seasonal variations, with the average difference in

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birthweight between the highest and lowest month in the NT being twice as large as the difference that Currie and Schwandt (2013) find in the USA, more than five times as large as what Torche and Corvalan (2010) find in Chile, and between six and 30 times larger than what McGrath et al. (2005) find in other parts of Australia. It is important to understand the reasons behind these very substantial seasonal patterns so that these early life health inequalities can be prevented in future.

This paper makes three contributions to our understanding of seasonal patterns in newborns' health.

First, it compares the magnitudes of effects of different seasonal risks. Many researchers have considered the effects of individual seasonal risk factors on birth outcomes – predominantly rainfall, disease or heat (Andalón et al., 2016; Dorélien, 2019; Maccini and Yang, 2009). Those studies provide valuable, detailed analysis on the nature of, and mechanisms behind, specific seasonal risks. This paper brings together evidence from this large body of work to answer a higher-level question: which seasonal risks are the most important determinants of newborns' health in the NT? The answer can help policymakers to identify the most effective means of addressing early life inequalities.

Second, it contributes evidence on the seasonal risks in tropical and arid climates, which are home to around half of the world's population.[2] While the relative importance of seasonal risk factors is likely to vary from country to country, some of the risks I analyse are climate-specific, such as very hot weather in arid climates and annual flooding in tropical climates. My estimates may therefore be indicative of the impacts of risks experienced by much of the world's population. The NT is a valuable context to study for this purpose: rich administrative data allow me to analyse relationships that likely exist in many parts of the world, but for which data are not available. Importantly, my estimates may be a lower bound on the magnitudes of these effects in other contexts, given that Australia is a high-income country with free public healthcare, meaning the population have greater access to climate adaptations, treatment and preventative care than most residents in lower-income countries located within tropical and arid climate zones.

Third, the rich administrative dataset that I use allows me to make several contributions in measurement and methodology, which can inform future research. I analyse birth outcomes for all children born within the NT over a 10-year period. The data contain gestational age, birthweight and Apgar scores[3] for all children, which I use to analyse how seasonality differs across these outcomes, and throughout the distribution of these outcomes. In contrast, most other studies focus only on average birthweight or a binary indicator of preterm birth (see Section 3.2.1). Additional administrative datasets from the NT allow me to analyse potential explanations of seasonality that are predicted by theory (see Section 2), but thus far have not been documented empirically. I am also able to link together siblings to estimate sibling fixed-effects models, which allow me to disentangle environmental effects from the effects of time-invariant family characteristics.

2. Background and conceptual framework

Much of the literature on seasonal and environmental determinants of health at birth considers individual seasonal risk factors. However, seasonal risks are often correlated. For instance, some diseases are most prevalent during the hottest months of the year, and both disease and heat can contribute to poorer newborn health. Therefore, in an analysis of the effect of heat exposure which does not consider concurrent disease prevalence, we may mistakenly conclude that it is a physiological response to heat, and not disease, which drives patterns in newborn health. Furthermore, there is the challenge that pregnancy spans multiple seasons. Without careful analysis, this means it is difficult to know, for example, whether it may be cold weather during the first trimester, hot weather during the third trimester, or something else entirely, that is driving worse outcome for babies born in the summer/wet season.

When our goal is to predict patterns in newborn health, this potential misattribution may not be a problem. However, attribution becomes important when our goal is to identify effective policy responses. The potential policy responses to disease prevalence are quite different from responses to heat exposure.

I aim to disentangle competing explanations for seasonality in birth outcomes and estimate their relative contributions to newborns' health in the Northern Territory of Australia. To do this, I identify a full range of potential explanations, drawing on the academic literature as well as local context. These explanations can be classified into four broad categories: weather-related, disease-related, economic conditions, and differential fertility patterns across socioeconomic groups. In my analysis, I then estimate the effect of each seasonal risk independently and compare this with the estimated effect after controlling for all other seasonal risks. This allows me to disentangle the contributions of each seasonal risk to overall seasonality in birth outcomes, avoiding the potential misattribution described above.

In the remainder of this section, I first outline some context around the Northern Territory and the seasonal risks present in this region, I then describe the existing evidence for each category of seasonal risk (see Appendix A for a graphical summary).

2.1. The Northern Territory

The Northern Territory (NT) is one of Australia's eight states and territories. It is a large and sparsely populated region, covering the central part of northern Australia. The NT had a population of around 210,000 people as at the 2011 Census, of whom just over half live in Darwin, the capital city in the tropical north of the NT. Residents have access to Medicare, Australia's universal public healthcare system which allows them to access primary care, perinatal care and public hospital services at no cost.

The NT has two distinct climate zones: tropical and arid. The north – which is more densely populated – has a tropical climate, with a wet season (November-April) and a dry season (May-October). During the wet season there are monsoonal rains, causing flooding and limiting road access to certain towns and communities. It is also particularly humid early on in the wet season, before heavy rain begins (sometimes called the 'build up').

The central and southern parts of the Northern Territory are made up of desert and grasslands; an arid climate, with very hot summers and mild or cold winters. While average temperatures are similar across the tropical and arid zones, the range varies, with temperatures reaching 40 degrees Celsius in the height of summer in the tropical zones, compared with up to 45 degrees in the arid zones. These climate zones contrast with the rest of the country, with all other major Australian cities falling into temperate or subtropical climates (Fig. 1).

Around one-quarter of the NT population is Indigenous, the vast majority of whom identify as Aboriginal. There are significant differences between the Aboriginal and non-Aboriginal populations in the NT, in terms of geography, exposure to circulating disease and economic resources. 80% of Aboriginal residents in the NT live outside of Darwin, many in remote Aboriginal communities which experience more extreme weather conditions. In addition, just under half of Aboriginal people in the NT live in housing classified as 'overcrowded' (Australian Bureau of Statistics, 2022), which is associated with greater exposure to infectious disease (Memmott et al., 2022). Median income for Aboriginal

[2] Approximately 43% of the world population lived in tropical areas (State of the Tropics, 2020), and 35% live in deserts and drylands (including hyper-arid, arid, semi-arid and subhumid climates) (United Nations Environment Management Group, 2011, p. 27). However, there is some overlap between these definitions.

[3] Apgar scores were developed by Virginia Apgar, and represent an index combining the birth attendant's observations of: skin colour, heart rate, reflex, muscle tone and respiratory effort. A birth attendance scores each on a scale of 0–2, 5 min after the baby is born.

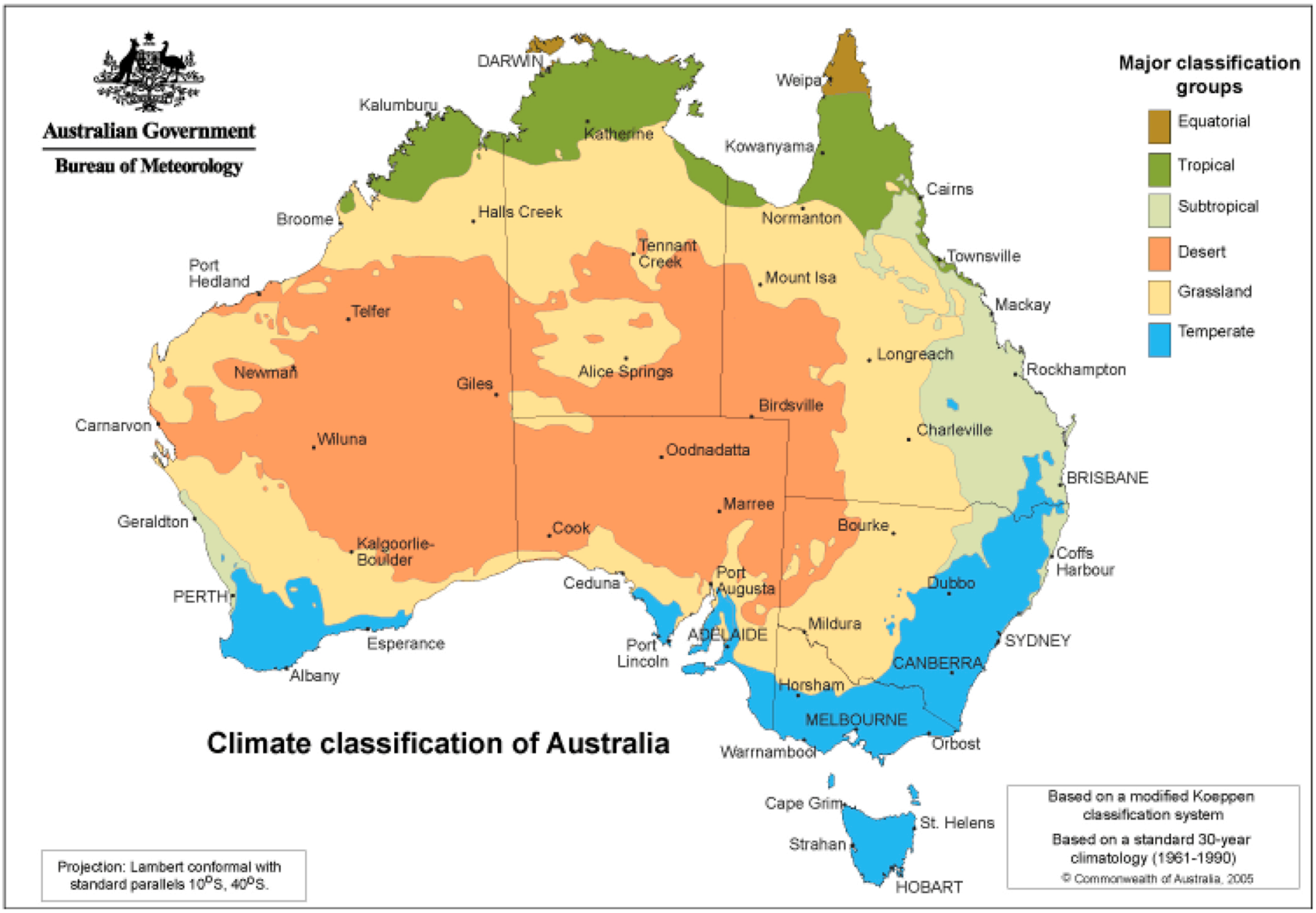


Fig. 1. Map showing seasonal zones of Australia, based on major Köppen seasonal climate zones.
Source: Australian Bureau of Meteorology (http://www.bom.gov.au) product code: IDCJCM0000. Lines on map delineate Australian states and territories. The Northern Territory is in the upper middle with Darwin as its capital.

people is one-quarter of the median for non-Aboriginal NT residents, and around 45% of Aboriginal households fall below the Australian poverty line, compared with 10% of non-Aboriginal NT households (Altman, 2017). This means that Aboriginal people both have fewer financial resources that might allow them to adapt and avoid seasonal risks (such as purchasing air conditioning), and that fluctuations in food prices and employment conditions are more likely to impact their consumption contemporaneously.

2.2. Weather

Exposure to hot weather in the late stages of pregnancy can bring forward labour. For example, in the USA, Barreca and Schaller (2019) find temperatures above 32 degrees Celsius can reduce gestation by up to two weeks. They suggest this occurs because heat increases pregnant women's oxytocin levels and cardiovascular stress, both of which can induce labour.

There is also evidence that heat exposure earlier in pregnancy can worsen newborns' health, though the mechanisms are less well understood. For example, Andalón et al. (2016) find that exposure to high heat any time during pregnancy lowers Apgar scores and gestational age in Colombia; for the USA, Sun et al. (2019) find that higher average temperatures throughout pregnancy increase the risk of babies being small for gestational age (SGA). Grace et al. (2015) find a similar pattern in 19 African countries, with exposure to additional days during pregnancy above 38 degrees Celsius corresponding to lower birthweight, particularly if that exposure was during the second trimester.

Some studies also consider the role of cold weather. They paint a mixed picture. Mathew et al. (2017) find that exposure to temperatures below freezing is associated with higher risk of preterm birth in central Australia. However, in Colombia, Andalón et al. (2016) find a coldwave during pregnancy has a small positive effect on Apgar scores.

Rainfall is often associated with healthier birth outcomes. This relationship is generally found in locations where a large share of the population is reliant on agriculture, since rainfall can contribute to stronger crop growth. For instance, higher rainfall during pregnancy is associated with higher birthweight in Mali and Kenya (Bakhtsiyarava et al., 2018), and with higher birthweight and longer gestation in Brazil (Rocha and Soares, 2015).

However, this impact is likely context specific. In the NT, agriculture makes up a very small share of the economy (2.4% of employment in 2020 (ABS, 2020)), meaning that most households are unlikely to be directly affected by agricultural cycles.

Besides contributing to agricultural cycles, rainfall can cause flooding. In the tropical north of the NT, flooding cuts off road access to some communities, limiting access to healthcare and fresh food during the wet season, sometimes for months at a time.[4] There is no analysis of the effect of flooding and seasonal migration on health outcomes in the NT. A small international literature, summarised by Mallett and Etzel

[4] E.g. see https://securent.nt.gov.au/prepare-for-an-emergency/flooding. Anecdotally, residents avoid exposure to these risks by moving to larger population centres during the wet season. However, I cannot measure this response with my data.

(2018), suggests flooding worsens birth outcomes and points to maternal stress to explain this finding. Chang et al. (2020) find long-term effects from such exposure in Southern India, with children exposed to heavy rainfall shocks in utero having poorer cognitive and non-cognitive skills at ages 5 and 15.

In this study, I include humidity as an additional seasonal risk. In most cases, humidity may not be expected to have any impact independent from rainfall. But in the tropical part of the NT, humidity is not directly linked to rainfall. It increases in the 'build up' to the wet season (September-December), which is a prolonged period with high humidity and temperatures but little or no rainfall. There could be two reasons for humidity to impact outcomes independently of heat and rainfall. First, the body's usual thermoregulation response is less effective in humid conditions (Oppermann et al., 2017), meaning that humidity may accentuate the physiological impacts of heat. Second, the humid 'build up' period is often anecdotally linked with domestic violence (e.g. see Australian Attorney General's Department et al., 2004). Though there is no quantitative evidence on this relationship, it is consistent, for instance, with Brunsdon et al. (2009) finding that in the UK, higher humidity is associated with a higher number of police calls for antisocial behaviour. If humidity does induce higher rates of domestic violence, this is likely to worsen newborn health (e.g. as found by Aizer, 2011 in the USA).

2.3. Disease prevalence

Many infectious diseases circulate seasonally (Grassly and Fraser, 2006), and pregnant women and their babies are at higher risk of complications if they become infected (Kourtis et al., 2014). It is therefore likely that seasonality in disease transmission contributes to seasonality in newborns' health.

Influenza has received more attention than other diseases in explaining seasonality in birth outcomes. For instance, Dorélien (2019) and Schwandt (2019) find that maternal influenza exposure during pregnancy worsens birth outcomes in the USA and Denmark, respectively. Nunes et al.'s (2016) systematic review concludes that providing influenza vaccines to pregnant women lowers rates of preterm birth and low birthweight.

However, influenza is not the only seasonal disease. Using reportable disease data (described below), I identify three additional groups of diseases that are transmitted seasonally in the NT (see Appendix B). They are diarrheal and gastro-intestinal illnesses, mosquito-borne diseases, and sexually transmitted infections (STIs). I group together diseases transmitted in the same way, as they have similar seasonal patterns (i.e. mosquito-borne diseases spreading during the wet season).

These diseases have been associated with worse newborn health. Newman et al. (2019) find that diarrheal illness during pregnancy is associated with higher rates of SGA in Nepal. Mullick et al. (2005) summarise evidence from developing countries on the negative effects of STIs on birth outcomes. Moore et al. (2017) find that mosquito-borne diseases (notably malaria) reduce gestational age and intrauterine growth. Seasonal transmission of these diseases may therefore be expected to contribute to seasonality in birth outcomes.

2.4. Economic conditions

Parents' economic circumstances have important effects on birth outcomes. There is strong evidence that providing parents with additional economic resources during pregnancy can improve newborns' health (e.g. Chorniy et al., 2020 and Amarante et al., 2016), likely because they are able to afford more or more nutritious food, and healthcare (in cases where care is not publicly provided). Given these findings, it is possible that seasonal patterns in parents' incomes and purchasing power may also affect birth outcomes.

In Australia, average food prices fluctuate by between 2% and 3% with the seasons, and are highest in the June quarter. This means that the purchasing power of a constant income is lowest at that time of year.[5] For some households, this could affect the affordability of a sufficient caloric intake. For others, the effects may come through substitution between different foods. For instance Prasad et al. (2010) find that in Finland, pregnant women's vegetable consumption is highest in summer, and lowest in winter. They attribute these patterns to seasonality in prices and availability of fresh food. Watson and McDonald (2007) find similar patterns for pregnant women in New Zealand.

Seasonality in incomes may also affect affordability of nutritious food and healthcare. While there is no research on the effects of seasonal variation in household income on birth outcomes, Kyriopoulos et al. (2019) find evidence of a macroeconomic business cycle effect. They show that in Greece, business cycle fluctuations affect birthweight and gestational age, with effects largest for parents from low socio-economic backgrounds. In the NT, employment levels are highest in the final months of the year (September – December) and lowest in January and February.[6] The magnitude of seasonal fluctuations is modest, but large in comparison with the rest of Australia.

2.5. Fertility and parental characteristics

Parental characteristics are strongly related to birth outcomes, and in some contexts, the socioeconomic characteristics of new parents differ throughout the year. That is, even without seasonal variation in individual parents' characteristics and economic circumstances, we may observe a seasonal pattern in aggregate because of differential fertility patterns between socioeconomic groups. The nature and magnitude of these seasonal patterns varies across countries (Dorélien, 2016), and even within countries such as Australia (Wilson et al., 2020).

Seasonal patterns in parents' characteristics may result from preferences to give birth at a particular time of year, and/or from some socioeconomic groups being better able to realise such preferences. For example, Clarke et al. (2019) find that women in the USA have a preference for giving birth in spring. These preferences are consistent with Currie and Schwandt's (2013) findings of a seasonal pattern in conceptions in the USA. Furthermore, Currie and Schwandt find that white, college-educated and married women – whose babies are generally less likely to be preterm or low birthweight – are more likely to give birth in spring. Their evidence suggests that a large part of the seasonality in birth outcomes in the USA is because of these differences in fertility patterns between socioeconomic groups.

However, this finding is not universal. Torche and Corvalan (2010) find parental characteristics play a more muted role in driving aggregate seasonality in Chile, and Dorélien (2016) finds that while some countries in Sub-Saharan Africa show strong seasonal patterns in conception, others exhibit very limited seasonality. In the NT, there is a seasonal pattern in the characteristics of mothers who conceive at different times of year, but no existing evidence on whether this drives seasonality in birth outcomes; I address this question in the Results section.

[5] Over the 40 year period from 1980 to 2020, the average level of the Consumer Price Index in Darwin (the capital city of the NT) was 1.1% higher in the June quarter than the year-average, roughly in line with patterns in other capital cities in Australia (Sydney: 1.3%, Melbourne, 1.3%, Perth: 1.0%).

[6] Over the 20-year period from 2000–2020, the average employment-to-population ratio in the NT was 70.4 from September to December, and 68.5 from January to February. On average, there are 3000 fewer jobs in the February than in November, out of an average workforce of 117,000. Total hours worked increase by around 5% within a year from trough to peak in the NT, while the equivalent number for Australia overall is 1%.

3. Methods

3.1. Data

I use de-identified administrative birth records for all children born in the NT, who were conceived between 2005 and 2014. These data are available through the Child and Youth Development Research Partnership (CYDRP). For this analysis, I link in:

- Observations of rainfall, humidity, maximum temperature and minimum temperature, from NASA's Power Data Access Viewer. I use daily observations measured at intervals of ½ x ½ degrees of latitude and longitude (roughly 50×55km), giving a total of just over 500 locations throughout the NT.
- Records of the date and location of flooding-related road closures or roads deemed impassable due to flooding[7]. These data were provided by the Northern Territory Department of Infrastructure, Planning and Logistics and are available from 2005 onwards. I construct a variable with the number of road closures in each month, by region[8].
- Region-specific disease prevalence, extracted from the Northern Territory Government's quarterly *Disease Control Bulletins*. These Bulletins report the number of confirmed cases of a range of reportable diseases, including influenza, mosquito-borne diseases, gastrointestinal-related diseases, and STIs. I converted case numbers to rates per 1000 residents, using population estimates from the Australian Bureau of Statistics.
- Quarterly consumer price indices for Darwin (the capital city of the NT), and monthly employment-to-population ratio data for the NT, both from the Australian Bureau of Statistics.

My analysis sample is limited to babies born in the NT, who were conceived from 2005 to 2014, to mothers whose usual place of residence was in the NT, and whose place of residence could be geo-coded.[9] This gives a sample of 35,199 observations, out of a total population of 38,866 babies born in the NT over this period. I include stillbirths (making up under 1% of births) and plural births (under 2.5% of births) in the analysis sample.

3.2. Measures

Table 1 shows the mean, standard deviation, minimum and maximum values of all variables that I use in analysis.

3.2.1. Outcomes

Most research on seasonality of infant health focuses on birthweight (Bakhtsiyarava et al., 2018; Deschênes et al., 2009; Grace et al., 2015), gestational age (Barreca and Schaller, 2019; Mathew et al., 2017; Strand et al., 2012), or both (Dorélien, 2019; Moore et al., 2017; K. L. Newman et al., 2019; Nunes et al., 2016; Rocha and Soares, 2015; Schwandt, 2019). Both birthweight and gestational age are commonly measured either in levels (i.e. grams or weeks), or converted to binary variables representing low birthweight (<2500 g), preterm birth (<37 weeks), or small for gestational age (SGA, below 10th birthweight percentile, given gestational age and sex). The reason for converting them to binary variables is that while weight and gestational age may fluctuate within healthy ranges, low levels are particularly concerning.

The advantage of these outcomes is that they are routinely collected and are therefore widely available for research. However, recent research has criticised the focus on birthweight, gestational age, and derived variables as primary measures of health at birth. Conti et al. (2020) show that birthweight provides only a limited picture of infant health. They show that other measures, including Apgar scores, perform better in predicting postnatal outcomes. Recent evidence confirms that seasonal risks can affect fetal development in ways that are not evident from the baby's weight and gestational age. For example, Schwandt (2019) finds that babies exposed to influenza in the second trimester did not have significantly higher rates of preterm birth or low birthweight, but they had significantly lower education attainment and adult wages.

In this paper, I consider 5 min Apgar scores (Apgar 5) in addition to

Table 1
Summary statistics for births in the Northern Territory, 2005–2014.

	Mean	SD	Minimum	Maximum
Outcomes				
Birthweight (g)[a]	3289.13	534.39	2160.00	4180.00
Preterm birth (probability)	0.10	0.31	0.00	1.00
SGA (probability)	0.13	0.34	0.00	1.00
Apgar 5 score	8.88	1.21	0.00	10.00
Other characteristics of births				
Born in hospital (probability)	0.99	0.09	0.00	1.00
Aboriginal or Torres Strait Islander mother (probability)	0.36	0.48	0.00	1.00
Number of antenatal visits	9.00	4.00	0.00	38.00
Urban area (probability)	0.65	0.48	0.00	1.00
Arid (vs tropical) climate (probability)	0.20	0.40	0.00	1.00
Weather in 39 weeks to birth				
Average maximum temperature (C)	30.94	1.74	24.26	36.93
Avg days with max> 35 C	38.16	44.46	0.00	190.00
Average minimum temperature (C)	22.44	4.19	10.56	28.03
Avg days with min< 0 C	0.12	10.55	0.00	5.00
Average daily rainfall (ml)	4.07	2.41	0.00	10.52
Avg days with> 50 ml	1.96	2.19	0.00	8.00
Avg relative humidity (%)	61.14	14.39	21.33	80.01
Avg days with relative humidity> 85%	25.09	24.06	0.00	140.00
Avg regional road closures in pregnancy, per month	6.72	3.89	0.00	24.44
Disease lab cases per 1000 residents				
Influenza	0.6	0.87	0.00	5.03
Sexually transmitted infections (STIs)[b]	7.39	5.17	2.39	19.86
Mosquito-borne diseases[c]	0.54	0.25	0.00	1.69
Gastro-intestinal related diseases[d]	1.35	0.55	0.56	3.24
Economic conditions				
Food price growth in year to birth (%)	2.19	2.22	-2.94	7.14
Average employment-to-population ratio during pregnancy (%)	69.75	1.97	64.30	72.50

Sources: Author's calculations based on Australian Bureau of Statistics; NASA; NT Centre For Disease Control Bulletins; NT Department of Infrastructure, Planning and Logistics; CYDRP.

[a] Variable is top- and bottom-coded at the 2.5th an 97.5th percentile to reduce the influence of extreme outliers.

[b] Includes: Chlamydia, gonococcal, trichomoniasis and syphilis.

[c] Includes: Malaria, Dengue, Kunjin virus, Chikungunya, Zika, Murray Valley encephalitis, Barmah Forest virus, Ross River Virus, Chikungunya and arbovirus – not elsewhere specified.

[d] Includes: Rotavirus, Salmonella, Shigellosis, Campylobacteriosis and Cryptosporidiosis.

[7] The NT Department of Infrastructure, Planning and Logistics lists a road as impassable if it frequently floods in the wet season, but staff are unable to reach the location to verify whether it is flooded. I refer to both flooded and impassable roads as 'road closures' in the remainder of this paper. Roads closed for reasons unrelated to flooding are not included in my measure.

[8] Regions are: Darwin and surrounds, East Arnhem, Barkly, Katherine, and Alice Springs and surrounds. These are the same regions for which the disease prevalence data are available.

[9] There are a small number of births for which the mother's place of residence as entered in the perinatal data could not be found, either using a fuzzy match with the R package 'geonames', or through manual search on Google, the NT Place Names Register (https://www.ntlis.nt.gov.au/placenames/) and BushTel (https://bushtel.nt.gov.au/).

the measures more commonly used in previous research: birthweight (in grams), preterm birth and SGA.[10] In Appendix C, I show that findings are similar for other commonly-used transformations of these variables (probability of low birthweight, gestational age in weeks, and low Apgar scores).

Apgar 5 is an index with values from 0 to 10, based on the birth attendant's judgement of the newborn's skin colour, heart rate, reflex, muscle tone and respiratory effort, 5 min after birth. Only one of the papers cited above (Andalón et al., 2016) uses Apgar scores as an outcome measure. However, they are commonly used in the medical literature, and lower scores are strongly associated with poor neonatal outcomes (Thavarajah et al., 2018), even among full-term pregnancies that are otherwise judged to be low-risk (H.-Y. Chen et al., 2020).[11]

3.2.2. Seasonal risk factors

I draw on the evidence discussed in Section 2 to construct measures of exposure to seasonal risks in utero. They are minimum and maximum temperature, rainfall, humidity, disease prevalence, road closures due to flooding, food price growth and the employment-to-population ratio. I standardise these variables to have a mean of zero and standard deviation of one when used in regression analysis, in order to compare the relative strengths of these competing explanations for seasonality in birth outcomes.

I focus primarily on exposure to seasonal risks throughout the full pregnancy. Therefore, I construct measures of average conditions that each mother was exposed to in the 39 weeks to birth (for weather variables), nine months to birth (for road closures and employment variables), or in the three calendar quarters after conception (for regional disease prevalence). Food price growth is measured as year-ended growth in the quarter of birth.

Some effects, and in particular temperature exposure, may be nonlinear and may depend on the timing of exposure. Therefore, I also construct measures of exposure to very hot and very cold temperatures by trimester, and for road closures and employment rates by trimester. While timing of exposure can be important for disease prevalence as well (Schwandt, 2019), analysis is not possible with my data, as disease prevalence is available only at a quarterly frequency.

This paper seeks to explain seasonality based on the baby's date of birth. Some researchers instead analyse seasonality by date of conception (Currie and Schwandt, 2013). I define the start and end date of the sample based on date of conception, to avoid methodological issues with definitions based on date of birth (Strand et al., 2011a), but in my regression analysis I use month of birth. Before undertaking this analysis, I compared seasonal patterns when measured based on month of conception and month of birth. I found that seasonality is slightly larger when measured based on month of birth (see Appendix D). Therefore, my analysis seeks to explain these patterns, and all descriptive statistics below are shown based on month of birth. As date of birth is directly observed and date of conception is estimated, this approach also reduces the scope for measurement error. In my regression analysis the distinction makes little difference, because I measure total exposure to seasonal risks throughout the pregnancy.

3.3. Analytical methods

The goal of this paper is to analyse the relationships between seasonal risk factors and newborns' health. To do this, I use ordinary least squares to estimate the following full model, which is based on the associations I described in the Conceptual Framework, adapted for data availability and specificity.

$$outcome_{itrj} = b_0 + b_1 \boldsymbol{W}_{tj} + b_2 R_{tr} + b_3 \boldsymbol{D}_{tr} + b_4 P_t + b_5 E_t + \gamma_m + \delta_y + \theta_j + \epsilon_i \quad (1)$$

In this model, I estimate birth outcomes for baby i, born on date t (year y, month m), and in town/city/community j, within the broader region r. I distinguish between small-area location j and region r because some explanatory variables are only measured at the region level. Birth outcomes are estimated as a function of weather variables W, road closures R, disease prevalence D, food price growth P and the employment-to-population ratio E. These variables are measured based on exposure averaged over the full pregnancy, though the underlying data vary in their frequency (as described in Section 3.2.2). I calculate confidence intervals using standard errors clustered at the level of the fixed effects (i.e either location-level, or sibling-level).[12]

The model includes fixed effects by location j, and the month m and year y of birth. Location fixed effects are based on geographic clusters, which have a maximum distance of 50 miles between any two points. There are 96 clusters in the sample; these are not necessarily nested within the larger regions at which the disease prevalence and road closure measures vary. I derive clusters using the mother's community, town or suburb of residence at the time of birth. In the NT, there are many communities with multiple names or 'aliases', and larger towns surrounded by suburbs and town camps. I first geocode each location to find the latitude and longitude coordinates for the centre of the community, town or suburb. I then use cluster analysis to convert these coordinates into geographic groupings based on distance between points, so that I group together all suburbs within the same city or town, and all 'aliases' for the same community.[13] Given the dispersed population of the NT, these clusters are small, with on average 360 births per cluster over the 10-year period.

Time fixed effects control for month and year of birth. I choose to include month and year separately in my main model estimates because my measures of economic conditions do not vary within a given month-year pair, and therefore could not be estimated using month-year fixed effects. However, my findings for the remaining seasonal risks are robust to inclusion of month-year fixed effects (see Appendix F).

The location and time fixed effects reflect my conceptualisation of seasonal risks as being relative to the average values across individuals within a specific location, year and month. This allows for the fact that residents adapt to typical conditions in their location and anticipate and adapt to regular seasonal variation. Importantly, this means that the seasonal effects in my analysis are identified by idiosyncratic variation, not from typical seasonal patterns. That is, for example, that my estimated impact of higher temperatures is identified from cases where temperatures were warmer than usual, given the location and time of year. This is the most common approach in the literature, with many studies using location and time fixed effects to identify the causal impact

[10] As defined by Dobbins et al. (2012)'s national birthweight percentile tables for Australia.

[11] A common distinction is between Apgar scores of 7–10 which are considered in the 'healthy' range, and scores of 6 or below. But a large population-linkage study from Sweden suggests that even newborns at the lower end of the 'healthy' range face higher health risks (Razaz et al., 2019). Therefore, I analyse Apgar scores in levels. Appendix C shows estimates for a binary measure of Apgar score.

[12] The reason for this is that location is not constant within all sibling groups (a small number of mothers move between cities/towns/communities), and therefore I cannot cluster standard errors in the sibling fixed effects model by location.

[13] The data I have on location is a text string with the suburb or community name, provide by the mother to the hospital at the time of birth. This may be the name of the community, town or city (e.g. Darwin) or the name of a suburb (e.g. within greater Darwin). By using geographic clusters, I group together points that are geographically close, to define a single fixed effect for each city, town or community. I chose a 50 mile distance as this would allow one cluster to cover all of greater Darwin (the capital city). However, my estimates are little changed if I instead define fixed effects using shorter distances such as 10 miles or 25 miles – see Appendix E.

of in utero exposure to weather conditions or disease prevalence (Andalón et al., 2016; Bakhtsiyarava et al., 2018; Barreca and Schaller, 2019; X. Chen et al., 2020; Dorélien, 2019; Grace et al., 2015; Hu and Li, 2019; Kim et al., 2021; Li et al., 2018; Maccini and Yang, 2009; Mrejen et al., 2020; Rocha and Soares, 2015; Schifano et al., 2016; Wilde et al., 2017). In Section 6, I discuss the implications of this modelling approach, and the assumptions required to interpret my estimates as evidence of the impacts of seasonal risks.

The model allows me to estimate the effects of a broad range of environmental factors on birth outcomes, holding other factors constant. However, as described above, parental characteristics may contribute both to the timing of conception (and therefore seasonal risk factors that the fetus is exposed to) and birth outcomes. I do not observe parental characteristics in the data, but I can link siblings together. This allows me to hold constant any time-invariant shared family background, so that I can analyse how important these unobserved characteristics are in explaining seasonality. Analysis of siblings is based on smaller sample size, with approximately 50% of the children in the sample having a sibling born during the 2005–2014 period. Therefore I present results with two versions of the model: one using the full sample without sibling fixed effects, and one with the addition of sibling fixed effects for this subsample.

4. Descriptive statistics

In the NT, babies born during the winter/dry season are healthier on average. They have higher average birthweight, higher Apgar 5 scores, and are less likely to be preterm (Fig. 2). In contrast, babies born in the wet season/summer – particularly in the middle of the wet season (January and February) – have lower average birthweight and Apgar 5 scores, and are more likely to be SGA or preterm. While birthweight and Apgar 5 are shown here as averages, their seasonal patterns are accentuated at the lower end of the distribution (see Appendix G).

We can compare the magnitudes with other studies based on birthweight, as this is the most commonly used outcome. Compared with other contexts, seasonality in the NT is large. In the NT, there is a standard deviation of 14 g in birthweight across the month averages. This is large relative to other influences on birthweight: for instance, the variation in birthweight based on month of birth in the NT is slightly larger than the impact that Reader (2023) finds of a modest cash transfer during pregnancy in the UK (of 8–12 g). The difference between birthweight in its lowest average month (January) and its highest average month (October) is around 55 g. This is twice as large as the difference that Currie and Schwandt (2013) find in the north-eastern USA (25 g), and more than 5 times as large as what Torche and Corvalan (2010) find in Chile (9 g). These seasonal patterns are also much larger than those in other parts of Australia. McGrath, Barnett and Eyles (2005) analyse seasonality in birthweight in the eastern states of Australia, finding small seasonal differences, ranging from 1.4 g (in Tasmania)to 7.7 g (in Queensland).[14]

Interestingly, seasonal patterns vary across the four birth outcomes. Seasonal variation is larger in magnitude for birthweight and preterm birth than for the other outcomes. The timing also differs across outcomes. Birthweight and preterm birth show more favourable outcomes first in April/May and again in October. In contrast, April is the month with the least favourable outcomes for SGA, while Apgar scores are highest in June and November. The different timing of these patterns suggests that not all birth outcomes are influenced by the same seasonal risks.

The pattern across the NT also obscures variation across climate zones and between urban and rural locations. There is more seasonal variation in arid ('desert') regions in the central and southern part of the NT, and in rural areas, than in tropical and urban areas. The timing is also different, with gestational age and birthweight peaking in May in tropical areas, and in October in arid regions, generating the two peaks seen in Fig. 2A and D (see Appendix H). I discuss these differences further in Section 5.3.

[14] Some of these studies consider only term births, with gestational age of 37 weeks and above. In the NT data, the 50-gram difference from highest average to lowest-average month remains, even if we also limit analysis to babies born from the 37th week onwards (see Appendix G).

5. Results

5.1. Which seasonal risks are associated with birth outcomes?

Almost all seasonal risks are associated with birth outcomes to a meaningful degree before adjusting for time and location fixed effects (Appendix I). It is unlikely that these associations represent causal effects. Instead, they may reflect variation between locations in exposure to seasonal risks, and the fact that many seasonal risks are correlated with each other in time – highlighting the importance of an analytical approach that disentangles these effects. The remainder of this section does so by individually and jointly analysing all seasonal risk factors, while controlling for time and location fixed effects.

5.2. Regression analysis

Fig. 3 summarises the primary estimates with 95% confidence intervals (see Appendix J for regression tables). The higher points indicate the coefficients on each seasonal risk, in a regression that includes fixed effects but does not control for other seasonal risk factors. The middle points show the coefficient when all seasonal risk factors are included in a single regression model (as specified in Eq. (1)). The lower points show the sibling fixed effects model. With some exceptions (discussed below), the estimates are similar in all three models, though confidence intervals are wider in the sibling fixed effects model, possibly reflecting the smaller sample size. Given the large number of effects estimated, in Appendix K I show a table of the benchmark model estimates, adjusted for multiple hypothesis testing using Anderson's (2008) Sharpened Q values. This adjustment does not affect my conclusions, but I note below where estimated effects are no longer statistically significant after this adjustment.

5.2.1. Relative humidity

We see no clear relationship between average humidity and birth outcomes in Fig. 3. One channel through which I proposed that humidity would affect birth outcomes in the NT was domestic violence – with the potential for high humidity to increase interpersonal violence (see Section 2.2). To analyse this mechanism further, I examined whether there is a seasonal pattern in domestic violence using child protection notifications.[15] However, I do not find evidence of seasonality in the number of incidences (see Appendix L).

5.2.2. Rainfall and road closure

There is no apparent relationship between average rainfall and birth outcomes. All coefficients are close to zero and not statistically significant. This is unsurprising given that the studies that have found a relationship between rainfall and birth outcomes have been from locations where a large share of households rely on agriculture (Bakhtsiyarava et al., 2018; Rocha and Soares, 2015), and this is not the case in the NT.

However, I do find some evidence that extreme values of rainfall – and resultant road flooding – can worsen birth outcomes. For the estimates shown in Fig. 3, the coefficients on road closures are small and not statistically significant. However, my measure of road closures is a

[15] In the NT, it is mandatory for certain professionals to report suspected child abuse and neglect, and this includes physical violence and exposure to family violence.

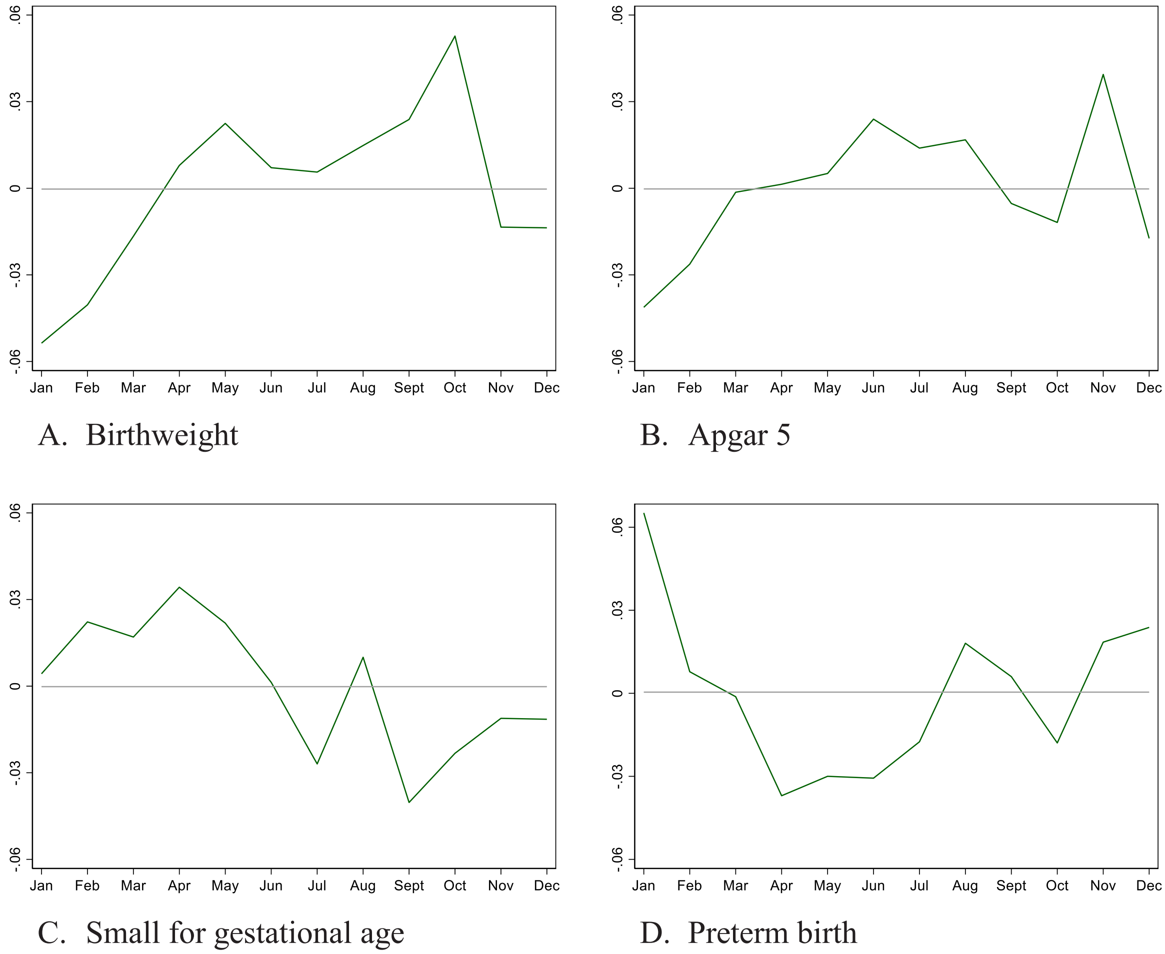


Fig. 2. Seasonal variations in birth outcomes, by month of birth, 2005–2014. Horizontal line represents the year-average for each outcome (standardised to zero). Vertical axis shows the number of standard deviations from the variable's average, to allow comparison in magnitudes across the four outcomes. Appendix D shows these same graphs in levels of the variable, and Appendix G shows these patterns with 95% confidence bands.

simple count of the number of road closures within the region. It does not identify individuals who were affected by each closure, the length of the closure, or the importance of the road. When I restrict analysis to Aboriginal mothers, who are more likely to live in the remote communities that are most inconvenienced by road closures, the coefficient on birthweight is negative and statistically significant at the 5% level (see Section 5.3.1). In addition, in the benchmark model with the full sample, when I run the model splitting exposure into the first two trimesters and the third trimester, more road closures in the first two trimesters are associated with statistically significantly lower birthweight and lower Apgar scores (see Appendix M).[16] Therefore, I interpret the small negative coefficients as suggestive evidence of an effect on the subset of pregnancies for which road closures affect access to healthcare and fresh food. However, my measure of closures is at the region level. In a month with a high number of closures, some communities will be severely affected, while most mothers within the region will be unaffected. Further research using a community-level measure of road closures would be needed both to verify this finding, and if it is verified, to quantify its magnitude more precisely.

5.2.3. Temperature

There are different effects of temperature across the four birth outcomes. I find that higher average minimum temperatures are associated with higher Apgar scores, but also with higher risk of SGA, preterm birth, and lower birthweight (Fig. 3). Higher average maximum temperatures are also associated with higher risk of SGA but have no statistically significant effect on the other outcomes. These effects remain statistically significant at the 5% or 10% level, after adjusting for multiple hypothesis testing (see Appendix K).

These somewhat conflicting findings may reflect the shortcomings of a linear analysis of temperatures based on averages over a 39-week period. Higher minimum temperatures in the dry season/winter mean absence of very cold weather in some parts of the NT, while high minimum temperatures in the wet season/summer can reflect a heatwave. We may therefore expect non-linear effects. In addition, it is possible that exposure at different times during pregnancy, or exposure to extreme cold or heat may be more important than average exposure throughout the whole pregnancy.

I therefore construct measures of exposure to very high and very low temperatures. These are counts of the number of days during pregnancy with maximum temperatures above 35 degrees Celsius, and with minimum temperatures below freezing (see Table 1 for summary statistics of these measures). I disaggregate these by trimester.

Fig. 4 reports estimates from regressions including those measures. It shows that additional days above 35 degrees during pregnancy – in any trimester – reduce birthweight and Apgar scores and increases risk of preterm birth. Exposure to additional days below freezing, in contrast,

[16] It may be that women expecting to give birth in a community prone to flooding during the wet season leave the community before floods begin, leading to little effect in the third trimester. In addition, pregnant women in remote communities are routinely transferred to their closest hospital at 37 weeks.

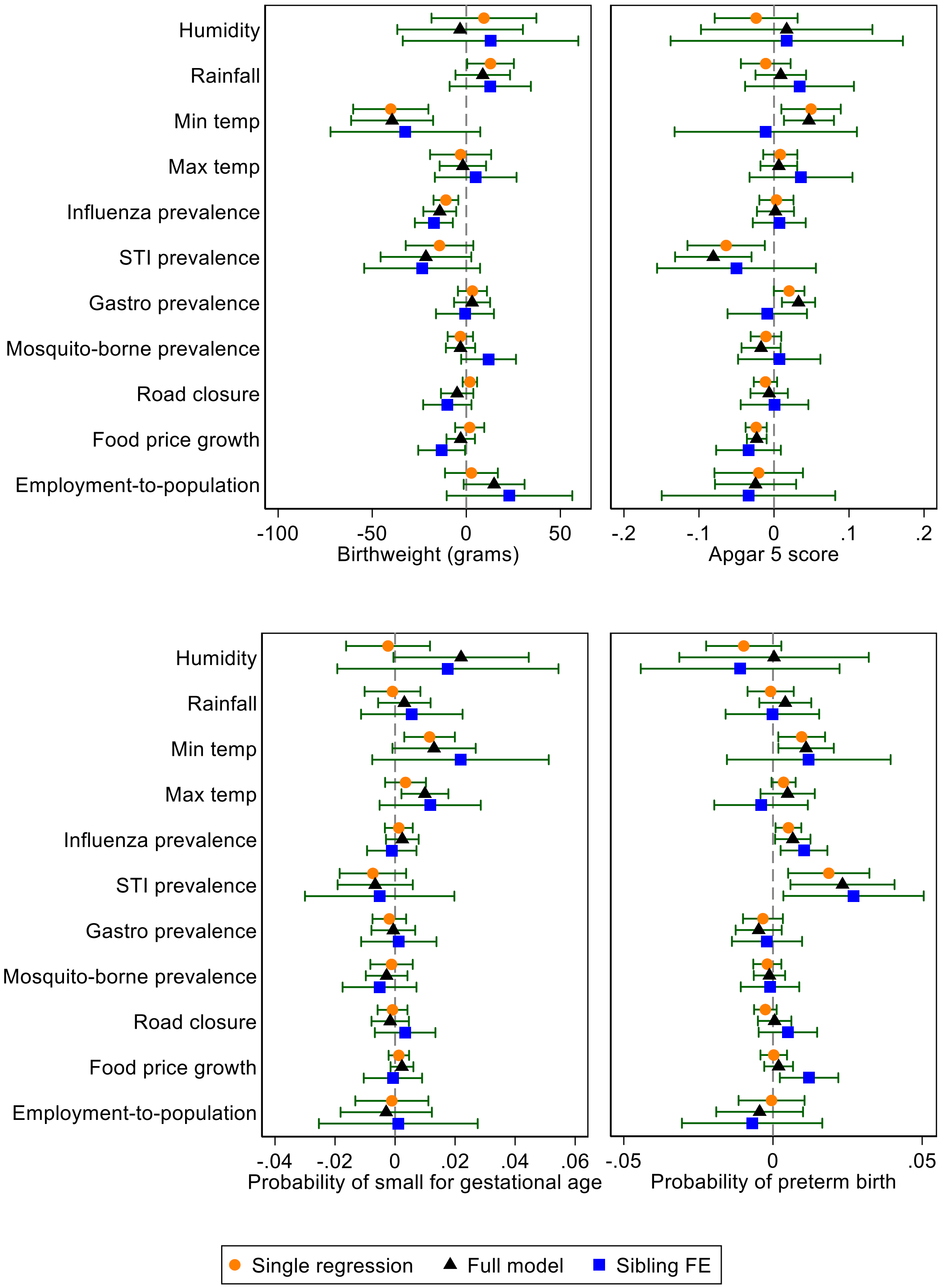


Fig. 3. Main regression coefficients with 95% confidence intervals. All explanatory variables are standardised to have a mean of zero and standard deviation of 1. The higher points (circles) represent estimates from a regression with fixed effects but without controlling for other seasonal factors (so that each point is an estimate from a different regression). The middle points (triangles) represent the coefficients from the full model, controlling for all other seasonal factors. The lower (squares) points represent coefficients from the full model with sibling fixed effects, in the subpopulation for whom a sibling is present in the data. Sample size 35,199 for full model, and 18,359 for sibling fixed effects model.

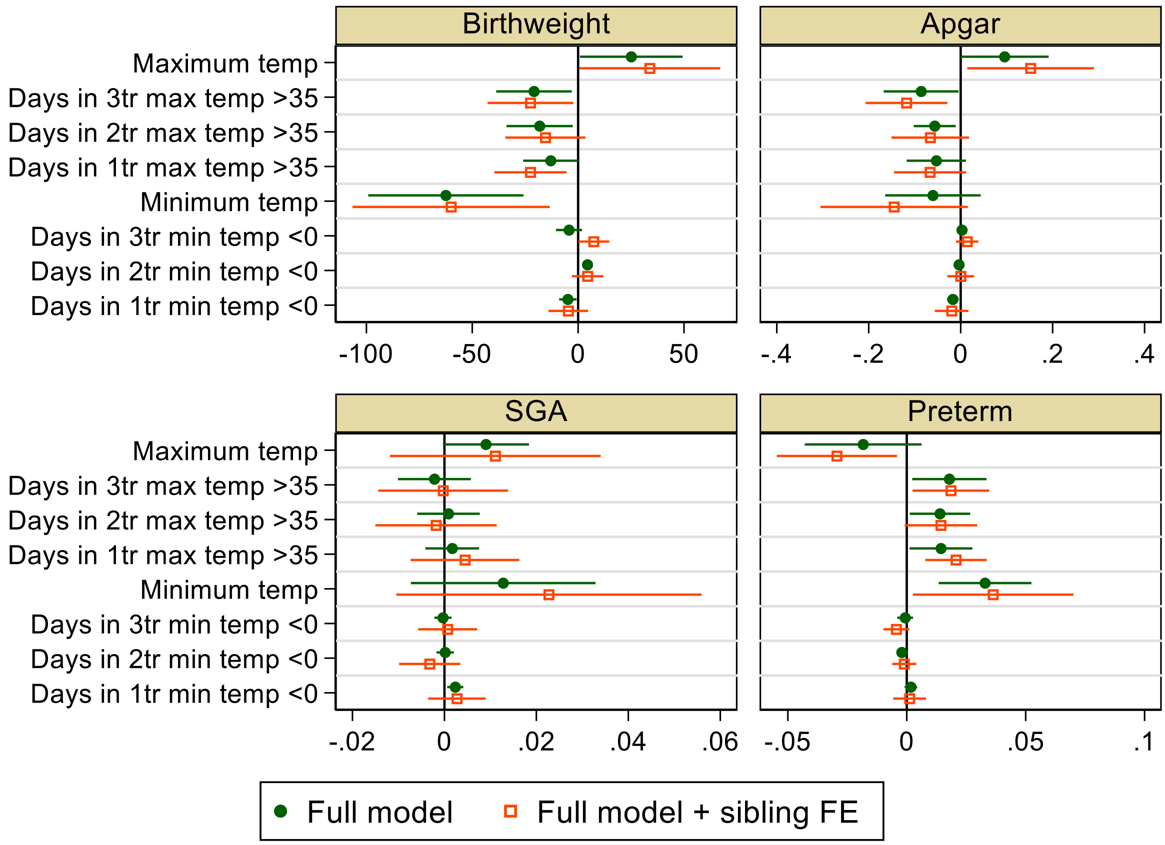


Fig. 4. Regression estimates controlling for extreme weather conditions, by trimester. These reflect coefficients from a single regression using the full sample, with all variables included – including other variables from the full model specified in Eq. (1) (circles), and from the sibling fixed effects model, using the smaller sample (squares). Sample size 35,199 for full model, and 18,359 for sibling fixed effects model.

has relatively small effects, but helps to clarify the independent effect of average minimum temperature. After controlling for exposure to very warm and very cold days, a higher average minimum temperature is associated with poorer birth outcomes, consistent with this variable indicating heatwaves. In addition, higher average maximum temperature is more consistently associated with healthier birth outcomes. This suggests that in the absence of heatwaves, warmer weather may improve birth outcomes.

5.2.4. *Disease prevalence*

Fig. 3 reveals a large and statistically significant relationship between prevalence of STIs during pregnancy and birth outcomes. One standard deviation increase in STI prevalence is associated with a 0.08 point decrease in Apgar 5 scores and a 2.4 percentage point increase in preterm births, statistically significant 10% and 5% levels respectively, after adjusting for multiple hypotheses. The confidence intervals around these estimates are wider in the sibling fixed effects model and are therefore not statistically significant at the 5% level, but the estimates themselves are similar for birthweight and preterm birth (though smaller for Apgar scores).

To analyse this relationship in more detail, I rerun the model separately for mothers who did not regularly attend antenatal care visits during pregnancy, because antenatal care appointments provide opportunities for testing and treatment of STIs.[17] I find a substantially larger association in this sub-sample (Appendix N). This relationship is suggestive of the role of antenatal testing and treatment of STIs in attenuating seasonality. However, it could also be that fewer antenatal visits reflects access to care more generally or the mother's socio-economic status (Australian Institute of Health and Welfare, 2020), both of which could be associated with greater exposure to STIs relative to the region-level case rate that is captured by the prevalence measure I use.

Influenza prevalence significantly increases the risk of preterm birth and lowers birthweight, consistent with findings from other contexts. After adjusting for multiple hypotheses, the relationship with birthweight is statistically significant at the 5% level, though the relationship with preterm birth is not statistically significant.

The coefficients on prevalence of mosquito-borne diseases are small and not statistically significant.

Surprisingly, Fig. 3 shows that prevalence of gastrointestinal-related diseases is associated with significantly higher Apgar scores after controlling for other factors. One potential reason for this could be that disease exposure may lead to fetal loss, such that only the fetuses that were already healthier survive (and appear in the birth records). There are no data on miscarriages, but birth records contain information on stillbirths – defined in the NT as fetal losses after 20 weeks of gestation. I find no statistically significant association between prevalence of gastrointestinal disease and live birth status (Appendix O), but it remains possible that fetal loss before 20 weeks may explain the positive relationship between gastrointestinal disease and Apgar scores.

5.2.5. *Economic conditions*

As may be expected, I find some evidence that higher price inflation is associated with worse birth outcomes and higher employment rates associated with better birth outcomes. In the sibling fixed effects model, the effects are large, with a standard deviation increase in food price growth associated with a 13 g decrease in birthweight and a 1

[17] Pregnant women in the NT are recommended to have 10 antenatal visits, and on average have 9 visits (see Table 1). In this analysis, I limit the sample to those who had 5 or fewer visits.

percentage point increase in preterm births. The fact that the effect is larger in this model may indicate that it is certain families (e.g. those with lower incomes) whose birth outcomes are most affected by seasonality in food affordability. For those household, seasonality in food affordability may impact intrauterine growth and general infant health.

However, while the coefficients move in the expected direction, they are small and not statistically significant within most models. Therefore, while other research tells us that income and food affordability are important for infant health (see Section 2.4 above), seasonal variation in aggregate economic conditions does not appear to be a major explanation for the seasonality we observe in population-average birth outcomes.

5.3. Heterogeneity of effects

5.3.1. By Aboriginal status

During the sample period, just over one-third of births in the NT were to Aboriginal mothers. On average, Aboriginal women face different environments from non-Aboriginal women during pregnancy – 72% of Aboriginal mothers lived outside of the two main cities (Darwin and Alice Springs), compared with just 14% of non-Aboriginal mothers. Many live in remote Aboriginal communities, where residents are likely to face challenges in accessing healthcare and fresh food, particularly during the wet season, as described in Section 2.2 above. In addition, Aboriginal people are disproportionately affected by other disadvantages that may influence maternal and infant health, including

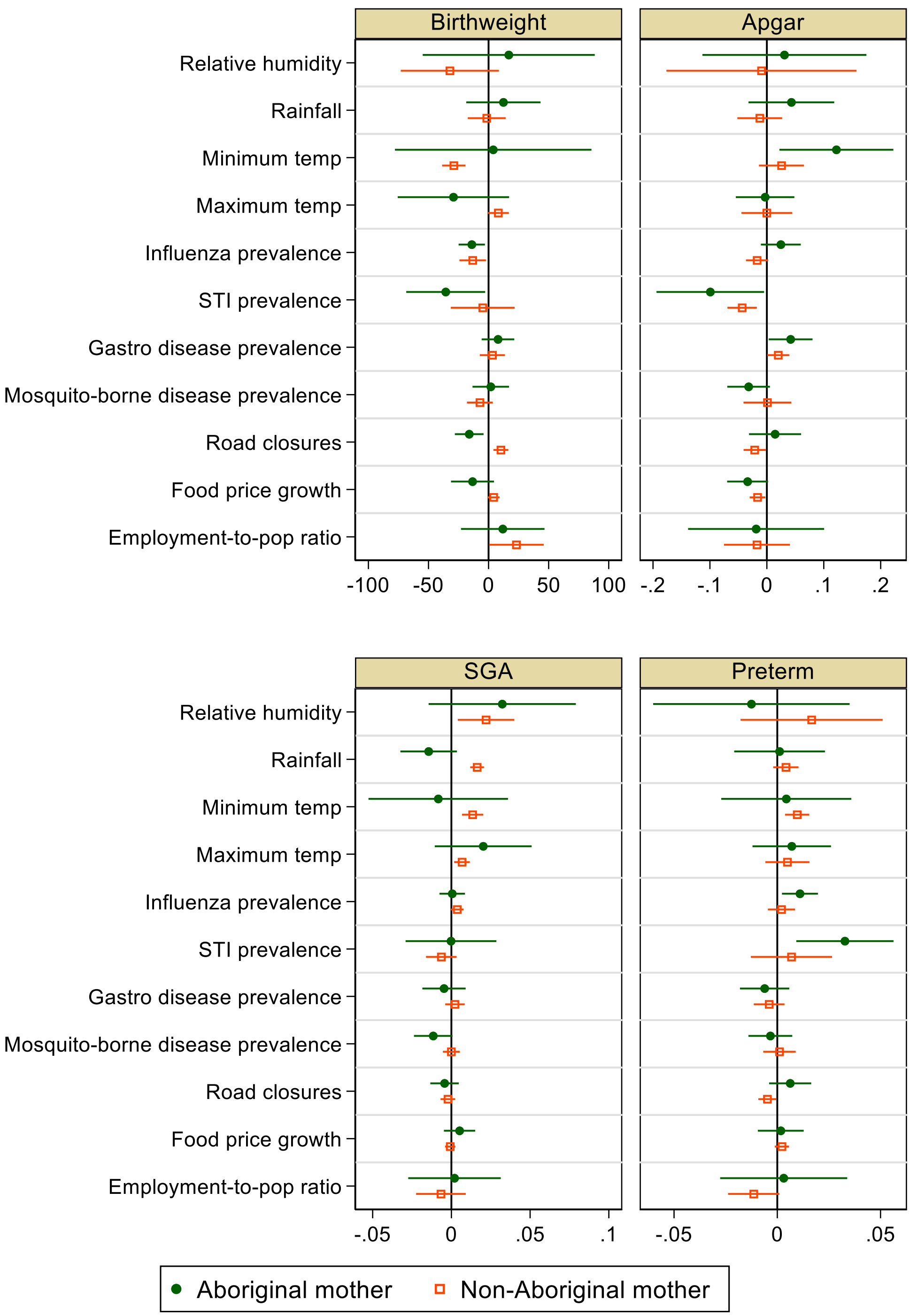
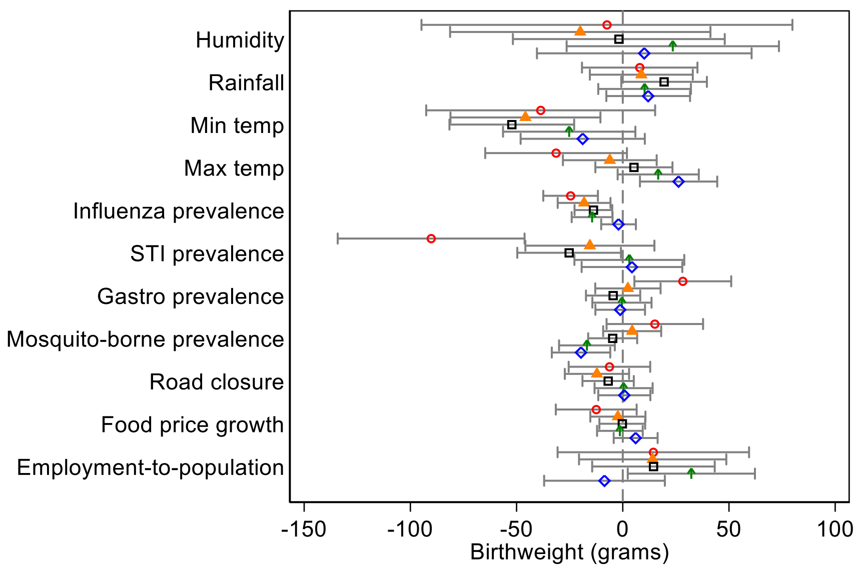


Fig. 5. Model estimates by Aboriginal status of mother. Estimates for mothers identified as Aboriginal or Torres Strait Islander are the higher, circular points (35% of all births) and estimates for all other mothers are the lower, square points (65% of all births). Estimates are for the full model including all seasonal risks in a single regression, but not including sibling fixed effects. All explanatory variables are standardised to have a mean of zero and standard deviation of 1. Note that 99% of people in the NT who identify as Aboriginal or Torres Strait Islander identify as solely Aboriginal or as both Aboriginal and Torres Strait Islander, hence the discussion centres around Aboriginal status. Sample sizes: 12,523 (Aboriginal) and 22,607 (non-Aboriginal).

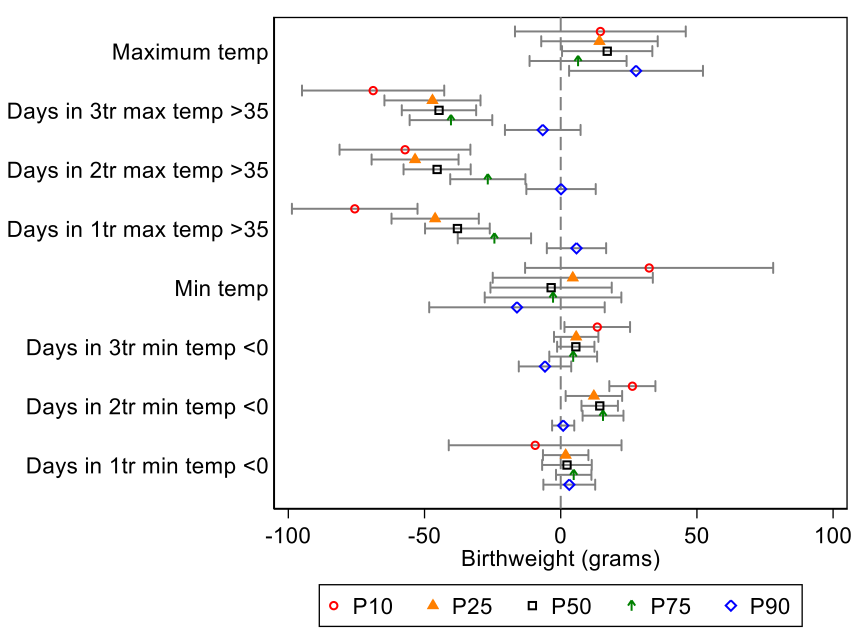
substantially lower-than-average economic resources, more crowded living conditions, and poorer health (Australian Bureau of Statistics, 2017). To test how these differences impact my estimates, I rerun the full model, for Aboriginal and non-Aboriginal mothers separately (Fig. 5).

Some findings stand out – for instance, there is a negative effect of road closures on birthweight for Aboriginal mothers, but not for the rest of the sample. This makes sense given that Aboriginal people are more likely to live in remote communities with just one major road in and out of the community, and therefore are more severely affected when roads are inaccessible. The point estimates on STI prevalence are also larger for Aboriginal mothers, potentially reflecting higher STI prevalence in Aboriginal communities (Gooley, 2021). However, in most cases, these estimates are consistent with the results from the aggregated sample – that is, showing that exposure to STIs and flu, and less favourable economic conditions worsen birth outcomes for Aboriginal and non-Aboriginal mothers alike.

The confidence intervals around the estimates in the Aboriginal subsample are larger. This is likely to reflect both the smaller sample, and diversity among Aboriginal peoples; Aboriginal communities are located throughout the NT, meaning there is greater diversity among Aboriginal mothers in their exposure to climactic and environmental conditions, and in access to healthcare. In contrast, most non-Aboriginal mothers live in Darwin, the capital city of the Northern Territory.



A. Main model



B. Extreme temperature exposure by trimester

Fig. 6. Quantile regressions of birthweight. These figures show the full model as in Figs. 3 and 4, with all variables included, but without sibling fixed effects. These are estimated using quantile regressions for the 10th, 25th, 50th, 75th and 90th percentiles of the birthweight distribution, with robust standard errors. Sample size: 35,199.

5.3.2. By health status

Fig. 6 shows quantile regression estimates for birthweight. They are based on the same specification as Eq. (1) but instead of estimating the effect on mean birthweight, they are estimated for babies at the 10th, 25th, 50th, 75th and 90th percentiles of the birthweight distribution.

These estimates suggest that seasonal risk factors may have small or no effects on babies that are otherwise healthy, but may interact with other health complications, for babies who may have had low birthweight even in the absence of seasonal risks. The effects of STI prevalence are especially large for babies at the 10th percentile of birthweight and are smaller or not statistically significant for heavier babies. While heat and influenza prevalence have effects throughout most of the distribution, the effects are largest for babies at lower percentiles.

5.3.3. By urban/rural location

Birth outcomes are more seasonal in rural areas than urban areas (Appendix H). There could be two potential explanations for this. One is

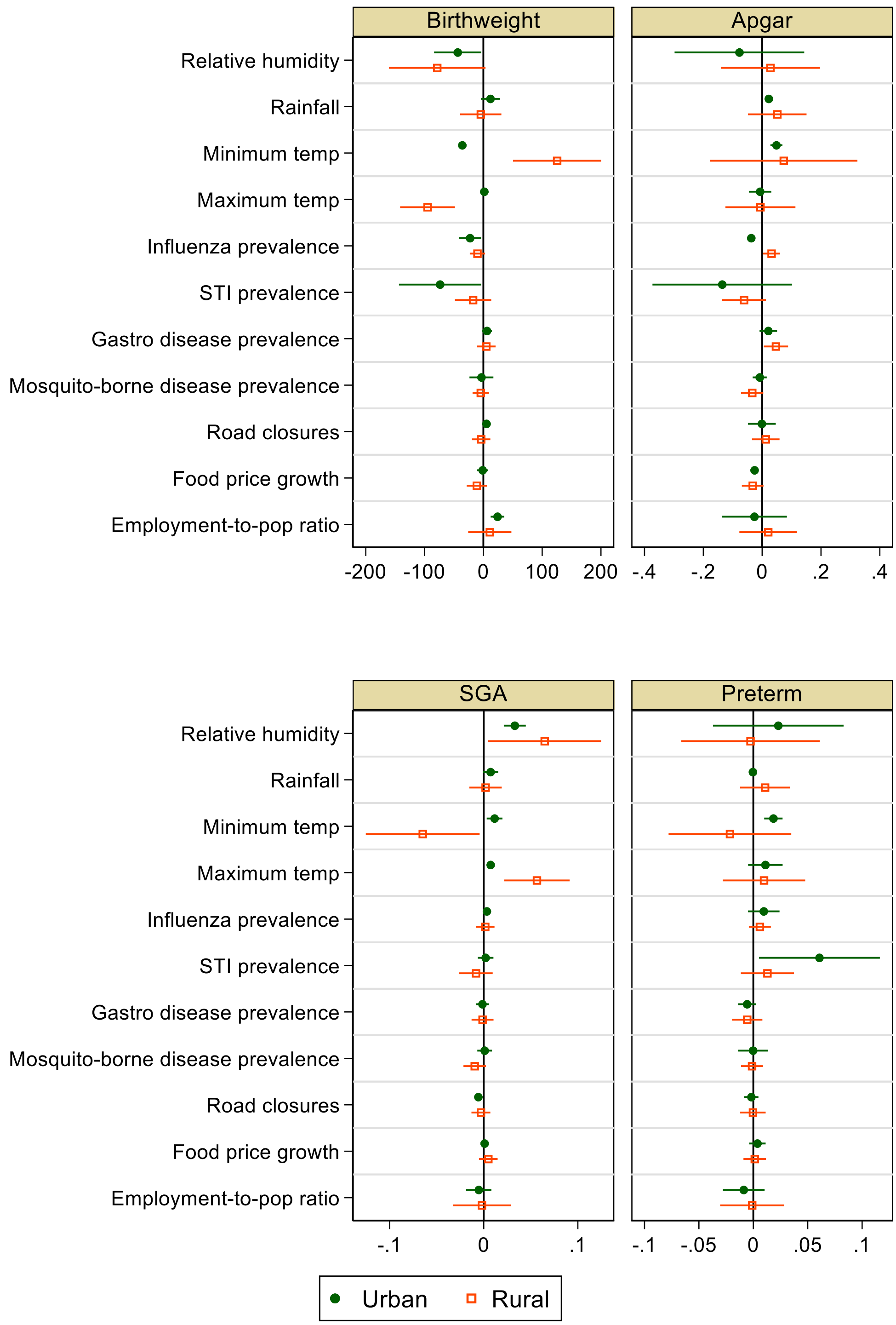


Fig. 7. Model estimates by urban/rural location. Urban is defined as the mother living in Darwin or Alice Springs at the time of birth, and rural is defined as the mother living in any other part of the NT. Estimates are for the full model including all seasonal risks in a single regression, but not including sibling fixed effects. All explanatory variables are standardised to have a mean of zero and standard deviation of 1. Sample sizes: 23,053 (urban) and 12,146 (rural).

different exposure to seasonal risks – e.g., that it is hotter in rural areas than urban areas. A second explanation is that people living in urban locations are better able to adapt to the same level of risk – for instance, by spending less time outdoors during the hottest part of the day or having more access to air conditioning.

To investigate these explanations, I fit the full model separately on the urban and rural subsamples (Fig. 7). The estimates suggest that the second explanation – that urban location moderates seasonal effects – better explains the data for most seasonal risk factors. The effects of the same unit of change in average weather conditions are substantially larger – and in some cases, work in different directions – in rural than in urban locations. A higher average maximum temperature, for instance, appears to have a large negative effect on birthweight in rural areas, but no effect in urban areas.

As an additional test, I compare the share of variance explained by the benchmark model with and without including seasonal risks (Appendix P). I find that within the rural subsample, the full set of seasonal risks explains a higher share of variance than in the urban sample for birthweight, Apgar 5 scores and SGA. I interpret this as additional suggestive evidence that the impacts of the same seasonal risks are slightly greater in rural than urban areas. The exception is for preterm birth, for which the explanatory power of the seasonal risks is greater in the urban sample. Based on the estimates shown in Fig. 7, this appears to be driven by the large coefficient on STI prevalence, perhaps reflecting the first explanation, that exposure to this particular seasonal risk (which is measured at the region level, and therefore measured prevalence rates are the same for urban and rural locations within a region, while actual prevalence may vary) is greater in urban area, and in particular in Alice Springs – see Section 6.

5.4. Parental characteristics

In the NT, there is some variation in the characteristics of women who become pregnant at different times of year (see Appendix Q).[18] To analyse whether this variation explains seasonality in birth outcomes, I revisit the sibling fixed-effects model. I focus on the subset of the sample living in rural areas, as the analysis presented above shows there is much less seasonality in the urban sample.

I present models with and without sibling fixed effects, to analyse whether and how the month coefficients (i.e. the unexplained seasonality) change after including sibling fixed effects. If time-constant parental characteristics are driving seasonality, I would expect the magnitude of the month coefficients, and the share of variance explained by them, to move closer to zero after adding sibling fixed effects.

Fig. 8 shows the month coefficient estimates graphically, while Appendix R presents a table with the share of variance explained by the month coefficients. The full model (Eq. (1), without sibling fixed effects) brings the month coefficients closer to zero. But this is not consistently the case after adding sibling fixed effects. The addition of sibling fixed effects produces larger month coefficients for Apgar scores and SGA, though it reduces the month coefficients slightly for preterm birth. In addition, the share of variance explained by the month coefficients increases with the addition of sibling fixed effects for birthweight, Apgar 5 and preterm birth (Appendix R), indicating this model is slightly less effective at explaining seasonality. This is also the case in the full sibling population, and the urban subpopulation.

Based on these estimates, I conclude that it is unlikely that time-invariant parental characteristics drive overall seasonal patterns in birth outcomes in the NT.

6. Implications – what is the effect of typical seasonal risks on newborns' health?

In this paper I have estimated the effects on newborns' health of in utero exposure to seasonal variation in weather, disease prevalence, economic conditions, and of seasonal patterns in fertility. I find that heat exposure and disease prevalence are associated with particularly large effects on birth outcomes in the NT (reductions in average birthweight of 23, 21 and 14 g per standard deviation change in exposure to very hot days in any trimester, STI prevalence, and influenza prevalence, respectively). I also find smaller, but economically and statistically significant effects of food price growth and road flooding for some outcomes and subpopulations. Seasonal fertility, rainfall and humidity do not appear to explain seasonality in birth outcomes in the NT.

While a thorough analysis of the causal mechanisms behind each of these findings is beyond the scope of this paper, my results are suggestive of causal effects, because these relationships are found after controlling for small-area location, month and year fixed effects, and after controlling for other seasonal risks. They are also little changed even after controlling for sibling fixed effects. My use of fixed effects allows for the fact that people adapt to usual conditions within their location, and abstracts from any additional unobserved monthly patterns unrelated to those I study here, which may influence month-average birth outcomes.

My use of month fixed effects does, however, mean that while I seek to explain regular seasonal patterns in birth outcomes across months, my coefficients are identified using variation within months.

In this section, I extrapolate from these coefficients, to estimate the effects of the seasonal risks that babies born in the NT are typically exposed to in utero, depending on their month of birth. I focus on the three main seasonal risks I have identified: heat exposure, influenza and STI prevalence. Such extrapolation assumes that within-month variation has the same effect as between-month variation. This means, for instance, that because August is typically slightly warmer than July, my estimates of the effect of heat exposure, identified using unseasonably warm days in July (and other months), are informative about the effects of typical heat exposure for a baby born in August instead of July.

Table 2 shows these extrapolated estimates. I show the effects for babies born in the month that would mean they had peak exposure to each risk throughout the pregnancy, compared with those born in the month with lowest exposure throughout the pregnancy.[19] The magnitude of these estimates depends on two factors: the strength of the association in my regression estimates, and the magnitude of typical seasonal variation of the risk factor.

Across all outcomes, the effects are largest for exposure to heat. Heat exposure is highest for babies born in April, and lowest for those born in September. Babies born in April experience on average 31 more days with maximum temperatures above 35 degrees. Lending a causal interpretation, this would suggest that on average, babies born in April are 21–25 g lighter, have a 1.9–2.1 percentage point higher probability of preterm birth, and Apgar scores 0.10 points lower, than babies born in September *because* of their differing exposure to very warm weather.

The effect of influenza is smaller, but still substantial. Influenza prevalence throughout the pregnancy is greatest for babies born in December, and lowest for those born in August. Because of this, babies born in December are 5–6 g lighter, and have a 0.2–0.4 percentage point higher chance of preterm birth.

In contrast, while the impact of one standard deviation in STI rates as

[18] Appendix Q shows variation over the year in the share of mothers who smoke or drink at their first antenatal visit, the number of antenatal visits, complications in the mother's medical history, age and Aboriginal status of mother. Some of these factors are time-varying. I do not have data on other maternal characteristics (e.g. socioeconomic status, education, employment or income) or any information about the father.

[19] That is, for example, I show the effect of being born in April, and hence in utero during the hottest months of the year, compared with being born in September, which is the month for which there are, on average, fewest days over 35 degrees in the preceding 9 months.

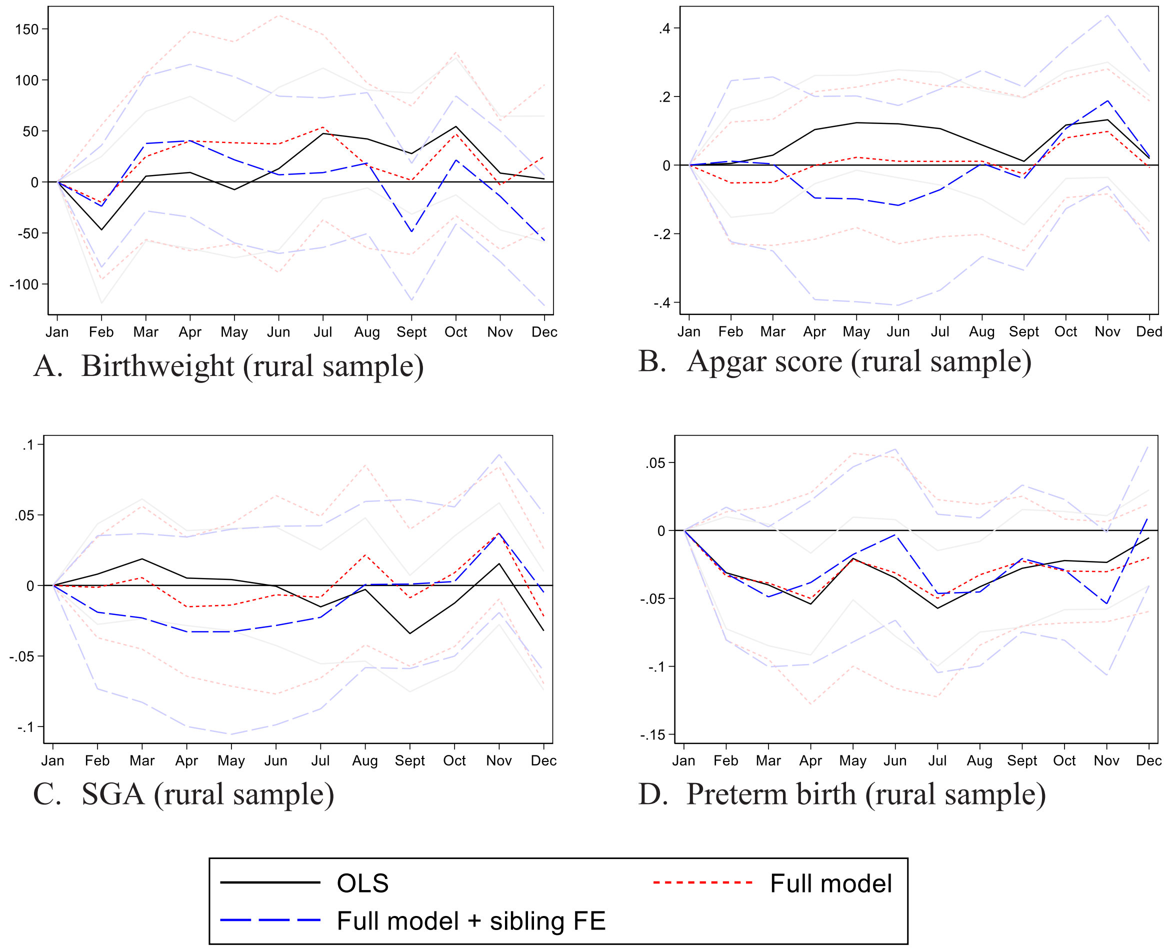


Fig. 8. The role of fixed parental characteristics. Estimated month coefficients and 95% confidence intervals from an OLS regression with only month dummies as covariates (solid line); the full model as in Eq. (1) (dotted line); the full model with sibling fixed effects (dashed line). Models are estimated on the subset of the sample in rural areas and with siblings, and therefore the coefficients in the OLS model and the full model are different from other estimates, and confidence intervals are wider. Because most mothers do not move between location clusters, the sibling fixed effects model includes controls for region instead of location cluster fixed effects. Sample size: 7016.

shown in Fig. 3 is large, much of the variance in STI rates is not seasonal. Babies born in August have highest exposure, and those born in May have the lowest exposure. But the difference is just 0.09 standard deviations. Therefore the impact of typical seasonal exposure is small, reducing birthweight by only 1.9–2.1 g on average and increasing preterm birth rates by 0.2 percentage points for babies in utero with the highest seasonal exposure.

However, STI patterns vary substantially by region. STIs are particularly seasonal in the Alice Springs region, with a 1.1 standard deviation difference in average rates between August and May. If I scale my regression estimates by STI rates in Alice Springs, these are much larger, and are of similar magnitude to the effect of heat exposure. They suggest that babies born in Alice Springs in August are, on average, 23–26 g smaller than babies born in Alice Springs in May, have a 2.2–2.6 percentage point higher chance of preterm birth, and have Apgar scores 0.1 points lower, because of their higher exposure to STIs.

This paper seeks to explain the reasons behind worse birth outcomes for babies born in the summer/wet season, compared with those born in the winter/dry season. The seasonal pattern implied by these three risk factors do not perfectly match up with the timing of the seasonal patterns we observe in Section 4: most notably, the risk of seasonal heat exposure is highest for babies born in April, though overall this is a month with more favourable birth outcomes (Fig. 2). This apparent contradiction suggests that there may either be additional seasonal risks that I have not considered, or there may be alternative ways of defining and measuring the risks, which may more fully capture the nature of their impacts on birth outcomes.[20] That said, my estimates come close to describing the overall seasonal pattern, and they move in the expected direction. Babies born in the summer/wet season have poorer birth outcomes, and are exposed to all three of the risks set out in Table 2 – they are in utero during the hottest months of the year, and during peak periods of flu and STI prevalence.

The magnitudes of these estimates are large within the context of other influences on birth outcomes. For instance, Almond, Hoynes and Schanzenbach (2011) find that the introduction of the US food stamps program during pregnancy increased average birthweight by 1–8 g, depending on the subpopulation studied. Reader (2023) finds that the UK's £ 190 Health in Pregnancy grant increased birthweight by 8–12 g. I find effects from typical seasonal variation in disease prevalence that are about the same as the impact from these substantial increases in income, and I find effects of heat exposure that are at least two times as large.

[20] For instance, as noted by Chersich (2020) and Wondmagegn (2019) in recent systematic reviews of the effect of heat exposure, there are many ways of defining heat exposure, with no consensus on the most appropriate definition. Some papers use average temperatures, high minimum temperatures, high maximum temperatures, a count of the number of heatwaves, length of exposure, etc. These analytical choices may affect the strength of the relationships identified and hence the extent to which the model can explain actual variation in birth outcomes.

Table 2
Estimated effects of typical annual differences in seasonal risk exposure on birth outcomes in the NT, derived from regression estimates.

Seasonal risk	Estimated impact on birthweight	Estimated impact on preterm birth rate	Estimated impact on Apgar scores	Estimated impact on SGA rates
Heat exposure (born in Apr vs Sept)	-21.29 to -25.37 g	1.94 to 2.06 ppts	-0.08 to -0.10 pts	No effect
Influenza prevalence (born in Dec vs Aug)	-5.07 to -6.11 g	0.23 to 0.37 ppts	No effect	No effect
STI prevalence (born in Aug vs May)	-1.90 to -2.08 g	0.18 to 0.21 ppts	0.00 to -0.01 pts	No effect
STI prevalence (born in Aug vs May in Alice Springs region)	-23.49 to -25.71 g	2.22 to 2.59 ppts	-0.05 to -0.09 pts	No effect

Note: Estimates are derived from the full model with and without sibling FE (giving the range). They show the impact of being born in the month with the highest exposure vs lowest exposure to each seasonal risk. They are calculated as the regression estimate divided by one standard deviation, multiplied by the difference in exposure between the peak month and the trough month for the seasonal risk. E.g. for influenza prevalence, there are on average 0.72 cases per 1000 residents in the 3 quarters ending in December, compared with 0.40 in the three quarters ending in August, giving a difference of 0.32 cases. I multiply the regression estimates (converted back to raw units from standard deviations) by 0.32. Estimates are shown for the three seasonal influences for which I find statistically significant effects across multiple birth outcomes, but are not shown for the SGA outcome or impact of influenza on Apgar scores, as these estimates were not statistically significant in either model. The estimates for heat exposure represent the sum of the effects of typical exposure in each trimester. Estimates for the impact of STI prevalence are shown separately for the Alice Springs region to illustrate the strong seasonal pattern in STI prevalence in that region.

However, my estimates are smaller than those of Bakhtsiyarava et al. (2018), who find that an additional month of temperatures above 35 degrees in food cropping communities in Kenya and Mali reduces average birthweight by 71 g (more than double my estimate in Table 2). This may be because higher average incomes, access to public healthcare and limited reliance on local agriculture may help to shield newborns in the NT from larger effects.

If readers do not accept the assumptions that produce the estimates in Table 2, my results remain informative. Idiosyncratic, a-seasonal weather events are increasingly common, and disease outbreaks are possible outside of their typical seasonal patterns. I find that these common events experienced in utero can have large impacts on birth outcomes.

6.1. Limitations

I identify three limitations to this study which could be addressed with further research.

First, my findings raise the possibility of interaction effects between seasonal risks, parents' characteristics and economic conditions. However, I am unable to explore this relationship because I do not have data on parents' socio-economic status. This may be an avenue for future research with alternative data sources.

Second, while I analyse a wide range of explanatory variables, many are not measured precisely; exposure to disease, road closures and economic conditions are measured at a broad regional level or higher. The fact that we still observe effects of these imprecisely measured seasonal risks suggests that their effects may be particularly large for some sub-groups. More detailed individual- or community-level data on these factors would help us to better understand these relationships. Similarly, even where exposure can be precisely measured, such as with daily location-specific temperature data, the literature provides many ways of defining heat exposure, with no consensus on the most appropriate approach (Chersich et al., 2020; Wondmagegn et al., 2019) – e.g. average temperatures, exposure to high temperatures, exposure to heatwaves, length of exposure and diurnal temperature ranges. In this analysis I have taken a simple approach of measuring average temperatures alongside a count of hot days. Future research could more directly compare different ways of measuring seasonal exposures to assess how much these analytical choices matter.

Finally, I have estimated the effect of a standard deviation change in each seasonal risk, and my findings suggest that some seasonal risks – in particular, heat exposure and disease prevalence – are more important determinants of infant health than others. However, an equally important consideration is the cost-effectiveness of any intervention to alleviate the effects of these seasonal risks. Future analysis may consider potential policy responses in more detail, alongside the cost and likely impacts of those responses.

7. Conclusion and policy applications

I draw three important conclusions from my analysis.

First, analysing multiple risk factors together is important for policy, but not necessarily for research. In this paper I have discussed the importance of considering many pieces of the puzzle together.

On one hand, my analysis indicates that it is possible to obtain reliable estimates of the effects of one seasonal risk without measuring other risks: within my fixed effects models, the estimated effects of each seasonal risk factor generally do not change after including other seasonal risks in the model. This suggests that any future research seeking to explore a specific seasonal risk in detail can do so without requiring data on all other seasonal risks.

On the other hand, my analysis provides more actionable policy implications than analysis of a single seasonal risk. Without analysing these factors together, we would not know, for instance, that policymakers seeking to reduce inequalities at birth may gain more traction at the population-level by finding ways to shield mothers from heat exposure than from influenza.

Second, we need more analysis on how STIs impact newborn health. Parts of Northern Australia have experienced an epidemic of STIs (Gooley, 2021), but such an epidemic is not unique to Australia (L. Newman et al., 2013). The association between STI prevalence and birth outcomes is large, even if the average impact of STI seasonality shown in Table 2 is small. A one standard deviation increase in regional prevalence of STIs reduces birthweight by 21 g, reduces Apgar scores by 0.08 points, and increases the risk of preterm birth by 2 percentage points. It is not clear whether this relationship is causal.

Linkage of individual-level data on STI diagnosis with birth records would help greatly in disentangling the impacts of STIs themselves from other co-varying risks. Another avenue for further research in helping to address this challenge is to analyse the reasons for non-attendance at antenatal care. Antenatal care is a key opportunity for testing and treatment of STIs, and I find a stronger link between STI prevalence and poorer birth outcomes for women with low rates of attendance. But we do not know whether these worse outcomes are the result of non-attendance, or the result of other factors correlated with both STI prevalence and non-attendance.

Third, seasonal effects may be greater in poorer parts of the world with tropical and arid climates. It is remarkable that there is such large seasonal variation in birth outcomes in the NT, especially in contrast with the smaller variation that McGrath et al. (2005) find in the sub-tropical and temperate climates of Australia's eastern states.

Climate can explain some of these differences. My estimates show large effects of exposure to very hot days and high minimum temperatures, indicative of heatwaves. These high temperatures are more common in tropical and arid climates.

It is likely that these climate effects interact with social and economic factors. While I do not have data on parents' socio-economic status, we know that there are more families with low income in the NT than in the rest of the country,[21] many of whom live in remote Aboriginal communities. Previous research shows that mothers with lower socioeconomic-status tend to have more underlying health conditions, higher exposure to circulating diseases, and less access to nutritious food (Aizer and Currie, 2014) – all of which would make them more vulnerable to seasonal risks (Cil and Kim, 2022; Nyadanu et al., 2022).

Together, these findings suggest that climate-related seasonal risks may be even more important contributors to poor birth outcomes in lower-income parts of the world. The fact that the effect of heat is smaller in urban areas suggests that adaptations (such as air conditioning, more common in urban areas) may moderate this relationship. In light of the changing climate, improving access to such adaptations will be of increasing importance in reducing inequalities at birth. This could include providing transfers to help low-income households pay for air conditioning or other adaptations during the hotter months, along the lines of the UK's Winter Fuel Payment and Cold Weather Payment.

Ethics

This research forms part of the CYDRP project, which has been approved through the Northern Territory Department of Health and Menzies School of Health Research Human Research Ethics Committee. This research has been approved by the CYDRP Steering Committee, and the First Nations Advisory Group at the Menzies Centre for Child Development and Education.

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Author Statement

This paper is sole-authored.

Data Availability

The authors do not have permission to share data.

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Conflicts

The author has no relevant financial or non-financial interests to disclose.

Data access

The datasets analysed in the current study are not publicly available, as they contain records of individual children. Other researchers seeking to access the data may be able to do so through the Northern Territory Child and Youth Development Research Partnership (CYDRP), Menzies School of Health Research. Weather data were obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2023.101287.

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