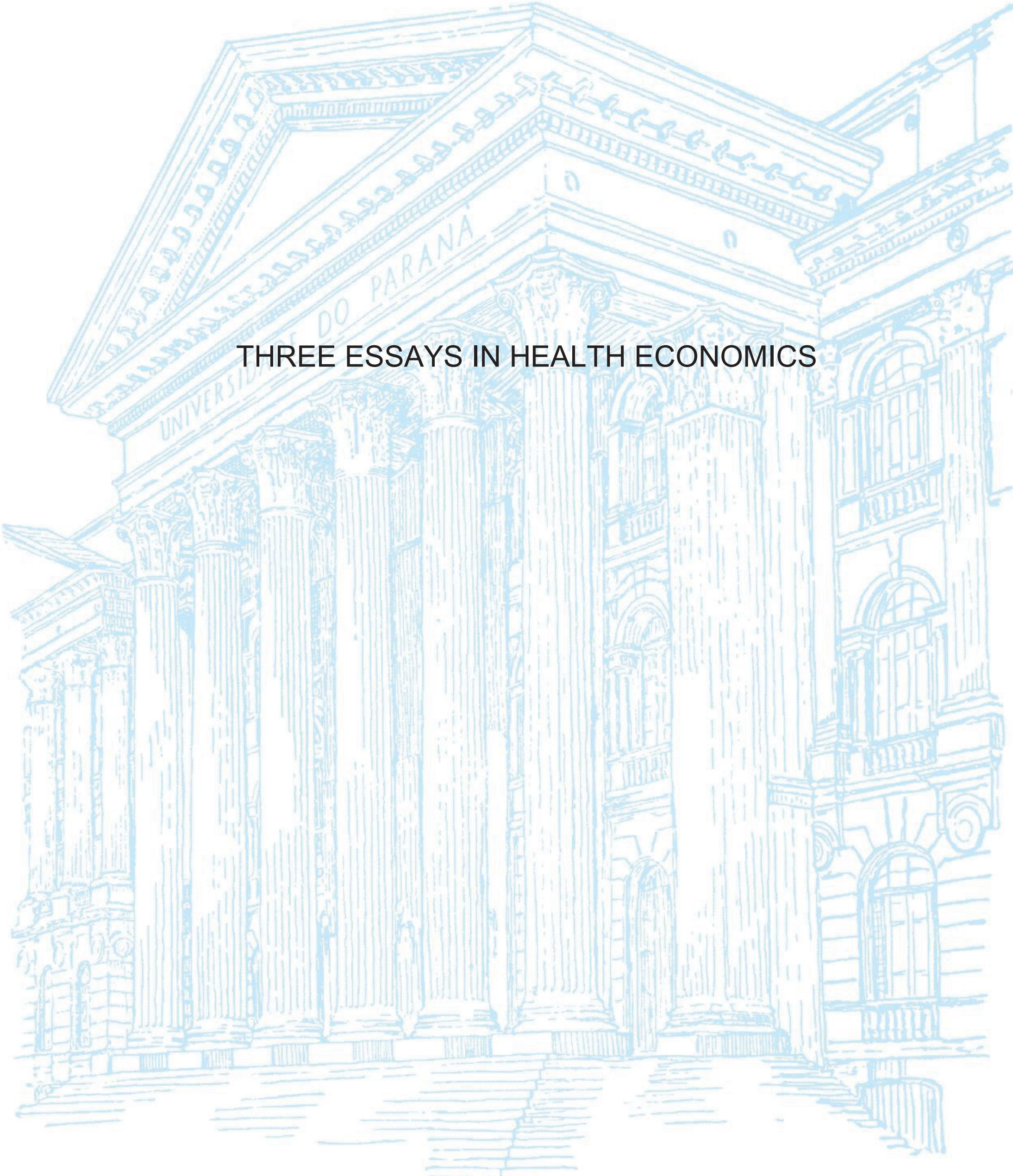
UNIVERSIDADE FEDERAL DO PARANÁ

TALLYS KALYNKA FELDENS



THREE ESSAYS IN HEALTH ECONOMICS

CURITIBA

2024

TALLYS KALYNKA FELDENS

THREE ESSAYS IN HEALTH ECONOMICS

Tese apresentada como requisito parcial à obtenção do grau de Doutora em Desenvolvimento Econômico, no Curso de Pós-Graduação em Desenvolvimento Econômico, Setor de Ciências Sociais Aplicadas, da Universidade Federal do Paraná.

Orientador: Prof. Dr. Victor Rodrigues de Oliveira

Coorientador: Prof. Dr. João Vasco Santos

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TERMO DE APROVAÇÃO

Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação DESENVOLVIMENTO ECONÔMICO da Universidade Federal do Paraná foram convocados para realizar a arguição da tese de Doutorado de **TALLYS KALYNKA FELDENS** intitulada: **THREE ESSAYS IN HEALTH ECONOMICS**, sob orientação do Prof. Dr. VICTOR RODRIGUES DE OLIVEIRA, que após terem inquirido a aluna e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.

A outorga do título de doutora está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

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À minha mãe.

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“Você não sente nem vê
Mas eu não posso deixar de dizer, meu amigo
Que uma nova mudança em breve vai acontecer
O que há algum tempo era jovem e novo, hoje é antigo
E precisamos todos rejuvenescer”
- Velha roupa colorida, Belchior, 1976

“Sonho e escrevo em letras grandes de novo
Pelos muros do país
João, o tempo andou mexendo com a gente, sim
John, eu não esqueço
Oh no, oh no, oh no
A felicidade é uma arma quente”
- Comentário a respeito de John, Belchior, 1979

RESUMO

Este estudo é composto por três ensaios em economia da saúde. No primeiro ensaio, a relação entre gastos em saúde, gastos com serviços sociais e diversos desfechos em saúde é abordada para os países da OCDE entre 1990 e 2018. Ambos as variáveis de gasto podem atuar como bens substitutos ou complementares com anos de vida ajustados pela qualidade de vida, expectativa de vida ao nascer, anos de vida ajustados por incapacidade e taxas de mortalidade. Assim, estimam-se as respectivas elasticidades do produto e a elasticidade de substituição entre esses dois insumos e esse conjunto de desfechos de saúde em uma função de produção translog. A seguir, o segundo ensaio foca em saúde brasileira. Considerando a crescente preocupação com as mudanças climáticas, a literatura recente sugere que há uma relação entre as condições climáticas às quais as gestantes estão expostas durante a gestação e os desfechos de saúde do recém-nascido. Estimamos esse impacto nos municípios brasileiros usando dados administrativos, climáticos e socioeconômicos. O terceiro ensaio é um exercício estimando os efeitos de diferentes cenários de mudanças climáticas futuras, levando em consideração características regionais, demográficas, e os resultados do segundo ensaio.

Palavras-chave: Economia da saúde; Gastos em saúde; Gastos sociais, Mudanças Climáticas; Peso ao nascer, Saúde Neonatal, Projeções Demográficas, Choques climáticos.

ABSTRACT

This study is composed of three essays on health economics. In the first essay, the relationship between health expenditures, social services expenditures and several health outcomes is addressed for OECD countries between 1990 and 2018. Both spending variables may act as a substitute or complementary goods with healthy-adjusted life years (HALE), life expectancy (LE), disability-adjusted life years (DALY) and death rates (DR). Thus, it is estimated the respective output elasticities and the elasticity of substitution between these two inputs and this set of health outcomes in a translog production function. Further on, the second essay focuses on Brazilian health. Considering the increasing concerns with climate change, recent literature suggests there is a relationship between the climatic conditions the pregnant are exposed to during their pregnancies and birth outcomes. We estimate this impact on Brazilian municipalities by using administrative, weather, and socioeconomic data. The third essay is an exercise estimating the effects of different scenarios of future climate change, taking into consideration regional and demographic characteristics and using the results found for the second essay.

Keywords: Health Economics; Health Expenditures; Social Expenditures; Climate Change; Birthweight, Neonatal Health, Demographic Projections, Weather shocks.

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SUMMARY

INTRODUCTION

Economics has become an interdisciplinary science. From its start as a social science that used to study market relationships, economics has already spread to behavioural sciences, earth sciences and health sciences, just to name a few. Advances in other sciences, feasibility of novel technologies, and estimation of future impact - can be seen through the glasses of economics. In a world where relationships are more intertwined than ever, economic theory and methods can be useful in a much broader sense. Health Economics as an economic field is an example of this - it blossomed from the study of health outcomes and grew due to the insights from medicine, epidemiology and public health sciences. In this thesis, we try to explore health economics themes and methods, returning to classic issues, presenting a currently discussed topic and exploring the future impacts of our choices as a society.

The last century has seen the rise of applications of the traditional firm theory to understand the demand for health, as in Grossman (1972). Later, the literature focused on using regression analysis to observational data to understand whether investment in health has been ameliorating health outcomes (Gravelle and Backhouse, 1987). The field has developed itself as long as new econometric tools were getting more popular and widespread, with novel approaches being considered to approach the issue of the endogeneity between income and health outcomes. In this context, revisiting the concepts of a health production function whose outputs deliver health to a national population, we defined the basis of the first chapter of this thesis. We retrieve the recent literature that claims that social expenditure can improve health outcomes, and propose different tests to check this hypothesis, using a panel made of 21 OECD countries and 28 years. We argue that social expenditures might have an impact on health, however, health expenditures should be taken into account. Proposing two different theoretical points of view, we found that social expenditures, once health expenditures are taken into account, do not play a beneficial role and may even depress the system due to possible funding competition. This finding, contrary to the current literature, shows that the decision on model specification can influence the results and the interpretation of what matters to improve health outcomes.

Our second chapter tries to cover a very current topic, climate change. In the 2000s, the escalation of concerns regarding the climate and the development of theories arguing that in-utero health shocks could be long-lasting and possibly dangerous (Deschenes et al, 2009; Almond and Currie, 2011), gave origin to a new branch of health economics. Now, exogenous factors such as the weather might be understood as exposure, whose effects might be felt by the pregnant and the baby. This time, endogeneity is no longer a concern, as we expect the weather to be (possibly) causal to human health but not otherwise. Thus, we hypothesize whether the Brazilian population has felt any change in newborn health outcomes due to climate change. For this estimation, we use individual data from the Brazilian administrative database from 2000 to 2020, contemplating almost 45 million births, and crossed with daily weather information to ascertain the exposition during the pregnancy for each mother. We controlled for several possible confounders and ruled out possible explanations for the phenomenon we have found. Our estimations relied on diverse specifications and time aggregations, henceforth, the results point to non-negligible effects of temperature on birthweight.

Considering that newborn health is a potential predictor of future health, future cognition and schooling achievements (Torche and Echevarría, 2011; Figlio et al., 2014; Rocha and Soares, 2015; Wilde et al., 2017), and thus potentially affecting human capital, we ought to also look into the future. The third chapter of this thesis then explored a projection exercise using effect coefficients found in the second chapter and applied to the future weather predictions for all Brazilian municipalities. By doing this, we tried to identify the areas where climate change and respective potential birthweight loss could be especially damaging. We found that the Central-West and South will be the regions that will suffer the biggest changes in historical climate patterns. Even considering the demographic changes that are happening throughout this century, such as the rise of the mother’s education and the decrease in fecundity levels; birthweight losses due to climate change could deepen social vulnerabilities in a country already marked by social inequalities.

With these three studies, we hope to bring to light a sample of intersectionality between economics, health, sociology, and earth sciences.

1 THE INTERPLAY BETWEEN SOCIAL AND HEALTH CARE – AN EMPIRICAL EXERCISE FOR OECD COUNTRIES

Abstract

Background: Public health and social security systems' goals are to deliver healthcare and social protection for the population. Some studies in the literature have been pointing to potential spill-over effects of social expenditures in improving health outcomes. This study aims to explore this interplay in their role regarding death rates and Disability-Adjusted Life Years (DALYs).

Methods: We estimated the relationship between public health and social expenditures using fixed-effects panel data from 29 years and 21 OECD countries. Instrumental variables and ridge regressions were used to estimate unbiased elasticities.

Results: Between 1990 and 2018 for these 21 countries, public health expenditures are found to be related to decreases in death rates and DALYs, but social expenditures are not found to boost health outcomes nor directly or indirectly. Our results imply that once endogeneity is treated and the model assumes health and social expenditures on the regression altogether, there is no substantial contribution of social expenditures in health for the data we used.

Conclusions:

Public health expenditures are still relevant for improving health care, and investments in the social sector cannot be claimed as a potential substitute. Thus, policymakers need to acknowledge the importance of continuing to invest in health care to achieve health gains.

Key-words: Health expenditure, social expenditure, health production function, substitution effect, translog, ridge regression, endogeneity.

1.1 INTRODUCTION

The average total health expenditure for all OECD countries tripled between 1990 and 2018. Other expenditure variables also have witnessed a raise, as is the case of social expenditures, whose per capita social expenditures doubled in the same period (OECD, 2023). In this meantime, death rates decreased by 34.85% and Disability-adjusted life years decreased by 38.70 % (GBD, 2019).

Nixon and Ullmann (2006) theorize that some populations' health may be viewed as the output of aggregated factors, which compound a production function. This approach was chosen extensively in the literature to ascertain the impacts of health spending and other factors treating them as inputs, while mortality or life expectancy measures are used as the output of the production function (Nixon and Ullmann, 2006, Gallet and Doucoliagos, 2017). Other studies in this literature, though, also raised the possibility of health spending not being the only channel through which policy may act to achieve better health outcomes, but also pointing to the importance of social spending towards health improvements (Bradley et al. 2011; Bradley et al., 2016; Thorpe and Joski, 2017; Reynolds and Avendano, 2018; Dutton et al. 2018).

Nonetheless, up until this point, social and health expenditures were modelled under subtly different assumptions when it comes to evaluating their role towards health outcomes improvement. Social and health spending were modelled separately (Bradley et al., 2011), together (Reynolds and Avendano, 2018), or using health spending and the ratio of social to health spending as covariates (Bradley et al. 2011; Bradley et al., 2016; Thorpe and Joski, 2017; Dutton et al. 2018). In this study, we ought to build a production function to ascertain the effects between the covariates using both a direct and an indirect approach. Henceforth, we aim to estimate how both types of expenditure variables (i.e. health and social expenditures) contribute to health outcomes; and how these two types of expenditure variables relate to each other over time under different modelling assumptions.

Some studies have found a positive impact of health investment in increasing life expectancy (Anand and Ravallion, 1993; Babazono and Hillman, 2004; Hall et al. 2012; Novignon et al., 2012; Gallet and Doucoliagos, 2017; Obrizan and Wehby, 2018); reducing mortality (Hitiris and Posnett, 1992, Bokhari et al., 2007, Farag et al., 2012; Moreno-Serra et al., 2015; Ochalek et al., 2020, Moler-Zapata et al, 2022), or reducing DALY rates (Ochalek et al, 2020). Some authors found that decreasing health expenditures is related to a decrease in life expectancy (Crémieux et al., 1999). Others have not found any impact at a macro level (Barlow and Vissandjée, 1999). The size of the effect and the presence or not of diminishing marginal returns depend on the modelling and data used (Lomas et al., 2018).

The relationship between health spending and health outcomes, however, is generally treated as endogenous, due to the expected reverse causality between them. On one side, better health outcomes may lead to higher income and more health expenditures, and on the other side, health spending may also lead to better health outcomes. The reverse causality problem is not the only possible cause of the endogeneity. In cross-section studies, the possible heterogeneity of measurement regarding the different definitions of what can be considered "health expenditures" may be linked to the occurrence of measurement errors, also introducing endogeneity in the estimation (Filmer and Pritchet, 1999). Additionally, omitted variable bias may be present when analysing national data. There is sound literature on this matter which develops strategies to deal with this particularity, most of them using instrumental variables approaches (Gravelle and Backhouse, 1987; Filmer and Pritchet, 1999; Bokhari et al., 2007; Bilgel and Tran, 2013; Moreno-Serra and Smith, 2015; Gallet and Doucoliagos, 2017; Gabani et al., 2021), while others use dynamic-panel data estimation (Moler-Zapata et al., 2022).

Social care expenditures directed to income support, nutrition, housing subsidies, employment programs, elderly population, long-term care, and pensions amongst others can also have an important impact on health outcomes (Bradley et al. 2011; Bradley et al., 2016; Thorpe and Joski, 2017; Reynolds and Avendano, 2018; Dutton et al. 2018). There is indeed a fine line between health and social care, also applicable to spending, with the best example being long-term care (LTC). In fact, among OECD countries, LTC is included in health care in some countries, and social care in others, while some distribution of LTC between social and health care also occurs (OECD, 2019a).

However, studies dedicated to better understanding the interrelationships between the two spending variables have only partially addressed the endogeneity concern (Bradley et al. 2011; Bradley et al., 2016; Dutton et al 2018, Reynolds and Avendano, 2018). Moreover, to the best of our knowledge, none have tried to fit a production function for the effects they have found or attributed specifically direct or indirect channels for it. To further explore it, we performed an empirical exercise utilizing OECD data for a long panel of 29 years and 21 countries. We fitted a translog production function and addressed the endogeneity concern.

This paper is organized as follows: in Section 2 we set out our methods and define the main model; in Section 3 we display the description of the sample, present the results, as well as the robustness checks; Section 4 contains the discussion, and section 5 add our conclusions.

1.2 METHODS

1.2.1 Data

This retrospective study used panel data comprising information on OECD countries between 1990 and 2018. The year 2019 was excluded due to the high proportion of missing data for the main variables of interest at the moment this study was being developed. For the purpose of our analysis, we used data from the 21 OECD countries that had available data for the full period. Health expenditure here is defined as Public Health Expenditure (PHE), which covers government spending on healthcare goods and services, both individual and collective, excluding investment. Social expenditure (SE), in turn, includes government cash benefits, goods or services for low-income households, social protection for the elderly, sick and disabled, training programs for the unemployed and young persons, among others (OECD, 2024). As PHE and SE are part of gross domestic product (GDP), we opted to not use GDP in our models due to this conceptual concern. We adjusted all data for 2018 U.S. dollars, adjusted for PPP. Descriptive statistics by country are presented in Table 1.1.

Different spending choices may affect different health outcomes heterogeneously. Hence, we opt to analyze the results DALYs and Death Rates (DR) to take into consideration both a measure of life span and a measure of quality of life. Health outcomes data by country and year was extracted through the Global Burden of Disease 2019 study (GBD, 2019).

Considering the concern about the endogeneity caused by reverse causality, we have collected data regarding possible candidates for instruments. A good instrument relies on three assumptions: i) the instrument is correlated with the endogenous variable; ii) the instrument is correlated with the outcome variable only through the endogenous variable and iii) the measurement error of the instrument should not be correlated with the measurement error of the endogenous variable (Filmer and Pritchett, 1999). We have collected data for two potential instruments from the V-DEM dataset, the regime corruption index and the deliberative democracy index (V-DEM, 2023).

The regime corruption index is a measure of how much public agents use the public system for private interests (V-DEM, 2023). The correlation between health expenditures and regime corruption in our dataset is 0.603. Following Makuta and O'Hare (2015), corruption mediates the relationship between health expenditures and health outcomes by directly affecting the health care sector. Due to the high correlation with the endogenous variable and empirically proved mediation behavior (Makuta and O'Hare, 2015; Wang et al., 2019), regime corruption became a suitable candidate for instrumental variables. Additionally, variables from the VDEM dataset are not from the same source as OECD health expenditure data, thus diminishing the chance of correlated measurement error.

Furthermore, we gathered the deliberative democracy index from the VDEM dataset to be a potential candidate for instrumentalizing social expenditures as well. Democracy indexes are not a novelty when it comes to instrumentalizing health expenditures and health outcomes – other authors also have used them in recent literature (Roessler and Schmidt, 2021). It is thought that democracy may play a significant role in enhancing health system efficiency and reducing the possibility of embezzlement within the system (Roessler and Schmidt, 2021). Due to the high correlation between the deliberative democracy index and social expenditures (0.710), we rely on it as an instrument candidate.

In order to control for socioeconomic variation, and because they may impact exogenously SE and PHE; we also included a vector of control variables by country. The unemployment rate and the percentage of the population above 65 years were included in the model; both were retrieved from the OECD database (OECD, 2023). As a proxy for education, we used the estimated average years of schooling from the IHME database (IHME, 2019).

1.2.2 Empirical Strategy

Grossman's model (1972) argued that on an individual level, each person is attributed with a stock of health capital that depreciates over time, and this stock is affected by ongoing investments in health care, healthy behaviors and environmental variables. A few years later, an article developed by Cochrane et al. (1978) modelled mortality rates as the result of the aggregated investment in health care, controlling for a few behavioral variables. This research agenda evolved until acquiring elements from the Theory of the Firm, such as the interpretation defined by Nixon and Ullman (2006). According to these authors, health on an aggregated level can be interpreted as the output of a production function that aims to produce health.

In the original Theory of the Firm, inputs put together product outputs, and this production will be optimized aiming for the profit of this firm depending on their production constraints. Production functions are continuous, strictly increasing and strictly quasiconcave – which means that inputs are always beneficial for production, even small changes in the level of inputs can produce small changes in the level of outputs, and there is some complementarity between the inputs on the production function (Jehle and Reny, 2011). The percentage change in the output for a given change on one of the inputs is their output elasticity. The combinations of inputs to achieve a fixed amount of output form the isoquants, and on the two-input situation, the slope of the isoquant shows the rate at which one input can be substituted by the other while producing the same output, the definition of the marginal rate of technical substitution. The measure of the curvature of this isoquant, in turn, will be the elasticity of substitution – an estimation that reflects the percentage change in the ratio of inputs, holding the other inputs and the output constant (Jehle and Reny, 2011).

For inputs, different variables can be used including financial resources (e.g. health expenditures), physical resources (e.g. infrastructures) or human resources (i.e. workforce). Due to policy implications and data availability, financial resources are the most often considered for the health production function, with health expenditure being usually used following Cochrane et al (1978). Despite the inconclusive evidence of the channels through which this link takes place, some authors point out that economic growth affects and is affected by health outcomes via increases in calory intake, access to medical services and overall standard of living (Anand and Ravallion, 1993; Weil, 2014; Lange and Vollmer, 2017; Cole, 2019).

The biggest part of the authors who used the interpretation mentioned by Nixon and Ullman (2006) estimated the elasticity of health investment fitting Cobb-Douglas production functions, adding socioeconomic, behavioral and other variables as control variables (Gravelle and Backhouse, 1987; Filmer and Pritchett, 1999; Bokhari et al., 2007; Moreno-Serra and Smith, 2015; Gabani et al., 2021). However, other functional forms could be also used to fit the relationship, such as the CES (Constant Elasticity of Substitution) and the translog (Transcendental Logarithmic). Both CES and Cobb-Douglas are translog's special cases.

Production function estimates need to adhere to several assumptions compatible with the dataset under study and the expected theoretical relationship between the variables. We opt for using translog estimation over the most used Cobb-Douglas and CES function for several reasons: i) Translog flexible structure allows for linear and quadratic interactions between the inputs, which is an advantage against the Cobb-Douglas production function; ii) CES production functions are non-linear, which leads to estimation problems concerning convergency; while translog are estimated in their logarithmic form; iii) CES production functions impose a restricted structure to the elasticity of substitution parameters, and we have no reasons to believe the elasticity of substitution is constant; and iv) in translog production function the elasticity of substitution is allowed to vary between the different pairs of inputs; and do not impose restrictions on returns to scale or technical change as well (Boisvert, 1982; Tzouvelekas, 2001; Lin and Xie, 2014; Lin and Ahmad, 2016; Lin and Liu, 2017).

Utilizing a flexible form has the advantage of not assuming only linear relationships, once empirical work has pointed out possible interaction terms (Bradley et al., 2011; Dutton et al., 2018) and diminishing marginal returns (Galama et al., 2012; Lomas et al., 2018, Reynolds, 2018, Obrizan and Wehby, 2018), which can be modelled using quadratic terms. By using panel data estimation, we may account for the historical shifts in both types of investment; and also consider country-fixed effects to deal with non-observable confounding factors.

We estimate a production function for the health care system, following Nixon and Ulmann's theory, using age-standardized mortality rates (DR) and disabilitiy-adjusted life years (DALYs) as outputs. For the inputs, we follow two different strategies: one assuming that health expenditures are the main channel to achieve health outcomes, thus social expenditures only act on health outcomes indirectly; and another assuming both as inputs on the production function. Besides this difference, we included in both estimations time as an input, to capture technology improvements over time that may have impacted our outcomes directly or indirectly by enhancing the productivity of health and social expenditures. Additionally, the time trend within this model intends to account for the population ageing that may not be directly linked with health expenditures.

Although the relationship between health expenditures and health outcomes has been studied for decades since Cochrane et al. (1978), the inclusion of social expenditures in this framework has only emerged in the recent literature (Bradley et al, 2011; Bradley et al., 2016; Reynolds and Avendano, 2018; Dutton et al, 2018). As such, some authors have preferred to deal with social expenditures as a direct driver and some chose to model it as an indirect force in affecting health outcomes.

Social expenditures aim to deliver social protection to individuals and families, so they can build effective societies (OECD, 2024). Although health gains are not mentioned in social expenditure objectives, we hypothesize that investments in social care can interact with health expenditures and support better health outcomes. For instance, social support can affect a family's access to health and health care. This approach is thus defined as indirect because its functionality is only through health spending.

However, if the effect of social expenditures is defined as indirect, their inclusion in the production function should not be regarded as an input. On a translog production function, the inputs present linear, quadratic and interacted terms with one another, and the remaining covariates are included only as control variables in their linear form (after log-transformation). If the role of social expenditures is modelled as indirect, health expenditures and time will be inputs, and a ratio[1] between social expenditures and health expenditures will characterize the indirect effect of social services on health care. This ratio represents the amount a country invests in social care in comparison with health care.

Although not claiming explicitly as indirect effect, other authors have already considered this assumption in their model, by using a ratio of social to health expenditures within their econometric specification (Bradley et al. 2011; Bradley et al., 2016; Thorpe and Joski, 2017; Dutton et al. 2018).

In the context of panel data estimation, we follow Baltagi and Griffin (1988) and Tzouvelekas (2001) by using time-trend as a possibly non-neutral and scale-augmenting technical change. Therefore, we present model (1) for the indirect channel:

[1] Following Bradley et al. (2016), the social-to-health spending ratio was calculated as social services plus public health spending, divided by public health spending.

$$ln\,Health_{it} = \beta_0 + \beta_{PHE} lnPHE_{it} + \gamma_1 t + \beta_{PHET} lnPHE_i t + \frac{1}{2}\gamma_2 t^2 + \frac{1}{2}\beta_{PHE2} ln\,PHE_{it}^2 + \beta_{ratio} lnRatio_{it} + \beta_Z Z_{it} \quad (1)$$

Where $Health_{it}$ represents our dependent variable in DR or DALY; PHE is public health expenditures per capita for a given country i and year t, and t is our time variable as a proxy for technical change. β_0, β_{PHE}, and γ_1 are parameters for the linear relationships, while β_{PHE2}, and γ_2 are parameters for the quadratic interactions. β_{PHET}, and β_{PHET} captures the interaction coefficient between inputs, β_{ratio} represents the parameter for the ratio between social and health care; and $\beta_Z Z_{it}$ is a vector containing our socio-economic control variables such as average unemployment rates by year, percentage of the population that is above 65 years old and estimated average years of study.

On a direct channel, we hypothesize that investments in social care can improve the quality of life – possibly also affecting chance of dying – and, on a micro level, save income that would otherwise be used to support families' social needs. Therefore, through improved quality of life and due to income effect, health outcomes can also be affected by social expenditures apart from their interaction with health expenditures alone. This is the core assumption of the direct channel: a potential spill-over effect beyond the goals of social expenditures.

Also, some expenses such as long-term care for disabled and sick people lay in between the two definitions of expenditures – so much that some countries categorize them as social expenditures, some on health and others on both (OECD, 2019a). It is equally plausible that investments in supporting disabled and sick people could therefore diminish aggregate age-standardized mortality rates and/or diminishing DALYs. Moreover, as stated in Grossman's model for health demand (1972), health is the result of health behaviors and other factors besides health investments, and, under the assumption of the direct channel, social support might be one of these factors.

Henceforth, our model (2) is specified as below:

$$ln\,Health_{it} = \beta_0 + \beta_{PHE} lnPHE_{it} + \beta_{SE} lnSE_i + \gamma_1 t + \beta_{PHESE} lnPHE_i lnSE_i + \beta_{PHET} lnPHE_i t + \beta_{SET} lnSE_i t + \frac{1}{2}\gamma_2 t^2 + \frac{1}{2}\beta_{PHE2} ln\,PHE_i^2 + \frac{1}{2}\beta_{SE2} ln\,SE_i^2 + \beta_Z Z_{it} \quad (2)$$

Where $Health_{it}$ represents our dependent variable in DR or DALY; PHE and SE are respectively public health and social expenditures per capita for a given country i and year t, and t is our time variable as a proxy for technical change. β_0, β_{PHE}, β_{SE}, and γ_1 are parameters for the linear relationships, while β_{SE2}, β_{PHE2}, and γ_2 are parameters for the quadratic interactions. β_{PHESE}, β_{PHET}, and β_{SET} captures the interaction coefficient between inputs, and $\beta_Z Z_{it}$ is a vector containing our socio-economic control variables.

Translog models can be estimated by OLS using a fixed-effects structure. However, due to the high parametrization and interaction terms, there is a huge chance of the model suffering from multicollinearity (Pavelescu, 2011). Taking this into account, we calculated the correlation matrix between our model variables and found that our model presents highly correlated coefficients (tests available upon request). Using a penalized regression instead of OLS classic estimation is thus an option for this analysis. Of the shrinkage methods that may deal with penalized regression, we opt for ridge regression, which is more used in the context of translog due to this multicollinearity concern (Lin and Xie, 2014; Lin and Ahmad, 2016; Lin and Liu, 2017). Other shrinkage methods such as Least Absolute Shrinkage and Selection Operator (LASSO regression) functioning rely on the possibility of forcing a coefficient to be zero, which is not consistent with the strategy of keeping the translog model using correlated coefficients that are not sparse. Ridge regression parameters are estimated by using a parameter k which biases the estimation to obtain efficient estimators; calculating the matrix $(X'X + kI) = X'Y$ where k is the ridge parameter and I is the identity matrix (Lin and Xie, 2014; Lin and Ahmad, 2016; Lin and Liu, 2017). The choice for the ridge parameter k was performed automatically by using the approach of Cule et al. (2013), available within the R software package named “ridge”. We used R version 4.2.1 to perform our econometric analysis.

Our empirical strategy to deal with endogeneity relies on an instrumental variable approach, performed by the 2SLS method. We had to choose 2SLS instead of GMM-IV due to the ridge regression structure.

Theoretically and empirically health expenditures should be considered endogenous (Gravelle and Backhouse, 1987; Filmer and Pritchet, 1999; Bokhari et al., 2007; Bilgel and Tran, 2013; Moreno-Serra and Smith, 2015; Gallet and Doucoliagos, 2017; Gabani et al., 2021), but no literature so far have argued that social expenditures are endogenous as well. By the nature of the relationship between social expenditures and health outcomes, we cannot say for sure there is no possibility of reverse causality, if it is assumed that social spending is an input on the production function it could have endogenous behaviour. This is the reason why, for our equation (2), we prepared two different specifications – one assuming social expenditures as exogenous, and therefore using it directly on the equation – and another assuming as endogenous and instrumentalizing it.

The first stage of the regressions was accomplished by regressing each possibly endogenous variable against a set of exogenous variables, which includes the instruments cited in the previous subsection and the other socio-demographic variables. In the second stage, we regressed the fitted values of the first stage with the exogenous variables in a Ridge regression structure.

Afterwards, we carried out weak instruments tests to test for the validity of the instruments. We should perform the Hausman test, which tests the apparent endogeneity of the spending variables. However, the regular Hausman test does not account for the multicollinearity present in the data. Without accounting for the multicollinearity, we might take the risk of wrongly deeming the spending variables as endogenous once they might not be. Considering IV regression has a greater variance than OLS regression, we should not use IV without clear evidence of its need. Therefore, we carried out an adapted version of the Hausman using the ridge estimators, following the approach of Sheikhi et al (2020). Both variables were found endogenous in our tests, justifying the IV approach. Our correlation matrix, weak instruments tests and Hausman tests are available in the Supplementary Material.

Apart from the translog estimation, we also estimated the output elasticities and returns to scale of each specification. Output elasticities estimations (η) are a way of considering altogether the effects of the coefficients estimated in the translog by input, thus pointing to the net effect each input has on the outcome holding the remaining the same. For the output elasticities, we used the following formulae:

$$\eta_{HE} = \frac{dHALE}{dHE} \cdot \frac{HE}{HALE} = \frac{d\, ln\, HALE}{d \ln HE} = \beta_{HE} + \beta_{HESE} ln\, SE + \beta_{HET} T + 2\beta_{HE2} ln\, HE$$
$$\eta_{SE} = \frac{dHALE}{dSE} \cdot \frac{SE}{HALE} = \frac{d\, ln\, HALE}{d \ln SE} = \beta_{SE} + \beta_{HESE} ln\, HE + \beta_{SET} T + 2\beta_{SE2} ln\, SE$$
$$\eta_{T} = \frac{dHALE}{dT} \cdot \frac{T}{HALE} = \frac{d\, ln\, HALE}{d \ln T} = \gamma_1 + \beta_{HET} ln\, HE + \beta_{SET} ln\, SE + 2\gamma_2 T$$

1.3 RESULTS

1.3.1 Descriptive statistics

Table 1.1 presents average measures by country for the period of analysis (1990-2018), for inputs, outcomes and control variables. It is noticeable the heterogeneity across countries, with Japan representing the lowest DALY, and Turkey the highest. The highest DR was found for Poland, and the lowest for Japan. Expenditures and socio-economic variables also displayed marked heterogeneity amongst countries between 1990 and 2018, where Luxembourg is the country that spends the most on both health and social expenditures per capita, and Turkey is the one that spends the least on both measures.

Figure 1.1 shows the evolution of PHE and SE over time (in logarithmic values). Between 1990 and 2015, PHE has increased consistently, especially between 1990 and 2010. From 2010 on, it increased at a slower pace. SE series is steadier, having risen more markedly between 1995 and 2008, and since then on a slight decrease.

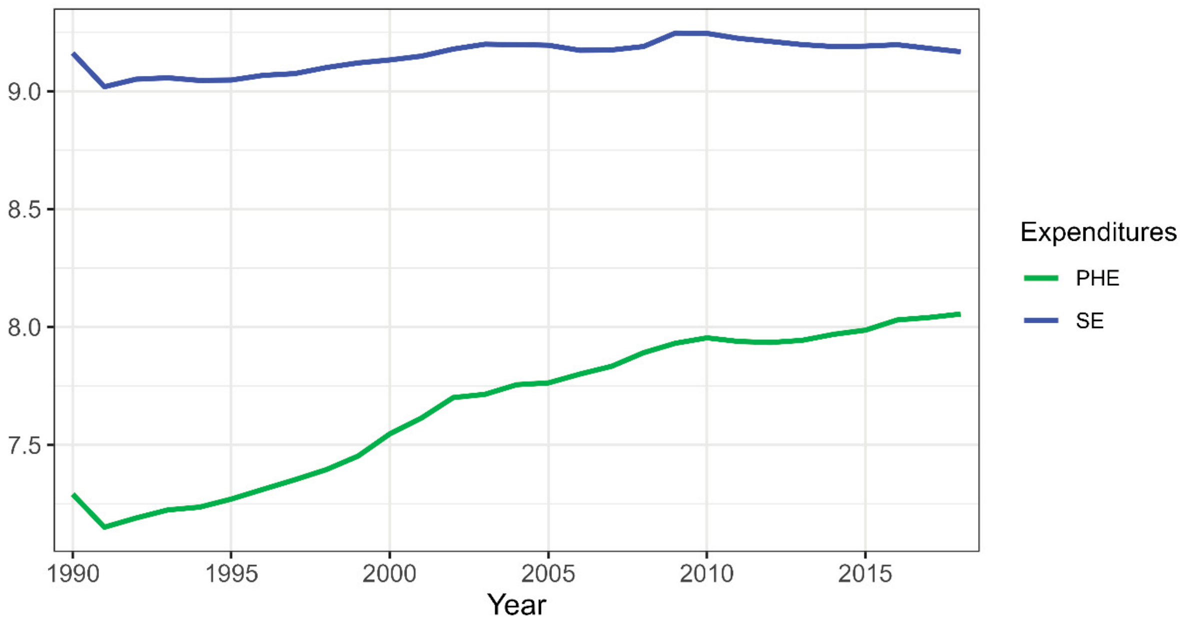
Table 1. 1 - Average inputs and control variables by country, 2000-2018

Country	DALY	Death	SE	PHE	Av. Edc.	% Eld.	% Up.
Australia	22011.11	484.37	6761.22	1958.20	12.47	13.05	6.63
Austria	22401.73	547.21	11964.05	2528.69	12.30	16.47	5.06
Canada	21303.77	494.96	6887.77	2276.72	13.63	13.47	7.93
Czech Republic	25687.39	723.53	4917.90	1347.05	12.52	14.87	6.02
Denmark	23518.75	601.21	11922.43	2604.56	14.26	16.17	6.10
Finland	22857.12	554.07	10289.58	1970.11	13.64	16.40	9.59
France	21567.49	494.35	10976.16	2528.31	12.86	16.38	9.94
Greece	22048.07	559.22	5763.02	1102.40	12.08	17.98	15.52
Ireland	23238.80	598.54	8345.54	2055.69	12.82	11.65	9.64
Italy	21170.22	493.50	9229.44	1790.14	11.39	19.10	9.67
Japan	18254.47	415.21	6437.96	2124.45	13.87	19.80	3.81
Luxembourg	22473.18	551.68	19892.24	3268.70	13.19	14.00	3.93
Netherlands	21283.12	543.55	8595.01	2640.95	13.89	14.84	6.06
New Zealand	23621.00	538.16	6269.12	1816.96	13.47	12.51	6.14
Norway	21484.04	517.81	12206.08	3088.60	14.48	15.57	4.15
Poland	27922.06	760.90	3871.62	705.83	12.34	13.00	11.70
Portugal	24293.69	600.86	5720.84	1211.35	9.94	17.28	8.81
Spain	20921.07	496.07	7136.90	1478.76	10.61	16.57	16.63

Turkey	30768.90	702.74	1693.06	446.60	10.30	6.63	10.11
United Kingdom	23400.48	566.11	7349.93	1995.72	13.14	16.37	6.62
United States	26833.03	587.98	8082.06	3459.98	13.22	13.15	5.92
Min	18254.47	415.21	942.72	410.70	8.47	5.50	3.48
Max	30768.90	919.73	19892.24	3459.98	14.91	19.80	16.63
Mean	23193.31	603.47	7140.63	1800.33	12.84	14.45	7.91

Source: author. DALY- disability-adjusted life years. Death rates (in age-adjusted rate). SE – Social expenditures (in average per capita 2018 US dollars, PPP adjusted). PHE – Public health expenditures (in average per capita 2018 US dollars, PPP adjusted). Av. educ. (average years of education). % Eld. (% of the population over 65 years). % Unem. (unemployment rate).

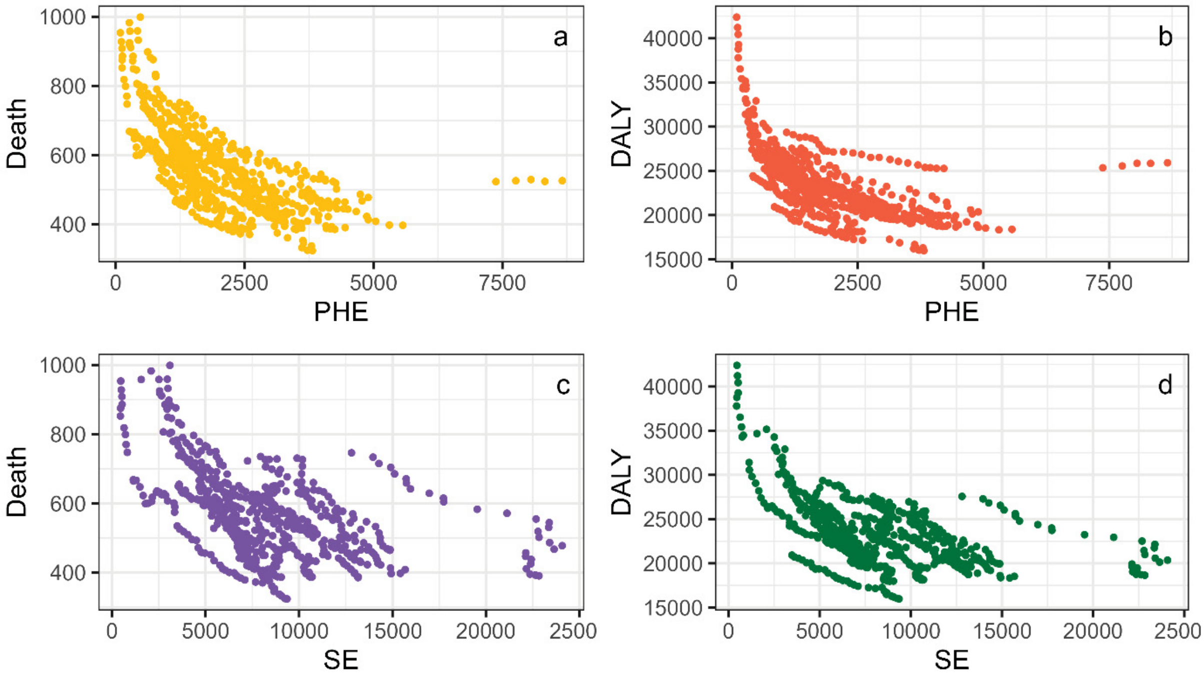
Figure 1. 1 - Timeline of log expenditure variables, for OECD Countries (1990-2018)



Source: author. PHE – Public health expenditures. SE – Social expenditures. All spending variables are in average per capita 2018 US dollars, PPP adjusted and log-transformed.

Figure 1.2 depicts the visual relationship between our variables of interest, namely, the two variables of spending (SE, PHE) and the health outcomes (DR, DALYs), where each point is a country-year combination. It is noticeable that DR and DALYs reflect a negative relationship with the spending variables. Moreover, the relationship between those combinations seems to be quadratic and decreasing rather than linear, which justifies our choice of using quadratic and interaction terms in our models.

Figure 1. 2 - Scatterplot between input and outputs variables, for OECD Countries 1990-2018.



Source: author. Panel A – Death Rates (DR, in age-adjusted rates) and Public Health Expenditures (PHE, in US 2018 dollars). Panel B – DALY (in age-standirdized rates), Public Health Expenditures (PHE, in US 2018 dollars). Panel C – Death Rates (DR, in age-adjusted rates) and Social Expenditures (SE, in US 2018 dollars. Panel D – DALY (in age-standirdized rates), Social Expenditures (SE, in US 2018 dollars). Each point is a combination of country-year.

1.3.2 Translog Estimations

In Table 1.2, we present the results of equation (1), using the indirect approach. Model (1) was estimated using OLS without controls, (2) OLS with controls included, and (3) with IV regression techniques. We noticed that the inclusion of socioeconomic controls was found significant for our model. On our estimations, the amount of elderly and unemployed seemed negatively related to DALY and DR, and the years of study were significant only for DR, suggesting that higher schooling is related to higher mortality.

Table 1. 2 - Translog estimations for the indirect channel

Death Rates (DR)					
(1)		(2)		(3)	
PHE	-3.615*** (0.417)	PHE	-1.352*** (0.273)	PHE	-1.223*** (0.247)
Ratio	0.645** (0.206)	Ratio	1.683*** (0.199)	Ratio	1.643*** (0.200)
time	-1.623*** (0.459)	time	-1.251*** (0.332)	time	-1.122*** (0.339)
PHE2	1.789*** (0.401)	PHE2	-0.133 (0.253)	PHE2	-0.297 (0.236)
t2	-0.318 (0.431)	t2	0.158 (0.357)	t2	0.196 (0.357)
PHET	-0.662 (0.476)	PHET	-0.388 (0.326)	PHET	-0.577* (0.336)
		p_eld	-1.395*** (0.132)	p_eld	-1.375*** (0.132)
		p_unen	-0.751*** (0.128)	p_unen	-0.761*** (0.128)
		y_stud	0.283* (0.148)	y_stud	0.306** (0.149)
Ridge (k)	0.007		0.010		0.010
Obs	609		609		609
R2	0.697		0.762		-

DALYs					
(1)		(2)		(3)	
PHE	-4.145 (0.252)***	PHE	-2.585 (0.252)***	PHE	-2.283 (0.246)***
Ratio	-0.406 (0.153)**	Ratio	0.500 (0.142)***	Ratio	0.570 (0.134)***
time	-2.086 (0.294)***	time	-1.921 (0.286)***	time	-1.774 (0.285)***
PHE2	2.151 (0.241)***	PHE2	1.461 (0.234)***	PHE2	1.053 (0.229)***
t2	0.1 (0.306)	t2	0.767 (0.271)**	t2	0.764 (0.271)**
PHET	0.09 (0.294)	PHET	0.307 (0.294)	PHET	0.237 (0.292)
		p_eld	-1.495 (0.093)***	p_eld	-1.472 (0.092)***
		p_unen	-0.481 (0.091)***	p_unen	-0.543 (0.091)***
		y_stud	-0.316 (0.105)**	y_stud	-0.253 (0.105)*
Ridge (k)	0.009		0.006		0.007
Obs	609		609		609
R2	0.666		0.773		-

Source: author. (1) Model without controls using OLS. (2) Model with added controls using OLS. (3) Model using regime corruption as IV. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. PHE – Public health expenditures. Ratio – Ratio between Social and Health expenditures over Health Expenditures alone. y_stud - estimated av. years of study. p_eld - % above 65 years population. p_unen - % unemployment rate.

Due to the results of the endogeneity tests, our preferred model is model (3), which covers IV assumptions. We found that public health expenditures are beneficial for health outcomes, and the effects are more prominent for DALY than DR. The relationship of PHE with DR is strictly decreasing, as the linear component of the model (3) was significant, and the quadratic one was not. Time alone is also significant and decreases DR: which is related to an aging population.

Higher PHE diminishes DALY, and the quadratic term (PHE2) here is significant and positive, in an example of decreasing returns. As the raise of PHE over time (PHET) was not found significant for DALY; the effect seems to be driven by improvements in PHE itself (PHE). Still, time alone contributes to decrease DALY in a decreasing way as the component t2 was significant and positive.

The ratio does not seem to contribute to our health outcomes variables – instead, their signals and significant levels point that the higher the ratio, the higher the DALY and the higher the DR. We theorise that SE should not restrict the effects of PHE, but there is a possible effect emerging from some competition of funding.

In Table 1.3 we present the results for the direct channel. Model (1) was estimated using OLS without controls, (2) OLS with controls included, (3) with IV regression and only PHE instrumentalized and (4) using instruments for both PHE and SE. Although we do not have theoretical evidence to deem SE as endogenous in this relationship, our preferred model of this table is model (4), which considers the results of our endogeneity tests. Still, the results for models (3) and (4) change very little in magnitude and change nothing in terms of significance levels – revealing that interpreting SE as endogenous does not change our interpretation.

Virtually the same relationships for the control variables were found – negative correlations with elderly and unemployed, and positive correlations with average schooling. This time, the coefficients for DR are somewhat higher in magnitude than for DALYs.

Table 1. 3 - Translog estimations for the direct channel

Death Rates (DR)							
(1)		(2)		(3)		(4)	
PHE	-3.422*** (0.370)	PHE	-2.492*** (0.280)	PHE	-2.484*** (0.270)	PHE	-2.063*** (0.267)
SE	-0.600 (0.375)	SE	1.460*** (0.270)	SE	1.944*** (0.262)	SE	1.567*** (0.259)
time	-0.786* (0.417)	time	-0.960*** (0.308)	time	-0.884*** (0.297)	time	-0.738** (0.301)
PHE2	0.899*** (0.263)	PHE2	-0.684*** (0.215)	PHE2	-1.600*** (0.208)	PHE2	-1.610*** (0.206)
SE2	1.134*** (0.288)	SE2	0.648*** (0.210)	SE2	0.848*** (0.206)	SE2	1.279*** (0.236)
t2	-0.190 (0.416)	t2	0.300 (0.358)	t2	0.267 (0.344)	t2	0.303 (0.347)
PHESE	-0.062 (0.235)	PHESE	-1.059*** (0.162)	PHESE	-1.161*** (0.154)	PHESE	-1.587*** (0.159)
SET	-1.903*** (0.300)	SET	-1.331*** (0.227)	SET	-0.722*** (0.215)	SET	-0.915*** (0.219)
PHET	0.141 (0.342)	PHET	0.294 (0.244)	PHET	0.040 (0.224)	PHET	0.002 (0.225)
		p_eld	-1.368*** (0.135)	p_eld	-1.390*** (0.129)	p_eld	-1.373*** (0.131)
		p_unen	-0.646*** (0.128)	p_unen	-0.849*** (0.126)	p_unen	-0.831*** (0.126)
		y_stud	0.259 (0.150)	y_stud	0.398*** (0.145)	y_stud	0.396*** (0.147)

Ridge (k)	0.008		0.011		0.011		0.011
Obs	609		609		609		609
R2	0.696		0.754		-		-

			DALYs				
	(1)		(2)		(3)		(4)
PHE	-3.036*** (0.239)	PHE	-2.3*** (0.216)	PHE	-2.231*** (0.214)	PHE	-2.096*** (0.217)
SE	-2.316*** (0.239)	SE	-0.372 (0.211)	SE	-0.182 (0.211)	SE	-0.031 (0.208)
time	-1.295*** (0.264)	time	-1.316*** (0.241)	time	-1.303*** (0.239)	time	-1.076*** (0.242)
PHE2	1.67*** (0.172)	PHE2	0.828*** (0.163)	PHE2	0.416* (0.162)	PHE2	0.572*** (0.168)
SE2	1.124*** (0.186)	SE2	0.633*** (0.161)	SE2	0.707*** (0.163)	SE2	0.709*** (0.187)
t2	0.197 (0.294)	t2	0.795** (0.259)	t2	0.783** (0.257)	t2	0.829** (0.258)
PHESE	0.814*** (0.147)	PHESE	-0.057 (0.128)	PHESE	-0.106 (0.126)	PHESE	-0.470*** (0.134)
SET	-1.163*** (0.193)	SET	-1.032***(0.176)	SET	-0.773*** (0.171)	SET	-1.203*** (0.174)
PHET	0.198 (0.212)	PHET	0.498* (0.194)	PHET	0.392* (0.184)	PHET	0.524** (0.194)
		p_eld	-1.435***(0.095)	p_eld	-1.445*** (0.094)	p_eld	-1.453*** (0.095)
		p_unen	-0.4*** (0.09)	p_unen	-0.482*** (0.091)	p_unen	-0.468*** (0.09)
		y_stud	-0.315** (0.105)	y_stud	-0.264* (0.106)	y_stud	-0.291** (0.106)
Ridge (k)	0.011		0.009		0.009		0.009
Obs	609		609		609		609
R2	0.679		0.768		-		-

Source: author. (1) Model without controls using OLS. (2) Model with added controls using OLS. (3) Model using regime corruption as IV for PHE. (4) Model using regime corruption as IV for PHE and deliberative democracy index as IV for SE. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. PHE – Public health expenditures. y_stud - estimated av. years of study. p_eld - % above 65 years population. p_unen - % unemployment rate.

The coefficient for PHE was found higher when assuming a direct channel for SE than when assumed the indirect channel. The quadratic coefficient for PHE was negatively related to DR, pointing to increasing returns, and the interaction with SE was also found beneficial to reducing DR. Time is still negative and significant in their linear form, but not on the quadratic one.

PHE is contributing to decrease DALYs considering the result of its linear coefficient. The quadratic coefficient was significant and positive, pointing this time to decreasing returns. The interaction of PHE and time on this equation, the linear time trend and the significance of the term (t2) point to a decreasing effect of time on DALYs as well. This may also point to convergence to some plateau point in the relationship between PHE and DALY rates.

The coefficient for SE had the opposite signal of PHE for DR and was not significant for DALYs. The linear component of SE seems to have an opposite effect of PHE on DR: while PHE diminishes DR, SE does the opposite. However, on SE being treated as an input, their other coefficients on the equation also offer insights on how it interplays with PHE and time. Although its quadratic term was still found non-contributing, the interaction terms with PHE and with time were relevant and beneficial for decreasing DR and DALYs. On a production function, we do not assume that an input causes a decrease in the production – instead, when the coefficients are negative, it may mean that this input does not contribute to the production; and the net effect calculated by the output elasticities will consider the estimations for all coefficients.

1.3.3 Output elasticities and returns to scale

Further on the results of the translog estimations, we may extract the output elasticities estimates of our preferred models (IV models) for each input; which are displayed in Table 1.4. Due to the structure of the translog production function, and based on our previous results, our spending variables have both positive relationships with the outcomes and negative relationships, which might be caused by some overlapping of services and/or competition for funding. Moreover, the spending variables in the equation appear also in interaction with themselves and with time. Thus, it is needed to ascertain the real effect of each spending variable considering the estimated parameters altogether. The output elasticities measurements are in logarithmic form, so we may interpret them as percentage changes, and the number represents how much each input contributes to raising the output when the other inputs are held constant.

Considering our results in Table 1.4, PHE elasticity to DR is negative, between -0.072 and -0.435 depending on the model. So, a raise of 1% on PHE is related to a decrease between -0.072 and -0.435% on DR. PHE elasticity to DALY is also negative, between -0.075 and -0.153 across the models. Paralelly, a raise of 1% on PHE can decrease -0.075 to -0.153% DALY rates.

Table 1. 4 - Output elasticities for the expenditure’s variables, DR and LE

Outcome	Channel	Output elasticity PHE	Output elasticity SE	Output Elasticity time	Scale
DR	Indirect	-0.072	-	-0.006	-0.078
DALY	Indirect	-0.153	-	-0.009	-0.023
DR	Direct	-0.435	0.257	-0.008	-0.186
DALY	Direct	-0.075	0.086	0	0.009

Source: author.

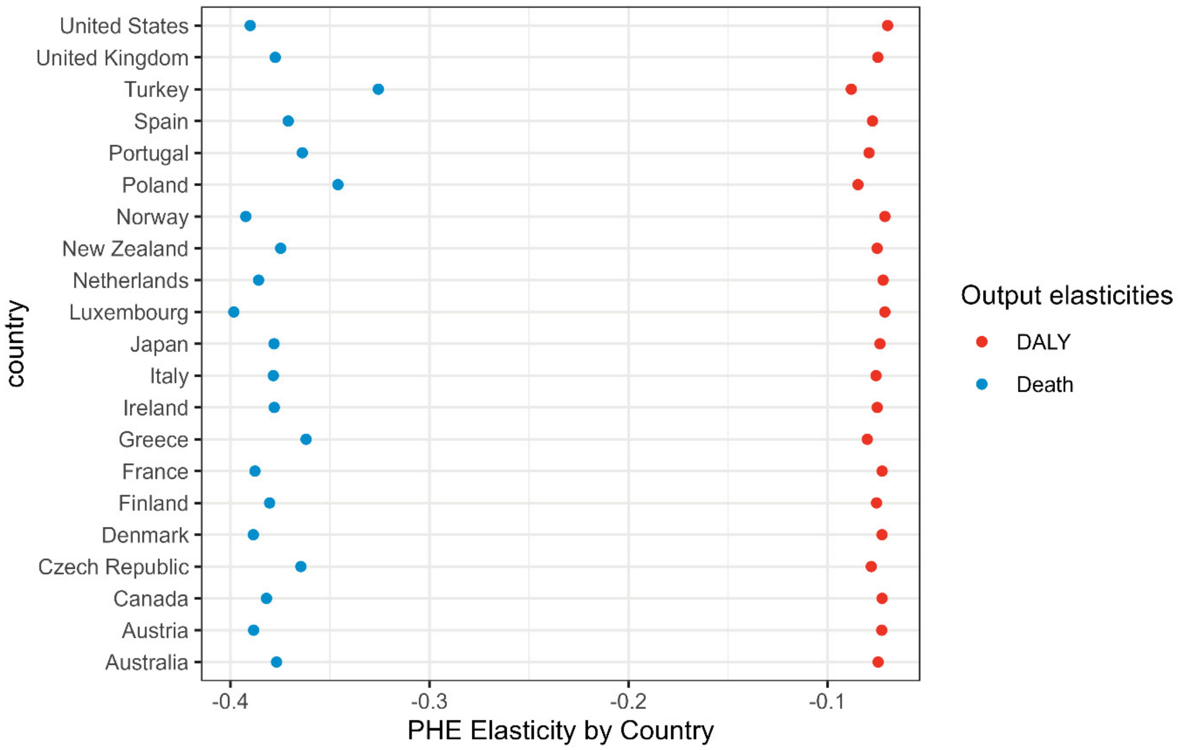
PHE – Public health expenditures. SE – Social expenditures.

Positive output elasticities for SE do not help diminish DR or DALY according to these estimations. Time has output elasticities close to zero in both specifications. As expected, the size of the scale effect is less than the unity, thus meaning the sum of the inputs put together impact health outcomes in a less than proportional way. The sum of the returns to scale hint that DR returns in this production function are negative (diminishing DR then) both on the direct and on the indirect setting. This is the case for DALYs under the indirect setting only, as PHE’s scale for DALY’s in the direct specification is offsetted by SE’s diverting effect.

Our results varied by country, especially for DR, as depicted in Figure 1.3. The countries who experienced a higher output elasticity for PHE (more elastic) were Luxembourg (-0.461), Norway (-0.454) and the United States (-0.452). This means that for these countries a higher PHE can produce a bigger reduction in DR than for countries such as Turkey (-0.377), Poland (-0.400) and Greece (-0.419), which hold the least elastic positions. On a different comparison, a 1% increase in PHE in Luxembourg is capable of diminishing DR by 0.084% more than the same 1% increase in PHE in Turkey. We assume these differences might be related to differences in health care systems and health policies or even efficiency in health care.

The heterogeneity by country for DALYs was more trivial, as the distribution of values is more concentrated. The countries who were more elastic for PHE and DALYs were this time Turkey (-0.088), Poland (-0.084) and Greece (-0.080); and the countries least elastic to PHE regarding DALYs were United States (-0.070), Luxembourg (-0.074) and Norway (-0.071). The absence of big heterogeneities in the output elasticities for DALY is another piece of evidence that supports the slower effects on DALYs for OECD countries. By these estimations, we can also point that health spending is being more useful to diminish disabilities in Turkey and Poland than diminishing mortality, while health systems of countries such as United States, Luxembourg and Norway experience enhancement on the mortality rates more markedly than on the morbidity side.

Figure 1. 3 - Output elasticities by OECD Country (1990-2018)



Source: author.

1.3.4 Lagged effects estimations

Equations (1) and (2) relied on contemporaneous effects, which means they assumed that spending on social services and health care affects our health outcomes in the same year. However, this hypothesis may not cover the delayed effects of investing in population health; as the literature points out they may exist (Reynolds and Avendano, 2018). To test this assumption; we also acknowledged non-contemporaneous effects, introducing one, two and five lags of year to check whether there are some measurable lag effects in the relationship between health and social expenditures by reestimating both equations. The results of the translog estimations and output elasticities are depicted in Tables S1.4, S1.5 and S1.6 of the supplementary material.

Our results suggest that there is a delayed effect of PHE up until 5 years after the spending for both DR and DALYs, and SE was not found beneficial for health outcomes enhancement in this specification as well.

Although the direction of the estimates and the interpretation of the main specifications still hold, the magnitude of the output elasticities has slightly changed for PHE. DR lagged effects are even larger than on our main specification, between -0.167 and -0.181. The estimates were between -0.009 and -0.167 for the DALY, close but more dispersed to our main specification. On the direct channel, DR elasticity to PHE is between -0.351 and -0.377; while DALY elasticity to PHE is between -0.081 and -0.350. Output elasticities for SE pointed in the opposite direction as PHE for both direct and indirect specifications. The results for lagged spending variables suggest that SE effects are not visible even when non-contemporary spending is taking into account.

1.4 DISCUSSION

In this study, we aimed to estimate a production function to understand how spending variables such as health and social expenditures can contribute to improving health outcomes. We developed our estimations using translog structure, for two health outcomes (DALY and DR), trying to cover the hypothesis of endogeneity amongst our spending variables and also investigating the possibility of cumulative effects. We have found that public health expenditures are still a valid source of health outcomes enhancement. The coefficients of the translog estimations indicate that PHE impacts our outcomes negatively and in an increasing way over time for DR and a decreasing way over time for DALY. We estimated the output elasticities for health and social expenditures and found that SE is not contributing to health outcomes in our analysis.

To further explore the role of SE, we adopted two different strategies. In one specification, we assumed that SE effects are indirect and mainly act potentializing PHE effects. We had several reasons for assuming indirect effects, for instance, the fact that SE is not designed to specifically achieve health gains; the lack of theoretical ground so far exposing why SE should be equally considered a contributor to health outcomes; and, lately, the possibility that any effects from social benefits would firstly affect the access to health care, and thus it would be a mediator rather than a significant effect modifier. Our results were out of the expected, pointing out that a higher ratio of social-to-health investment is significantly related to a rise in DR and DALY. The indirect effect, if considered, points to a competitive behaviour between the spending variables – or that indirectly the raise of SE can contribute to DR and DALY's increase. This conclusion differs from the claims of Bradley et al. (2011) and Dutton et al. (2018) who used ratios as explanatory variables.

The second specification regarded SE as directly capable of influencing health outcomes. There are also good reasons for assuming such hypothesis: if social support can affect income, housing, health behaviours and preferences – therefore it may impact health outcomes without relying solely on health care supply as a mediator. Besides, the intersectionality between the spending variables is noteworthy: there are services such as LTC that appear both on SE and PHE reports from the OECD (OECD, 2019a). Moreover, the definition of social assistance and health assistance may be blurred when we take into account cash transfers for injured, disabled and sick people. Even within this framework, SE effects were not found relevant when PHE is on the equation. The results of the coefficients and output elasticities show that under the structure of a production function, SE as an input does not imply a rise in the production of health. Our strategy differs from Reynolds and Avendano (2018), who modelled social expenditures together with health expenditures, breaking down the levels of SE into six categories, from which only two (education and old-age support) were significant. Also, SE coefficients were the opposite of the ones found for PHE, signalling a competitive behaviour similar to the one found via the indirect channel. One could expect that if not for DR, at least DALY's could be impacted by the enhancement of social support, but we did not verify this within our sample and specifications.

These results suggest that disregarding the specification, when we deal with endogeneity, control for socioeconomic variation and take both spending variables on the equation together, PHE will not only outperform SE but SE's role can be of a competitor. One of the possible reasons behind this phenomenon might be some level of competition for funding since both types of spending are subject to economic policy.

To the best of our knowledge, the existing literature has not employed the translog structure so far, and the sample of countries differs in each study. Consequently, one should be wary of making a direct comparison of the output elasticities' magnitudes with the previous studies. For DR, our results of -0.072 to -0.435 are relatively close to Ochalek et al. (2020) who have returned a value of -0.685, and between the limits Gallet and Doucoliagos (2007) found in their systematic review, within the range of -1.10 to 0.09. Hitiris and Posnett (1992) in their turn pointed to an elasticity between -0.059 and -0.080. Ochalek et al. (2020) found an elasticity of -0.260 for DALYs, while we have found -0.153 and -0.075.

Other differences in the model specification arise from previous authors. Bradley et al. (2016) for instance modelled the ratio of social-to-health spending against the health outcomes directly, without controlling for health expenditures. For Bradley et al. (2011), who modelled a specification with health expenditures and another without, the ratio was only significant for the specification that omitted health investment. Only Dutton et al. (2018) and Reynolds and Avendano (2018) presented significant estimates for SE once health expenditures were included in the model. It is worth mentioning that as the impact of health investment coexists with the alleged impact of SE; and it is probably affected by its interplay, one should not model SE without at least considering health expenditures as a control variable to avoid misspecification.

Time was considered as an input, intending to comprehend technology advances that may have impacted our results apart from spending variables. Also, including time in the model is a way of characterizing the economic activity. We found that time has been playing a relevant role in enhancing health outcomes over time: on a negative decreasing way for DALY and on a steady negative way for DR. When we consider the effect from all the coefficients together in the output elasticities, time estimates magnitudes are less than the other inputs, but its effect is non-negligible and the use of it as input is justifiable. Still on the results of time, our results suggested evidence of lagged effects for PHE, which also agrees with previous findings (Bradley et al., 2016; Thorpe and Joski, 2017; Gallet and Doucoliagos, 2017).

The output elasticities of our translog function slightly varied by country, notably a bit more for DR than for DALY. We assume these differences are caused by the differences in health systems and policies, or maybe efficiency differences. We tried to confirm whether the countries we found as the more elastic (Luxembourg, Norway, United States, Denmark) are among the most efficient in other studies as well (Varabyova and Muller, 2016; Gavurová et al., 2021), but the link is weak. In their study, Varabyova and Muller (2016) perform a systematic review of the efficiency of healthcare systems. They point out that there is a lack of internal consistency when it comes to defining efficiency, and even among studies of efficiency, the rankings do not match perfectly. Due to data limitations, we could not go further in investigating why these countries were more elastic to PHE than their peers on OECD, but future works should address this beyond the efficiency debate.

Our study has several limitations. Firstly, we acknowledge that not only health and social expenditures determine health outcomes. Individual factors such as biological or behavioural amongst others may have an important impact on health outcomes. Still, we used population-based observational data, using panel data estimation to overcome the country-fixed prevalence that may be correlated to these and other non-observable variables. The output elasticity and the results of the translog are also dependent on the initial state of health of each country. By using this technique, we also tried to cover this heterogeneity. It is noteworthy to mention that our results are dependent on the output variables we chose. Other outcome variables, especially non-life-threatening ones, might display different responses to PHE, SE and different substitutability patterns as well because not all health investments are reflected within our set of outcomes.

An important caveat of our study is the inability to ascertain incontestably the correction of the endogeneity problem. The results for our control variables such as education, the share of elderly and the unemployment rate do not agree with previous studies on how these socioeconomic variables impact health outcomes (Bayati et al 2013, OECD, 2017), giving counterintuitive signals, and we do not have an obvious reason for that. These circumstances might mean we could not overcome completely the endogeneity issue present in our data, even utilizing instruments that have been chosen carefully and passed the tests. This prevents the possibility of claiming strong causality within our estimates, rather than a correlation. The usage of aggregated data on spending and health outcomes is inherently difficult in finding good and useful instruments. We performed the estimations taking into consideration all the available techniques for dealing with this source of bias, by employing instrumental variables that were available in the literature. We also tried additional instruments that did not pass the tests for relevance. As supplementary attempts to deal with the endogeneity in our data, we undertook dynamic panel estimations, which gave no practical results due to the format of our panel being long and with a short number of countries. Thus, this approach was not presented in this study.

We used expenditure data from OECD countries, in terms of dollars per capita. Due to data availability, we did not account for differences in prices between or within countries, which prevented us from going further on price-elasticities measures or cost impacts. We also did not evaluate separately by health system once it would be difficult to categorize the specificities of our sample. Our subanalysis by country tried to overcome this limitation.

1.5 CONCLUSION

In this study, we concluded that health expenditures and social expenditures' interaction with each other is not necessarily contributive. The main implication of our findings is that we should be prudent in relying on spill-over effects from SE apart from its core goals. Our results suggest that SE cannot substitute PHE when we are aiming for specific population health issues such as DR and DALY rates. One should, instead, understand which channels of PHE can be enhanced with support from SE. Further works should assess with detail the channels of this potential interaction in the future.

Besides, further studies should investigate the possibility of competing funding and verify whether these effects we found for the OECD countries are reflected in low- and middle-income countries datasets.

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SUPPLEMENTARY MATERIAL

Table S1. 1 - Correlation matrix for the candidates of instrumental variables

	Reg_corr	Delib_dem
PHE	-0.603	0.588
SE	-0.682	0.710
DEATH	0.289	-0.269
LE	-0.341	0.346

Source: author. PHE – Public health expenditures. SE – Social expenditures. DEATH – age-standardized all-cause mortality rates. LE – Life expectancy at birth. Reg_corr – Regime corruption from V-DEM dataset. Delib_dem - Deliberative democracy index from V-DEM dataset.

Table S1. 2 - Weak instruments test

Model (1)	Res.Df	F	Pr(>F)
PHE	581		
	582	57.636	1.264e-13**
Model (2)	Res.Df	F	Pr(>F)
PHE	580		
	581	6.285	1.245e-2**
Model (3)	Res.Df	F	Pr(>F)
PHE	582		
	583	28.421	1.398e-7***
SE	582		
	583	14.106	1.902e-4***

Source: author. PHE – Public health expenditures. SE – Social expenditures

Table S1. 3 - Hausmann-Ridge endogeneity tests

Variable	Outcome	chi-squared statistic	chi-squared critical value
Model (1)			
PHE	Death	-2.130e-3	16.92
	LE	-8.559e-4	16.92
Model (2)			
PHE	Death	-4.045e-2	21.03
	LE	-1.150e-3	21.03
Model (3)			
PHE	Death	-1.091e-2	21.03
	LE	-2.371e-4	21.03
SE	Death	-1.899e-3	21.03
	LE	-5.199e-4	21.03

Source: author. Null hypothesis: joint endogeneity.

Table S1. 4 - Translog estimation for the indirect channel, including lagged spending variables

Death Rates (DR)					
1-y lag		2-y lag		5-y lag	
PHE	-0.838*** (0.251)	PHE	-0.759*** (0.24)	PHE	-0.452** (0.199)
Ratio	1.693*** (0.181)	Ratio	1.631*** (0.176)	Ratio	1.556*** (0.163)
time	-1.056*** (0.319)	time	-1.145*** (0.312)	time	-1.000*** (0.275)
PHE2	-0.818*** (0.231)	PHE2	-0.787*** (0.22)	PHE2	-0.789*** (0.18)
t2	0.371 (0.355)	t2	0.567 (0.357)	t2	0.878*** (0.336)
PHET	-0.631** (0.307)	PHET	-0.674** (0.297)	PHET	-0.784*** (0.252)
p_eld	-1.318*** (0.125)	p_eld	-1.313*** (0.123)	p_eld	-1.248*** (0.118)
p_unen	-0.764*** (0.124)	p_unen	-0.64*** (0.122)	p_unen	-0.38*** (0.115)
y_stud	0.424*** (0.144)	y_stud	0.418*** (0.143)	y_stud	0.393*** (0.139)
Ridge (k)	0.012		0.011		0.014
Obs	588		567		504

DALY					
1-y lag		2-y lag		5-y lag	
PHE	-2.052*** (0.236)	PHE	-1.844*** (0.226)	PHE	-0.452* (0.199)
Ratio	0.537*** (0.131)	Ratio	0.506*** (0.127)	Ratio	1.556*** (0.163)
time	-1.803*** (0.279)	time	-1.815*** (0.272)	time	-1*** (0.275)
PHE2	0.909*** (0.218)	PHE2	0.785*** (0.208)	PHE2	-0.789*** (0.18)
t2	0.896** (0.277)	t2	1.001*** (0.281)	t2	0.878** (0.336)
PHET	0.174 (0.282)	PHET	0.124 (0.273)	PHET	-0.784** (0.252)
p_eld	-1.458*** (0.09)	p_eld	-1.442*** (0.088)	p_eld	-1.248*** (0.118)
p_unen	-0.478*** (0.089)	p_unen	-0.408*** (0.087)	p_unen	-0.38*** (0.115)
y_stud	-0.254* (0.104)	y_stud	-0.252* (0.103)	y_stud	0.393** (0.139)
Ridge (k)	0.007		0.007		0.014
Obs	588		567		504

Source: author. Models using IV estimation. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. PHE – Public health expenditures. y_stud - estimated av. years of study. p_eld - % above 65 years population. p_unen - % unemployment rate.

Table S1. 5 - Translog estimation for the direct channel, including lagged spending variables

Death Rates (DR)					
1-y lag		2-y lag		5-y lag	
PHE	-1.773*** (0.259)	PHE	-1.63*** (0.247)	PHE	-1.249*** (0.209)
SE	1.839*** (0.227)	SE	1.689*** (0.217)	SE	1.393*** (0.184)
time	-0.506* (0.291)	time	-0.589** (0.278)	time	-0.591** (0.233)
PHE2	-1.379*** (0.206)	PHE2	-1.339*** (0.196)	PHE2	-1.329*** (0.169)
SE2	0.53*** (0.182)	SE2	0.524*** (0.176)	SE2	0.501*** (0.156)
t2	0.625* (0.356)	t2	0.793** (0.358)	t2	1.048*** (0.336)
PHESE	-1.279*** (0.137)	PHESE	-1.168*** (0.13)	PHESE	-0.923*** (0.105)
SET	-1.38*** (0.212)	SET	-1.356*** (0.206)	SET	-1.133*** (0.183)
PHET	-0.25 (0.229)	PHET	-0.336 (0.217)	PHET	-0.586*** (0.174)
p_eld	-1.38*** (0.131)	p_eld	-1.359*** (0.129)	p_eld	-1.249*** (0.124)
p_unen	-0.632*** (0.124)	p_unen	-0.5*** (0.122)	p_unen	-0.259** (0.118)
y_stud	0.305** (0.147)	y_stud	0.31** (0.146)	y_stud	0.306** (0.144)
Ridge (k)	0.012		0.013		0.017
Obs	588		567		504

DALY					
1-y lag		2-y lag		5-y lag	
PHE	-1.907*** (0.202)	PHE	-1.63*** (0.247)	PHE	-1.249*** (0.209)
SE	0.188 (0.181)	SE	1.689*** (0.217)	SE	1.393*** (0.184)
time	-1.107*** (0.23)	time	-0.589* (0.278)	time	-0.591* (0.233)
PHE2	0.455** (0.158)	PHE2	-1.339*** (0.196)	PHE2	-1.329*** (0.169)
SE2	0.422** (0.14)	SE2	0.524** (0.176)	SE2	0.501** (0.156)
t2	0.936*** (0.262)	t2	0.793* (0.358)	t2	1.048** (0.336)
PHESE	-0.374*** (0.111)	PHESE	-1.168*** (0.13)	PHESE	-0.923*** (0.105)
SET	-1.136*** (0.165)	SET	-1.356*** (0.206)	SET	-1.133*** (0.183)
PHET	0.422* (0.184)	PHET	-0.336 (0.217)	PHET	-0.586*** (0.174)
p_eld	-1.443*** (0.093)	p_eld	-1.359*** (0.129)	p_eld	-1.249*** (0.124)
p_unen	-0.406*** (0.088)	p_unen	-0.5*** (0.122)	p_unen	-0.259* (0.118)
y_stud	-0.291** (0.104)	y_stud	0.31* (0.146)	y_stud	0.306* (0.144)
Ridge (k)	0.010		0.013		0.017
Obs	588		567		504

Source: author. Models using IV estimation and assuming PHE and SE endogenous. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. PHE – Public health expenditures. y_stud - estimated av. years of study. p_eld - % above 65 years population. p_unen - % unemployment rate.

Table S1. 6 - Output elasticities for the expenditure variables, DR and DALY, including lagged spending variables

Outcome	Channel	Lag	Output elasticity PHE	Output elasticity SE	Output elasticity time	Scale
DR	Indirect	1-y	-0.181	-	-0.008	-0.189
DR	Indirect	2-y	-0.175	-	-0.01	-0.185
DR	Indirect	5-y	-0.167	-	-0.002	-0.168
DALY	Indirect	1-y	-0.009	-	0	-0.010
DALY	Indirect	2-y	-0.013	-	0	-0.013
DALY	Indirect	5-y	-0.167	-	-0.001	-0.168
DR	Direct	1-y	-0.377	0.168	-0.007	-0.216
DR	Direct	2-y	-0.362	0.161	-0.003	-0.203
DR	Direct	5-y	-0.351	0.15	-0.003	-0.204
DALY	Direct	1-y	-0.081	0.044	-0.002	-0.039
DALY	Direct	2-y	-0.361	0.161	-0.002	-0.203
DALY	Direct	5-y	-0.350	0.149	-0.003	-0.204

Source: author. PHE – Public health expenditures. SE – Social expenditures. DR – Death Rates. DALY – Disability-adjusted life years.

2 CLIMATE CHANGE AND BIRTH OUTCOMES – EVIDENCE FROM BRAZIL

Abstract

Background: Climate change is the biggest challenge of our century. Its impacts cover environmental, economic, social and health effects. However, little is known about the impacts of climate change on newborn health in Brazil.

Methods: We used a dataset of almost 45 million observations to ascertain whether there is any impact of both hotter temperatures and shifts from the historical averages on newborns' birth weights across Brazilian municipalities during the period of 2000 to 2020.

Results: According to our results, both additional hotter days and shifts from the established weather are capable of decreasing birthweight across our samples. Although positive shocks were more frequent, also cold shocks are damaging to perinatal health; and the third trimester was found the most sensitive to weather shocks. Results for precipitation, however, remain unclear. The estimates are especially higher for the population living on isolated areas.

Conclusions: Our results imply that climate change effects have already arrived in Brazil. In a country that still suffers with severe social inequalities, vulnerable populations should be protected, and coping mechanisms should be widespread to decrease the risk of climatic exposure.

Keywords: Health economics, Maternal and child health, Climate change, birthweight, in-utero exposure.

2.1 INTRODUCTION

Climate warming in the last few decades has been unambiguous – air temperature and ocean temperatures have risen substantially, and ice sheets have been losing mass (IPCC, 2024). Climate change estimates for the future are pointing to several shifts in temperature, precipitation, and other weather variables. The average global temperature will likely be increased by 1.5ºC in the 2081-2100 period[2], which will not be regionally uniform. Not only heat shocks, but estimates point that some regions could be affected by extreme colds, and abrupt changes in the weather will become more common. Along with these changes, we may expect that atmospheric circulation, water and carbon cycle, and ocean currents will be affected by shifts from their historical paths (Collins et al, 2013; IPCC, 2024a).

In this context, Brazil is one of the regions expected to be most affected by rising temperatures (Krusell and Smith Jr, 2022). As the country strives to combat poverty, it continues to grapple with significant social inequality, land use problems, and deforestation. These issues increase the climate vulnerability of many people, leaving them more exposed to the impacts of climate change (IPCC, 2024b).

Economics of climate change is a growing field of economic study, with examples being present in introductory economics textbooks – which shows climate change economics has become mainstream economics in the few last years (Charmetant et al., 2024). This field focuses on the impacts climate change has been inflicting in several areas such as agriculture, labour productivity, economic growth and income, international trade, industrial services output, energy supply and demand, population structure and growth, migration, political stability, crime and aggression, and, of course, health (Deschênes et al., 2009; Dell et al., 2014; Deryugina and Hsiang, 2014; Carleton and Hsiang, 2016; Tol, 2024). In one meta-analysis that estimated the total economic impact of climate change, health impact costs ranked second position, only behind labour productivity losses (Tol, 2024).

On health impacts from weather changes, heatwaves and colds are linked to increasing cause-specific mortality rates, including cardiovascular, respiratory, and

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[2] According to Intergovernmental Panel on Climate Change (IPCC) scenarios RCP4.5,RCP6.0 and RCP8.5.

cerebrovascular diseases (Anderson and Bell, 2009; Basagaña et al., 2011; Alahmad et al., 2022). Other studies pointed out the effects on mental health emergencies or even suicides (Mullings and White, 2019; White et al., 2023).

Further on health impacts, climate change exposure literature has blossomed in the last two decades, when it merged with the fetal-origins hypothesis (Almond and Currie, 2011). According to this theory, events that happened in utero, proxied by birth outcomes, have long-lasting effects on health, schooling, and cognitive outcomes later in life (Torche and Echevarría, 2011; Figlio et al., 2014; Rocha and Soares, 2015; Wilde et al., 2017). In testing this set of assumptions, weather shocks and hotter weather were found to be related to poor outcomes in newborns in many papers (Deschênes et al., 2009; Grace et al., 2015; Poursafa et al., 2015; Andalón et al., 2016; Molina and Saldariaga, 2017; Hajdu and Hajdu, 2021, Zhang et al., 2017; Le and Nguyen, 2021). Other studies, however, did not find such a clear relationship (Wolf and Armstrong, 2012).

The literature so far focuses on in-utero exposure to weather variations such as hot and cold days (Deschênes et al., 2009; Chen et al., 2020; Cil and Kim, 2022), heat or cold waves (Bruckner et al., 2014; Hajdu and Hajdu, 2021; Andriano, 2023), droughts and water shocks (Rocha and Soares, 2015; Le and Nguyen, 2021; Abiona and Ajefu, 2022), or extreme events like hurricanes and other tropical storms (Currie and Rossin-Slater, 2013; Parayiwa and Behie, 2018; Sun et al., 2020). Another branch of the literature instead tries to focus on the changes from the established long-term climate and its impact on birth outcomes (Pereda et al., 2014; Andalón et al., 2016; Molina and Saldarriaga, 2017; Cil and Kim, 2022).

Considering this literature, and the shortage of previous evidence for in-utero exposure to climate change for the Brazilian population, we will estimate whether the temperature and precipitation in the period between 2000 and 2020 have affected birth outcomes in Brazilian municipalities. There are many reasons for that. Firstly, Brazil has the biggest population in Latin America. Henceforth, acknowledging weather effects for this population has an importance on its own. Also, with such several observations, our sample of almost 45 million observations may have a better accuracy in ascertaining the relationship between weather variables and birth weight, if there is one. Apart from the sample size, the heterogeneity of different climates and subclimates spread over more than five thousand municipalities contribute to favourable asymptotic characteristics, which can enhance the reliability of the statistical estimates being discussed.

Secondly, developing countries may be more sensitive to weather shocks once air conditioning and other coping mechanisms are not available or affordable for the whole population (Molina and Saldarriaga, 2017, Meierrieks, 2021). For instance, even though Brazil is mostly under tropical weather, only 43% of the residences have access to air conditioning (EPE, 2018; Bezerra et al., 2021). The evidence so far has already pointed to a higher degree of weather vulnerability in low- and middle-income countries (Grace et al., 2015; Andalón et al. 2016; Meierrieks, 2021).

Besides, birth weight is a predictor of future health and education attainment (Torche and Echelvarría, 2011; Falcão et al., 2020), thus affecting the formation of the country's human capital. Understanding the effects of climate change is essential to overcome the obstacles of reducing poverty and inequality cycles across the country. By estimating the effects on the Brazilian population, we aim to provide empirical guidance for public policies on climatic change effects.

This study is organized as follows. Besides this introduction, in the second section, we provide a literature review of the empirical findings of climate change health economics. In the third section, we introduce our data and methods. The fourth section is dedicated to the results, followed by a discussion on the fifth section and a conclusion on the sixth section.

2.2 EMPIRICAL LITERATURE

The first study which addressed the birth outcomes effects of in-utero exposure to temperature shocks due to climatic change was by Deschênes et al (2009). Since then, several other studies have been dedicated to developing a better understanding of this relationship.

The most used outcome is birth weight. The usage of birth weight relies on at least three bases: i) the growing literature of the fetal-origins hypothesis, where the shocks that happened during pregnancy are theoretically capable of affecting perinatal and future health (Almond and Currie, 2011); ii) the literature reflecting long-lasting effects of birth weight on educational achievements and human capital formation (Torche and Echelvarría, 2011, Figlio et al., 2014; Wilde et al., 2017) and iii) the relative superiority and convergence of this variable as the best proxy for pregnancy outcomes (Almond and Currie, 2011).

Some authors estimated the effects by using either birthweight as a continuous variable or a categoric variable for low birthweight (LBW), while temperature and precipitation lead as the independent variables under study within this field (Deschênes et al., 2009; Torche and Corvaland, 2010; Wolf and Armstrong, 2012; Pereda et al., 2014; Rocha and Soares, 2015; Poursafa et al., 2015; Grace et al., 2015; Andalón et al., 2016; Ha et al., 2017; Molina and Saldarriaga, 2017; Chen et al., 2020; Hajdu and Hajdu, 2021; Ding et al., 2023; Andriano, 2023). Some studies have extended the discussion by inserting other birth outcomes such as preterm birth, height/size, APGAR score[3] and infant mortality (Wolf and Armstrong, 2012; Rocha Soares, 2015, Poursafa et al 2015; Andalón et al., 2016; Molina and Saldarriaga, 2017; Ha et al., 2017; Cil and Kim, 2022); while others have collected evidence from pregnancy outcomes such as eclampsia, preeclampsia or using hospital admissions of the pregnant women (Wolf and Armstrong, 2012; Poursafa et al., 2015; Rocha and Soares, 2015; Kim et al., 2020; Cil and Kim, 2022). Additionally, other weather variables such as sunlight and relative humidity also appear in empirical studies as controls (Torche and Corvaland, 2010, Pereda et al., 2014).

The literature that found effect so far is broad and has already pointed out that weather shocks might affect birthweight through biological, psychological, and socioeconomic factors. Moreover, these possible transmission channels might interact with one another, and until now, these associations are not fully known.

On the biological dimension, it is thought that weather shocks, specifically hotter temperatures, are capable of harming protein synthesis and provoking dehydration, which can be linked-to in-utero growth restriction and thus loss of birth weight (Poursafa et al., 2015; Rocha and Soares, 2015; Andalón et al., 2016). During heat exposure, oxytocin levels are raised, and antidiuretic hormones are launched, anticipating the delivery (Poursafa et al 2015, Andriano, 2023); which means some babies may be born before the optimal time and with a lighter weight (Andalón et al., 2016; Andriano, 2023). During heat, the human body diverts blood for cooling, which can affect other organs functioning and alter placenta blood exchanges (Ha et al., 20107; Carleton and Hsiang, 2016; Cil and Kim, 2022; Ding et al., 2023). Placenta

[3] APGAR score is a scoring system to evaluate the vital signs of the newborn for the first one and five minutes after birth.

growth itself may also be damaged by heat, as already found in other animals (Lawrence et al., 2020). Placenta malfunctioning may therefore affect directly fetal nutrition (Lawrence et al., 2020; Ding et al., 2023), ultimately altering birthweight. Other authors also pointed out the rise of weather-related infectious diseases which may lead to fetus malnutrition (Poursafa et al., 2015; Wolf and Armstrong, 2012; Andalón et al., 2016; Carleton and Hsiang, 2016; Kim et al, 2020) and increased pollution effects due to heat (Wolf and Armstrong, 2012; Ha et al., 2017; Hajdu and Hajdu, 2021).

Stress hormones can also affect placental exchanges and may affect intra-uterine growth (Chen et al., 2020), which is the idea behind the psychological dimension of transmission channels. Post-traumatic responses after weather-related events may be pointed to as sources of stress (Parayiwa and Behie, 2018; Helldén et al. 2021), or, likewise, stress due to income-related losses caused by these extreme events (Andalón et al., 2016; Chen et al., 2020). Another possibility is that during heat people may change their lifestyle and alter their behaviours towards physical activity and diet (Lawrence et al., 2020).

On the socioeconomic dimension, some authors argue that weather shocks affect agriculture and food production, which may cause detrimental effects on birthweight due to malnutrition or food insecurity issues (Grace et al., 2015; Andalón et al., 2016; Molina and Saldarriaga, 2017; Andriano, 2023). From another possible point of view, the loss of agricultural income might be one of the reasons behind the birthweight loss (Chen et al., 2020; Le and Nguyen, 2021; Andriano, 2023). In Chart 2.1 we summarize the main transmission channels pointed out in the literature so far.

Some studies have found that the weather shocks felt in the second or third trimester of pregnancy are more determinant of lower birth weight, which suggests that fetus development is affected in the late stages of pregnancy (Deschênes et al., 2009; Pereda et al., 2014; Ngo and Horton, 2016; Hajdu and Hajdu, 2021; Le and Nguyen, 2021; Cil and Kim, 2022; Andriano, 2023). Carleton and Hsiang (2016) and Hajdu and Hajdu (2021) also mentioned the role of fetus selection, where those fetuses who are more sensitive to heat exposure are lost during the first trimester of the pregnancy, thus the effect concentrates during the remaining trimesters.

One of the biggest advantages of investigating the effects of climate change on health outcomes is the exogeneity of the effect. In other words, the literature agrees that weather variables exert an exogenous influence on pregnancy and birth outcomes, thus avoiding the risk of reverse causality. Still, the risk of omitted variables could be a concern (Dell et al., 2014). For this reason, many studies have added control variables to have a more plausible estimation. Overall, many socioeconomic variables are used as control variables. The most common ones are mother's information on educational level, income level, access to piped water and electricity, parent's employment and marital status, prenatal care and urbanization status of the locality (Torche and Corvaland, 2010; Pereda et al., 2014; Grace et al., 2015; Ngo and Horton, 2016; Basu et al., 2018; Hajdu and Hajdu, 2021, Le and Nguyen, 2021).

Chart 2. 1 - Transmission channels pointed in the literature

Dimensions	Transmission Channels	Authors
Biological	- In utero growth restriction - Heat stress - Dehydration - Increased incidence of infectious diseases and malnutrition - Increased pollution	Andalón et al. (2016) Rocha and Soares (2015) Grace et al. (2015) Poursafa et al. (2015) Andalon et al. (2016) Lawrence et al. (2020) Ha et al. (2017) Chen et al. (2020) Le and Nguyen (2021) Ding et al. (2023) Andriano (2023)
Psychological	- Distress caused by extreme events - Behavior changes due to climate change	Andalón et al. (2016) Parayiwa and Behie (2018) Lawrence et al. (2020) Chen et al. (2020)
Socioeconomic	- Agricultural shocks causing loss of income and food insecurity - Loss of access to healthcare	Grace et al. (2015) Andalón et al. (2016) Molina and Saldarriaga (2017) Chen et al. (2020) Le and Nguyen (2021) Andriano (2023)

Source: author.

Some studies use deviation of the historical weather to map out the temperature and precipitation shocks (Pereda et al., 2014; Andalón et al., 2016; Molina e Saldarriaga, 2017; Cil and Kim, 2022). Others, in trying to account for the non-linearities in temperature effects, opt to categorize temperature and precipitation variables in bins and estimate the effects from the number of times in which the weather variables fall within those categories (Deschênes et al., 2009; Dell et al., 2014; Kim et al., 2020; Hadju and Hadju, 2021). Generally, authors report using location-year fixed effects (Deschênes et al., 2009; Kim et al., 2010; Deschênes, 2014; Rocha and Soares, 2015; Grace et al., 2015; Andalón et al., 2016; Molina and Saldarriaga, 2017;

Wilde et al., 2017; Chen et al., 2020; Kim et al., 2020; Hajdu and Hajdu, 2021; Cil and Kim, 2022).

The authors often deal with other modifiers of the effect. Migration, if possible, must be ruled out of the sample, as it becomes difficult to identify those pregnant who are effectively exposed to weather shocks in a given location (Molina and Saldarriaga, 2017; Kim et al., 2020; Chen et al., 2020). Optimally, adaptation to weather shocks should also be accounted for whenever possible. As these measures may mitigate part of the effects of climate change, their protective effects have an interest on their own. The literature to this point has inconsistent evidence in this regard, with studies pointing to benefits (Barreca et al., 2016) while others have found the adaptation has no effect at all (Deschênes, 2014; Deryugina and Hsiang, 2014; Mullins and White, 2019).

We have found two studies on this topic for the Brazilian population. Pereda et al (2014) have estimated the climatic effects on birth outcomes using SIAB information ("Sistema de Informações da Atenção Básica", from Portuguese), using the 2005-2012 period. They took advantage of using panel data estimation, however, due to limitations in Brazilian sources of weather station data back then, the estimation was restricted to less than one million observations, using aggregated level data. Nonetheless, their findings point to a negative effect on birthweight, while the mother's education and access to piped water were found to be positive modifiers of the effect. Rocha and Soares (2015) have estimated the birthweight effect of water scarcity in the Northeastern region of Brazil, a region historically classified as semi-arid which faces yearly precipitation levels lower than 800mm. Their findings point out that negative shocks on water access are associated with poor birth outcomes such as lower birthweight, shorter gestational periods and higher infant mortality.

2.3 METHODS

2.3.1 Data

2.3.1.1 Population data

This impact evaluation study uses data from SINASC ("Sistema de Informações sobre Nascidos Vivos", from Portuguese), for Brazilian births between 2000 and 2020. SINASC is an administrative record, which covers the universality of the Brazilian live births. Deliveries that took place at the hospital or outside it are both recorded in the SINASC database. Newborn information such as birth weight, location of birth, race, sex, type of delivery (caesarean or vaginal), gestational age, and other information are available. Also, the mother's information such as age, marital status, education, number of previous pregnancies, municipality of residence, municipality of delivery, and the number of prenatal appointments taken during the pregnancy are available.

On the SINASC database, birth weight is a discrete variable reported in grams. Although the average birthweight in Brazil during our period was 3244g, some observations that reported values on the extremes of the distribution were viewed with scepticism. This is the case for observations that reported weight equal to zero (7886 observations) and weight of unlikely high values (499 observations). According to Da Silva et al. (2010), babies that weigh less than 1000g are underreported in SINASC; which might be one of the reasons why so many observations were reported as zero[4]. On the upper limit of distribution, babies with weights such as 8000g, 9000g or more are probably measurement errors. For example, according to the news, the heaviest baby ever born in Brazil until 2020[5] weighed 6800g (Taylor, 2023). Considering these concerns, we selected our sample for birthweights between 1000g and 6800g[6]. On Figure 2.1, it is depicted the smoothed distribution of birthweight for our sample.

Several conditions related to epidemiological trends in birthweight were addressed within our sample design to avoid confounding factors. Mothers of multiple births (duplets, triplets, etc) may bias the sample, once low birth weight offspring are common in this case and non-necessarily weather-related (da Silva et al., 2010; Molina and Saldarriaga, 2017; Falcão et al., 2020). Another significant factor is the mother's age. Birthweight increases as the mother's age increases, but for the extremes in age distribution (teenagers and women close to the menopausal period), birthweight is statistically lower (Swamy et al., 2012; Falcão et al., 2020). Henceforth, we selected only births from mothers within the average fertile period, between 16 and 45 years.

[4] The Federal Council of Medicine on the Resolution n.º 1779 established that babies that are born under 500g and that do not present live signals are considered Fetal Deaths (CFM). So, another hypothesis might be that fetal deaths are sometimes misreported with weight equal to zero in our dataset.

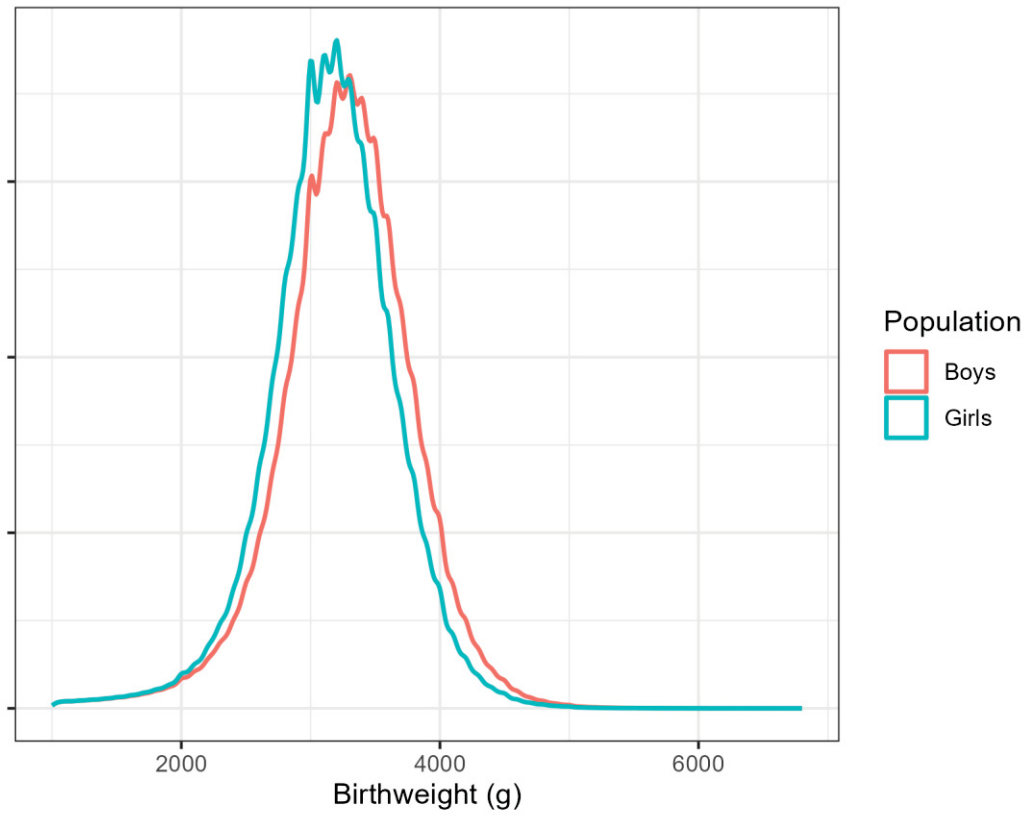
[5] The record of 6800g was substituted by a baby that was born with 7300g, but only in 2023.

[6] The full universe of babies born between 2000-2020 is 62,021,526 individuals. After removing those who had incomplete and/or inconsistent information and complied our inclusion criteria, our sample ended up with 44,993,971 newborns.

Lastly, the number of previous pregnancies was also collected as the literature shows that birth weight increases with birth order (Falcão et al., 2020).

Newborns of female sex have average lighter birthweight worldwide and higher rates of intra-uterine growth restriction (Kiserud et al., 2018; Falcão et al., 2020). Due to these reasons, we stratified our sample by gender. Figure 2.1 reflects these differences, as the distribution of boys is more at the right than for girls.

Figure 2. 1 - Birthweight distribution



Source: author.

Gestational age (in weeks) is a variable whose collection technique has changed during our period of analysis. Until 2010, gestational age was recorded using six categories[7], and from 2011 on, it started to be recorded as a discrete variable counting from the date of the last menstrual period (LMP). When the woman is not certain about her LMP, an ultrasound and/or physical examination might be used to ascertain the gestational age during the prenatal appointments (Matijasevich et al.

[7] Less than 22 weeks, between 22 to 27 weeks, between 28 to 31 weeks, between 32 to 36 weeks, between 37 to 41 weeks and more than 42 weeks.

2013; Szwarcwald et al., 2019). For consistency, we reclassified the discrete variables into the same categories of the early years' classification, and we excluded observations that did not report gestational age. To assess the exposition period for each pregnant, we estimated the approximate date of conception for each newborn, based on the gestational age and date of birth information. The approximate date of conception was also used to estimate the dates that enclose each gestational trimester per observation.

Other variables regarding mother characteristics were selected to build the set of possible covariates. This is the case of the mother's marital status, years of study and the number of attended prenatal appointments. While the two first are meant to cover part of the socio-economic background of the family, the prenatal care variable tries to acknowledge the heterogeneity of access to gestational care on the health system's structure, besides the mother's preferences.

Table 2. 1 - Descriptive Statistics for mother and newborns characteristics

Variable	Boys		Girls	
	%	Number	%	Number
N = 44,993,971	51.26	23065618	48.74	21928353
Mother's marital status				
married	36.43	8403655	36.40	7983098
non-married	63.57	14661963	63.60	13945255
Years of Study				
zero	1.55	356641	1.55	340436
1 to 3 years	6.72	1549912	6.74	1478221
4 to 7 years	25.34	5846109	25.38	5565773
8 to 11 years	49.50	11416768	49.48	10849472
12 years or more	16.89	3896188	16.85	3694451
Gestational Weeks				
> 22	0.01	3303	0.01	3006
22 to 27	0.12	26823	0.09	20938
28 to 31	0.67	151471	0.59	129108
32 to 36	7.10	1638500	6.68	1462027
37 to 41	90.17	20798487	90.64	19877137
42 >	1.93	447034	1.99	436137
Nº of prenatal visits				
zero	1.89	435462	1.88	412705
1 to 3	7.26	1674808	7.16	1570298
4 to 6	28.35	6539283	28.00	6140443
7 or more	62.50	14416065	62.96	13804907

Birthweight			
	Mean	3273.99	3164.44
	Max	6800	6800
	Min	1001	1001
Mother age			
	Mean	26.10	26.12
	Max	45	45
	Min	16	16
Nº previous children (parity)			
	Mean	1.10	1.10
	Max	20	20
	Min	0	0

Source: author.

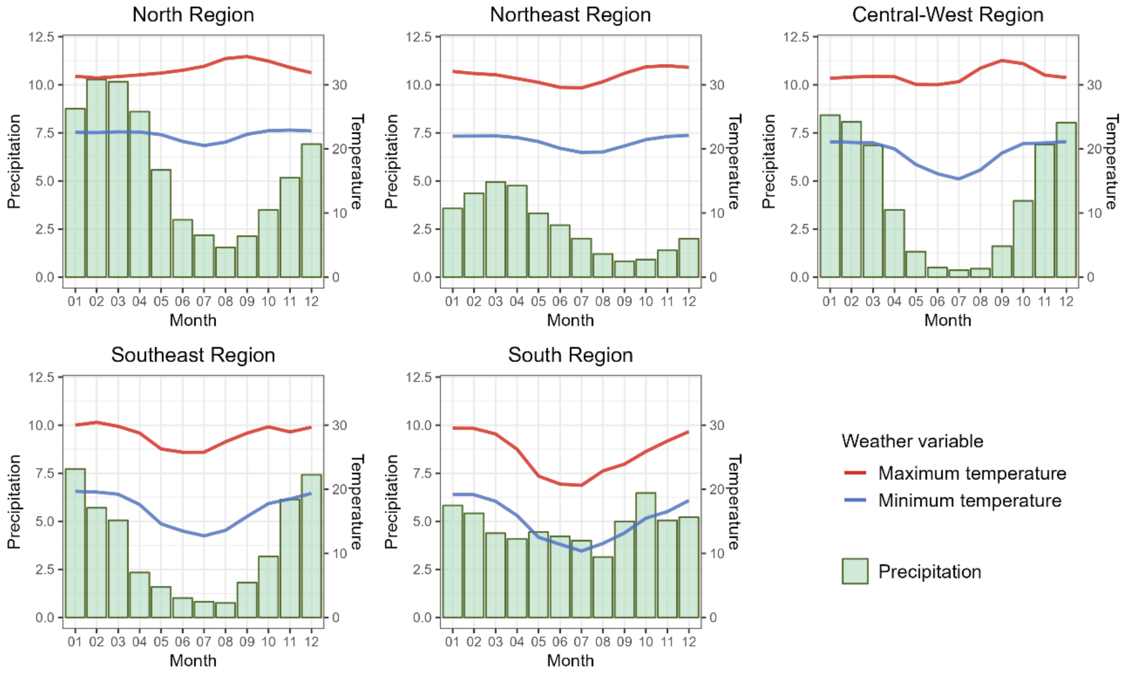
2.3.1.2 Weather data

Our weather data is from the Comprehensive Brazilian Meteorological Gridded Dataset (BR-DWGD), obtained from the R package named 'brclimr'. The data from the package is derived from interpolations of 11,473 rain gauges and 1,252 weather stations, in a spatial resolution of 0.1º x 0.1º. We chose this format of data over the raw weather station data provided by the INMET (Brazilian Institute of Meteorology) for data availability reasons. Due to this issue, Dell et al (2014) recommended that developing countries should be wary of using station data alone, and several other studies also preferred gridded weather data as a source due to the same concerns (Rocha and Soares, 2015; Grace et al., 2015; Andalón et al., 2016; Molina and Saldarriaga, 2017). We collected daily data from maximum and minimum temperatures and average daily precipitation by municipality. Almost all the 5570 Brazilian municipalities had their own measurements, apart from nine municipalities that did not. For these nine municipalities, we gathered data from the biggest neighboring municipality for which the data was available, except for the Fernando de Noronha Archipelago[8].

[8] The municipalities for which weather data were not available were Raposa-MA (2109452), for which it was used the weather variables of Paço do Lumiar-MA (2107506); Senador Georgino Avelino-RN (2413201) and Tibau do Sul-RN (2414209), for which it was used the weather variables of Arês-RN (2401206); Cabedelo-PB (2503209) and Lucena-PB (2508604), for which it was used the weather variables of João Pessoa-PB (2507507); Ilha de Itamaracá-PE (2607604), for which it was used the weather variables of Itapissuma-PE (2607752), Madre de Deus-BA (2919926), for which it was used the weather variables of São Francisco do Conde-BA (2929206), and Ilhabela-SP (3520400), for which it was used the weather variables of São Sebastião-SP (3550704). Only Fernando de Noronha-PE (2605459) was not substituted by neighbouring municipalities due to this geographic position, being 350km apart from the coast, isolated in the Atlantic Ocean with no neighbours around. So, the archipelago known as Fernando de Noronha was the only municipality that was ruled out of our analysis.

The range of weather variables in Brazil is heterogeneous according to the country region. Brazil has an area of 8.510.417,771 km², with five comprehensive types and 51 subtypes of climate across the territory (IBGE, 2024), varying according to the complex combinations of latitude, hydrographic basins, and topography. Figure 2.2 depicts the climograms of the weather variables across regions, with average precipitations depicted on the main axis and temperature on the secondary axis.

Figure 2. 2 - Climogram of Brazilian regions



Source: author.

Not only do the range of temperatures and precipitation patterns vary throughout the regions, but also their frequency. In the region North, which is mostly under the equatorial climate and encompasses a good part of the Amazon rainforest, months between December and April concentrate most of the annual precipitation, achieving the highest levels of all regions and sometimes passing 10mm/m² a day. Due to this high humidity characteristic, the temperature is stable at around 25º, with the biggest variation during the dryer months. In the Northeast region, daily precipitation is generally below 5mm/m², with small variations in the temperatures as well. In this region, tropical, equatorial and semi-arid areas form a unique and complex weather. In the Central-West region, both the temperature and the precipitation patterns are subject to marked changes, where the driest season is between April and

October. In this area, which is far from the ocean, maximum temperatures may achieve more than 35º during the warmer months and less than 15º in the colder months. In the Southeast region, the dryer season is between April and October, followed by bigger differences in the temperature. The temperatures may be around 30º in the warmer months and around 12º in the colder months. It is noteworthy to mention that in both North and Northeast, regions that are among lower latitudes, dryer seasons are followed by higher temperatures, a trend that is inverted in Central-West and Southeast, regions with medium latitudes. In the South region, the coldest region in Brazil, temperatures may reach 30º during summer and 10º during the winter. This region is situated below the tropic of Capricorn and is classified as a temperate climate, with distributed precipitation during the year.

We gathered two sets of weather data, one as a benchmark for the long-run weather (thus defined as climate) per municipality (1961-1995) and another comprising our period of analysis (2000-2020). According to the World Meteorological Organization (WMO), a climate is the specific weather of a given locality for an average of at least 30 years. As the series of weather variables in our data source started in 1961, we collected data until 1995 to have a comprehensive period and categorize a locality's climate. Descriptive statistics are found in Table 2.2.

Table 2. 2 - Descriptive Statistics for weather data

Historical data			
	mean	min	max
Dates (D/M/Y)		01/01/1961	31/12/1995
Minimum temperature (C)	17.72	-9.45	32.65
Maximum temperature (ºC)	28.57	1.31	43.59
Precipitation (mm)	3.80	0.00	398.70

Study period data	mean	min	max
Dates (D/M/Y)		01/01/2000	31/07/2020
Minimum temperature (ºC)	18.50	-8.25	29.88
Maximum temperature (ºC)	29.34	-0.31	43.63
Precipitation (mm)	3.78	0.00	229.80

Source: author.

2.3.2 Empirical strategy

2.3.2.1 Conceptual framework

As detailed by Victora et al. (1997), when trying to acknowledge the effect of a variable in a health outcome, one should try to ascertain the conceptual links between the exposure and the covariates rather than simply estimate their statistical significance. Furthermore, the relationships may be classified in a hierarchical way, where the variables are organized as distal or proximal of the given outcome, and the causal chains between them should be accounted for as confounding variables (Victora et al., 1997). Thus, we hypothesize that birthweight is the result of an intricate relationship that has roots in socioeconomic characteristics but is also affected by the environment, mother's characteristics and preferences.

In our framework, birth weight is affected on a more proximal level by environmental exposure, maternal reproductive characteristics and behavioural/psychological factors. By environmental exposure, we define all circumstances derived from the environment where the pregnant lives that may damage her health (or the fetus' health). The whole theoretical set of environmental stressors would contain air, ground and water pollution, food contamination, mould, radiation, pesticide exposure and several others. However, in this study, we are specifically interested in the role of weather variables such as temperature and precipitation on pregnancy outcomes.

Maternal reproductive characteristics in our framework are all biological features that may be relevant for birth outcomes, such as the baby's gender, the mother's age, the number of children she already has (if so), and others. Additionally, psychological and behavioural factors that may affect these characteristics are considered here, for instance, the behaviour towards lifestyle, diet, smoking, physical activity, willingness to seek health care monitoring, marital status, the psychological handling against stress, anxiety and depression, and others.

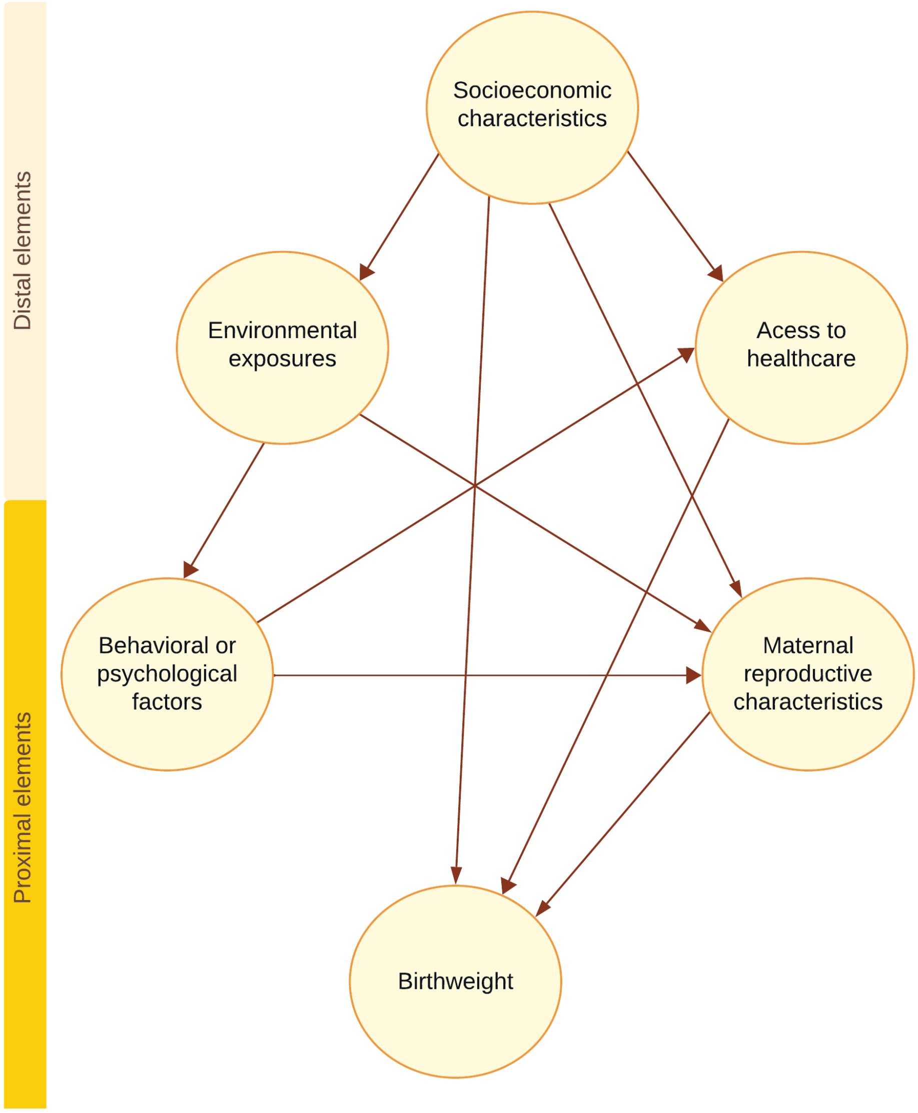
On a more distant level, socioeconomic characteristics influence the environment such as housing and sanitation conditions, access to health care, but also may interact with the behavioral and psychological factors. Socioeconomic conditions may furthermore have a direct link via wealth and nutritional availability during pregnancy, thus affecting birth weight. Figure 2.3 presents a summary of our conceptual model.

2.3.2.2 Model

Our identification strategy relies upon a few assumptions. Firstly, we consider that conception and weather variables are independent. So, as independent events, we theorize that if there is an effect from climate change, this effect is solely one-way and there is no reverse causality in this relationship.

Still, one can assume that planned pregnancies may consider the expected weather variables of a given region when planning to conceive; but weather shocks are not completely predictable with accuracy for the full pregnancy length. Additionally, multicentered studies in Brazil have already shown that more than 60% of Brazilian pregnancies are not planned (Nilson et al., 2023). Moreover, when trying to conceive, several other variables take place (Mersselian et al., 2017; Boivin et al., 2018) and the conception itself might not be completely under control. In the case of a planned conception according to the expected weather for the pregnancy months, the seasonality pattern can be treated by using month fixed-effects.

Figure 2. 3 - Conceptual model



Source: author.

Our second assumption states that the transmission channel of the impacts of climate change on newborns' birthweight is a set of possible reasons rather than one in particular, following our conceptual framework and the suggestions of Dell et al. (2014) and Meierieckss et al. (2021). The up-to-date literature has pointed to several non-excluding reasons for the effects found so far, and it is out of the scope of this work to prove one transmission channel over another. So, by not pointing to one of the reasons in Chart 1 as the leading one, we are acknowledging that if there is an effect of weather on birthweight, this effect may be driven by any of these transmission channels (socioeconomic, biologic, psychologic) or, more plausibly, by an interaction between them.

Our third assumption is about the geographical attribution of the exposure. The SINASC dataset presents information about the mother's location of residence and the location of delivery. Considering 12,145,231 mothers had their delivery in a different location from the municipality where they live, we used information on the residence to attribute the exposure to the weather. By doing so, we are assuming that a considerable number of mothers did not move to other municipalities during pregnancy and did not spend considerable time outside their residence locality. One reason that supports this assumption is that Brazilian access to health care is residence-based. For instance, for a pregnant to be attended by a physician, and have access to prenatal care and prenatal exams, she must use the allocated local care unit based on where she lives. Also, according to our conceptual framework, as the environment plays a significant role in access to health care and exposure to environmental stressors, we had to define the geographical limits of what constitutes the environment within our model as the municipality of residence where the mother lives.

Following our conceptual framework, socioeconomic shocks may also be of considerable importance in impacting pregnancy outcomes, as other studies have already found (Kaplan and Tylavsky, 2017; Mrejen and Machado, 2019; Gailey et al., 2022; De Cao et al., 2022). Additionally, when climate change causes socioeconomic shocks due to changes in food supply, prices and employment levels, it may function as a transmission channel for the effects (Grace et al., 2015). From another possible point of view, socioeconomic shocks might be related to an increase in stress levels, which is one of the possible explanations already pointed out for the decrease in birthweight during recessions (Kaplan and Tylavsky, 2017; De Cao et al., 2022). To take these possibilities into account and rule out part of the direct effect of socioeconomic changes, we also included the rate of unemployment in the year of conception as a control variable for each pregnancy[9], and it is expected that unemployment rates would display a negative effect on birthweight.

Besides unemployment as a proxy for socio-economic context, we also included a few other controls on an individual level that may exert some influence on

[9] The unemployment rate was retrieved from National Household Sample Survey (PNAD in Portuguese), at state and year level. Years 2000 and 2010 were interpolated. Although the method of generating this variable have changed over time, we assume that rate of unemployment is a consistent indicator of socio-economic context. For years of 2012 on, we used the new version of the survey using quarterly data. Quarters were averaged to achieve a yearly measure. For births that took place in september, october, november and december the same year was used, for the remaining months, the previous year's estimation of unemployment rate was chosen.

the pregnancy outcome. Using the individual data available on the SINASC, we used years of study of each mother in four classes (no study, between one to three, between four to eight, between eight to eleven and more than eleven years), which will also be, to some extent, a proxy for income as this information was not available within our dataset.

Another variable that was included as part of the socio-economic context is marital status, which might be relevant to distinguish some level of individual vulnerability within our dataset. We expect that higher educated mothers would hold better conditions for a healthy pregnancy, which would lead to a higher birthweight. Using the same rationale, mothers with a partner might be in a more stable wealth situation, which could be associated with better health outcomes and higher birthweight as a result. Previous evidence suggests that being unmarried is associated with lower intrauterine growth and lower birthweight (Shah et al., 2010; Frimmel and Pruckner, 2013; Falcão et al., 2020). Although the reason behind this is still being discussed in the literature, some authors point out that women-headed families are more exposed to stress, family instability, lack of psychosocial support and lower income, and there is a self-selection to marriage status that must be accounted for (Shah et al., 2010; Frimmel and Pruckner, 2013; Shapiro et al., 2018).

In Figure 2.3 we assume that maternal reproductive characteristics will also be key drivers in influencing birthweight. Thus, we included the mother's age and the number of previous children per mother as biological markers of reproduction and fertility, that are already found empirically linked to birthweight (Swamy et al., 2012; Falcão et al., 2020). To acknowledge the gestational length, we have included as a control variable the number of gestational weeks of birth for each individual. Following the literature (Swamy et al., 2012; Falcão et al., 2020), we expect that the higher the gestational length, the higher the number of previous children and the higher the age of the woman, the higher the newborn birthweight.

Another important control variable is the number of prenatal appointments, which tries to incorporate jointly both a measure of the mother's behavior in seeking health services and a measure of the local availability of these services. Especially, in a country where local access to health care has equality problems (Coube et al., 2023), the level of access should be accounted for. As prenatal appointments are highly recommended for all mothers (WHO, 2016); we hypothesize that a higher number of appointments attended are a proxy of health awareness rather than concerns about specific health issues. Thus, we expect this relationship to be positive with birthweight as well.

Birthweight in its discrete form in grams is our outcome variable, due to the extensive literature that has already found a link with climate change. Also, the quality of the data on birthweight in Brazil is superior when compared with others such as low birth weight, fetal deaths and prematurity (Guimarães et al., 2012; Szwarcwald et al., 2019; Pedraza, 2021). Moreover, the APGAR score during our period of analysis presents a relevant number of missing variables, thus restricting our possible sample size.

The literature reporting evidence of climate change birth effects has been using different strategies to ascertain the existence and the size of these effects. In this approach, two alternative approaches will be tested to understand whether there is an effect and how the different empirical strategies may be complementary. Also, some authors reported that the trimester of the pregnancy where the shocks occurred may also be impactful (Deschênes et al., 2009; Pereda et al., 2014; Hajdu and Hajdu, 2021; Le and Nguyen, 2021; Cil and Kim, 2022; Andriano, 2023). Thus, we added temporal markers in all models to account for the possibility of one trimester being more sensitive than the others.

Some papers in the literature rely on estimating the number of days during pregnancy where the temperature falls within a given slot of temperature (Deschênes et al., 2009; Deryugina and Hsiang, 2014; Ngo and Horton, 2016; Kim et al., 2020; Chen et al., 2020; Hajdu and Hajdu, 2021; Cil and Kim, 2022). This strategy tries to estimate the effects of hot and cold weather by intensity, and its major benefit is the ability to overcome non-linearities that might be present in the data. Also, this strategy has an easy implementation, and its interpretability is straightforward. Instead of using maximum and minimum temperatures, it is often used the arithmetic mean between them by time units.

Previous studies that used temperature and precipitation bins are mostly estimated for countries above the tropics, where colder temperatures (less than 5ºC or even 0ºC) are more frequent and hot temperatures (above 25ºC or 30ºC) are less frequent. Some studies chose to separate into 10 or 11 classes (Deryugina et al., 2014; Chen et al., 2020; Cil and Kim, 2022); others less (Deschênes et al., 2009, Ngo and Horton, 2016; Hajdu and Hajdu, 2021). Considering the distribution of Brazilian temperatures by region depicted in Figure 2.2, the average temperature across months and regions in Brazil is between 10ºC to 35ºC. To account for a certain degree of variability and taking into consideration having an appropriate number of observations in each bin, we decided to separate into eight slots of 3ºC temperature bins departing from 15ºC on and ending at 33ºC: until 15º, between 15º and 18º, between 18º and 21º, between 21º and 24º (reference value), between 24º and 27º, between 27º and 30º, between 30º and 33º and more than 33º. We also considered the distribution of precipitation in six different slots of daily precipitation, between 0mm/m² and 2.5 mm/m² (reference value), between 2.5 mm/m² and 5 mm/m², between 5 mm/m² and 7.5 mm/m², between 7.5 mm/m² and 10 mm/m², between 10 mm/m² and 12.5 mm/m², and more than 12.5 mm/m².

Using this strategy, we will be able to estimate the effects of higher (lower) temperatures and precipitation distribution on birthweight, in equation (1) as follows:

$$\begin{gathered} Bw_{igtc} = \beta_1 \sum_{d=1}^{8} TempBin_{1c} + \beta_2 \sum_{p=1}^{6} PrecBin_{1c} + \\ \beta_3 \sum_{d=1}^{8} TempBin_{2c} + \beta_4 \sum_{p=1}^{6} PrecBin_{2c} + \\ \beta_5 \sum_{d=1}^{8} TempBin_{3c} + \beta_6 \sum_{p=1}^{6} PrecBin_{3c} + \\ \theta_1 Gweek_i + \theta_2 \tau_{st} + \theta_3 \mu_m + y_t + m_t + c + \varepsilon_i \end{gathered} \tag{1}$$

Where Bw_{igtc} is the birthweight of an individual i, gender g, born in a date t and a municipality c. The variables of interest are $TempBin_{qc}$ and $PrecBin_{qc}$, that represent respectively the sum of days during pregnancy when the mother μ was exposed to one of the given slots of temperature d and precipitation p in the municipality c, by gestational trimester $q = \{1,2,3\}$. $Gweek_i$ represents a categorical variable indicating the gestational week of birth. μ_m is a vector of the mother's characteristics such as age, years of study, marital status, number of prenatal appointments and number of previous children to account for the fertility history. τ_{st} is the unemployment rate at state and year level, y_t is fixed effect for the year of conception, which allows to absorb further socio-economic shocks that might have impacted pregnancies apart from climate issues and unemployment rates. m_t are fixed effects for the month of conception, which was included to deal with seasonality of date of conception[10]; and c is fixed effects per municipality, to account for locality characteristics such as region of the country, biome, and other non-observable factors more or less fixed in time. β_i for $i \epsilon [1,6]$ are the parameters for weather variables, and θ_i for $i \epsilon [1,3]$ are the remaining parameters. We estimated equation (1) using fixed-effects OLS[11].

Using this approach, we are willing to test the following hypothesis:

1. If any slots of temperature and precipitation might be linked to changes in birthweight, then:

$$\beta_i \neq 0$$

2. If a higher frequency of hot days is related to intensified effects in birthweight, then:

$$\beta_i \sum_{d=n}^{8} TempBin_{qc} < \beta_i \sum_{d=m}^{8} TempBin_{qc}, \qquad for\ m > n$$

3. If the amount of precipitation is important to predict birthweight:

$$\beta_i \sum_{d=1}^{6} PrecBin_{qc} \neq 0$$

---

[10] To test whether there is any seasonality within our data, we checked the frequency of births according to the month of the year, available in Figure S2.1 on the Supplementary material. Even leaving out the year of 2020 (for which we only have data of the first semester), there is a seasonality pattern pointing to relative more frequent deliveries on the months of March, April and May.

[11] To perform FEOLS (Fixed-effects OLS), we used R studio, package “fixest”; and Stata, package reghdfe.

4. If there is a gestational trimester specifically more sensitive to weather conditions:

$$\begin{cases} \beta_1 \neq \beta_3 \neq \beta_5 \\ \beta_2 \neq \beta_4 \neq \beta_6 \end{cases}$$

Climate change effects are not limited to increases in temperature. By raising ocean temperatures, maritime and wind currents are also affected in their routes and seasonality, changing climate patterns that are historically consolidated within a given region. For instance, heat and cold waves may happen out of the season when they are expected; and extreme events such as windstorms, floods and droughts might become more frequent. Thus, one of our alternative assumptions relies on historical data to consider the weather shocks that have been occurring apart from what is expected in a given locality and month of the year, following the example of Andalón et al. (2016). We estimated averages per municipality month utilizing weather data of daily precipitation, and minimum and maximum temperature from 1961 to 1995 to build our historical benchmark. The strategy of using maximum and minimum temperatures separately tries to acknowledge not only patterns of average weather but also changes in the range of temperatures a given location may reach beyond the expected values per locality month. In Figure 2.1 it is noteworthy that each region in Brazil has its pattern of weather variability. If, for instance, the patterns of weather variability are also changing, it might be relevant to understand whether it is followed or not by any relevant effect on birthweight.

Shocks' magnitude may also display varying results. To test if the effects are heterogeneous by shock size, we categorized 10 classes of temperature shock intensity measured in standard deviations (SD) from the historical mean. For our analysis, and following Andalón et al. (2016), shocks are characterized only for values above 0.7 SD of the historical mean (positive or negative); and values between zero and 0.7 SD (positive or negative) were considered reference values throughout our estimations. The shocks' thresholds were retrieved from Andalón et al. (2016), and the class of 1.5 to 2.0 SD shock was included to allow for an upper-intermediate level of shock intensity.

The shock variable takes into consideration three possibilities of aggregation. Daily shocks consider the number of days during each pregnancy where a temperature shock of a given intensity happened, no matter whether the shocks were consecutive or not. This strategy will make it possible to understand if a shock in the lowest level of a single day has any effect on newborn birthweights.

However, some authors favoured waves of temperature shocks rather than daily shocks (Hajdu and Hajdu, 2021; Andriano, 2023). This approach considers that persistent shocks may have a stronger biological link with pregnancy outcomes than instantaneous shocks. Hence, we used a moving average of seven days, reflecting the number of times during the pregnancy when the weather of the last week was considered out of the historical mean expected for this month of the year.

Andalón et al. (2016) used monthly shocks. Following their strategy, we performed a third aggregation approach relying on monthly data. In this case, a variable pointing to a whole month out of the historical climate is given the value of one and zero otherwise. In this design, we are acknowledging that even more persistent shocks might have an impact on pregnancy outcomes.

So, model (2) is defined as follows:

$$
\begin{gathered}
Bw_{igtc} = \beta_1 \sum_{j} \sum_{d=1}^{10} TminShock_{1c} + \beta_2 \sum_{j} \sum_{d=1}^{10} TmaxShock_{1c} + \beta_3 \sum_{j} \sum_{p>0} PrecShock_{1c} + \\
\beta_4 \sum_{j} \sum_{p<0} PrecShock_{1c} + \beta_5 \sum_{j} \sum_{d=1}^{10} TminShock_{2c} + \beta_6 \sum_{j} \sum_{d=1}^{10} TmaxShock_{2c} + \\
\beta_7 \sum_{j} \sum_{p>0} PrecShock_{2c} + \beta_8 \sum_{j} \sum_{p<0} PrecShock_{2c} + \beta_9 \sum_{j} \sum_{d=1}^{10} TminShock_{3c} + \\
\beta_{10} \sum_{j} \sum_{d=1}^{10} TmaxShock_{3c} + \beta_{11} \sum_{j} \sum_{p>0} PrecShock_{3c} + \beta_{12} \sum_{j} \sum_{p<0} PrecShock_{3c} + \\
\theta_1 Gweek_i + \theta_2 \tau_{st} + \theta_3 \mu_m + y_t + m_t + c + \varepsilon_i
\end{gathered}
$$

(2)

Where Bw_{igtc} is the birthweight of an individual i, gender g, born in a municipality c and a date t. $TmaxShock_{qc}$ and $TminShock_{qc}$represents the sum of shocks in temperature of intensity d observed for a unit of time j (day, week, month) that happened in a locality c during a gestational trimester $q = \{1,2,3\}$. $PrecShock_{qc}$ represents the number of positive ($p > 1$) or negative shocks ($p < 1$) of any intensity beyond 0.7 SD that happened during each pregnancy. β_i for $i \epsilon [1,12]$ are the parameters for weather variables, and θ_i for $i \epsilon [1,3]$ are the remaining parameters.

The remaining variables are the same as in equation (1), and equation (2) was also estimated using Fixed-effects OLS.

Brazil, being a tropical country, is geographically subject to high temperatures. In fact, according to the climogram in Figure 2.2, most of the temperatures across regions range from 10º to 35º. Henceforth, populations exposed to higher temperatures might have established coping mechanisms to deal with the weather. However, changes from historical patterns may give a clue to weather vulnerabilities and coping mechanisms that were not yet fully developed. Thus, this strategy tries to test the remaining hypothesis:

5. If the shift from the historical weather is relevant to predicting birth weight changes, then:

$$\beta_i \neq 0$$

6. If there is a clear difference between shocks that occur at the maximum and the minimum temperature, then:

$$\sum_{j}\sum_{d=m}^{10} \beta_i TminShock_{qc} \neq \sum_{j}\sum_{d=m}^{10} \beta_i TmaxShock_{qc}$$

7. If a higher shock size on the temperatures is related to intensified effects in birthweight, then:

$$\begin{cases} \beta_i \sum_{j}\sum_{d=n}^{10} TminShock_{qc} < \beta_i \sum_{j}\sum_{d=m}^{10} TminShock_{qc}, & for\ m > n \\ \beta_i \sum_{j}\sum_{d=n}^{10} TmaxShock_{qc} < \beta_i \sum_{j}\sum_{d=m}^{10} TmaxShock_{qc}, & for\ m > n \end{cases}$$

8. If positive or negative precipitation shocks are significantly related to birth weight, then:

$$\sum_{j}\sum_{p>0} \beta_i PrecShock_{qc} \vee \sum_{j}\sum_{p<0} \beta_i PrecShock_{qc} \neq 0$$

9. If there are differences between the time aggregation strategies, then:

$$\beta_i \sum_{j=day} \sum_{d=m}^{10} TmaxShock_{qc} \neq \beta_i \sum_{j=week} \sum_{d=m}^{10} TmaxShock_{qc} \neq \beta_i \sum_{j=month} \sum_{d=m}^{10} TmaxShock_{qc}$$

$$\beta_i \sum_{j=day} \sum_{d=m}^{10} TminShock_{qc} \neq \beta_i \sum_{j=week} \sum_{d=m}^{10} TminShock_{qc} \neq \beta_i \sum_{j=month} \sum_{d=m}^{10} TminShock_{qc}$$

$$\beta_i \sum_{j=day} \sum_{p<0} PrecShock_{qc} \neq \beta_i \sum_{j=week} \sum_{p<0} PrecShock_{qc} = \beta_i \sum_{j=month} \sum_{p<0} PrecShock_{qc}$$

$$\beta_i \sum_{j=day} \sum_{p>0} PrecShock_{qc} \neq \beta_i \sum_{j=week} \sum_{p>0} PrecShock_{qc} = \beta_i \sum_{j=month} \sum_{p>0} PrecShock_{qc}$$

10. If the effects are heterogeneous according to the gestational trimester, then:

$$\beta_1 \neq \beta_5 \neq \beta_9,$$
$$\beta_2 \neq \beta_6 \neq \beta_{10},$$
$$\beta_3 \neq \beta_7 \neq \beta_{11},$$
$$\beta_4 \neq \beta_8 \neq \beta_{12}$$

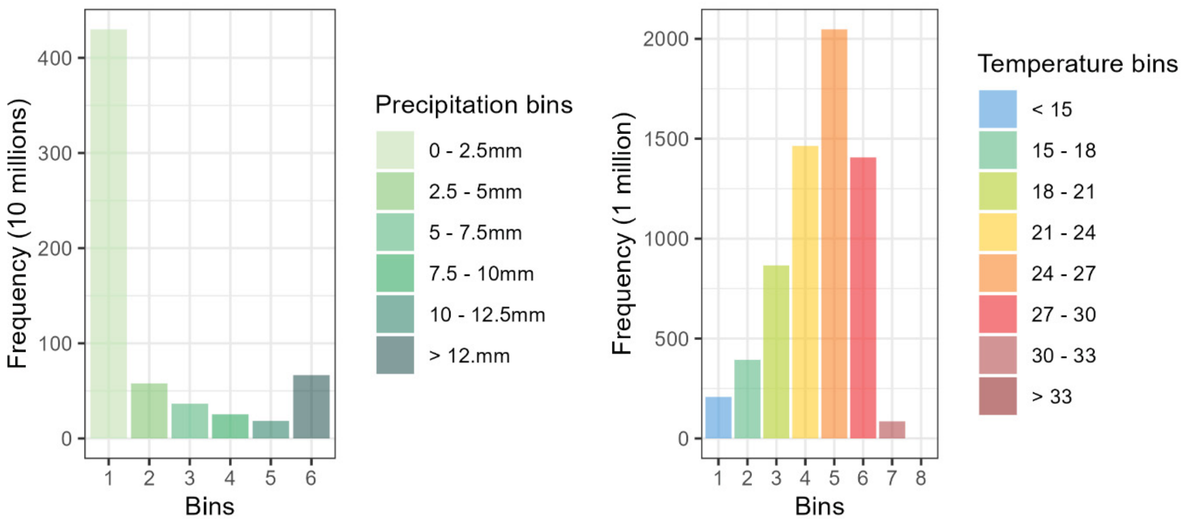
2.4 RESULTS

2.4.1 Main Results

Figure 2.4 presents the histogram of temperature bins and precipitation bins, while Figure 2.5 depicts the histogram of weather shocks from the historical average. In Figure 2.4, it is noticeable that the reference bin with 0-2.5mm/m² holds the biggest frequency of observations. The temperature distribution shows that most days are slotted between 21º and 30ºC (bins 4, 5 and 6), with daily mean temperatures around 24ºC and 27ºC being the most frequent.

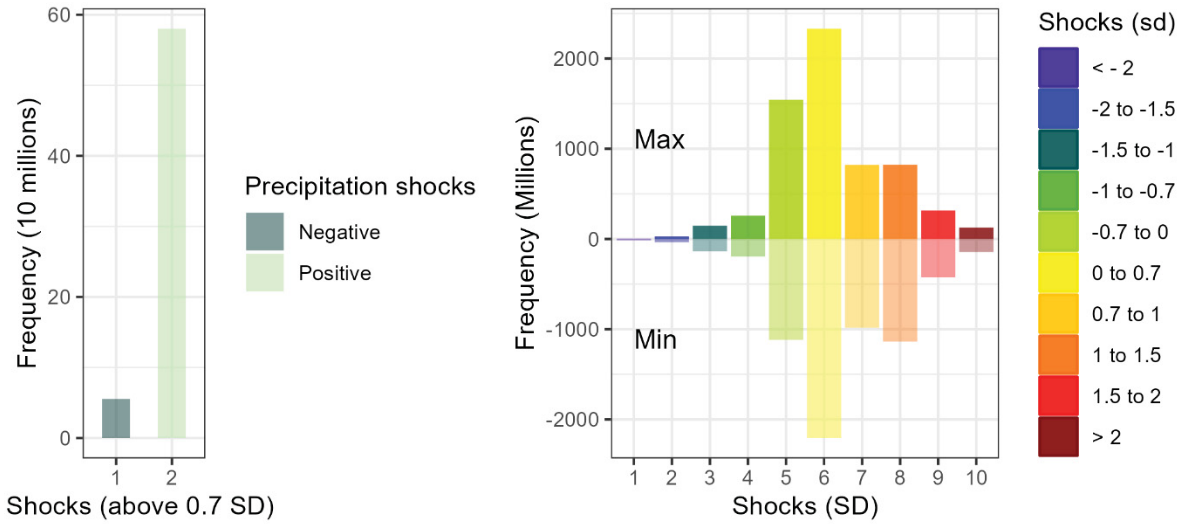
Figure 2.5 shows that positive precipitation shocks (above 0.7 SD from the historical precipitation levels) are much more frequent than negative shocks. Shocks on maximum temperature are depicted on the upper side of the graphs, while shocks on the minimum are depicted on the lower side. Taking green and yellow as reference values (between 0 and 0.7 SD), it is noticeable positive shocks above 0.7 SD (light orange) are more frequent at both maximum and minimum temperatures. Moreover, the frequency of positive shocks is bigger on the minimum temperature, which shows that the population has been experiencing hotter weather more than colder weather when compared with the historical mean.

Figure 2. 4 - Weather bins for the sample (2000-2020)



Source: author.

Figure 2. 5 - Weather shocks for the sample (2000-2020)



Source: author.

All estimates presented below were calculated using the control variables detailed in the last section. Mother characteristics such as education and age, number of antenatal appointments and parity order (number of previous pregnancies) were all significant and positively associated with increments in birthweight across our models. Marital status as married was also significant and positively linked to birthweight increases. Gestational week was found significant and positively associated with our outcome, as it is one of the main predictors of birthweight.

Unemployment was negatively associated with our outcome, suggesting that the effect of socioeconomic variables even at a higher level of aggregation (state level) can affect birth outcomes at an individual level. In sum, all the control variables hypothesized by our conceptual framework and econometric model were proven to be relevant to predict birthweight. Complete estimations are on the Supplementary material (Tables S2.1 to S2.4).

Table 2. 3 - Estimations of birthweight per bin of temperature and precipitation

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.237*** (0.027)	0.212*** (0.025)
15-18	0.135*** (0.032)	0.162*** (0.028)
18-21	0.059* (0.026)	0.080** (0.025)
24-27	-0.143*** (0.024)	-0.133*** (0.024)
27-30	-0.352*** (0.043)	-0.333*** (0.041)
30-33	-0.428*** (0.065)	-0.419*** (0.064)
>33	-0.536 (0.738)	-0.178 (0.876)
Precip. (mm/m²)		
2.5 to 5	-0.072. (0.040)	-0.064 (0.041)
5 to 7.5	-0.114. (0.067)	-0.066 (0.064)
7.5 to 10	-0.233*** (0.064)	-0.248*** (0.062)
10 to 12.5	-0.070 (0.082)	-0.091 (0.080)
> 12.5	-0.137*** (0.031)	-0.085** (0.030)

Source: author. Temp. – Temperature. Precip. – Precipitation.

Table 2.3 displays the results of our estimations for equation (1) for different slots of temperature and precipitation. According to the estimations, temperatures below 15º until 18º are related to birthweight gains for boys and girls, comparatively with the reference values (22-24º). However, from the bin of 24-27º on, birthweight decreases with higher temperatures. In particular, the bin of average temperature between 30-33º is significant at a 1% level for both genders, suggesting that one additional day of temperatures in this range can diminish up to 0.4g of a newborn weight, always comparing against the reference values. The effects were slightly more severe for boys.

Daily precipitation between 7.5-10 mm/m² was significantly associated with birthweight losses for both boys and girls, which was also significant for the slot of daily precipitation heavier than 12.5 mm/m².

Table 2.4 displays the results of our equation (2) using days as time aggregation. The estimations suggest that both positive and negative shocks on maximum and minimum temperatures may affect birthweight.

Table 2. 4 - Estimations of birthweight per daily deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.039 (0.245)	-0.022 (0.061)	-0.074 (0.179)	-0.096* (0.038)
-2 to -1.5	-0.034 (0.106)	-0.238** (0.085)	-0.279** (0.089)	-0.226*** (0.061)
-1.5 to -1	-0.014 (0.042)	0.044 (0.046)	-0.029 (0.045)	0.022 (0.037)
-1 to -0.7	0.035 (0.037)	-0.007 (0.040)	0.009 (0.039)	-0.068. (0.036)
0.7 to 1	-0.099*** (0.023)	-0.029 (0.019)	-0.115*** (0.023)	-0.034 (0.023)
1 to 1.5	-0.029 (0.018)	-0.027. (0.015)	-0.071*** (0.017)	-0.038* (0.016)
1.5 to 2	-0.151*** (0.026)	-0.040 (0.025)	-0.160*** (0.025)	-0.035 (0.027)
>2	-0.105** (0.040)	-0.073** (0.025)	-0.110** (0.037)	-0.095*** (0.025)
Precip.				
Neg.	-0.025 (0.046)		-0.003 (0.051)	
Pos.	-0.001 (0.020)		-0.002 (0.022)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Negative shocks represent environments colder than the historical temperatures. Negative shocks between -2 to -1.5 SD are found related to birthweight losses in both boys and girls, especially on the minimum temperatures.

Positive shocks, in their turn, represent environments hotter than historical patterns. Coefficients for boys and girls point out that a hotter climate is related to lighter birth weights using daily deviations from historical means. The effect is present for both genders and in several degrees of shock intensity, but in a non-linear and non-monotonic way. This is to say, for some categories, the biggest effect is found in the interval between 2 and 1.5 SD rather than above two. In the positive shocks, the effects on the maximum temperature present higher coefficients than for the minimum, showing that the effect is driven by the maximum temperatures. Regarding precipitation, both positive and negative shocks were not found significant in this specification.

Table 2.5 displays the results of our equation (2) using weeks. Now, positive (negative) shocks reflect days when the average of the last week was above (below) a given intensity measured in SD. Thus, is a proxy of the effect of one day during a heat (cold) wave. Although colder days with temperature shocks over 1.5 SD were found detrimental for girls, when considering waves of cold weather instead, the effect is no longer significant. Apart from this difference, roughly the same relationships and magnitudes were found for the other samples, with slightly lower and significant coefficients. These results suggest that the impact of one additional day above the shock threshold, under a heat wave, has a slightly less intense effect on birthweight. No significant coefficients were found for positive and negative precipitation shocks.

Table 2. 5 - Birthweight per weekly deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.112 (0.248)	-0.031 (0.058)	0.428. (0.253)	-0.084* (0.038)
-2 to -1.5	-0.065 (0.110)	-0.202* (0.080)	-0.039 (0.113)	-0.170* (0.068)
-1.5 to -1	-0.012 (0.042)	0.051 (0.047)	-0.032 (0.042)	0.014 (0.038)
-1 to -0.7	0.036 (0.037)	0.005 (0.038)	0.007 (0.037)	-0.055 (0.038)
0.7 to 1	-0.084*** (0.021)	-0.008 (0.018)	-0.082*** (0.024)	-0.025 (0.020)
1 to 1.5	-0.013 (0.018)	-0.024 (0.015)	-0.040* (0.017)	-0.032. (0.017)
1.5 to 2	-0.132*** (0.026)	-0.027 (0.025)	-0.157*** (0.026)	-0.027 (0.026)
>2	-0.103* (0.041)	-0.067** (0.024)	-0.097* (0.042)	-0.085*** (0.025)
Precip.				
Neg.	0.005 (0.046)		-0.014 (0.050)	
Pos.	0.014 (0.020)		0.021 (0.020)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table 2.6 below displays the results of the same equation (2), now using months for time aggregation. Negative shocks were not significant in this specification. For positive shocks, maximum and minimum temperatures relate to varying levels of birthweight decreases. The biggest effect is for girls, for whom one additional month of temperatures around 1.5 and 2 SD hotter than usual is related to a decrease of 3.2g in their birth weight. Monthly precipitation apart from expected historical patterns was not found significant. Additionally, shocks on the maximum temperature report higher coefficients than shocks on the minimum for most cases, pointing out once again that the rise in the maximum temperature might be driving the effect.

Table 2. 6 - Birthweight per monthly deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-19.590 (13.142)	-0.870 (0.945)	-11.075 (13.274)	-2.119* (0.911)
-2 to -1.5	-0.477 (5.909)	-1.494 (1.389)	-3.019 (6.943)	-2.287. (1.296)
-1.5 to -1	4.404** (1.560)	-2.180** (0.693)	3.962** (1.480)	-1.307* (0.599)
-1 to -0.7	-0.706 (0.787)	-0.019 (0.564)	-0.732 (0.782)	-0.492 (0.563)
0.7 to 1	-1.076*** (0.281)	-0.623** (0.209)	-1.231*** (0.270)	-0.701** (0.217)
1 to 1.5	-1.978*** (0.328)	-0.738** (0.275)	-2.114*** (0.337)	-0.714* (0.280)
1.5 to 2	-2.980*** (0.561)	-1.367** (0.503)	-3.239*** (0.545)	-1.178* (0.505)
>2	-2.182* (0.918)	-1.931** (0.596)	-2.506** (0.949)	-2.393*** (0.610)
Precip.				
Neg.	0.768 (3.188)		5.197 (2.857)	
Pos.	0.091 (0.466)		0.771 (0.395)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

2.4.2 Results by trimester

Estimations for equations (1) and (2) were also conducted using the gestational trimester separately. Complete estimations are on the Supplementary material (Tables S2.5 to S2.8). Table 2.7 presents the estimation per bin and gestational trimester. The results point out that below 21º (compared with the reference values) both genders experience gains in birthweight, which happens especially during the third trimester. For the bins above 24º, again boys and girls report losses in birthweight, with the strongest effect found during the third trimester. Days of heavier precipitation were associated with negative effects on birthweight also especially during the third trimester.

Table 2. 7 - Birthweight per bins of temperature and precipitation, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)	
Temp.	Tri	Boys	Girls
<15	1st	0.463*** (0.048)	0.367*** (0.045)
	2nd	0.044 (0.030)	0.072* (0.028)
	3rd	0.581*** (0.061)	0.498*** (0.056)
15-18	1st	0.119** (0.037)	0.137*** (0.036)
	2nd	0.054. (0.031)	0.100*** (0.028)
	3rd	0.397*** (0.055)	0.386*** (0.046)
18-21	1st	0.146*** (0.031)	0.157*** (0.030)
	2nd	0.094*** (0.025)	0.118*** (0.026)

	3rd	0.183*** (0.031)	0.195*** (0.030)
24-27	1st	-0.117*** (0.029)	-0.106*** (0.026)
	2nd	0.046** (0.017)	0.042* (0.018)
	3rd	-0.332*** (0.037)	-0.321*** (0.035)
27-30	1st	-0.284*** (0.046)	-0.265*** (0.045)
	2nd	0.014 (0.023)	0.000 (0.022)
	3rd	-0.759*** (0.075)	-0.720*** (0.072)
30-33	1st	-0.356*** (0.061)	-0.366*** (0.058)
	2nd	-0.214*** (0.054)	-0.208*** (0.049)
	3rd	-0.826*** (0.097)	-0.792*** (0.098)
>33	1st	-0.076 (1.051)	0.120 (1.251)
	2nd	-0.760 (1.287)	-0.939 (0.929)
	3rd	-0.471 (1.008)	1.053 (1.250)
Precip.			
2.5 to 5	1st	-0.042 (0.059)	-0.021 (0.051)
	2nd	-0.134** (0.048)	-0.077. (0.046)
	3rd	-0.188*** (0.056)	-0.202*** (0.056)
5 to 7.5	1st	-0.002 (0.088)	0.096 (0.079)
	2nd	-0.092 (0.080)	-0.095 (0.066)
	3rd	-0.262** (0.082)	-0.183* (0.084)
7.5 to 10	1st	-0.125. (0.076)	-0.201** (0.075)
	2nd	-0.083 (0.078)	-0.081 (0.069)
	3rd	-0.425*** (0.091)	-0.401*** (0.097)
10 to 12.5	1st	0.151 (0.099)	0.203* (0.095)
	2nd	0.207* (0.093)	0.126 (0.088)
	3rd	-0.316** (0.101)	-0.321** (0.109)
> 12.5	1st	-0.123** (0.044)	-0.042 (0.038)
	2nd	0.087* (0.040)	0.110** (0.037)
	3rd	-0.276*** (0.044)	-0.193*** (0.043)

Source: author. Tri. – Trimester. Temp. – Temperature. Precip. - Precipitation

Table 2.8 below shows the results of the estimations per daily deviations from historical means, considering shocks by gestational trimester. Negative shocks on all trimesters have been pointed out as damaging for boys and girls in different intensity shocks. Positive shocks are found negatively associated with birthweight across all samples and trimesters. Still, the third trimester presents a slightly higher magnitude pointing to a higher sensibility regarding birthweight losses. Precipitation shocks were found not significant.

Table 2. 8 - Birthweight per daily deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	0.100 (0.356)	-0.004 (0.135)	-0.018 (0.248)	-0.256*** (0.053)
	2nd	0.224 (0.313)	0.046 (0.059)	-0.164 (0.235)	0.121 (0.081)
	3rd	-0.293 (0.346)	-0.137 (0.102)	-0.195 (0.217)	-0.170* (0.066)
-2 to -1.5	1st	0.156 (0.151)	-0.287** (0.111)	-0.284* (0.125)	-0.189* (0.084)
	2nd	-0.010 (0.154)	-0.182. (0.104)	-0.330* (0.134)	-0.350*** (0.098)
	3rd	-0.298* (0.140)	-0.273* (0.133)	-0.215. (0.124)	-0.041 (0.104)
-1.5 to -1	1st	-0.069 (0.059)	0.023 (0.071)	-0.060 (0.058)	-0.022 (0.056)
	2nd	0.080 (0.063)	0.061 (0.063)	-0.063 (0.056)	-0.003 (0.057)
	3rd	-0.071 (0.057)	0.126. (0.072)	-0.039 (0.059)	0.088 (0.076)
-1 to -0.7	1st	-0.059 (0.051)	-0.066 (0.054)	-0.105* (0.048)	-0.138* (0.062)
	2nd	-0.009 (0.052)	-0.109. (0.056)	0.033 (0.050)	-0.132* (0.054)
	3rd	0.075 (0.055)	0.105 (0.064)	0.083 (0.063)	0.055 (0.057)
0.7 to 1	1st	-0.078* (0.030)	0.012 (0.026)	-0.068* (0.028)	0.028 (0.031)
	2nd	-0.063* (0.027)	-0.024 (0.025)	-0.115*** (0.027)	-0.058* (0.028)
	3rd	-0.143*** (0.031)	-0.064** (0.024)	-0.170*** (0.031)	-0.054. (0.030)
1 to 1.5	1st	-0.013 (0.025)	0.039* (0.019)	-0.071** (0.026)	0.007 (0.020)
	2nd	0.006 (0.022)	-0.014 (0.019)	-0.028 (0.020)	-0.004 (0.021)
	3rd	-0.100*** (0.025)	-0.081*** (0.024)	-0.128*** (0.023)	-0.111*** (0.022)
1.5 to 2	1st	-0.147*** (0.039)	0.026 (0.029)	-0.139*** (0.036)	0.039 (0.034)
	2nd	-0.089** (0.033)	0.016 (0.030)	-0.109*** (0.031)	-0.041 (0.028)
	3rd	-0.207*** (0.035)	-0.135*** (0.041)	-0.244*** (0.034)	-0.078. (0.044)
>2	1st	-0.158** (0.049)	-0.021 (0.035)	-0.193*** (0.046)	-0.069. (0.037)
	2nd	0.005 (0.043)	0.022 (0.032)	0.000 (0.040)	0.004 (0.032)
	3rd	-0.140* (0.057)	-0.214*** (0.042)	-0.142** (0.051)	-0.242*** (0.039)
Precip.					
Pos.	1st	0.022 (0.028)		0.054* (0.026)	
	2nd	0.012 (0.025)		-0.008 (0.026)	
	3rd	-0.050 (0.032)		-0.051. (0.030)	
Neg.	1st	0.132 (0.083)		0.154* (0.061)	
	2nd	0.003 (0.059)		-0.115* (0.050)	
	3rd	-0.092 (0.064)		0.018 (0.063)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature. Tri. – gestational trimester.

Table 2.9 below depicts the same estimations as Table 2.8, but now using weeks for time aggregation. Both negative and positive shocks are related to losses in birth weight, with the third trimester also concentrating on the biggest values. There is no clear evidence of intensifying effects from cold and heat waves, as the magnitudes are heterogeneous between higher and lower than the previous estimation. Still, no specification with precipitation was found significant.

Table 2. 9 - Birthweight per weekly deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	-0.331 (0.372)	-0.180 (0.172)	0.446 (0.340)	-0.276** (0.101)
	2nd	0.269 (0.274)	0.066 (0.094)	0.566 (0.355)	0.131 (0.091)
	3rd	0.201 (0.266)	-0.127 (0.105)	0.217 (0.292)	-0.197** (0.067)
-2 to -1.5	1st	0.123 (0.146)	-0.301* (0.150)	0.117 (0.139)	-0.107 (0.094)
	2nd	0.215. (0.130)	-0.287* (0.146)	0.015 (0.153)	-0.250** (0.094)
	3rd	-0.265* (0.111)	-0.316* (0.150)	-0.245. (0.147)	-0.120 (0.130)
-1.5 to -1	1st	-0.069 (0.058)	0.102 (0.097)	-0.071 (0.060)	-0.059 (0.057)
	2nd	0.120* (0.056)	0.049 (0.095)	0.018 (0.054)	0.039 (0.056)
	3rd	-0.081. (0.048)	0.098 (0.110)	-0.103. (0.058)	0.125. (0.075)
-1 to -0.7	1st	-0.099. (0.053)	-0.157* (0.078)	-0.086. (0.048)	-0.155* (0.062)
	2nd	-0.165*** (0.049)	0.090 (0.080)	-0.036 (0.047)	-0.136* (0.061)
	3rd	0.160*** (0.046)	0.007 (0.097)	0.099 (0.067)	0.033 (0.060)
0.7 to 1	1st	-0.061* (0.028)	0.022 (0.034)	-0.053. (0.030)	0.011 (0.028)
	2nd	0.011 (0.023)	-0.006 (0.031)	-0.064* (0.028)	-0.052. (0.027)
	3rd	-0.101*** (0.030)	-0.011 (0.032)	-0.148*** (0.034)	-0.042 (0.027)
1 to 1.5	1st	-0.027 (0.024)	0.038 (0.025)	-0.029 (0.026)	0.015 (0.020)
	2nd	0.061** (0.020)	-0.044. (0.024)	-0.017 (0.021)	-0.014 (0.022)
	3rd	-0.069*** (0.020)	-0.034 (0.028)	-0.098*** (0.023)	-0.094*** (0.023)
1.5 to 2	1st	-0.130*** (0.036)	-0.080* (0.031)	-0.140*** (0.037)	0.048 (0.033)
	2nd	0.042 (0.027)	-0.007 (0.028)	-0.078* (0.033)	-0.016 (0.031)
	3rd	-0.149*** (0.028)	-0.092** (0.035)	-0.254*** (0.036)	-0.094* (0.043)
>2	1st	-0.156*** (0.047)	0.138*** (0.027)	-0.192*** (0.049)	-0.063. (0.034)
	2nd	0.038 (0.037)	-0.291*** (0.040)	0.023 (0.043)	0.054. (0.030)
	3rd	-0.153*** (0.044)	0.210*** (0.024)	-0.139* (0.056)	-0.254*** (0.045)
Precip.					
Pos.	1st	0.022 (0.028)		0.054* (0.026)	
	2nd	0.012 (0.025)		-0.008 (0.026)	
	3rd	-0.050 (0.032)		-0.051. (0.030)	
Neg.	1st	0.132 (0.083)		0.154* (0.061)	
	2nd	0.003 (0.059)		-0.115* (0.050)	
	3rd	-0.092 (0.064)		0.018 (0.063)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature. Tri. – gestational trimester.

Table 2.10 reports the estimations per trimester of monthly shocks. Negative shocks especially for girls are found detrimental to birthweight. However, a coefficient for a negative shock between -1.5 and 1 SD seemed to contribute to boys birthweight. Decreases in the average birthweight were also found for the positive shocks across the samples, on an increasing way with the shock size, where a whole month hotter than average during the pregnancy is related to decreases of up to 7g on girls' birthweight when it is on the third trimester. Precipitation monthly shocks' coefficients were not significant.

Table 2. 10 - Birthweight per monthly deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	-6.976 (8.865)	0.655 (1.537)	0.949 (12.952)	-3.824** (1.422)
	2nd	-22.028 (14.180)	-1.671 (1.606)	-21.290 (15.445)	1.962 (1.979)
	3rd	-23.619 (34.936)	-2.206 (1.780)	1.966 (16.136)	-4.495** (1.694)
-2 to -1.5	1st	2.371 (6.955)	-0.531 (1.678)	-0.903 (7.626)	-1.513 (2.033)
	2nd	4.230 (6.712)	-2.004 (1.998)	0.648 (8.993)	-0.277 (2.661)
	3rd	3.165 (6.673)	-2.198 (2.556)	3.473 (9.275)	-3.445 (3.076)
-1.5 to -1	1st	1.251 (2.011)	-1.708 (1.098)	3.755. (2.080)	-1.158 (1.038)
	2nd	6.051*** (1.733)	-1.724 (1.253)	0.639 (1.545)	-1.731 (1.143)
	3rd	-0.133 (2.046)	-1.045 (1.450)	4.473* (2.081)	-0.788 (1.306)
-1 to -0.7	1st	-1.663. (0.893)	-0.560 (0.687)	-0.933 (0.873)	-0.737 (0.725)
	2nd	1.861* (0.905)	0.571 (0.785)	0.478 (0.913)	0.506 (0.684)
	3rd	-1.183 (0.892)	1.244 (1.064)	-0.766 (0.884)	-0.731 (0.919)
0.7 to 1	1st	0.002 (0.325)	-0.027 (0.239)	-0.494. (0.293)	-0.023 (0.254)
	2nd	0.013 (0.240)	-0.418. (0.221)	-0.411 (0.252)	-0.511* (0.210)
	3rd	-2.274*** (0.345)	-0.969* (0.404)	-2.162*** (0.310)	-0.985* (0.395)
1 to 1.5	1st	-1.336** (0.421)	0.488 (0.321)	-1.657*** (0.438)	0.274 (0.306)
	2nd	-0.424 (0.262)	-0.453 (0.318)	-0.432 (0.273)	-0.172 (0.287)
	3rd	-2.607*** (0.432)	-1.631** (0.508)	-3.140*** (0.405)	-1.627*** (0.447)
1.5 to 2	1st	-3.427*** (0.613)	-0.509 (0.550)	-3.417*** (0.613)	-0.406 (0.548)
	2nd	0.993. (0.565)	1.157* (0.529)	0.406 (0.500)	1.014* (0.418)
	3rd	-4.848*** (0.745)	-3.866*** (0.827)	-4.847*** (0.762)	-3.784*** (0.869)
>2	1st	-2.558* (1.110)	-1.651* (0.816)	-3.982*** (1.018)	-2.008** (0.759)
	2nd	0.783 (0.923)	2.672*** (0.681)	2.016* (0.942)	3.030*** (0.695)
	3rd	-3.542** (1.208)	-5.837*** (1.043)	-5.014*** (1.091)	-6.966*** (1.066)
Precip.					
Pos.	1st	0.562 (0.519)		1.283* (0.525)	
	2nd	0.526 (0.546)		0.387 (0.494)	
	3rd	0.277 (0.588)		-0.046 (0.521)	
Neg.	1st	4.767 (4.258)		1.540 (3.892)	
	2nd	-1.113 (3.229)		2.882 (3.504)	
	3rd	0.606 (4.603)		3.330 (4.006)	

Source: author. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Max. – Maximum daily temperature. Min. – Minimum daily temperature. Tri. – gestational trimester.

2.4.3 Robustness Checks

To check if our estimations are robust to alternative assumptions, we performed robustness checks estimations.

Due to data limitations, we could not determine whether the newborns and the mothers within our sample suffered from any other comorbidities. Birth weight might act in some cases as a proxy of non-necessarily weather-related health issues of the mother and the baby. Prematurity has already been studied and found related to weather shocks in some other previous studies (Wolf and Armstrong, 2012; Bruckner et al., 2014; Ngo and Horton, 2016; Cim and Kim, 2022), but babies born before 37 weeks (preterms) might have been affected by weather alone or by other non-observable factors we cannot control for. Also, babies born with more than 4000g are characterized as macrosomic babies[12], an anomaly associated with mother characteristics such as the presence of diabetes, obesity and other factors (Czarnobay et al., 2019). Although the effects of weather shocks might be linked with those poor birth outcomes, we are also interested in determining whether there is any sizeable effect for babies that are among normal birth outcomes thresholds. To account for these possible confounding factors, we conducted a robustness check restricting our sample to only term babies (newborns between 37 and 41 gestational weeks), with no clinically low birth weight (above 2500g) and no macrosomia (below 4000g). The results in Tables S2.9 to S2.12 report that although our estimates changed in magnitude, the general results still hold, and the effect is still significant even for healthier babies.

Albeit the municipality’s characteristics are covered by the inclusion of locality-fixed effects, it is worth exploring the role of the health care supply. In our main estimation, we included the number of antenatal appointments attended by each individual as a marker of healthcare access, but this variable may not be reflected in the environment’s health supply. In an alternative setting, health supply could instead be reflected by the installed capacity of the health care system in terms of human and fixed capital. By using the capacity, we may theorize that these variables reflect the health system's ability to prevent complicated pregnancies from having bad deliveries or bad birth outcomes. Also, the scale and scope of the health supply would be

[12] Macrosomic babies definition is 4000g or bigger or equal to 4000g (Czarnobay et al., 2019).

addressed more consistently; and both private and public systems would be thoroughly encompassed.

Health supply variables are only available in Brazil from 2007 on, using the database of the CNES[13]. We chose the number of health professionals and the number of hospital beds for every 10,000 inhabitants and included them in our main estimation as control variables. Results for this alternative estimation are reported in tables S2.13 to S2.16; showing that including healthcare supply controls change the magnitude of a few coefficients, but weather variables remain significantly related to birthweight losses.

Another test we ran tried to strengthen the evidence regarding the exposition process. Along with our standard specification, we also included as control variables the weather variables of one year before the conception, by an individual. If, for example, shocks before the pregnancy were significant and shocks during the pregnancy were not, we could conclude that weather shocks had an indirect effect on birthweight and would probably be linked with agricultural outcomes and price adaptations before the exposition period rather than from the weather itself. However, our results reported in tables S2.17 to S2.20 showed that even when including previous weather variables, the coefficients of the actual values are still significant and do not change significantly in magnitude. These results confirm that the actual exposition period seems to be relevant to explain the effects we found.

To further explore the causality of the weather shocks, we also prepared a placebo test using weather variables of one year after the actual exposure dates on each of our estimations. If weather shocks and hotter weather are independent of the mother's characteristics, one should expect coefficients of equations (1) and (2) would not be significant. Although a few coefficients remain significant, the same relationships found from our main estimations do not hold anymore and the coefficients do not display consistency throughout the models. More detail on these estimations is presented in tables S2.21 to S2.24.

The three specifications covered by equation (2) consider deviations from historical weather. To relax the hypothesis of historical weather, we also gathered data regarding deviations from seasonal patterns (spring, summer, fall and winter) from our 21-year period alone. If there is a relevant effect, we can assume that weather shocks

[13] In Portuguese, "Cadastro Nacional dos Estabelecimentos de Saúde".

in a wider variety of configurations might influence birthweight. We run estimations depicted in tables S2.25 to S2.27 using this specification, and, according to our results, weather shocks apart from the seasonal averages are also significantly related to birthweight losses, particularly for the more intense shocks (over 1.5 SD).

Still on other possible configurations of weather variables, El Niño and its counterpart La Niña-Southern Oscillation are two natural phenomena that cause respectively an increase and a decrease of the Pacific Ocean temperature, particularly in the equatorial area. According to the World Meteorological Organization, because of the anomalous oscillation in the ocean temperature, there are changes in the atmospheric patterns that affect air temperatures and precipitation in several parts of the world. The effects of the El Niño and La Niña alone are attributed to cause several climatic shocks themselves such as droughts and floods, which are also followed by relevant agricultural or economic losses. While the El Niño may last for up to 18 months, the longest La Niña lasted around 3 years. Although these phenomena may alter the established climate patterns, the interaction with the effects of climate change is still not fully understood. However, it is thought that climatic changes may intensify the effects of the El Niño and La Niña and make extreme events more frequent. Furthermore, each time one of these phenomena is happening, it interacts with several other factors, making each occurrence unique (WMO, 2024).

Due to this reason, we opted to run all our regressions controlling for the El Niño and La Niña oscillations. To account for both the occurrence and the intensity of the two phenomena, we performed an alternative setting using the Oceanic Niño Index (ONI)[14] as a control variable within all our estimations. The coefficient of this variable was found significant in the majority of estimations and was found to be negatively associated with birthweight. However, the results for our weather shocks and weather bins still hold, which suggests that El Niño or La Niña do not drive our results alone and there is probably an interplay between them. The results of these estimations are available in Tables S2.28 to S2.31.

Lastly, in Brazil also other factors such as pollution from wildfires (mainly from deforestation initiatives) were already previously linked to birthweight losses (Carrilo et al., 2019). To control for this possible confounding factor, we have run alternative

[14] ONI index variable is the 3-month moving average of the sea surface temperature on the latitudes affected by the El Niño and La Niña phenomena. For more information regarding the variable, please refer to https://origin.cpc.ncep.noaa.gov/.

settings including the number of detected wildfires per municipality-year retrieved from Terra Brasilis dataset [15]. Results are depicted in Tables S2.32 to S2.35. In general, the wildfires coefficient was not significant and did not alter the relationships we have found for the weather variables. One exception is for the monthly aggregation, where a higher number of wildfires were significant for raising boys' birthweight. We do not have a particular reason for that.

2.4.4 Social vulnerabilities – heterogeneous effects

Following our conceptual framework, weather conditions may affect different people from more vulnerable backgrounds due to the environment they are from. Therefore, we run further estimations trying to define the role of social vulnerability in our results.

Considering that Brazil has a significant heterogeneity in terms of urbanized centres and remote/rural areas, we hypothesize that effects could differ according to the relative isolation of the area. Once basic services can be less widespread within more remote areas, adaptation measures to weather conditions could be relatively less available. We tested this possibility by performing equations (1) and (2) on a subset of municipalities that were below the average urbanization rate[16], retrieved from the IBGE Census (2010). According to our results, presented in tables S2.36 to S2.39; isolated areas are more vulnerable to weather shocks and hotter temperatures. In the same temperature bins, people from isolated areas suffer a decrease of more 0.1g per day than for the whole sample. For weather shocks, one additional day of shock in an isolated area also accounts for a loss of more 0.1-0.2g. A heat wave causes 0.2g more damage per day in an isolated area. For the month aggregation, the results are mixed.

Income restraints and poverty are important socioeconomic variables that define the environment as we stated in the conceptual model. Unfortunately, the SINASC dataset does not report income individual information. However, another possibility of looking at the wealth effect on protection against weather effects is to map how much each municipality relies on poverty alleviation strategies. A poor

[15] An iniciative from the National Institute of Spacial Research (INPE) that contains geoprocessed data from detected wildfires focus. For more information please refer to https://terrabrasilis.dpi.inpe.br/queimadas/situacao-atual/estatisticas/estatisticas_estados/ (In Portuguese).

[16] The average urbanization rate in Brazilian municipalities is 63.83%.

environment is likely to reflect food insecurity, poor housing and/or inadequate sanitation conditions, which are empirically linked to birthweight losses (Vettore et al., 2010; Rocha and Soares, 2015; Simonovich et al., 2020). Brazilian “Bolsa Família” is a government conditional cash transfer program that started in 2003, whose objectives are to guarantee a basic income for poorer families[17] (Brazilian Ministry of Social Assistance, 2024). Data from the “CadÚnico” were then gathered to identify the number of beneficiaries of this program by municipality-month-year since 2004, and we built a variable of the ratio of this value per total population. At first, we used this ratio as a control variable, whose results are available in Tables S2.40 to S2.43. The magnitude of our weather coefficients decreases on some estimations, with the coefficient of the program found negatively correlated with the outcome of birthweight. Still, our results continue to hold as they keep significance. In this context, it may mean that municipalities with more poor families would have a lower birthweight on average.

To understand in a deeper sense the role of poverty in our sample, we also subseted the municipalities that had the top 80% ratio of reliance on poverty alleviation strategies and ran the equations (1) and (2). In our specification with bins, we found some coefficients significant (Table S2.44), with lower coefficients than for the whole sample. On our specifications with historical deviations (Tables S2.45 to S2.47), many of the coefficients were found non-significant, a few higher and others lower. Thus, it is not clear if the weather effects are heterogeneous for this population. In this context, it is also plausible that the effect of the program itself protects to some extent the vulnerable population against the climate effects we found for the general sample.

2.5 DISCUSSION

In this study, we sought to verify whether there are sizeable effects on birthweight due to climatic change in Brazil. Henceforth, we used two strategies to deal with the weather variables. They complement each other in the sense that both phenomena will be more likely due to climate change: changes on the historical patterns and hotter temperatures.

Bins of colder temperatures (<15º-18º for boys and girls) were associated with gains in birth weight, and one additional day in one of the hotter temperature bins is

[17] The threshold for being eligible to receive the financial transfer is earning less than $ 44 dollars per person/month (apr/2024).

associated with a decrease in birthweight of up to 0.4g. The frequency of hot and cold days was important to predict birthweight, as several estimates were significant. Hotter weather conditions are related to stronger effects on our variable of interest, in increasing but not necessarily linear or monotonic ways. Additionally, the third trimester was found more sensitive to hotter weather.

Not only hotter temperatures, but the shift from the historical weather was also relevant in predicting birthweight changes, as both positive and negative shocks above 0.7 SD were found significantly related to lower birth weight. Shocks on maximum and minimum temperatures might cause the effect, however, shocks on the maximum temperature seem to be more severe and detrimental for all our samples. The size of the shock generally increases the size of the effect, with a few exceptions contradicting this logic. Even the smaller unit of days had meaningful effects.

Some studies have reported effects for hot days and heat waves, but our study also tested the effects for cold days and cold waves. However, our results for days in the middle of a week of hot and cold waves are mixed and no conclusions can be drawn.

Our results point out that negative shocks are less common than positive shocks and the effects are not homogenous across genders, the effect being more sensible when the shock occurs at the maximum temperature instead of at the minimum. As was the case for the estimation with bins, the third trimester seems to be the most sensitive across our results for shifts from the historical mean as well.

Another novelty of our approach was to include precipitation levels as variables of interest and also test if changes from the historical pattern of precipitation inflict any impact on birthweight. Our estimates for equation (1) point out that heavier precipitation is linked to birthweight losses; however, shifts from the historical precipitation patterns in equation (2) are non-significant for all other specifications. Maybe the daily volume of precipitation is more important to predicting birthweight than shocks from what is expected, but we do not exclude the possibility that our data may not have been able to fully address the role of precipitation in our sample. However, we kept the variables on our specification as control variables because of the obvious interplay between temperature and precipitation. Further studies should investigate this in detail.

Our results are in line with the literature that found effects of lower weight associated with hotter weather (Deschênes et al., 2009; Grace et al., 2015; Ngo and Norton, 2016; Chen et al., 2020; Andriano, 2023). The size of our estimates on the daily exposition approach was around -0.4g, which are close to the findings of Grace et al (2015) for sub-Saharan Africa (-0.85g), the estimates of Ngo and Norton (2016) for New York City (-1.7g) and Chen et al. (2020) for China (-1.6g). As the estimates for heat and cold waves were mixed, our estimates do not align completely with previous findings in this regard (Hajdu and Hajdu, 2021; Andriano et al., 2023).

The estimates for shifts from historical weather are also in agreement with Andalón et al. (2006). In their estimation, a month above average was linked to a decrease of 3.6g in a newborn birthweight, which is comparable to our estimation, between 2g and 3.2g across the samples. Although the results are not comparable due to the different approaches, our results are also in line with Molina and Saldarriaga (2017) and Andriano (2023), who also found that shifts from the established weather are detrimental to birth outcomes. According to our estimates, the third trimester of gestation is the most sensitive to the effects of the heat; which also agrees with previous literature on this matter (Deschênes et al., 2009; Chen et al., 2020; Andriano, 2023). On the other hand, the first and second trimesters are the most sensitive to cold days/cold waves, agreeing with the findings of Ngo and Norton (2016).

Although is out of the scope of this study to focus on weather variability itself, our results suggest that weather variability is also harmful for birthweight measures, as daily shifts from the established weather and different effects between minimum and maximum temperatures were significant regarding our outcome. This is aligned with the findings of Jakpor et al. (2020), who claimed that weather variability is damaging to birthweight.

This study also tries to acknowledge heterogeneity concerning gender, as biological links might be different for girls and boys. Girls' average weight is smaller than boys', and estimates are mixed towards stronger effects for girls and boys depending on the specification and aggregation strategy. Our effects sometimes agree with previous findings of higher effects for boys (Basu et al., 2018; Jakpor et al., 2020; Andriano, 2023), and sometimes with higher effects for girls (Chen et al., 2020), thus being inconclusive in this sense. Our control variables were also aligned with the literature, as is the case for education (Grace et al., 2015; Andalón et al., 2016; Le and Nguyen, 2021), marital status (Grace et al., 2015), parity (number of previous deliveries) (Grace et al., 2015; Andalón et al., 2016) and mother age (Andalón et al., 2016), that all had performed a positive relationship with our outcome.

We found our estimations are more intense for people living in isolated areas, which is a signalling of the relative lack of weather adaptation strategies in rural environments. When we controlled for the “Bolsa Família” program, we found part of the effect is captured by this variable. This variable tries to act as a poverty proxy; therefore, this may mean part of our result is explained by the poverty rates in each municipality. However, when we subsampled only the municipalities with the higher reliance on the program, we lost most of the statistical significance. One possible explanation is that the program itself has an alleviation influence on weather effects via wealth. Further works should specifically address the impact the Bolsa Família program may have on climate change effects in Brazil.

We first defined the possible transmission channels pointed out in the literature and then chose to not attribute one in particular as the driver of our results. However, our results hint at a few possibilities. We tested if one year’s past weather variables were significant in predicting birthweight, which we found they are – but not to the point that actual weather variables become nonsignificant. If they were significant alone, without contemporaneous weather, this might mean that weather shocks had affected harvests and income, as price adaptation would not be instantaneous; and maybe this could be the channel of the effect we found. By making this test, the results hint that the agricultural/wealth link does not seem to be the main driver of our result, as the actual exposure was significant. Moreover, the result of our specifications with trimesters suggested that the third trimester is the most sensitive to shocks on the birthweight. This is in line with the mechanism described by Andriano (2023), who claims in her study that shocks in the third trimester affect the gestational length rather than the intrauterine growth. So, by shortening gestational length, babies are born with a lighter weight than they would in the normal setting; and the most plausible biological link is the anticipated delivery rather than a nutritional loss.

This study has worth mentioning limitations. Our results rely on the gestational length variable, which is retrieved from either remembrance of the last period date before pregnancy or by clinical examination using ultrasonography. Several studies point out that the gestational length is a variable with low quality of retrieving and has consistency problems within the SINASC database (Bonilha et al., 2018; Pedraza et al., 2021). Thus, our exposition estimates might be subject to measurement error.

More clinical reasons might be behind changes in birth weight apart from weather. Unfortunately, we did not have access to more detailed information at birth regarding congenital anomalies, which might be related to both extremes of weight. To separate part of the effect, we estimated our robustness check using only term babies between the ranges of normal/healthy weight. Another concern is the link between climate change and obesity. Climate change has been considered a risk factor for obesity (Trentinaglia et al., 2021), and obese pregnant are more likely to give birth to heavier babies. So, there might exist a counterforce to the birthweight effects. The lack of behavioural and medical information on an individual level is thus a noteworthy limitation, and we expect that the antenatal appointments variable rule out part of this variation. Still, our results may be interpreted as the lower bound effects.

Due to data limitations, we could not determine the effects of migration or adaptation in our dataset. We assume that each pregnancy was exposed to weather conditions entirely on the residence municipality and that all individuals had access to the same coping mechanisms. About this last, including variables from the socio-economic background and fixed effects per municipality is an attempt to overcome this limitation.

Also, climate change effects on birthweight should be regarded as cumulative changes over time, that might be caused by several different pathaways. Thus, our results are not easily attributed to one transmission channel.

The results we found were robust to different sample sets (whole sample, term babies sample), alternative controls (health supply, El Niño/La Niña, wildfires), other specifications (shocks by season) and mechanism testing (including last year’s information on the equation). Thus, our results strongly suggest that there is a significant effect of the weather on birth outcomes. Although the size of our effects may seem small for a hotter day or a shock beyond the historical weather, one should consider that the effects are cumulative as each pregnancy may have several events of exposure.

Birthweight is considered an outcome that reflects pregnancy history but also impacts future life. According to Figlio et al. (2014), birthweight losses are correlated with lower cognitive attainment, which is not compensated by schooling. Torche and Echevalrría (2011) also pointed out that lower achievements in schooling are linked to lower birthweight and acknowledged that poor families face a deeper gap in this regard. So, our results alert to the potential loss of human capital derived from climate change – in a country already marked by deep heterogeneity and poverty.

2.6 CONCLUSION

In this study, we verified that climate change has been affecting birth weight by changing the patterns of the established climate and inducing hotter days, which affects pregnancy due to in-utero exposure. Although the channels through which this effect happens are not clear yet, further studies should determine how they work and interact to produce these damaging effects.

So far, our results point out that isolated communities are at a more serious climate risk, and the supply of health care does not seem to protect the population against the damaging effects of climate change. This means that protecting and providing mitigation alternatives to the health of vulnerable populations should go beyond the investment in health care, while also paying particular attention to other factors that may define the community level of environmental exposure.

Brazil is amongst the countries with a greater risk of suffering serious climatic vulnerabilities. As climate change damage has a long-term impact, it is important to understand whether coping mechanisms might offer protection to vulnerable populations and how the government can help defeat this public health emergency.

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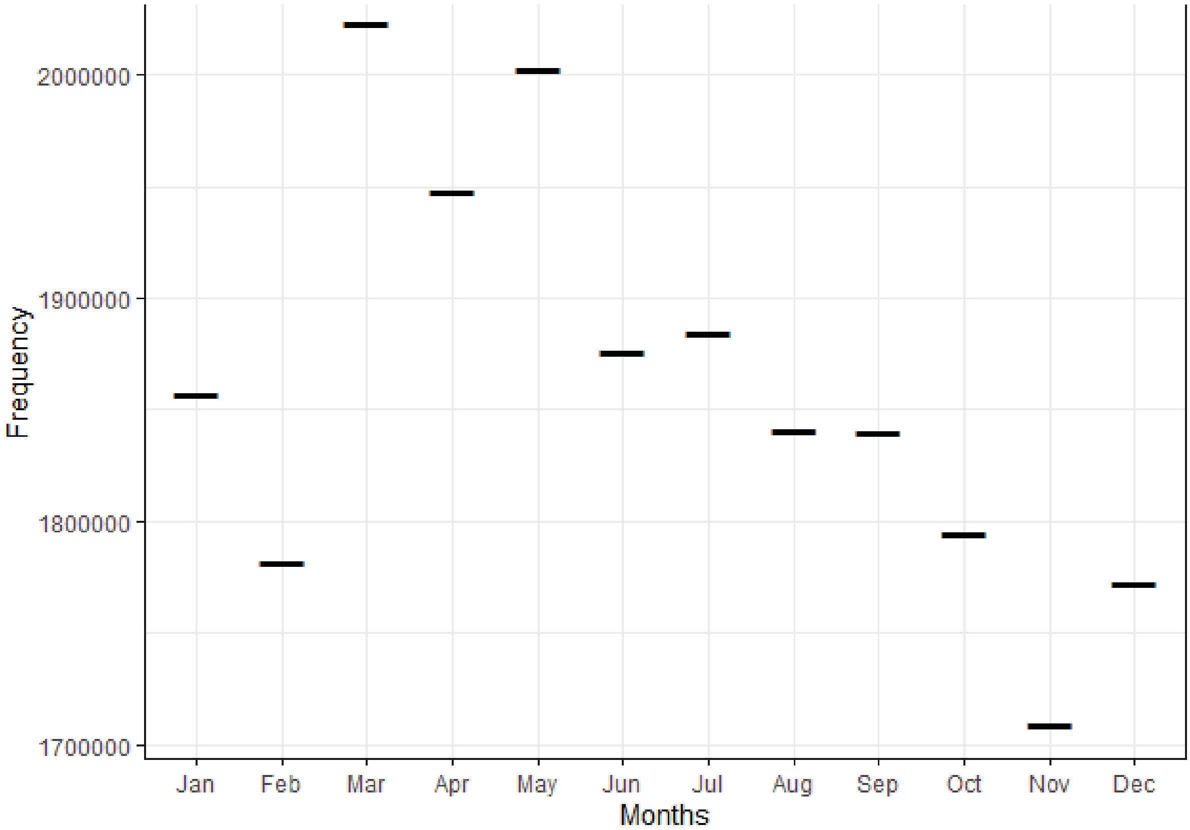
SUPPLEMENTARY MATERIAL

Figure S2. 1 - Frequency of births by month between 2000-2019



In this graph, year 2020 was subtracted from the sample due to data availability issues. As the data is only available for the first semester of 2020, evaluation of seasonality using this year would be biased.

Table S2. 1 - Complete table of estimations of birthweight per bin of temperature and precipitation

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.237*** (0.027)	0.212*** (0.025)
15-18	0.135*** (0.032)	0.162*** (0.028)
18-21	0.059* (0.026)	0.080** (0.025)
24-27	-0.143*** (0.024)	-0.133*** (0.024)
27-30	-0.352*** (0.043)	-0.333*** (0.041)
30-33	-0.428*** (0.065)	-0.419*** (0.064)
>33	-0.536 (0.738)	-0.178 (0.876)
Prec. (mm/m²)		
2.5 to 5	-0.072. (0.040)	-0.064 (0.041)
5 to 7.5	-0.114. (0.067)	-0.066 (0.064)
7.5 to 10	-0.233*** (0.064)	-0.248*** (0.062)
10 to 12.5	-0.070 (0.082)	-0.091 (0.080)
> 12.5	-0.137*** (0.031)	-0.085** (0.030)
y2000	-3.189. (1.706)	-3.101. (1.660)
y2001	-15.476*** (1.993)	-15.805*** (1.865)
y2002	-24.142*** (2.332)	-22.662*** (2.450)
y2003	-30.617*** (1.885)	-29.831*** (1.930)
y2004	-18.060*** (1.867)	-16.543*** (1.851)
y2005	-17.927*** (1.911)	-15.499*** (1.913)
y2006	-20.933*** (1.823)	-19.417*** (1.785)
y2007	-27.304*** (2.218)	-24.913*** (2.212)
y2008	-26.226*** (2.052)	-24.045*** (2.104)
y2009	-25.729*** (2.902)	-24.583*** (2.843)
y2010	-19.550*** (1.993)	-19.127*** (2.065)
y2011	2.683 (2.127)	0.567 (2.102)
y2012	3.445 (2.192)	1.537 (2.228)
y2013	1.679 (2.504)	0.702 (2.548)
y2014	1.213 (2.848)	1.165 (2.918)
y2015	3.865 (3.423)	2.495 (3.216)
y2016	5.853* (2.538)	5.131* (2.510)
y2017	4.393. (2.468)	5.562* (2.473)
y2018	4.045 (2.814)	4.260 (2.877)
y2019	10.913*** (3.052)	10.336*** (3.133)
y2020	50.525 (53.755)	75.709 (61.762)
m02	-0.531 (0.661)	-1.034. (0.557)
m03	-6.255*** (0.882)	-6.225*** (0.785)
m04	4.959*** (0.818)	5.008*** (0.672)
m05	9.188*** (0.789)	7.195*** (0.733)
m06	8.774*** (1.013)	6.873*** (0.930)
m07	13.904*** (1.532)	11.443*** (1.388)
m08	15.424*** (1.764)	12.781*** (1.685)
m09	15.878*** (1.564)	14.226*** (1.601)
m10	13.919*** (1.277)	12.401*** (1.280)
m11	10.918*** (0.977)	9.640*** (1.059)

m12	8.845*** (0.648)	7.830*** (0.705)
years of study - zero	49.161*** (1.680)	44.925*** (1.601)
years of study - 1 to 3 y	68.847*** (1.988)	63.753*** (1.888)
years of study - 4 to 7 y	89.840*** (2.299)	84.387*** (2.172)
years of study - 8 to 11 y	80.901*** (2.963)	71.059*** (2.961)
marital status - married	19.198*** (0.670)	18.273*** (0.733)
pre_appoint	57.564*** (0.751)	51.673*** (0.693)
une	-1.314** (0.492)	-1.449** (0.522)
mother_age	0.871*** (0.071)	0.968*** (0.068)
gest_age - 22 to 27 w	-1,010.867*** (24.858)	-879.818*** (25.171)
gest_age - 28 to 31 w	-1,052.762*** (17.814)	-1,035.927*** (19.434)
gest_age - 32 to 36 w	-216.428*** (16.487)	-262.083*** (15.693)
gest_age - 37 to 41 w	415.943*** (17.647)	336.133*** (15.859)
gest_age - more than 42 w	510.788*** (18.425)	418.691*** (16.183)
parity	30.321*** (0.317)	27.792*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,065,618	21,928,353
R2	0.18561	0.16880
Within R2	0.17703	0.15911

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 2 - Complete table of estimations of birthweight per daily deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.039 (0.245)	-0.022 (0.061)	-0.074 (0.179)	-0.096* (0.038)
-2 to -1.5	-0.034 (0.106)	-0.238** (0.085)	-0.279** (0.089)	-0.226*** (0.061)
-1.5 to -1	-0.014 (0.042)	0.044 (0.046)	-0.029 (0.045)	0.022 (0.037)
-1 to -0.7	0.035 (0.037)	-0.007 (0.040)	0.009 (0.039)	-0.068. (0.036)
0.7 to 1	-0.099*** (0.023)	-0.029 (0.019)	-0.115*** (0.023)	-0.034 (0.023)
1 to 1.5	-0.029 (0.018)	-0.027. (0.015)	-0.071*** (0.017)	-0.038* (0.016)
1.5 to 2	-0.151*** (0.026)	-0.040 (0.025)	-0.160*** (0.025)	-0.035 (0.027)
>2	-0.105** (0.040)	-0.073** (0.025)	-0.110** (0.037)	-0.095*** (0.025)
Precip.				
Neg.	-0.025 (0.046)		-0.003 (0.051)	
Pos.	-0.001 (0.020)		-0.002 (0.022)	
y2000	-6.968*** (1.393)		-7.235*** (1.329)	
y2001	-23.854*** (1.719)		-20.343*** (1.692)	
y2002	-30.989*** (1.879)		-28.620*** (2.046)	
y2003	-33.683*** (1.793)		-32.779*** (1.856)	
y2004	-21.890*** (1.721)		-19.799*** (1.714)	
y2005	-22.980*** (1.716)		-20.565*** (1.825)	
y2006	-25.826*** (1.703)		-26.825*** (1.778)	
y2007	-31.065*** (2.119)		-31.506*** (2.323)	
y2008	-30.361*** (2.025)		-31.387*** (2.213)	
y2009	-31.737*** (2.426)		-33.207*** (2.556)	
y2010	-23.331*** (1.985)		-25.731*** (2.054)	
y2011	1.731 (2.049)		-4.270* (2.068)	
y2012	0.691 (1.993)		-4.701* (2.173)	
y2013	-1.375 (2.379)		-6.304* (2.521)	
y2014	-3.503 (2.588)		-7.618** (2.834)	
y2015	-0.818 (2.753)		-5.111. (2.916)	
y2016	2.341 (2.287)		-1.755 (2.381)	
y2017	-0.218 (2.259)		-2.621 (2.202)	
y2018	-2.234 (2.505)		-5.239* (2.477)	
y2019	4.824. (2.542)		1.381 (2.641)	
y2020	44.419 (47.172)		66.227 (61.672)	
m02	1.258* (0.559)		0.690 (0.547)	
m03	-3.648*** (0.643)		-3.945*** (0.608)	
m04	6.197*** (0.698)		5.887*** (0.618)	
m05	6.653*** (0.812)		4.447*** (0.718)	
m06	1.336. (0.718)		-0.614 (0.619)	
m07	2.275*** (0.674)		-0.216 (0.578)	
m08	1.930** (0.619)		-0.854. (0.515)	
m09	3.034*** (0.699)		1.490** (0.558)	
m10	4.034*** (0.592)		2.509*** (0.532)	
m11	4.600*** (0.571)		3.319*** (0.565)	
m12	5.958*** (0.484)		4.910*** (0.504)	

years of study - zero	48.904*** (1.687)	44.954*** (1.636)
years of study - 1 to 3 y	68.647*** (1.998)	63.637*** (1.934)
years of study - 4 to 7 y	89.183*** (2.307)	84.156*** (2.210)
years of study - 8 to 11 y	79.613*** (2.968)	70.736*** (2.979)
marital status - married	18.797*** (0.674)	18.125*** (0.734)
pre_appoint	58.524*** (0.743)	51.502*** (0.684)
une	-0.986* (0.490)	-1.153* (0.516)
mother_age	0.779*** (0.073)	0.964*** (0.068)
gest_age - 22 to 27 w	-620.671*** (26.107)	-880.048*** (25.789)
gest_age - 28 to 31 w	-189.976*** (33.366)	-1,040.558*** (20.025)
gest_age - 32 to 36 w	703.270*** (41.377)	-268.753*** (15.628)
gest_age - 37 to 41 w	1,334.626*** (45.768)	327.566*** (15.523)
gest_age - more than 42 w	1,425.909*** (46.623)	408.288*** (15.762)
parity	30.695*** (0.318)	27.782*** (0.320)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,126,365	21,913,936
R2	0.21150	0.16891
Within R2	0.20301	0.15921

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 3 - Complete table of estimations of birthweight per weekly deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.039 (0.245)	-0.022 (0.061)	-0.074 (0.179)	-0.096* (0.038)
-2 to -1.5	-0.034 (0.106)	-0.238** (0.085)	-0.279** (0.089)	-0.226*** (0.061)
-1.5 to -1	-0.014 (0.042)	0.044 (0.046)	-0.029 (0.045)	0.022 (0.037)
-1 to -0.7	0.035 (0.037)	-0.007 (0.040)	0.009 (0.039)	-0.068. (0.036)
0.7 to 1	-0.099*** (0.023)	-0.029 (0.019)	-0.115*** (0.023)	-0.034 (0.023)
1 to 1.5	-0.029 (0.018)	-0.027. (0.015)	-0.071*** (0.017)	-0.038* (0.016)
1.5 to 2	-0.151*** (0.026)	-0.040 (0.025)	-0.160*** (0.025)	-0.035 (0.027)
>2	-0.105** (0.040)	-0.073** (0.025)	-0.110** (0.037)	-0.095*** (0.025)
Precip.				
Neg.	-0.025 (0.046)		-0.003 (0.051)	
Pos.	-0.001 (0.020)		-0.002 (0.022)	
y2000	-10.963*** (1.401)		-7.717*** (1.321)	
y2001	-26.258*** (1.870)		-27.944*** (2.099)	
y2002	-35.350*** (1.982)		-31.284*** (2.093)	
y2003	-38.030*** (1.867)		-33.620*** (1.870)	
y2004	-26.508*** (1.802)		-21.266*** (1.718)	
y2005	-27.985*** (1.825)		-21.924*** (1.824)	
y2006	-31.108*** (1.862)		-25.737*** (1.769)	
y2007	-36.041*** (2.270)		-30.097*** (2.212)	
y2008	-35.287*** (2.199)		-29.399*** (2.131)	
y2009	-37.898*** (2.577)		-32.754*** (2.465)	
y2010	-28.920*** (2.202)		-24.595*** (2.055)	
y2011	-3.585 (2.258)		-2.274 (2.044)	
y2012	-5.640** (2.169)		-3.498. (2.107)	
y2013	-7.653** (2.560)		-4.948* (2.436)	
y2014	-10.162*** (2.796)		-6.484* (2.749)	
y2015	-8.370** (2.938)		-5.270. (2.851)	
y2016	-2.522 (2.616)		-1.303 (2.346)	
y2017	-5.978* (2.432)		-1.748 (2.246)	
y2018	-9.392*** (2.601)		-5.098* (2.510)	
y2019	-3.794 (2.616)		0.898 (2.631)	
y2020	-141.070*** (38.860)		-62.482 (44.311)	
m02	1.297* (0.541)		0.484 (0.562)	
m03	-3.535*** (0.617)		-4.162*** (0.620)	
m04	6.340*** (0.688)		6.107*** (0.633)	
m05	6.744*** (0.783)		4.573*** (0.720)	
m06	1.129 (0.739)		-0.348 (0.650)	
m07	2.292*** (0.665)		0.080 (0.579)	
m08	1.999** (0.618)		-0.445 (0.537)	
m09	3.111*** (0.735)		1.943*** (0.560)	
m10	3.928*** (0.613)		2.815*** (0.536)	
m11	4.456*** (0.581)		3.372*** (0.582)	

m12	5.681*** (0.483)	4.901*** (0.521)
years of study - zero	49.402*** (1.691)	44.893*** (1.682)
years of study - 1 to 3 y	69.024*** (1.973)	63.651*** (1.938)
years of study - 4 to 7 y	89.729*** (2.255)	84.077*** (2.201)
years of study - 8 to 11 y	81.518*** (2.885)	71.308*** (2.969)
marital status - married	18.999*** (0.681)	17.864*** (0.717)
pre_appoint	59.321*** (0.759)	53.779*** (0.715)
une	-1.076* (0.488)	-1.177* (0.506)
mother_age	0.771*** (0.072)	0.850*** (0.069)
gest_age - 22 to 27 w	-376.559*** (29.621)	-436.862*** (27.741)
gest_age - 28 to 31 w	105.022** (33.331)	27.555 (30.970)
gest_age - 32 to 36 w	1,004.121*** (36.846)	888.585*** (34.912)
gest_age - 37 to 41 w	1,634.474*** (40.246)	1,484.845*** (38.484)
gest_age - more than 42 w	1,725.245*** (41.190)	1,563.928*** (39.060)
parity	30.751*** (0.326)	28.339*** (0.334)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,715,657	21,486,570
R^2	0.21529	0.20071
Within R^2	0.20756	0.19214

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 4 - Complete table of estimations of birthweight per monthly deviations from historical means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-19.590 (13.142)	-0.870 (0.945)	-11.075 (13.274)	-2.119* (0.911)
-2 to -1.5	-0.477 (5.909)	-1.494 (1.389)	-3.019 (6.943)	-2.287. (1.296)
-1.5 to -1	4.404** (1.560)	-2.180** (0.693)	3.962** (1.480)	-1.307* (0.599)
-1 to -0.7	-0.706 (0.787)	-0.019 (0.564)	-0.732 (0.782)	-0.492 (0.563)
0.7 to 1	-1.076*** (0.281)	-0.623** (0.209)	-1.231*** (0.270)	-0.701** (0.217)
1 to 1.5	-1.978*** (0.328)	-0.738** (0.275)	-2.114*** (0.337)	-0.714* (0.280)
1.5 to 2	-2.980*** (0.561)	-1.367** (0.503)	-3.239*** (0.545)	-1.178* (0.505)
>2	-2.182* (0.918)	-1.931** (0.596)	-2.506** (0.949)	-2.393*** (0.610)
Precip.				
Neg.	0.768 (3.188)		5.197. (2.857)	
Pos.	0.091 (0.466)		0.771. (0.395)	
y2000	-7.557*** (1.348)		-7.356*** (1.291)	
y2001	-19.859*** (1.662)		-19.812*** (1.607)	
y2002	-30.118*** (1.777)		-28.111*** (1.897)	
y2003	-33.644*** (1.766)		-32.745*** (1.856)	
y2004	-22.036*** (1.687)		-20.202*** (1.679)	
y2005	-22.312*** (1.655)		-19.551*** (1.720)	
y2006	-25.752*** (1.658)		-23.972*** (1.690)	
y2007	-30.505*** (2.014)		-27.961*** (2.104)	
y2008	-29.371*** (1.943)		-26.961*** (2.036)	
y2009	-30.802*** (2.285)		-29.095*** (2.291)	
y2010	-23.181*** (1.918)		-22.288*** (1.953)	
y2011	1.296 (1.956)		-0.765 (1.977)	
y2012	-0.050 (1.915)		-1.532 (2.024)	
y2013	-2.298 (2.325)		-2.943 (2.384)	
y2014	-4.080 (2.492)		-3.644 (2.641)	
y2015	-0.966 (2.625)		-1.470 (2.687)	
y2016	1.941 (2.182)		1.898 (2.225)	
y2017	-0.198 (2.220)		1.386 (2.204)	
y2018	-2.846 (2.427)		-2.064 (2.447)	
y2019	4.295. (2.466)		4.295. (2.505)	
y2020	41.520 (53.731)		68.414 (61.583)	
m02	1.283* (0.538)		0.679 (0.543)	
m03	-3.645*** (0.605)		-3.779*** (0.590)	
m04	6.400*** (0.663)		6.327*** (0.594)	
m05	6.889*** (0.773)		4.881*** (0.678)	
m06	1.502* (0.704)		-0.229 (0.616)	
m07	2.098** (0.661)		-0.006 (0.557)	
m08	1.322* (0.613)		-0.788 (0.504)	
m09	2.668*** (0.674)		1.632** (0.524)	
m10	3.547*** (0.577)		2.594*** (0.512)	
m11	4.192*** (0.565)		3.311*** (0.559)	

m12	5.624*** (0.477)	4.819*** (0.498)
years of study - zero	49.221*** (1.693)	45.010*** (1.616)
years of study - 1 to 3 y	69.015*** (2.007)	63.969*** (1.914)
years of study - 4 to 7 y	90.007*** (2.317)	84.592*** (2.196)
years of study - 8 to 11 y	81.046*** (2.982)	71.240*** (2.986)
marital status - married	19.178*** (0.673)	18.258*** (0.734)
pre_appoint	57.615*** (0.746)	51.730*** (0.687)
une	-0.955. (0.493)	-1.065* (0.516)
mother_age	0.867*** (0.071)	0.964*** (0.069)
gest_age - 22 to 27 w	-1,016.319*** (25.233)	-884.114*** (25.515)
gest_age - 28 to 31 w	-1,063.732*** (17.923)	-1,045.608*** (19.645)
gest_age - 32 to 36 w	-231.142*** (16.079)	-274.935*** (15.397)
gest_age - 37 to 41 w	397.658*** (17.109)	320.413*** (15.376)
gest_age - more than 42 w	489.197*** (17.873)	400.020*** (15.653)
parity	30.322*** (0.317)	27.795*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,126,365	21,913,936
R2	0.21150	0.16891
Within R2	0.20301	0.15921

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 5 - Complete table of estimations of birthweight per bin of temperature and precipitation, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)	
Temp.	Tri	Boys	Girls
<15	1st	0.463*** (0.048)	0.367*** (0.045)
	2nd	0.044 (0.030)	0.072* (0.028)
	3rd	0.581*** (0.061)	0.498*** (0.056)
15-18	1st	0.119** (0.037)	0.137*** (0.036)
	2nd	0.054. (0.031)	0.100*** (0.028)
	3rd	0.397*** (0.055)	0.386*** (0.046)
18-21	1st	0.146*** (0.031)	0.157*** (0.030)
	2nd	0.094*** (0.025)	0.118*** (0.026)
	3rd	0.183*** (0.031)	0.195*** (0.030)
24-27	1st	-0.117*** (0.029)	-0.106*** (0.026)
	2nd	0.046** (0.017)	0.042* (0.018)
	3rd	-0.332*** (0.037)	-0.321*** (0.035)
27-30	1st	-0.284*** (0.046)	-0.265*** (0.045)
	2nd	0.014 (0.023)	0.000 (0.022)
	3rd	-0.759*** (0.075)	-0.720*** (0.072)
30-33	1st	-0.356*** (0.061)	-0.366*** (0.058)
	2nd	-0.214*** (0.054)	-0.208*** (0.049)
	3rd	-0.826*** (0.097)	-0.792*** (0.098)
>33	1st	-0.076 (1.051)	0.120 (1.251)
	2nd	-0.760 (1.287)	-0.939 (0.929)
	3rd	-0.471 (1.008)	1.053 (1.250)
Precip.			
2.5 to 5	1st	-0.042 (0.059)	-0.021 (0.051)
	2nd	-0.134** (0.048)	-0.077. (0.046)
	3rd	-0.188*** (0.056)	-0.202*** (0.056)
5 to 7.5	1st	-0.002 (0.088)	0.096 (0.079)
	2nd	-0.092 (0.080)	-0.095 (0.066)
	3rd	-0.262** (0.082)	-0.183* (0.084)
7.5 to 10	1st	-0.125. (0.076)	-0.201** (0.075)
	2nd	-0.083 (0.078)	-0.081 (0.069)
	3rd	-0.425*** (0.091)	-0.401*** (0.097)
10 to 12.5	1st	0.151 (0.099)	0.203* (0.095)
	2nd	0.207* (0.093)	0.126 (0.088)
	3rd	-0.316** (0.101)	-0.321** (0.109)
> 12.5	1st	-0.123** (0.044)	-0.042 (0.038)
	2nd	0.087* (0.040)	0.110** (0.037)
	3rd	-0.276*** (0.044)	-0.193*** (0.043)
y2000		-2.548 (1.688)	-2.553 (1.641)
y2001		-14.652*** (1.959)	-15.199*** (1.822)
y2002		-24.196*** (2.244)	-22.813*** (2.369)
y2003		-30.998*** (1.843)	-30.238*** (1.897)
y2004		-17.605*** (1.862)	-16.176*** (1.838)
y2005		-18.240*** (1.866)	-15.903*** (1.865)

y2006	-20.681*** (1.809)	-19.262*** (1.784)
y2007	-27.680*** (2.172)	-25.308*** (2.172)
y2008	-26.404*** (2.033)	-24.318*** (2.088)
y2009	-26.123*** (2.786)	-25.098*** (2.738)
y2010	-20.290*** (1.998)	-19.886*** (2.065)
y2011	2.728 (2.128)	0.556 (2.103)
y2012	3.388 (2.116)	1.437 (2.155)
y2013	1.399 (2.476)	0.408 (2.517)
y2014	1.797 (2.806)	1.654 (2.879)
y2015	3.815 (3.313)	2.392 (3.121)
y2016	5.366* (2.474)	4.669. (2.457)
y2017	4.628. (2.476)	5.610* (2.465)
y2018	5.016. (2.759)	5.006. (2.814)
y2019	10.513*** (2.980)	9.751** (3.038)
y2020	52.847 (53.594)	77.177 (61.769)
m02	7.051*** (0.730)	6.011*** (0.746)
m03	5.397*** (0.861)	4.912*** (0.935)
m04	18.005*** (1.075)	17.959*** (1.141)
m05	21.387*** (1.204)	19.811*** (1.356)
m06	19.657*** (1.598)	18.455*** (1.591)
m07	21.341*** (1.742)	19.795*** (1.688)
m08	17.077*** (1.454)	15.582*** (1.451)
m09	9.792*** (0.857)	9.643*** (0.905)
m10	2.352** (0.779)	2.491** (0.761)
m11	-1.420 (0.873)	-1.257 (0.841)
m12	1.118. (0.652)	0.877 (0.651)
years of study - zero	49.250*** (1.680)	45.026*** (1.599)
years of study - 1 to 3 y	68.970*** (1.982)	63.891*** (1.880)
years of study - 4 to 7 y	89.966*** (2.291)	84.531*** (2.164)
years of study - 8 to 11 y	81.002*** (2.956)	71.171*** (2.955)
marital status - married	19.172*** (0.670)	18.243*** (0.733)
pre_appoint	57.552*** (0.751)	51.661*** (0.694)
une	-1.391** (0.487)	-1.507** (0.515)
mother_age	0.872*** (0.071)	0.969*** (0.068)
gest_age - 22 to 27 w	-1,013.107*** (24.643)	-882.265*** (25.032)
gest_age - 28 to 31 w	-1,049.295*** (17.837)	-1,032.495*** (19.399)
gest_age - 32 to 36 w	-207.974*** (16.654)	-253.745*** (15.762)
gest_age - 37 to 41 w	427.472*** (17.709)	347.589*** (15.824)
gest_age - more than 42 w	519.237*** (18.390)	427.399*** (16.043)
parity	30.322*** (0.316)	27.793*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,065,618	21,928,353

R2	0.18572	0.16891
Within R2	0.17714	0.15922

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 6 - Complete table of estimations of birthweight per daily deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	0.100 (0.356)	-0.004 (0.135)	-0.018 (0.248)	-0.256*** (0.053)
	2nd	0.224 (0.313)	0.046 (0.059)	-0.164 (0.235)	0.121 (0.081)
	3rd	-0.293 (0.346)	-0.137 (0.102)	-0.195 (0.217)	-0.170* (0.066)
-2 to -1.5	1st	0.156 (0.151)	-0.287** (0.111)	-0.284* (0.125)	-0.189* (0.084)
	2nd	-0.010 (0.154)	-0.182. (0.104)	-0.330* (0.134)	-0.350*** (0.098)
	3rd	-0.298* (0.140)	-0.273* (0.133)	-0.215. (0.124)	-0.041 (0.104)
-1.5 to -1	1st	-0.069 (0.059)	0.023 (0.071)	-0.060 (0.058)	-0.022 (0.056)
	2nd	0.080 (0.063)	0.061 (0.063)	-0.063 (0.056)	-0.003 (0.057)
	3rd	-0.071 (0.057)	0.126. (0.072)	-0.039 (0.059)	0.088 (0.076)
-1 to -0.7	1st	-0.059 (0.051)	-0.066 (0.054)	-0.105* (0.048)	-0.138* (0.062)
	2nd	-0.009 (0.052)	-0.109. (0.056)	0.033 (0.050)	-0.132* (0.054)
	3rd	0.075 (0.055)	0.105 (0.064)	0.083 (0.063)	0.055 (0.057)
0.7 to 1	1st	-0.078* (0.030)	0.012 (0.026)	-0.068* (0.028)	0.028 (0.031)
	2nd	-0.063* (0.027)	-0.024 (0.025)	-0.115*** (0.027)	-0.058* (0.028)
	3rd	-0.143*** (0.031)	-0.064** (0.024)	-0.170*** (0.031)	-0.054. (0.030)
1 to 1.5	1st	-0.013 (0.025)	0.039* (0.019)	-0.071** (0.026)	0.007 (0.020)
	2nd	0.006 (0.022)	-0.014 (0.019)	-0.028 (0.020)	-0.004 (0.021)
	3rd	-0.100*** (0.025)	-0.081*** (0.024)	-0.128*** (0.023)	-0.111*** (0.022)
1.5 to 2	1st	-0.147*** (0.039)	0.026 (0.029)	-0.139*** (0.036)	0.039 (0.034)
	2nd	-0.089** (0.033)	0.016 (0.030)	-0.109*** (0.031)	-0.041 (0.028)
	3rd	-0.207*** (0.035)	-0.135*** (0.041)	-0.244*** (0.034)	-0.078. (0.044)
>2	1st	-0.158** (0.049)	-0.021 (0.035)	-0.193*** (0.046)	-0.069. (0.037)
	2nd	0.005 (0.043)	0.022 (0.032)	0.000 (0.040)	0.004 (0.032)
	3rd	-0.140* (0.057)	-0.214*** (0.042)	-0.142** (0.051)	-0.242*** (0.039)
Precip.					
Pos	1st	0.022 (0.028)		0.054* (0.026)	
	2nd	0.012 (0.025)		-0.008 (0.026)	
	3rd	-0.050 (0.032)		-0.051. (0.030)	
Neg	1st	0.132 (0.083)		0.154* (0.061)	
	2nd	0.003 (0.059)		-0.115* (0.050)	
	3rd	-0.092 (0.064)		0.018 (0.063)	
y2000		-7.051*** (1.456)		-6.544*** (1.379)	
y2001		-20.024*** (1.825)		-20.571*** (1.755)	
y2002		-31.079*** (1.929)		-29.600*** (2.030)	
y2003		-34.761*** (1.832)		-33.679*** (1.884)	
y2004		-21.247*** (1.719)		-19.644*** (1.737)	
y2005		-23.592*** (1.784)		-21.251*** (1.835)	
y2006		-25.961*** (1.724)		-26.577*** (1.813)	
y2007		-31.707*** (2.116)		-32.138*** (2.300)	
y2008		-29.729*** (1.992)		-31.093*** (2.230)	
y2009		-31.592*** (2.486)		-33.216*** (2.584)	
y2010		-24.291*** (2.013)		-26.272*** (2.099)	

y2011	1.782 (2.075)	-4.084. (2.133)
y2012	-0.346 (2.037)	-4.761* (2.197)
y2013	-2.384 (2.358)	-6.001* (2.551)
y2014	-4.630. (2.588)	-7.719** (2.871)
y2015	-2.584 (2.828)	-5.482. (2.948)
y2016	0.482 (2.293)	-2.404 (2.384)
y2017	-1.627 (2.300)	-2.649 (2.266)
y2018	-3.347 (2.489)	-5.109* (2.468)
y2019	2.107 (2.534)	0.280 (2.652)
y2020	31.727 (58.182)	53.769 (67.975)
m02	1.846** (0.649)	1.698** (0.589)
m03	-2.529*** (0.750)	-2.171*** (0.610)
m04	7.555*** (0.725)	7.572*** (0.649)
m05	8.500*** (0.889)	6.194*** (0.813)
m06	3.242*** (0.809)	1.403* (0.688)
m07	4.278*** (0.780)	1.835** (0.647)
m08	3.104*** (0.803)	1.462* (0.622)
m09	4.193*** (0.840)	3.080*** (0.642)
m10	4.263*** (0.678)	3.440*** (0.611)
m11	4.635*** (0.645)	3.731*** (0.627)
m12	5.248*** (0.540)	4.606*** (0.553)
years of study - zero	49.887*** (1.713)	44.784*** (1.690)
years of study - 1 to 3 y	69.327*** (2.003)	63.500*** (1.946)
years of study - 4 to 7 y	90.624*** (2.283)	84.051*** (2.219)
years of study - 8 to 11 y	81.859*** (2.945)	70.426*** (2.988)
marital status - married	19.211*** (0.688)	18.180*** (0.760)
pre_appoint	57.560*** (0.751)	51.651*** (0.686)
une	-0.932. (0.485)	-1.159* (0.513)
mother_age	0.870*** (0.072)	0.948*** (0.070)
gest_age - 22 to 27 w	-1,012.051*** (27.118)	-896.736*** (27.180)
gest_age - 28 to 31 w	-1,055.345*** (20.147)	-1,054.739*** (21.141)
gest_age - 32 to 36 w	-220.602*** (18.042)	-282.149*** (16.394)
gest_age - 37 to 41 w	409.214*** (18.782)	314.625*** (16.107)
gest_age - more than 42 w	500.517*** (19.468)	393.996*** (16.324)
parity	30.363*** (0.318)	27.880*** (0.326)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	17,901,983	17,898,704
R2	0.18562	0.16885
Within R2	0.17695	0.15909

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Tri – trimester. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 7 - Complete table of estimations of birthweight per weekly deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	-0.331 (0.372)	-0.180 (0.172)	0.446 (0.340)	-0.276** (0.101)
	2nd	0.269 (0.274)	0.066 (0.094)	0.566 (0.355)	0.131 (0.091)
	3rd	0.201 (0.266)	-0.127 (0.105)	0.217 (0.292)	-0.197** (0.067)
-2 to -1.5	1st	0.123 (0.146)	-0.301* (0.150)	0.117 (0.139)	-0.107 (0.094)
	2nd	0.215. (0.130)	-0.287* (0.146)	0.015 (0.153)	-0.250** (0.094)
	3rd	-0.265* (0.111)	-0.316* (0.150)	-0.245. (0.147)	-0.120 (0.130)
-1.5 to -1	1st	-0.069 (0.058)	0.102 (0.097)	-0.071 (0.060)	-0.059 (0.057)
	2nd	0.120* (0.056)	0.049 (0.095)	0.018 (0.054)	0.039 (0.056)
	3rd	-0.081. (0.048)	0.098 (0.110)	-0.103. (0.058)	0.125. (0.075)
-1 to -0.7	1st	-0.099. (0.053)	-0.157* (0.078)	-0.086. (0.048)	-0.155* (0.062)
	2nd	-0.165*** (0.049)	0.090 (0.080)	-0.036 (0.047)	-0.136* (0.061)
	3rd	0.160*** (0.046)	0.007 (0.097)	0.099 (0.067)	0.033 (0.060)
0.7 to 1	1st	-0.061* (0.028)	0.022 (0.034)	-0.053. (0.030)	0.011 (0.028)
	2nd	0.011 (0.023)	-0.006 (0.031)	-0.064* (0.028)	-0.052. (0.027)
	3rd	-0.101*** (0.030)	-0.011 (0.032)	-0.148*** (0.034)	-0.042 (0.027)
1 to 1.5	1st	-0.027 (0.024)	0.038 (0.025)	-0.029 (0.026)	0.015 (0.020)
	2nd	0.061** (0.020)	-0.044. (0.024)	-0.017 (0.021)	-0.014 (0.022)
	3rd	-0.069*** (0.020)	-0.034 (0.028)	-0.098*** (0.023)	-0.094*** (0.023)
1.5 to 2	1st	-0.130*** (0.036)	-0.080* (0.031)	-0.140*** (0.037)	0.048 (0.033)
	2nd	0.042 (0.027)	-0.007 (0.028)	-0.078* (0.033)	-0.016 (0.031)
	3rd	-0.149*** (0.028)	-0.092** (0.035)	-0.254*** (0.036)	-0.094* (0.043)
>2	1st	-0.156*** (0.047)	0.138*** (0.027)	-0.192*** (0.049)	-0.063. (0.034)
	2nd	0.038 (0.037)	-0.291*** (0.040)	0.023 (0.043)	0.054. (0.030)
	3rd	-0.153*** (0.044)	0.210*** (0.024)	-0.139* (0.056)	-0.254*** (0.045)
Precip.					
Pos	1st	0.045 (0.027)		0.072** (0.025)	
	2nd	0.076*** (0.022)		0.021 (0.027)	
	3rd	-0.078** (0.024)		-0.031 (0.029)	
Neg	1st	0.070 (0.070)		0.131. (0.071)	
	2nd	0.016 (0.054)		-0.061 (0.058)	
	3rd	-0.194** (0.061)		-0.076 (0.064)	
y2000		-8.457*** (1.519)		-7.749*** (1.343)	
y2001		-21.084*** (1.748)		-27.896*** (2.133)	
y2002		-32.803*** (1.928)		-32.266*** (2.080)	
y2003		-34.639*** (1.820)		-34.401*** (1.901)	
y2004		-23.426*** (1.731)		-21.116*** (1.720)	
y2005		-24.749*** (1.769)		-23.216*** (1.851)	
y2006		-27.575*** (1.702)		-26.043*** (1.749)	
y2007		-32.251*** (2.069)		-31.294*** (2.212)	
y2008		-31.254*** (1.961)		-29.011*** (2.102)	
y2009		-35.341*** (2.450)		-32.979*** (2.469)	
y2010		-24.740*** (1.993)		-25.457*** (2.062)	

y2011	1.973 (2.007)	-2.324 (2.045)
y2012	-1.326 (1.963)	-4.091. (2.104)
y2013	-2.829 (2.335)	-5.336* (2.442)
y2014	-5.798* (2.506)	-6.792* (2.740)
y2015	-5.267. (2.729)	-5.722* (2.843)
y2016	0.027 (2.374)	-2.348 (2.328)
y2017	-0.446 (2.184)	-2.451 (2.223)
y2018	-3.068 (2.395)	-5.170* (2.472)
y2019	2.806 (2.434)	-0.697 (2.603)
y2020	-69.196 (45.001)	-87.290. (49.446)
m02	0.688 (0.590)	1.083. (0.596)
m03	-3.868*** (0.661)	-3.159*** (0.667)
m04	5.757*** (0.700)	7.588*** (0.690)
m05	7.114*** (0.891)	6.204*** (0.849)
m06	1.920* (0.798)	1.778* (0.741)
m07	2.336** (0.751)	2.494*** (0.703)
m08	2.378*** (0.709)	1.663* (0.654)
m09	3.203*** (0.828)	3.502*** (0.707)
m10	4.153*** (0.684)	3.576*** (0.626)
m11	5.335*** (0.643)	3.334*** (0.597)
m12	6.545*** (0.562)	4.607*** (0.555)
years of study - zero	48.602*** (1.766)	45.298*** (1.697)
years of study - 1 to 3 y	67.986*** (2.095)	64.122*** (1.938)
years of study - 4 to 7 y	88.100*** (2.350)	84.599*** (2.186)
years of study - 8 to 11 y	78.181*** (3.052)	71.789*** (2.906)
marital status - married	18.482*** (0.666)	17.776*** (0.715)
pre_appoint	58.578*** (0.736)	53.619*** (0.731)
une	-1.392** (0.484)	-1.159* (0.501)
mother_age	0.755*** (0.074)	0.854*** (0.069)
gest_age - 22 to 27 w	-400.555*** (31.149)	-444.652*** (28.934)
gest_age - 28 to 31 w	78.704* (34.489)	23.649 (32.338)
gest_age - 32 to 36 w	977.276*** (38.026)	883.769*** (36.250)
gest_age - 37 to 41 w	1,604.913*** (41.365)	1,481.464*** (39.814)
gest_age - more than 42 w	1,696.438*** (42.402)	1,559.529*** (40.421)
parity	30.794*** (0.328)	28.262*** (0.331)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	17,994,788	17,996,650
R2	0.21452	0.20066
Within R2	0.20669	0.19207

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Tri – trimester. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 8 - Complete table of estimations of birthweight per monthly deviations from historical means, by gestational trimester

Weather var.		Dependent variable – Birthweight (g)			
		Boys		Girls	
Shock Size (SD)	Tri	Max.	Min.	Max.	Min.
<-2	1st	-6.976 (8.865)	0.655 (1.537)	0.949 (12.952)	-3.824** (1.422)
	2nd	-22.028 (14.180)	-1.671 (1.606)	-21.290 (15.445)	1.962 (1.979)
	3rd	-23.619 (34.936)	-2.206 (1.780)	1.966 (16.136)	-4.495** (1.694)
-2 to -1.5	1st	2.371 (6.955)	-0.531 (1.678)	-0.903 (7.626)	-1.513 (2.033)
	2nd	4.230 (6.712)	-2.004 (1.998)	0.648 (8.993)	-0.277 (2.661)
	3rd	3.165 (6.673)	-2.198 (2.556)	3.473 (9.275)	-3.445 (3.076)
-1.5 to -1	1st	1.251 (2.011)	-1.708 (1.098)	3.755. (2.080)	-1.158 (1.038)
	2nd	6.051*** (1.733)	-1.724 (1.253)	0.639 (1.545)	-1.731 (1.143)
	3rd	-0.133 (2.046)	-1.045 (1.450)	4.473* (2.081)	-0.788 (1.306)
-1 to -0.7	1st	-1.663. (0.893)	-0.560 (0.687)	-0.933 (0.873)	-0.737 (0.725)
	2nd	1.861* (0.905)	0.571 (0.785)	0.478 (0.913)	0.506 (0.684)
	3rd	-1.183 (0.892)	1.244 (1.064)	-0.766 (0.884)	-0.731 (0.919)
0.7 to 1	1st	0.002 (0.325)	-0.027 (0.239)	-0.494. (0.293)	-0.023 (0.254)
	2nd	0.013 (0.240)	-0.418. (0.221)	-0.411 (0.252)	-0.511* (0.210)
	3rd	-2.274*** (0.345)	-0.969* (0.404)	-2.162*** (0.310)	-0.985* (0.395)
1 to 1.5	1st	-1.336** (0.421)	0.488 (0.321)	-1.657*** (0.438)	0.274 (0.306)
	2nd	-0.424 (0.262)	-0.453 (0.318)	-0.432 (0.273)	-0.172 (0.287)
	3rd	-2.607*** (0.432)	-1.631** (0.508)	-3.140*** (0.405)	-1.627*** (0.447)
1.5 to 2	1st	-3.427*** (0.613)	-0.509 (0.550)	-3.417*** (0.613)	-0.406 (0.548)
	2nd	0.993. (0.565)	1.157* (0.529)	0.406 (0.500)	1.014* (0.418)
	3rd	-4.848*** (0.745)	-3.866*** (0.827)	-4.847*** (0.762)	-3.784*** (0.869)
>2	1st	-2.558* (1.110)	-1.651* (0.816)	-3.982*** (1.018)	-2.008** (0.759)
	2nd	0.783 (0.923)	2.672*** (0.681)	2.016* (0.942)	3.030*** (0.695)
	3rd	-3.542** (1.208)	-5.837*** (1.043)	-5.014*** (1.091)	-6.966*** (1.066)
Precip.					
Pos	1st	0.562 (0.519)		1.283* (0.525)	
	2nd	0.526 (0.546)		0.387 (0.494)	
	3rd	0.277 (0.588)		-0.046 (0.521)	
Neg	1st	4.767 (4.258)		1.540 (3.892)	
	2nd	-1.113 (3.229)		2.882 (3.504)	
	3rd	0.606 (4.603)		3.330 (4.006)	
y2000		-7.991*** (1.373)		-7.738*** (1.322)	
y2001		-20.708*** (1.652)		-20.368*** (1.651)	
y2002		-31.749*** (1.799)		-29.742*** (1.877)	
y2003		-34.620*** (1.823)		-33.847*** (1.895)	
y2004		-22.642*** (1.736)		-20.600*** (1.713)	
y2005		-23.766*** (1.710)		-21.319*** (1.778)	
y2006		-26.593*** (1.713)		-24.705*** (1.727)	
y2007		-31.988*** (2.040)		-28.907*** (2.179)	
y2008		-29.665*** (1.996)		-27.178*** (2.075)	
y2009		-32.977*** (2.320)		-30.953*** (2.312)	
y2010		-24.418*** (1.967)		-23.631*** (1.991)	

y2011	0.250 (2.014)	-1.517 (2.031)
y2012	-2.104 (1.941)	-3.236 (2.068)
y2013	-3.556 (2.346)	-3.614 (2.406)
y2014	-6.076* (2.527)	-5.321* (2.674)
y2015	-4.442. (2.688)	-4.081 (2.693)
y2016	-0.426 (2.191)	-0.049 (2.283)
y2017	-1.315 (2.232)	-0.017 (2.271)
y2018	-4.049 (2.481)	-2.974 (2.452)
y2019	1.826 (2.545)	2.239 (2.614)
y2020	57.737 (61.791)	20.349 (70.518)
m02	2.366*** (0.621)	0.915 (0.590)
m03	-2.839*** (0.650)	-3.131*** (0.631)
m04	7.428*** (0.733)	6.773*** (0.641)
m05	7.427*** (0.794)	5.271*** (0.748)
m06	2.424** (0.762)	0.098 (0.643)
m07	3.120*** (0.712)	0.605 (0.601)
m08	2.251*** (0.683)	0.003 (0.596)
m09	3.234*** (0.770)	1.994*** (0.583)
m10	3.846*** (0.665)	2.910*** (0.555)
m11	4.785*** (0.609)	3.207*** (0.590)
m12	5.798*** (0.555)	4.791*** (0.581)
years of study - zero	49.009*** (1.763)	44.892*** (1.704)
years of study - 1 to 3 y	68.607*** (2.060)	64.015*** (1.990)
years of study - 4 to 7 y	89.600*** (2.362)	84.805*** (2.261)
years of study - 8 to 11 y	81.025*** (2.998)	71.371*** (3.016)
marital status - married	19.066*** (0.667)	18.272*** (0.739)
pre_appoint	57.717*** (0.728)	51.669*** (0.692)
une	-1.104* (0.492)	-1.188* (0.512)
mother_age	0.869*** (0.073)	0.968*** (0.068)
gest_age - 22 to 27 w	-1,005.626*** (26.563)	-879.141*** (25.553)
gest_age - 28 to 31 w	-1,055.881*** (19.832)	-1,041.637*** (20.143)
gest_age - 32 to 36 w	-221.750*** (18.358)	-271.288*** (16.103)
gest_age - 37 to 41 w	406.508*** (19.362)	324.050*** (16.268)
gest_age - more than 42 w	498.624*** (20.067)	403.689*** (16.536)
parity	30.335*** (0.319)	27.792*** (0.322)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	17,994,789	17,994,666
R2	0.18551	0.16884
Within R2	0.17685	0.15910

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Tri – trimester. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 9 - Estimations of birthweight per bin of temperature and precipitation, term babies between 2500g and 4000g

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.013 (0.018)	0.032. (0.018)
15-18	0.020 (0.019)	0.050* (0.023)
18-21	0.004 (0.017)	0.024 (0.017)
24-27	-0.014 (0.010)	-0.015 (0.011)
27-30	-0.068*** (0.012)	-0.080*** (0.013)
30-33	-0.128*** (0.027)	-0.157*** (0.030)
>33	-0.352 (0.426)	0.104 (0.656)
Prec. (mm/m²)		
2.5 to 5	0.022 (0.025)	0.022 (0.028)
5 to 7.5	0.022 (0.034)	0.018 (0.032)
7.5 to 10	-0.076. (0.044)	-0.082. (0.049)
10 to 12.5	-0.005 (0.056)	-0.005 (0.055)
> 12.5	-0.048* (0.019)	-0.016 (0.019)
y2000	-2.379** (0.860)	-2.645** (0.879)
y2001	-8.927*** (0.994)	-10.783*** (1.034)
y2002	-14.973*** (1.181)	-16.213*** (1.299)
y2003	-16.720*** (1.164)	-18.463*** (1.229)
y2004	-7.796*** (1.032)	-9.074*** (1.129)
y2005	-9.045*** (1.054)	-9.346*** (1.124)
y2006	-11.482*** (1.001)	-11.821*** (1.059)
y2007	-14.955*** (1.122)	-15.019*** (1.310)
y2008	-14.275*** (1.155)	-14.660*** (1.268)
y2009	-17.668*** (1.329)	-18.990*** (1.524)
y2010	-17.990*** (1.145)	-20.316*** (1.301)
y2011	-11.901*** (1.278)	-14.723*** (1.389)
y2012	-12.193*** (1.265)	-16.037*** (1.463)
y2013	-12.000*** (1.438)	-14.501*** (1.618)
y2014	-11.795*** (1.566)	-13.622*** (1.821)
y2015	-10.436*** (1.774)	-13.024*** (1.929)
y2016	-3.820** (1.462)	-6.037*** (1.691)
y2017	-0.325 (1.677)	-0.814 (1.901)
y2018	0.088 (1.879)	-1.452 (2.199)
y2019	3.071 (2.014)	1.824 (2.385)
y2020	(dropped)	(dropped)
m02	1.144* (0.461)	0.291 (0.455)
m03	-2.375*** (0.503)	-3.108*** (0.464)
m04	4.503*** (0.486)	3.772*** (0.425)
m05	2.342*** (0.567)	0.897* (0.445)
m06	-0.955. (0.523)	-2.118*** (0.479)
m07	0.603 (0.622)	-0.698 (0.579)
m08	0.142 (0.636)	-1.209. (0.651)
m09	0.738 (0.626)	0.417 (0.639)
m10	0.613 (0.587)	0.260 (0.528)

m11	1.454** (0.506)	0.718 (0.559)
m12	3.238*** (0.412)	2.250*** (0.528)
years of study - zero	30.954*** (1.091)	27.620*** (1.046)
years of study - 1 to 3 y	44.604*** (1.233)	40.100*** (1.178)
years of study - 4 to 7 y	61.071*** (1.489)	55.663*** (1.410)
years of study - 8 to 11 y	59.751*** (1.950)	46.729*** (2.081)
marital status - married	13.475*** (0.431)	11.797*** (0.593)
pre_appoint	28.879*** (0.489)	25.814*** (0.425)
une	-1.766*** (0.308)	-1.950*** (0.360)
mother_age	0.789*** (0.047)	1.194*** (0.049)
parity	16.251*** (0.230)	15.838*** (0.229)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,643,514	18,136,979
R2	0.01562	0.01773
Within R2	0.00840	0.00817

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 10 - Estimations of birthweight per daily deviations from historical means, term babies between 2500g and 4000g

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.014 (0.171)	0.004 (0.033)	0.022 (0.117)	-0.024 (0.033)
-2 to -1.5	0.014 (0.068)	-0.040 (0.049)	-0.247*** (0.056)	-0.111* (0.045)
-1.5 to -1	0.005 (0.029)	0.022 (0.032)	-0.029 (0.029)	0.007 (0.030)
-1 to -0.7	-0.031 (0.026)	-0.044. (0.027)	-0.042 (0.027)	-0.045 (0.028)
0.7 to 1	-0.049** (0.016)	-0.011 (0.013)	-0.082*** (0.018)	-0.016 (0.016)
1 to 1.5	-0.017 (0.011)	-0.003 (0.010)	-0.043*** (0.012)	-0.009 (0.010)
1.5 to 2	-0.093*** (0.017)	0.019 (0.016)	-0.118*** (0.017)	0.007 (0.018)
>2	-0.084*** (0.024)	0.003 (0.014)	-0.078** (0.025)	-0.020 (0.016)
Precip.				
Neg.	0.061. (0.035)		0.076* (0.032)	
Pos.	0.005 (0.012)		0.006 (0.015)	
y2000	-2.816** (0.898)		-3.510*** (0.898)	
y2001	-10.701*** (1.032)		-11.815*** (1.104)	
y2002	-15.804*** (1.260)		-17.281*** (1.400)	
y2003	-17.344*** (1.165)		-19.349*** (1.263)	
y2004	-8.518*** (1.037)		-10.047*** (1.154)	
y2005	-9.929*** (1.086)		-10.768*** (1.217)	
y2006	-12.210*** (1.059)		-14.270*** (1.151)	
y2007	-15.345*** (1.181)		-16.988*** (1.489)	
y2008	-14.824*** (1.223)		-17.271*** (1.381)	
y2009	-18.635*** (1.369)		-21.279*** (1.635)	
y2010	-18.370*** (1.168)		-22.091*** (1.356)	
y2011	-11.953*** (1.284)		-16.422*** (1.440)	
y2012	-12.242*** (1.300)		-17.370*** (1.587)	
y2013	-12.277*** (1.452)		-16.463*** (1.717)	
y2014	-11.930*** (1.628)		-15.788*** (1.981)	
y2015	-10.140*** (1.699)		-13.773*** (2.009)	
y2016	-3.722* (1.477)		-7.632*** (1.747)	
y2017	-1.136 (1.659)		-3.798* (1.891)	
y2018	-0.933 (1.890)		-4.401* (2.185)	
y2019	2.363 (1.997)		-0.538 (2.409)	
y2020	(dropped)		(dropped)	
m02	1.426** (0.453)		0.655 (0.463)	
m03	-2.052*** (0.488)		-2.790*** (0.449)	
m04	4.494*** (0.480)		3.607*** (0.433)	
m05	1.602** (0.575)		-0.066 (0.445)	
m06	-2.426*** (0.503)		-4.093*** (0.438)	
m07	-1.383** (0.506)		-3.439*** (0.419)	
m08	-2.049*** (0.461)		-4.261*** (0.433)	
m09	-1.342** (0.503)		-2.411*** (0.431)	
m10	-1.067* (0.477)		-1.916*** (0.417)	
m11	0.352 (0.466)		-0.632 (0.483)	

m12	2.730*** (0.395)	1.744*** (0.499)
years of study - zero	31.097*** (1.092)	27.802*** (1.059)
years of study - 1 to 3 y	44.838*** (1.227)	40.351*** (1.196)
years of study - 4 to 7 y	61.274*** (1.479)	55.859*** (1.413)
years of study - 8 to 11 y	59.940*** (1.941)	46.881*** (2.054)
marital status - married	13.452*** (0.431)	11.720*** (0.590)
pre_appoint	28.871*** (0.486)	25.720*** (0.418)
une	-1.589*** (0.297)	-1.689*** (0.355)
mother_age	0.786*** (0.047)	1.190*** (0.049)
parity	16.237*** (0.230)	15.848*** (0.228)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,652,764	18,124,298
R2	0.01563	0.01777
Within R2	0.00841	0.00820

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 11 - Estimations of birthweight per weekly deviations from historical means, term babies between 2500g and 4000g

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.026 (0.170)	-0.010 (0.034)	0.400* (0.177)	-0.030 (0.033)
-2 to -1.5	-0.020 (0.066)	-0.011 (0.046)	-0.002 (0.065)	-0.022 (0.047)
-1.5 to -1	0.012 (0.030)	0.022 (0.032)	-0.019 (0.028)	-0.001 (0.030)
-1 to -0.7	-0.020 (0.026)	-0.030 (0.026)	-0.040 (0.026)	-0.033 (0.028)
0.7 to 1	-0.044** (0.015)	-0.004 (0.012)	-0.054** (0.017)	-0.008 (0.014)
1 to 1.5	-0.011 (0.010)	-0.002 (0.010)	-0.025* (0.012)	-0.004 (0.011)
1.5 to 2	-0.088*** (0.017)	0.021 (0.015)	-0.112*** (0.018)	0.017 (0.017)
>2	-0.083*** (0.024)	0.004 (0.014)	-0.069** (0.026)	-0.011 (0.015)
Precip.				
Neg.	0.062. (0.035)		0.051 (0.036)	
Pos.	0.007 (0.011)		0.014 (0.013)	
y2000	-5.485*** (0.916)		-3.811*** (0.893)	
y2001	-13.223*** (1.081)		-14.933*** (1.342)	
y2002	-18.747*** (1.273)		-17.914*** (1.413)	
y2003	-20.253*** (1.163)		-19.382*** (1.254)	
y2004	-11.458*** (1.088)		-10.195*** (1.136)	
y2005	-12.791*** (1.109)		-10.652*** (1.188)	
y2006	-15.131*** (1.103)		-13.017*** (1.128)	
y2007	-18.111*** (1.223)		-15.767*** (1.382)	
y2008	-17.593*** (1.304)		-15.470*** (1.344)	
y2009	-21.435*** (1.438)		-20.267*** (1.577)	
y2010	-21.250*** (1.250)		-21.045*** (1.330)	
y2011	-14.780*** (1.337)		-15.053*** (1.395)	
y2012	-15.187*** (1.349)		-16.427*** (1.526)	
y2013	-15.070*** (1.497)		-15.149*** (1.664)	
y2014	-14.642*** (1.678)		-14.482*** (1.913)	
y2015	-13.016*** (1.738)		-13.162*** (1.944)	
y2016	-5.662*** (1.614)		-6.460*** (1.709)	
y2017	-3.992* (1.714)		-2.393 (1.875)	
y2018	-4.113* (1.887)		-3.424 (2.182)	
y2019	-1.275 (1.921)		0.254 (2.366)	
y2020	(dropped)		(dropped)	
m02	1.516*** (0.452)		0.624 (0.455)	
m03	-1.873*** (0.486)		-2.714*** (0.448)	
m04	4.587*** (0.476)		3.785*** (0.435)	
m05	1.635** (0.574)		-0.069 (0.448)	
m06	-2.566*** (0.521)		-4.024*** (0.439)	
m07	-1.218* (0.507)		-3.482*** (0.414)	
m08	-1.857*** (0.457)		-4.265*** (0.428)	
m09	-1.279* (0.528)		-2.398*** (0.428)	
m10	-0.995* (0.491)		-1.855*** (0.412)	
m11	0.352 (0.468)		-0.637 (0.486)	

m12	2.701*** (0.403)	1.689*** (0.494)
years of study - zero	31.512*** (1.084)	28.069*** (1.086)
years of study - 1 to 3 y	45.263*** (1.220)	40.810*** (1.209)
years of study - 4 to 7 y	61.618*** (1.470)	56.422*** (1.436)
years of study - 8 to 11 y	60.359*** (1.936)	47.364*** (2.124)
marital status - married	13.326*** (0.441)	11.551*** (0.591)
pre_appoint	28.869*** (0.485)	25.921*** (0.428)
une	-1.529*** (0.296)	-1.686*** (0.347)
mother_age	0.776*** (0.047)	1.188*** (0.049)
parity	16.282*** (0.232)	15.922*** (0.232)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,313,652	17,708,132
R2	0.01561	0.01767
Within R2	0.00839	0.00821

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 12 - Estimations of birthweight per monthly deviations from historical means, term babies between 2500g and 4000g

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-10.933 (9.806)	0.002 (0.848)	-8.771 (10.413)	-1.087 (0.808)
-2 to -1.5	-0.258 (4.158)	0.123 (0.928)	1.707 (3.726)	-0.451 (0.831)
-1.5 to -1	1.953* (0.929)	-0.412 (0.513)	2.559** (0.927)	0.156 (0.453)
-1 to -0.7	0.111 (0.439)	0.240 (0.381)	-0.332 (0.486)	0.040 (0.399)
0.7 to 1	-0.446* (0.186)	-0.147 (0.125)	-0.604** (0.189)	-0.184 (0.145)
1 to 1.5	-0.963*** (0.203)	0.258 (0.174)	-1.159*** (0.218)	0.104 (0.178)
1.5 to 2	-1.672*** (0.312)	0.155 (0.284)	-1.862*** (0.338)	0.147 (0.310)
>2	-2.066*** (0.575)	0.137 (0.360)	-1.998*** (0.595)	-0.346 (0.387)
Precip.				
Neg.	3.695 (2.582)		3.675. (1.969)	
Pos.	-0.024 (0.252)		0.389 (0.298)	
y2000	-2.748** (0.879)		-3.187*** (0.851)	
y2001	-9.299*** (0.986)		-11.224*** (1.029)	
y2002	-15.675*** (1.149)		-16.944*** (1.252)	
y2003	-17.316*** (1.151)		-19.082*** (1.233)	
y2004	-8.528*** (1.018)		-9.825*** (1.112)	
y2005	-9.934*** (1.039)		-10.244*** (1.115)	
y2006	-12.253*** (1.002)		-12.694*** (1.072)	
y2007	-15.211*** (1.122)		-15.385*** (1.326)	
y2008	-14.746*** (1.169)		-15.111*** (1.275)	
y2009	-18.301*** (1.279)		-19.505*** (1.454)	
y2010	-18.471*** (1.109)		-20.656*** (1.244)	
y2011	-11.925*** (1.233)		-14.754*** (1.344)	
y2012	-12.280*** (1.235)		-16.085*** (1.453)	
y2013	-12.236*** (1.404)		-14.795*** (1.610)	
y2014	-11.793*** (1.519)		-13.819*** (1.803)	
y2015	-10.277*** (1.599)		-12.720*** (1.824)	
y2016	-3.632* (1.425)		-5.808*** (1.657)	
y2017	-0.893 (1.640)		-1.465 (1.882)	
y2018	-0.813 (1.815)		-2.440 (2.130)	
y2019	2.156 (1.929)		0.855 (2.291)	
y2020	(dropped)		(dropped)	
m02	1.365** (0.449)		0.542 (0.461)	
m03	-2.102*** (0.474)		-2.787*** (0.443)	
m04	4.530*** (0.469)		3.794*** (0.425)	
m05	1.706** (0.563)		0.083 (0.428)	
m06	-2.318*** (0.500)		-3.916*** (0.424)	
m07	-1.340** (0.506)		-3.321*** (0.404)	
m08	-2.084*** (0.462)		-4.182*** (0.419)	
m09	-1.329** (0.500)		-2.246*** (0.414)	
m10	-1.021* (0.475)		-1.762*** (0.401)	
m11	0.372 (0.462)		-0.571 (0.479)	

m12	2.735*** (0.394)	1.680*** (0.485)
years of study - zero	31.094*** (1.092)	27.738*** (1.049)
years of study - 1 to 3 y	44.833*** (1.231)	40.312*** (1.179)
years of study - 4 to 7 y	61.284*** (1.487)	55.859*** (1.411)
years of study - 8 to 11 y	59.960*** (1.948)	46.923*** (2.082)
marital status - married	13.470*** (0.431)	11.795*** (0.593)
pre_appoint	28.892*** (0.486)	25.831*** (0.423)
une	-1.606*** (0.301)	-1.763*** (0.353)
mother_age	0.789*** (0.047)	1.194*** (0.049)
gest_age - 22 to 27 w	16.251*** (0.230)	15.838*** (0.229)
gest_age - 28 to 31 w	1.365** (0.449)	0.542 (0.461)
gest_age - 32 to 36 w	-2.102*** (0.474)	-2.787*** (0.443)
gest_age - 37 to 41 w	4.530*** (0.469)	3.794*** (0.425)
gest_age - more than 42 w	1.706** (0.563)	0.083 (0.428)
parity	-2.318*** (0.500)	-3.916*** (0.424)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,648,856	18,142,295
R2	0.01563	0.01775
Within R2	0.00842	0.00818

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 13 - Estimations of birthweight per bin of temperature and precipitation, controlling for supply of health services

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.256*** (0.035)	0.232*** (0.032)
15-18	0.162** (0.052)	0.177*** (0.042)
18-21	0.115*** (0.032)	0.096** (0.032)
24-27	-0.214*** (0.033)	-0.207*** (0.031)
27-30	-0.473*** (0.058)	-0.449*** (0.053)
30-33	-0.573*** (0.076)	-0.528*** (0.067)
>33	0.155 (0.862)	0.306 (0.971)
Prec. (mm/m²)		
2.5 to 5	-0.057 (0.051)	-0.029 (0.049)
5 to 7.5	-0.227*** (0.051)	-0.179*** (0.044)
7.5 to 10	-0.178* (0.075)	-0.203** (0.065)
10 to 12.5	-0.133. (0.079)	-0.208** (0.078)
> 12.5	-0.185*** (0.035)	-0.142*** (0.032)
y2007	129.954*** (8.201)	-7.178*** (1.077)
y2008	132.846*** (8.306)	-4.163*** (0.933)
y2009	135.595*** (8.074)	-2.284 (1.629)
y2010	138.005*** (8.071)	-0.494 (1.007)
y2011	157.190*** (7.656)	16.706*** (0.824)
y2012	159.492*** (7.969)	18.807*** (1.116)
y2013	157.781*** (7.625)	18.366*** (1.053)
y2014	157.961*** (7.741)	19.198*** (1.647)
y2015	161.880*** (7.819)	22.018*** (2.090)
y2016	161.106*** (8.355)	21.933*** (1.397)
y2017	156.837*** (8.837)	18.795*** (1.838)
y2018	156.732*** (9.604)	17.281*** (2.778)
y2019	163.036*** (9.427)	23.071*** (3.171)
y2020	100.647. (56.173)	-5.265 (64.183)
m02	-2.151* (0.940)	-2.229** (0.757)
m03	-8.041*** (1.184)	-7.088*** (1.061)
m04	6.551*** (0.977)	5.831*** (0.903)
m05	13.186*** (0.968)	9.835*** (0.899)
m06	13.651*** (1.447)	11.097*** (1.328)
m07	19.541*** (2.271)	16.733*** (2.007)
m08	22.497*** (2.563)	19.032*** (2.338)
m09	22.707*** (2.251)	20.685*** (2.211)
m10	21.295*** (1.728)	19.482*** (1.782)
m11	16.388*** (1.334)	14.921*** (1.415)
m12	12.933*** (0.909)	11.454*** (1.003)
years of study - zero	67.188*** (3.043)	61.654*** (2.859)
years of study - 1 to 3 y	90.987*** (3.207)	83.587*** (3.098)
years of study - 4 to 7 y	114.357*** (3.368)	106.004*** (3.262)
years of study - 8 to 11 y	104.715*** (3.900)	91.123*** (3.872)
marital status - married	12.304*** (0.581)	10.883*** (0.636)

pre_appoint	64.657*** (0.888)	57.550*** (0.765)
une	-0.882. (0.477)	-0.714 (0.437)
prof_pc	798.069** (252.414)	666.571** (228.561)
beds_pc	820.550 (631.094)	973.709. (578.125)
mother_age	0.454*** (0.075)	0.668*** (0.072)
gest_age - 22 to 27 w	-865.861*** (29.263)	-734.102*** (30.294)
gest_age - 28 to 31 w	-979.565*** (21.161)	-966.954*** (24.480)
gest_age - 32 to 36 w	-161.519*** (17.951)	-216.366*** (18.259)
gest_age - 37 to 41 w	427.333*** (20.411)	344.087*** (18.771)
gest_age - more than 42 w	508.963*** (21.042)	417.494*** (19.015)
parity	35.536*** (0.446)	32.692*** (0.473)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	14,109,018	13,419,399
R2	0.18619	0.16820
Within R2	0.17891	0.16009

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. prof_pc- number of health care professionals per 10,000 inhabitants. Beds_pc – number of hospital beds per 10,000 inhabitants. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 14 - Estimations of birthweight per daily deviations from historical means, controlling for supply of health services

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.714* (0.322)	0.035 (0.130)	-0.370 (0.283)	0.119 (0.124)
-2 to -1.5	-0.042 (0.153)	-0.402*** (0.109)	-0.034 (0.156)	-0.366*** (0.088)
-1.5 to -1	-0.064 (0.044)	0.163*** (0.046)	-0.041 (0.044)	0.139** (0.048)
-1 to -0.7	-0.016 (0.044)	0.070 (0.046)	-0.040 (0.043)	0.018 (0.042)
0.7 to 1	-0.095*** (0.022)	-0.050* (0.022)	-0.065** (0.023)	-0.055* (0.022)
1 to 1.5	-0.026 (0.017)	-0.059*** (0.017)	-0.048** (0.016)	-0.054*** (0.016)
1.5 to 2	-0.084** (0.027)	-0.108*** (0.021)	-0.085*** (0.024)	-0.073*** (0.020)
>2	-0.076** (0.029)	-0.105*** (0.022)	-0.069* (0.027)	-0.112*** (0.022)
Precip.				
Neg.	-0.084. (0.044)		-0.052 (0.046)	
Pos.	0.013 (0.023)		0.015 (0.020)	
y2007	-5.642 (50.525)		-6.685*** (1.100)	
y2008	-3.259 (50.603)		-4.220*** (0.891)	
y2009	-3.435 (50.652)		-5.640*** (1.203)	
y2010	1.805 (50.697)		-1.085 (1.159)	
y2011	24.101 (50.552)		18.516*** (0.867)	
y2012	24.373 (50.527)		18.253*** (1.076)	
y2013	22.096 (50.574)		17.443*** (0.906)	
y2014	20.003 (50.503)		16.032*** (1.316)	
y2015	23.238 (50.471)		18.360*** (1.582)	
y2016	24.659 (50.472)		20.482*** (1.299)	
y2017	21.514 (50.352)		18.155*** (1.728)	
y2018	19.259 (50.270)		14.226*** (2.324)	
y2019	25.298 (50.150)		19.998*** (2.501)	
y2020	(dropped)		-9.375 (64.007)	
m02	0.415 (0.692)		0.233 (0.665)	
m03	-4.268*** (0.773)		-3.548*** (0.734)	
m04	8.553*** (0.789)		7.597*** (0.774)	
m05	9.830*** (1.002)		6.582*** (0.914)	
m06	3.721*** (0.889)		1.480. (0.811)	
m07	3.979*** (0.821)		1.643* (0.739)	
m08	4.591*** (0.795)		1.527* (0.692)	
m09	5.901*** (0.881)		4.385*** (0.740)	
m10	8.482*** (0.841)		6.910*** (0.694)	
m11	8.271*** (0.748)		6.876*** (0.686)	
m12	9.282*** (0.674)		7.558*** (0.671)	
years of study - zero	67.077*** (3.035)		61.597*** (2.864)	
years of study - 1 to 3 y	90.894*** (3.222)		83.556*** (3.108)	
years of study - 4 to 7 y	113.754*** (3.390)		105.964*** (3.276)	
years of study - 8 to 11 y	103.438*** (3.919)		91.094*** (3.889)	
marital status - married	11.847*** (0.579)		10.886*** (0.636)	
pre_appoint	65.851*** (0.882)		57.561*** (0.766)	

une	-0.882. (0.486)	-0.646 (0.445)
prof_pc	644.419** (244.890)	530.350* (224.793)
leitos_pc	1,002.602 (623.321)	1,024.863. (571.059)
mother_age	0.349*** (0.077)	0.662*** (0.072)
gest_age - 22 to 27 w	-643.168*** (29.505)	-741.020*** (31.047)
gest_age - 28 to 31 w	-252.432*** (39.949)	-981.194*** (25.056)
gest_age - 32 to 36 w	616.479*** (52.535)	-235.259*** (17.974)
gest_age - 37 to 41 w	1,201.326*** (59.608)	320.379*** (18.137)
gest_age - more than 42 w	1,278.094*** (60.038)	390.229*** (18.340)
parity	36.087*** (0.448)	32.692*** (0.474)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	14,136,845	13,419,520
R2	0.21019	0.16805
Within R2	0.20298	0.15994

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. prof_pc- number of health care professionals per 10,000 inhabitants. Beds_pc – number of hospital beds per 10,000 inhabitants. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 15 - Estimations of birthweight per weekly deviations from historical means, controlling for supply of health services

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.497 (0.338)	0.016 (0.135)	-0.367 (0.291)	0.114 (0.124)
-2 to -1.5	-0.090 (0.160)	-0.366*** (0.110)	-0.063 (0.164)	-0.376*** (0.094)
-1.5 to -1	-0.052 (0.046)	0.165*** (0.049)	-0.052 (0.044)	0.141** (0.048)
-1 to -0.7	-0.009 (0.044)	0.097* (0.045)	-0.056 (0.045)	0.012 (0.043)
0.7 to 1	-0.059** (0.021)	-0.017 (0.020)	-0.070** (0.024)	-0.054* (0.023)
1 to 1.5	-0.007 (0.017)	-0.047** (0.017)	-0.043** (0.016)	-0.052** (0.017)
1.5 to 2	-0.060* (0.027)	-0.089*** (0.021)	-0.078** (0.025)	-0.076*** (0.021)
>2	-0.067* (0.030)	-0.090*** (0.022)	-0.074* (0.029)	-0.116*** (0.023)
Precip.				
Neg.	-0.056 (0.044)		-0.054 (0.047)	
Pos.	0.035 (0.025)		0.018 (0.021)	
y2007	-15.674*** (1.799)		82.846. (45.337)	
y2008	-13.539*** (1.433)		85.403. (45.461)	
y2009	-15.384*** (1.673)		83.407. (45.421)	
y2010	-9.439*** (1.325)		88.553. (45.399)	
y2011	13.508*** (1.072)		108.706* (45.418)	
y2012	12.162*** (0.850)		108.027* (45.396)	
y2013	10.235*** (1.136)		106.972* (45.473)	
y2014	7.721*** (1.319)		105.260* (45.397)	
y2015	9.554*** (1.567)		107.072* (45.505)	
y2016	13.883*** (1.212)		109.124* (45.398)	
y2017	9.339*** (1.389)		106.944* (45.391)	
y2018	5.103* (2.021)		102.706* (45.415)	
y2019	9.505*** (1.958)		108.103* (45.341)	
y2020	-182.462*** (37.533)		(dropped)	
m02	0.307 (0.703)		-0.119 (0.693)	
m03	-4.138*** (0.763)		-4.162*** (0.732)	
m04	8.630*** (0.808)		7.438*** (0.773)	
m05	9.799*** (0.991)		6.464*** (0.893)	
m06	3.357*** (0.964)		1.481. (0.796)	
m07	3.979*** (0.835)		1.904* (0.752)	
m08	4.710*** (0.818)		1.839** (0.709)	
m09	5.913*** (0.983)		4.914*** (0.764)	
m10	8.288*** (0.921)		7.078*** (0.706)	
m11	7.974*** (0.767)		6.962*** (0.698)	
m12	8.746*** (0.689)		7.447*** (0.684)	
years of study - zero	67.022*** (3.055)		61.560*** (2.859)	
years of study - 1 to 3 y	90.935*** (3.228)		83.214*** (3.085)	
years of study - 4 to 7 y	113.964*** (3.371)		105.355*** (3.235)	
years of study - 8 to 11 y	105.313*** (3.889)		91.480*** (3.821)	
marital status - married	12.144*** (0.579)		10.750*** (0.625)	
pre_appoint	66.827*** (0.860)		59.900*** (0.775)	

une	-0.797 (0.487)	-0.661 (0.444)
prof_pc	689.298** (245.240)	556.622* (230.174)
leitos_pc	1,042.084. (624.401)	1,074.794. (592.289)
mother_age	0.323*** (0.075)	0.536*** (0.071)
gest_age - 22 to 27 w	-347.702*** (31.610)	-404.070*** (31.078)
gest_age - 28 to 31 w	138.738*** (35.695)	59.342. (34.781)
gest_age - 32 to 36 w	1,020.336*** (42.155)	902.971*** (41.601)
gest_age - 37 to 41 w	1,604.123*** (47.607)	1,460.605*** (46.951)
gest_age - more than 42 w	1,680.147*** (48.366)	1,529.442*** (47.322)
parity	36.107*** (0.459)	33.268*** (0.490)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	13,939,136	13,461,025
R2	0.21867	0.20314
Within R2	0.21222	0.19602

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. prof_pc- number of health care professionals per 10,000 inhabitants. Beds_pc – number of hospital beds per 10,000 inhabitants. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 16 - Estimations of birthweight per monthly deviations from historical means, controlling for supply of health services

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-14.311 (18.899)	4.215 (4.897)	-16.932* (7.200)	0.393 (3.569)
-2 to -1.5	-13.975. (7.755)	-5.030 (3.404)	-21.409* (9.415)	-3.757 (3.061)
-1.5 to -1	3.035 (2.298)	-0.009 (1.315)	2.077 (2.046)	0.239 (0.988)
-1 to -0.7	-0.143 (0.921)	1.112 (0.769)	-0.497 (0.841)	0.440 (0.680)
0.7 to 1	-0.784*** (0.223)	-0.712* (0.294)	-1.012*** (0.206)	-0.794** (0.288)
1 to 1.5	-1.590*** (0.269)	-1.692*** (0.339)	-1.703*** (0.267)	-1.472*** (0.296)
1.5 to 2	-1.731*** (0.515)	-2.785*** (0.430)	-1.953*** (0.498)	-2.449*** (0.400)
>2	-0.958 (0.709)	-2.556*** (0.577)	-1.257. (0.731)	-2.891*** (0.579)
Precip.				
Neg.	1.676 (3.011)		6.337** (2.417)	
Pos.	0.167 (0.596)		0.177 (0.479)	
y2007	134.048*** (8.409)		-6.735*** (1.058)	
y2008	136.742*** (8.592)		-3.999*** (0.897)	
y2009	135.918*** (8.321)		-5.135*** (1.075)	
y2010	140.723*** (8.386)		-1.132 (1.141)	
y2011	162.793*** (7.930)		18.617*** (0.813)	
y2012	162.213*** (8.349)		18.124*** (1.013)	
y2013	159.972*** (7.888)		17.033*** (0.876)	
y2014	158.072*** (7.833)		16.071*** (1.283)	
y2015	161.463*** (7.953)		18.823*** (1.513)	
y2016	162.685*** (8.527)		20.474*** (1.203)	
y2017	160.083*** (9.245)		18.534*** (1.817)	
y2018	156.842*** (9.922)		14.194*** (2.366)	
y2019	163.426*** (9.709)		20.345*** (2.516)	
y2020	98.118. (56.301)		-9.503 (63.932)	
m02	0.548 (0.672)		0.297 (0.666)	
m03	-4.004*** (0.729)		-3.308*** (0.723)	
m04	8.799*** (0.755)		7.951*** (0.753)	
m05	10.093*** (0.955)		6.950*** (0.884)	
m06	3.752*** (0.901)		1.812* (0.815)	
m07	3.550*** (0.813)		1.734* (0.731)	
m08	3.584*** (0.788)		1.311. (0.682)	
m09	5.021*** (0.830)		4.178*** (0.715)	
m10	7.467*** (0.783)		6.594*** (0.680)	
m11	7.490*** (0.715)		6.629*** (0.674)	
m12	8.646*** (0.652)		7.487*** (0.663)	
years of study - zero	67.214*** (3.044)		61.621*** (2.860)	
years of study - 1 to 3 y	91.032*** (3.214)		83.597*** (3.110)	
years of study - 4 to 7 y	114.390*** (3.378)		106.004*** (3.279)	
years of study - 8 to 11 y	104.758*** (3.911)		91.133*** (3.887)	
marital status - married	12.313*** (0.582)		10.887*** (0.636)	
pre_appoint	64.678*** (0.890)		57.563*** (0.765)	

une	-0.736 (0.497)	-0.559 (0.449)
prof_pc	644.652** (245.232)	517.315* (225.672)
leitos_pc	925.866 (633.925)	1,083.254. (577.752)
mother_age	0.447*** (0.075)	0.662*** (0.072)
gest_age - 22 to 27 w	-874.857*** (30.000)	-742.064*** (31.044)
gest_age - 28 to 31 w	-996.428*** (21.626)	-982.962*** (25.100)
gest_age - 32 to 36 w	-183.962*** (17.334)	-237.552*** (18.044)
gest_age - 37 to 41 w	399.565*** (19.347)	318.039*** (18.159)
gest_age - more than 42 w	476.437*** (19.965)	386.979*** (18.378)
parity	35.536*** (0.446)	32.690*** (0.474)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	14,109,149	13,419,520
R2	0.18604	0.16806
Within R2	0.17876	0.15995

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. prof_pc- number of health care professionals per 10,000 inhabitants. Beds_pc – number of hospital beds per 10,000 inhabitants. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality.

Table S2. 17 - Estimations of birthweight per bin of temperature and precipitation, controlling for pre-pregnancy municipality weather variables

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.283*** (0.027)	0.245*** (0.025)
15-18	0.176*** (0.031)	0.193*** (0.028)
18-21	0.107*** (0.026)	0.116*** (0.024)
24-27	-0.124*** (0.024)	-0.117*** (0.024)
27-30	-0.343*** (0.043)	-0.323*** (0.041)
30-33	-0.434*** (0.064)	-0.425*** (0.062)
>33	-0.681 (0.694)	-0.341 (0.795)
Prec. (mm/m²)		
2.5 to 5	-0.070. (0.040)	-0.060 (0.040)
5 to 7.5	-0.095 (0.067)	-0.047 (0.063)
7.5 to 10	-0.218*** (0.065)	-0.228*** (0.064)
10 to 12.5	-0.034 (0.083)	-0.055 (0.080)
> 12.5	-0.111*** (0.030)	-0.055. (0.029)
Temp. (ºC)		
<15 (pre)	-0.065*** (0.018)	-0.031. (0.018)
15-18 (pre)	-0.043. (0.023)	-0.045* (0.022)
18-21 (pre)	-0.179*** (0.014)	-0.128*** (0.014)
24-27 (pre)	-0.112*** (0.009)	-0.084*** (0.010)
27-30 (pre)	-0.071*** (0.010)	-0.061*** (0.010)
30-33 (pre)	-0.014 (0.043)	0.002 (0.048)
>33 (pre)	2.439* (1.019)	3.816** (1.334)
Prec. (mm/m²)		
2.5 to 5 (pre)	0.024 (0.036)	0.003 (0.044)
5 to 7.5 (pre)	-0.116 (0.072)	-0.079 (0.074)
7.5 to 10 (pre)	-0.230** (0.077)	-0.177* (0.076)
10 to 12.5 (pre)	-0.058 (0.080)	-0.087 (0.086)
> 12.5 (pre)	-0.098* (0.039)	-0.088* (0.036)
y2000	-2.265 (1.687)	-2.516 (1.611)
y2001	-14.537*** (1.951)	-15.175*** (1.819)
y2002	-23.263*** (2.307)	-22.062*** (2.418)
y2003	-30.211*** (1.879)	-29.527*** (1.924)
y2004	-17.125*** (1.844)	-15.863*** (1.820)
y2005	-17.624*** (1.885)	-15.284*** (1.886)
y2006	-20.538*** (1.838)	-19.147*** (1.789)
y2007	-26.980*** (2.183)	-24.678*** (2.186)
y2008	-25.883*** (2.046)	-23.871*** (2.107)
y2009	-24.835*** (2.832)	-24.013*** (2.763)
y2010	-18.938*** (2.044)	-18.662*** (2.106)
y2011	3.707. (2.159)	1.401 (2.121)
y2012	3.939. (2.197)	1.840 (2.226)
y2013	1.826 (2.529)	0.803 (2.564)
y2014	1.746 (2.836)	1.463 (2.904)
y2015	4.302 (3.359)	2.787 (3.161)

y2016	6.232* (2.573)	5.438* (2.534)
y2017	5.293* (2.524)	6.238* (2.501)
y2018	5.092. (2.808)	4.934. (2.848)
y2019	12.269*** (3.131)	11.337*** (3.164)
y2020	48.432 (53.785)	74.255 (61.733)
m02	-1.062 (0.697)	-1.467** (0.551)
m03	-8.942*** (0.935)	-8.386*** (0.783)
m04	-20.061*** (1.637)	-14.775*** (1.340)
m05	-13.609*** (1.417)	-10.724*** (1.178)
m06	-10.464*** (1.267)	-8.226*** (1.210)
m07	-1.722 (1.554)	-0.835 (1.500)
m08	3.144. (1.717)	3.102. (1.698)
m09	6.627*** (1.507)	6.890*** (1.576)
m10	7.477*** (1.216)	7.257*** (1.266)
m11	7.135*** (0.925)	6.594*** (1.053)
m12	7.758*** (0.642)	6.953*** (0.717)
years of study - zero	49.141*** (1.682)	44.919*** (1.601)
years of study - 1 to 3 y	68.804*** (1.989)	63.737*** (1.885)
years of study - 4 to 7 y	89.779*** (2.304)	84.359*** (2.173)
years of study - 8 to 11 y	80.888*** (2.965)	71.067*** (2.960)
marital status - married	19.204*** (0.669)	18.276*** (0.731)
pre_appoint	57.566*** (0.750)	51.676*** (0.693)
une	-1.414** (0.485)	-1.521** (0.518)
mother_age	0.871*** (0.071)	0.968*** (0.068)
gest_age - 22 to 27 w	-1,009.285*** (24.811)	-878.787*** (25.135)
gest_age - 28 to 31 w	-1,049.442*** (17.787)	-1,033.569*** (19.429)
gest_age - 32 to 36 w	-212.501*** (16.493)	-259.271*** (15.713)
gest_age - 37 to 41 w	420.564*** (17.702)	339.431*** (15.907)
gest_age - more than 42 w	515.614*** (18.498)	422.128*** (16.242)
parity	30.320*** (0.317)	27.791*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,065,618	21,928,353
R2	0.18565	0.16883
Within R2	0.17707	0.15914

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 18 - Estimations of birthweight per daily deviations from historical means, controlling for pre-pregnancy municipality shocks

Weather var.	Dependent variable – Birthweight (g)			
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.064 (0.247)	0.074 (0.055)	-0.116 (0.173)	-0.017 (0.043)
-2 to -1.5	-0.009 (0.106)	-0.238** (0.080)	-0.281** (0.090)	-0.233*** (0.064)
-1.5 to -1	-0.030 (0.042)	0.064 (0.045)	-0.044 (0.048)	0.030 (0.036)
-1 to -0.7	0.005 (0.038)	0.002 (0.037)	-0.010 (0.041)	-0.044 (0.036)
0.7 to 1	-0.097*** (0.022)	-0.026 (0.018)	-0.111*** (0.022)	-0.035 (0.021)
1 to 1.5	-0.030. (0.017)	-0.023 (0.014)	-0.072*** (0.016)	-0.037* (0.015)
1.5 to 2	-0.144*** (0.024)	-0.030 (0.023)	-0.162*** (0.023)	-0.036 (0.024)
>2	-0.081* (0.033)	-0.054* (0.021)	-0.090** (0.031)	-0.089*** (0.022)
Precip.				
Neg.	0.002 (0.048)		0.013 (0.051)	
Pos.	0.008 (0.020)		0.007 (0.020)	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2 (pre)	-0.156. (0.082)	-0.153*** (0.045)	-0.089 (0.093)	-0.126** (0.045)
-2 to -1.5 (pre)	0.106 (0.067)	0.120* (0.058)	0.125. (0.067)	0.124* (0.056)
-1.5 to -1 (pre)	0.079 (0.050)	-0.016 (0.044)	0.066 (0.049)	-0.004 (0.040)
-1 to -0.7 (pre)	0.239*** (0.048)	-0.059 (0.050)	0.215*** (0.048)	-0.097. (0.056)
0.7 to 1 (pre)	0.085** (0.032)	0.043 (0.034)	0.070* (0.033)	0.034 (0.037)
1 to 1.5 (pre)	0.052* (0.022)	0.036. (0.021)	0.039. (0.023)	0.047* (0.022)
1.5 to 2 (pre)	-0.009 (0.032)	-0.015 (0.027)	-0.002 (0.034)	-0.021 (0.028)
>2 (pre)	0.000 (0.029)	-0.030 (0.024)	-0.002 (0.030)	-0.017 (0.025)
Precip.				
Neg. (pre)	-0.005 (0.028)		0.010 (0.027)	
Pos. (pre)	-0.137*** (0.036)		-0.179*** (0.036)	
y2000	-6.068*** (1.381)		-6.519*** (1.298)	
y2001	-18.909*** (1.690)		-19.798*** (1.619)	
y2002	-29.437*** (1.831)		-28.460*** (1.967)	
y2003	-33.370*** (1.802)		-32.746*** (1.890)	
y2004	-21.693*** (1.664)		-19.988*** (1.691)	
y2005	-21.805*** (1.642)		-20.064*** (1.733)	
y2006	-25.041*** (1.688)		-26.339*** (1.750)	
y2007	-30.185*** (2.113)		-31.271*** (2.288)	
y2008	-28.952*** (2.016)		-30.524*** (2.148)	
y2009	-31.571*** (2.476)		-33.101*** (2.520)	
y2010	-23.148*** (1.999)		-25.695*** (2.076)	
y2011	1.453 (2.018)		-4.424* (2.035)	
y2012	1.001 (1.966)		-3.461. (2.078)	
y2013	-1.199 (2.288)		-5.412* (2.393)	
y2014	-3.619 (2.507)		-6.948* (2.720)	
y2015	-1.492 (2.716)		-4.404 (2.823)	
y2016	2.814 (2.300)		-0.908 (2.427)	
y2017	0.304 (2.215)		-1.949 (2.184)	
y2018	-2.989 (2.500)		-5.391* (2.472)	
y2019	3.870 (2.517)		0.941 (2.611)	

y2020	42.312 (53.734)	66.578 (61.708)
m02	0.965. (0.554)	0.245 (0.557)
m03	-4.180*** (0.642)	-4.575*** (0.620)
m04	5.884*** (0.697)	5.499*** (0.623)
m05	6.648*** (0.790)	4.484*** (0.691)
m06	1.544* (0.676)	-0.240 (0.575)
m07	2.493*** (0.640)	0.320 (0.554)
m08	2.037*** (0.611)	-0.240 (0.544)
m09	3.322*** (0.648)	2.164*** (0.565)
m10	4.232*** (0.579)	3.205*** (0.560)
m11	4.836*** (0.574)	3.947*** (0.581)
m12	6.037*** (0.487)	5.308*** (0.509)
years of study - zero	49.274*** (1.692)	45.023*** (1.636)
years of study - 1 to 3 y	69.094*** (2.009)	63.787*** (1.937)
years of study - 4 to 7 y	90.112*** (2.316)	84.333*** (2.209)
years of study - 8 to 11 y	81.105*** (2.986)	70.869*** (2.982)
marital status - married	19.164*** (0.673)	18.111*** (0.733)
pre_appoint	57.646*** (0.745)	51.546*** (0.682)
une	-0.952* (0.471)	-1.068* (0.502)
mother_age	0.868*** (0.071)	0.965*** (0.068)
gest_age - 22 to 27 w	-1,015.976*** (25.243)	-880.371*** (25.835)
gest_age - 28 to 31 w	-1,063.965*** (17.941)	-1,041.871*** (20.092)
gest_age - 32 to 36 w	-232.102*** (16.160)	-271.091*** (15.627)
gest_age - 37 to 41 w	395.482*** (17.249)	324.114*** (15.482)
gest_age - more than 42 w	487.291*** (18.047)	404.496*** (15.722)
parity	30.321*** (0.317)	27.780*** (0.320)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,072,322	21,913,936
R2	0.18553	0.16893
Within R2	0.17695	0.15923

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 19 - Estimations of birthweight per weekly deviations from historical means, controlling for pre-pregnancy municipality shocks

Weather var.	Dependent variable – Birthweight (g)			
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.083 (0.251)	-0.014 (0.060)	0.387 (0.252)	-0.066 (0.042)
-2 to -1.5	-0.061 (0.103)	-0.226** (0.085)	-0.025 (0.109)	-0.183** (0.070)
-1.5 to -1	-0.003 (0.042)	0.059 (0.049)	-0.022 (0.042)	0.018 (0.039)
-1 to -0.7	0.047 (0.035)	-0.003 (0.037)	0.018 (0.036)	-0.048 (0.037)
0.7 to 1	-0.083*** (0.020)	-0.010 (0.018)	-0.079*** (0.023)	-0.022 (0.020)
1 to 1.5	-0.017 (0.017)	-0.021 (0.015)	-0.046** (0.016)	-0.028. (0.016)
1.5 to 2	-0.128*** (0.024)	-0.026 (0.025)	-0.156*** (0.024)	-0.021 (0.025)
>2	-0.090** (0.033)	-0.062** (0.024)	-0.081* (0.034)	-0.079** (0.025)
Precip.				
Neg.	-0.017 (0.043)		-0.032 (0.046)	
Pos.	0.010 (0.019)		0.019 (0.019)	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2 (pre)	0.436 (0.288)	26.158* (12.057)	0.165 (0.270)	-1.793 (14.703)
-2 to -1.5 (pre)	-0.037 (0.104)	6.770 (4.177)	-0.031 (0.106)	3.609 (5.093)
-1.5 to -1 (pre)	-0.053 (0.037)	-3.206** (1.102)	-0.005 (0.037)	-4.182*** (1.073)
-1 to -0.7 (pre)	-0.035 (0.037)	0.322 (0.771)	-0.012 (0.036)	0.618 (0.748)
0.7 to 1 (pre)	-0.023 (0.021)	-0.150 (0.129)	-0.017 (0.020)	-0.401** (0.144)
1 to 1.5 (pre)	0.009 (0.016)	-0.091 (0.081)	0.023 (0.015)	-0.131. (0.079)
1.5 to 2 (pre)	-0.066** (0.024)	-0.177** (0.064)	-0.039 (0.025)	-0.231*** (0.066)
>2 (pre)	-0.018 (0.029)	-0.260*** (0.055)	-0.032 (0.028)	-0.318*** (0.059)
Precip.				
Neg. (pre)	0.034. (0.019)		0.054** (0.019)	
Pos. (pre)	-0.103* (0.050)		-0.176*** (0.047)	
y2000	-11.258*** (1.406)		-8.059*** (1.289)	
y2001	-24.257*** (1.817)		-24.765*** (1.895)	
y2002	-33.561*** (1.898)		-29.535*** (1.987)	
y2003	-36.890*** (1.877)		-32.805*** (1.911)	
y2004	-25.957*** (1.783)		-21.038*** (1.694)	
y2005	-25.796*** (1.796)		-20.061*** (1.782)	
y2006	-28.906*** (1.838)		-24.002*** (1.731)	
y2007	-33.935*** (2.262)		-28.598*** (2.200)	
y2008	-33.185*** (2.186)		-27.891*** (2.096)	
y2009	-35.635*** (2.599)		-31.036*** (2.420)	
y2010	-27.311*** (2.205)		-23.733*** (2.051)	
y2011	-2.263 (2.250)		-1.538 (2.043)	
y2012	-4.027. (2.158)		-2.364 (2.075)	
y2013	-4.671. (2.517)		-2.641 (2.411)	
y2014	-7.269** (2.779)		-4.166 (2.733)	
y2015	-5.155. (2.914)		-2.275 (2.799)	
y2016	0.776 (2.571)		1.657 (2.353)	
y2017	-3.768 (2.410)		0.362 (2.211)	
y2018	-7.033** (2.611)		-3.239 (2.542)	
y2019	-0.890 (2.606)		3.000 (2.635)	

y2020	29.888 (56.103)	61.353 (61.590)
m02	1.406** (0.536)	0.629 (0.546)
m03	-3.455*** (0.636)	-3.925*** (0.624)
m04	6.380*** (0.681)	6.123*** (0.626)
m05	6.785*** (0.796)	4.807*** (0.740)
m06	1.512. (0.774)	0.066 (0.679)
m07	2.963*** (0.723)	0.716 (0.614)
m08	2.812*** (0.708)	0.395 (0.589)
m09	3.980*** (0.819)	2.598*** (0.598)
m10	4.506*** (0.663)	3.429*** (0.543)
m11	4.676*** (0.590)	3.720*** (0.566)
m12	5.904*** (0.480)	5.100*** (0.504)
years of study - zero	49.823*** (1.680)	45.407*** (1.676)
years of study - 1 to 3 y	69.634*** (1.974)	64.582*** (1.950)
years of study - 4 to 7 y	90.579*** (2.268)	85.287*** (2.228)
years of study - 8 to 11 y	81.639*** (2.917)	71.708*** (3.023)
marital status - married	18.922*** (0.682)	17.823*** (0.721)
pre_appoint	57.669*** (0.749)	52.010*** (0.694)
une	-0.847. (0.497)	-0.981. (0.514)
mother_age	0.853*** (0.073)	0.954*** (0.069)
gest_age - 22 to 27 w	-1,004.212*** (25.511)	-868.266*** (25.938)
gest_age - 28 to 31 w	-1,045.444*** (18.755)	-1,024.167*** (20.535)
gest_age - 32 to 36 w	-204.333*** (17.074)	-244.070*** (16.388)
gest_age - 37 to 41 w	432.864*** (18.320)	359.986*** (16.983)
gest_age - more than 42 w	529.014*** (19.208)	445.295*** (17.574)
parity	30.440*** (0.322)	27.985*** (0.327)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,645,501	21,416,710
R2	0.18554	0.16853
Within R2	0.17694	0.15893

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 20 - Estimations of birthweight per monthly deviations from historical means, controlling for pre-pregnancy municipality shocks

Weather var.	Dependent variable – Birthweight (g)			
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-20.248 (13.960)	1.149 (1.196)	-11.180 (14.240)	0.523 (0.922)
-2 to -1.5	-1.686 (6.195)	-0.361 (1.532)	-3.716 (7.033)	-1.044 (1.519)
-1.5 to -1	4.036** (1.521)	-1.784** (0.658)	3.545* (1.418)	-0.935 (0.569)
-1 to -0.7	-0.814 (0.766)	0.266 (0.524)	-0.832 (0.755)	-0.209 (0.517)
0.7 to 1	-0.953*** (0.251)	-0.619** (0.194)	-1.121*** (0.243)	-0.679** (0.207)
1 to 1.5	-1.815*** (0.296)	-0.636** (0.236)	-1.950*** (0.302)	-0.623** (0.241)
1.5 to 2	-2.566*** (0.506)	-1.152** (0.409)	-2.852*** (0.494)	-0.966* (0.401)
>2	-1.515. (0.798)	-1.711*** (0.487)	-1.814* (0.826)	-2.151*** (0.510)
Precip.				
Neg.	-0.337 (3.183)		3.746 (2.824)	
Pos.	0.157 (0.469)		0.872* (0.416)	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2 (pre)	-8.224 (19.161)	-0.706 (1.270)	-4.988 (14.336)	-2.570* (1.293)
-2 to -1.5 (pre)	11.976* (6.081)	-4.745*** (1.197)	-1.364 (5.113)	-2.608* (1.166)
-1.5 to -1 (pre)	1.372 (1.209)	-1.501. (0.859)	2.286. (1.291)	-2.251* (1.074)
-1 to -0.7 (pre)	0.151 (0.682)	-1.116. (0.589)	-0.021 (0.678)	-0.474 (0.485)
0.7 to 1 (pre)	-0.390 (0.255)	0.025 (0.183)	-0.577* (0.256)	0.093 (0.180)
1 to 1.5 (pre)	-0.863** (0.310)	-0.235 (0.235)	-0.655* (0.309)	-0.272 (0.248)
1.5 to 2 (pre)	-1.730*** (0.487)	-0.752. (0.452)	-1.571** (0.489)	-0.635 (0.482)
>2 (pre)	-0.731 (0.712)	-0.949. (0.506)	-1.249. (0.723)	-1.016. (0.557)
Precip.				
Neg. (pre)	-1.041 (2.889)		-1.695 (2.915)	
Pos. (pre)	-0.800. (0.482)		-0.076 (0.438)	
y2000	-6.930*** (1.365)		-6.838*** (1.309)	
y2001	-18.744*** (1.681)		-18.959*** (1.651)	
y2002	-29.002*** (1.825)		-27.118*** (1.942)	
y2003	-31.217*** (1.907)		-30.552*** (2.031)	
y2004	-21.148*** (1.725)		-19.679*** (1.744)	
y2005	-20.691*** (1.691)		-18.078*** (1.777)	
y2006	-24.192*** (1.686)		-22.537*** (1.725)	
y2007	-28.872*** (1.984)		-26.523*** (2.089)	
y2008	-28.114*** (1.959)		-25.842*** (2.047)	
y2009	-29.897*** (2.300)		-28.518*** (2.293)	
y2010	-20.333*** (1.962)		-20.008*** (2.018)	
y2011	3.297. (1.913)		0.915 (1.937)	
y2012	1.113 (1.897)		-0.673 (2.006)	
y2013	0.657 (2.342)		-0.243 (2.407)	
y2014	-2.215 (2.488)		-1.998 (2.636)	
y2015	0.712 (2.683)		-0.005 (2.741)	
y2016	6.098** (2.303)		5.631* (2.343)	
y2017	2.145 (2.223)		3.464 (2.172)	
y2018	-2.014 (2.491)		-1.421 (2.473)	
y2019	5.669* (2.554)		5.407* (2.571)	

y2020	43.324 (53.714)	69.766 (61.622)
m02	1.307* (0.546)	0.712 (0.543)
m03	-3.662*** (0.616)	-3.777*** (0.595)
m04	6.386*** (0.670)	6.307*** (0.596)
m05	6.876*** (0.772)	4.861*** (0.679)
m06	1.541* (0.702)	-0.193 (0.612)
m07	2.155** (0.665)	0.072 (0.558)
m08	1.368* (0.620)	-0.716 (0.508)
m09	2.742*** (0.683)	1.720** (0.532)
m10	3.575*** (0.587)	2.638*** (0.513)
m11	4.160*** (0.573)	3.293*** (0.562)
m12	5.621*** (0.479)	4.819*** (0.498)
years of study - zero	49.348*** (1.697)	45.126*** (1.622)
years of study - 1 to 3 y	69.234*** (2.013)	64.182*** (1.919)
years of study - 4 to 7 y	90.234*** (2.324)	84.816*** (2.199)
years of study - 8 to 11 y	81.241*** (2.990)	71.428*** (2.989)
marital status - married	19.151*** (0.673)	18.231*** (0.733)
pre_appoint	57.648*** (0.743)	51.765*** (0.685)
une	-0.749 (0.494)	-0.849. (0.513)
mother_age	0.869*** (0.071)	0.966*** (0.068)
gest_age - 22 to 27 w	-1,016.206*** (25.228)	-884.060*** (25.507)
gest_age - 28 to 31 w	-1,063.350*** (17.929)	-1,045.290*** (19.635)
gest_age - 32 to 36 w	-230.559*** (16.086)	-274.448*** (15.378)
gest_age - 37 to 41 w	398.587*** (17.105)	321.199*** (15.332)
gest_age - more than 42 w	490.220*** (17.860)	400.918*** (15.600)
parity	30.319*** (0.317)	27.791*** (0.322)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,072,322	21,934,835
R2	0.18554	0.16874
Within R2	0.17696	0.15905

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 21 - Estimations of birthweight per bin of temperature and precipitation, placebo test 1 year after exposure

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.282*** (0.028)	0.254*** (0.028)
15-18	0.077** (0.029)	0.090** (0.028)
18-21	0.077** (0.024)	0.091*** (0.021)
24-27	-0.079*** (0.019)	-0.063*** (0.019)
27-30	-0.227*** (0.034)	-0.208*** (0.032)
30-33	-0.180*** (0.048)	-0.163** (0.050)
>33	-1.160 (0.769)	0.328 (0.672)
Prec. (mm/m²)		
2.5 to 5	-0.064. (0.034)	-0.063. (0.037)
5 to 7.5	-0.045 (0.053)	-0.046 (0.051)
7.5 to 10	-0.267*** (0.061)	-0.295*** (0.061)
10 to 12.5	-0.190* (0.079)	-0.148. (0.085)
> 12.5	-0.132*** (0.030)	-0.130*** (0.029)
y2000	-9.358*** (1.275)	-9.253*** (1.179)
y2001	-20.429*** (1.722)	-20.802*** (1.636)
y2002	-37.332*** (1.751)	-35.611*** (1.783)
y2003	-36.128*** (1.761)	-35.251*** (1.817)
y2004	-25.002*** (1.741)	-23.368*** (1.700)
y2005	-25.914*** (1.744)	-23.367*** (1.778)
y2006	-30.609*** (1.849)	-28.866*** (1.836)
y2007	-33.769*** (2.039)	-31.426*** (2.103)
y2008	-28.107*** (2.085)	-25.880*** (2.141)
y2009	-36.992*** (2.482)	-35.556*** (2.441)
y2010	-29.689*** (2.295)	-28.861*** (2.259)
y2011	0.494 (2.056)	-1.927 (2.039)
y2012	-5.707** (2.045)	-7.678*** (2.112)
y2013	-3.624 (2.441)	-4.891* (2.465)
y2014	-4.126 (2.635)	-4.595. (2.733)
y2015	-9.567*** (2.859)	-10.944*** (2.848)
y2016	-4.042. (2.325)	-4.705* (2.318)
y2017	-1.039 (2.244)	0.317 (2.213)
y2018	-5.564* (2.412)	-4.981* (2.446)
y2019	-22.664*** (3.220)	-20.671*** (3.260)
m02	-0.468 (0.630)	-1.039. (0.550)
m03	-6.350*** (0.814)	-6.401*** (0.735)
m04	4.047*** (0.750)	4.278*** (0.646)
m05	7.496*** (0.747)	5.707*** (0.671)
m06	5.934*** (0.909)	3.961*** (0.824)
m07	9.664*** (1.375)	7.149*** (1.263)
m08	10.342*** (1.621)	7.831*** (1.542)
m09	11.028*** (1.438)	9.623*** (1.481)
m10	10.026*** (1.169)	8.650*** (1.181)
m11	8.060*** (0.843)	7.049*** (0.938)

m12	6.743*** (0.566)	5.947*** (0.623)
years of study - zero	49.003*** (1.661)	44.702*** (1.587)
years of study - 1 to 3 y	68.632*** (1.966)	63.447*** (1.880)
years of study - 4 to 7 y	89.427*** (2.285)	83.930*** (2.171)
years of study - 8 to 11 y	80.283*** (2.985)	70.470*** (3.030)
marital status - married	19.280*** (0.686)	18.368*** (0.749)
pre_appoint	57.393*** (0.750)	51.457*** (0.690)
une	-1.130* (0.493)	-1.347** (0.518)
mother_age	0.888*** (0.073)	0.979*** (0.070)
gest_age - 22 to 27 w	-1,025.295*** (24.636)	-894.129*** (25.026)
gest_age - 28 to 31 w	-1,062.167*** (17.592)	-1,041.938*** (19.243)
gest_age - 32 to 36 w	-227.176*** (16.478)	-269.221*** (15.535)
gest_age - 37 to 41 w	405.848*** (17.644)	329.556*** (15.787)
gest_age - more than 42 w	500.360*** (18.452)	411.593*** (16.134)
parity	30.100*** (0.317)	27.581*** (0.323)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,331,338	21,229,048
R2	0.18549	0.16868
Within R2	0.17671	0.15877

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 22 - Estimations of birthweight per daily deviations from historical means, placebo test 1 year after exposure

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.341*** (0.085)	0.763 (1.513)	-0.201* (0.087)	0.382 (1.829)
-2 to -1.5	0.142* (0.058)	0.185 (1.002)	-0.254*** (0.062)	0.080 (0.755)
-1.5 to -1	0.231*** (0.040)	0.362 (0.526)	-0.056 (0.057)	0.804* (0.394)
-1 to -0.7	0.002 (0.046)	1.245** (0.404)	0.098 (0.070)	0.171 (0.356)
0.7 to 1	0.039 (0.028)	0.160 (0.140)	0.107* (0.052)	0.236 (0.173)
1 to 1.5	-0.003 (0.015)	0.286*** (0.082)	-0.083** (0.031)	0.294*** (0.078)
1.5 to 2	-0.037 (0.024)	0.160* (0.065)	-0.036 (0.031)	0.023 (0.072)
>2	-0.033 (0.031)	0.024 (0.028)	-0.098** (0.032)	0.044** (0.017)
Precip.				
Neg.	0.126** (0.044)		-0.031 (0.059)	
Pos.	-0.007 (0.023)		-0.049 (0.041)	
y2000	-8.703*** (1.271)		-9.407*** (1.176)	
y2001	-21.012*** (1.626)		-22.787*** (1.590)	
y2002	-36.551*** (1.708)		-33.775*** (1.851)	
y2003	-35.872*** (1.757)		-34.381*** (1.895)	
y2004	-24.762*** (1.705)		-23.266*** (1.725)	
y2005	-25.580*** (1.696)		-23.365*** (1.765)	
y2006	-29.610*** (1.716)		-25.993*** (1.729)	
y2007	-32.625*** (1.996)		-29.525*** (2.108)	
y2008	-30.372*** (1.999)		-27.896*** (2.082)	
y2009	-37.095*** (2.442)		-34.878*** (2.398)	
y2010	-27.422*** (2.056)		-24.951*** (2.035)	
y2011	0.708 (1.985)		-1.216 (2.014)	
y2012	-5.257** (1.950)		-6.109** (2.047)	
y2013	-3.680 (2.341)		-5.783* (2.387)	
y2014	-6.643** (2.483)		-7.465** (2.574)	
y2015	-9.503*** (2.777)		-10.967*** (2.743)	
y2016	-2.474 (2.215)		-3.643 (2.256)	
y2017	-0.959 (2.213)		-0.034 (2.227)	
y2018	-4.629. (2.368)		-5.048* (2.415)	
y2019	-7.637* (3.825)		-10.393*** (2.650)	
m02	1.607** (0.549)		0.586 (0.547)	
m03	-3.164*** (0.626)		-3.894*** (0.582)	
m04	6.002*** (0.656)		6.004*** (0.591)	
m05	6.560*** (0.787)		4.857*** (0.655)	
m06	1.386. (0.760)		-0.548 (0.602)	
m07	1.897* (0.777)		-0.650 (0.564)	
m08	0.935 (0.709)		-1.601** (0.534)	
m09	1.780* (0.760)		0.608 (0.524)	
m10	2.596*** (0.616)		1.603** (0.529)	
m11	3.362*** (0.562)		2.754*** (0.604)	
m12	4.852*** (0.510)		4.227*** (0.523)	

years of study - zero	48.966*** (1.672)	44.436*** (1.604)
years of study - 1 to 3 y	68.582*** (1.975)	63.074*** (1.903)
years of study - 4 to 7 y	89.149*** (2.291)	83.314*** (2.182)
years of study - 8 to 11 y	79.213*** (2.994)	69.089*** (2.973)
marital status - married	18.947*** (0.683)	18.033*** (0.721)
pre_appoint	57.270*** (0.748)	51.304*** (0.692)
une	-1.317** (0.499)	-1.511** (0.513)
mother_age	0.870*** (0.073)	0.958*** (0.070)
gest_age - 22 to 27 w	-1,030.308*** (24.777)	-897.938*** (25.267)
gest_age - 28 to 31 w	-1,072.753*** (17.511)	-1,050.050*** (19.414)
gest_age - 32 to 36 w	-242.101*** (16.432)	-280.261*** (15.398)
gest_age - 37 to 41 w	386.274*** (18.089)	315.425*** (15.614)
gest_age - more than 42 w	478.048*** (19.072)	395.430*** (15.950)
parity	30.204*** (0.317)	27.695*** (0.325)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,331,338	21,229,048
R2	0.18546	0.16864
Within R2	0.17667	0.15873

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 23 - Estimations of birthweight per weekly deviations from historical means, placebo test 1 year after exposure

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.552. (0.310)	17.104 (14.768)	0.411 (0.314)	-3.142 (3.788)
-2 to -1.5	-0.052 (0.095)	-1.158 (2.336)	0.049 (0.093)	4.161 (3.114)
-1.5 to -1	-0.019 (0.040)	0.116 (1.174)	-0.072. (0.041)	-2.670* (1.244)
-1 to -0.7	-0.068. (0.039)	2.124** (0.698)	-0.047 (0.040)	2.624** (0.858)
0.7 to 1	-0.030 (0.026)	0.386** (0.122)	-0.029 (0.026)	0.228. (0.124)
1 to 1.5	-0.022 (0.015)	0.217** (0.067)	-0.017 (0.016)	0.186** (0.065)
1.5 to 2	-0.093*** (0.024)	0.255*** (0.051)	-0.114*** (0.025)	0.191*** (0.056)
>2	-0.084* (0.039)	0.070* (0.028)	-0.063. (0.037)	0.024 (0.026)
Precip.				
Neg.	-0.024 (0.048)		-0.026 (0.044)	
Pos.	-0.055** (0.019)		-0.062*** (0.018)	
y2000	-8.858*** (1.283)		-8.799*** (1.179)	
y2001	-21.708*** (1.623)		-22.003*** (1.602)	
y2002	-35.602*** (1.711)		-34.060*** (1.793)	
y2003	-34.989*** (1.786)		-34.182*** (1.872)	
y2004	-24.841*** (1.725)		-23.210*** (1.700)	
y2005	-25.580*** (1.733)		-23.165*** (1.788)	
y2006	-28.516*** (1.732)		-27.026*** (1.730)	
y2007	-32.110*** (2.030)		-29.939*** (2.081)	
y2008	-29.143*** (2.040)		-26.821*** (2.124)	
y2009	-35.865*** (2.457)		-34.474*** (2.444)	
y2010	-26.100*** (2.033)		-25.468*** (2.061)	
y2011	1.490 (2.001)		-0.806 (2.031)	
y2012	-4.955* (2.003)		-6.914** (2.123)	
y2013	-4.662. (2.414)		-5.873* (2.465)	
y2014	-5.302* (2.529)		-5.495* (2.708)	
y2015	-8.829** (2.862)		-10.170*** (2.874)	
y2016	-3.223 (2.270)		-3.903. (2.323)	
y2017	-2.490 (2.232)		-1.054 (2.210)	
y2018	-6.529** (2.316)		-6.047* (2.353)	
y2019	-7.969* (3.739)		-12.090*** (3.284)	
m02	1.283* (0.537)		0.559 (0.542)	
m03	-3.639*** (0.621)		-3.982*** (0.584)	
m04	5.701*** (0.665)		5.763*** (0.601)	
m05	6.443*** (0.801)		4.588*** (0.697)	
m06	1.215 (0.747)		-0.692 (0.660)	
m07	1.815* (0.754)		-0.503 (0.620)	
m08	0.965 (0.705)		-1.240* (0.580)	
m09	2.107** (0.779)		1.005. (0.561)	
m10	2.990*** (0.626)		1.813*** (0.536)	
m11	3.776*** (0.573)		2.773*** (0.553)	
m12	5.142*** (0.501)		4.166*** (0.503)	

years of study - zero	48.929*** (1.676)	44.631*** (1.605)
years of study - 1 to 3 y	68.610*** (1.984)	63.434*** (1.899)
years of study - 4 to 7 y	89.409*** (2.305)	83.919*** (2.189)
years of study - 8 to 11 y	80.233*** (3.008)	70.438*** (3.052)
marital status - married	19.278*** (0.687)	18.363*** (0.750)
pre_appoint	57.423*** (0.750)	51.483*** (0.690)
une	-0.979* (0.493)	-1.200* (0.515)
mother_age	0.886*** (0.073)	0.977*** (0.070)
gest_age - 22 to 27 w	-1,030.522*** (24.774)	-897.791*** (25.081)
gest_age - 28 to 31 w	-1,073.302*** (17.487)	-1,049.796*** (19.057)
gest_age - 32 to 36 w	-242.893*** (16.352)	-279.882*** (15.366)
gest_age - 37 to 41 w	385.199*** (17.969)	315.943*** (16.082)
gest_age - more than 42 w	476.765*** (18.911)	396.025*** (16.592)
parity	30.102*** (0.317)	27.583*** (0.323)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,331,338	21,229,048
R2	0.18543	0.16863
Within R2	0.17665	0.15872

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 24 - Estimations of birthweight per monthly deviations from historical means, placebo test 1 year after exposure

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-34.400*** (2.889)	-0.773 (1.232)	-32.699*** (4.574)	-1.707 (1.096)
-2 to -1.5	-4.306 (6.178)	-0.266 (1.538)	-2.386 (5.285)	0.984 (1.606)
-1.5 to -1	2.358. (1.322)	-0.167 (0.864)	2.623. (1.421)	-0.745 (0.860)
-1 to -0.7	-0.844 (0.766)	0.339 (0.519)	-0.866 (0.757)	-0.201 (0.550)
0.7 to 1	-0.727** (0.238)	-0.083 (0.193)	-0.506* (0.238)	-0.217 (0.190)
1 to 1.5	-1.383*** (0.321)	-0.139 (0.276)	-1.418*** (0.312)	-0.348 (0.281)
1.5 to 2	-2.253*** (0.530)	-0.342 (0.483)	-2.166*** (0.573)	-0.169 (0.501)
>2	-1.499 (0.941)	-1.957** (0.669)	-0.936 (0.891)	-1.929** (0.659)
Precip.				
Neg.	2.736 (2.749)		-0.134 (2.712)	
Pos.	-1.084** (0.404)		-0.833* (0.413)	
y2000	-9.565*** (1.278)		-9.413*** (1.189)	
y2001	-21.795*** (1.615)		-21.942*** (1.578)	
y2002	-35.849*** (1.671)		-34.312*** (1.768)	
y2003	-35.249*** (1.743)		-34.510*** (1.819)	
y2004	-25.260*** (1.699)		-23.575*** (1.658)	
y2005	-25.913*** (1.672)		-23.438*** (1.713)	
y2006	-29.402*** (1.716)		-27.898*** (1.741)	
y2007	-32.706*** (1.974)		-30.451*** (2.049)	
y2008	-28.699*** (1.919)		-26.435*** (1.991)	
y2009	-35.830*** (2.356)		-34.502*** (2.334)	
y2010	-26.814*** (2.037)		-26.265*** (2.067)	
y2011	1.541 (1.937)		-0.860 (1.959)	
y2012	-5.164** (1.957)		-7.147*** (2.057)	
y2013	-4.295. (2.320)		-5.484* (2.372)	
y2014	-4.230. (2.375)		-4.491. (2.534)	
y2015	-7.886** (2.773)		-9.463*** (2.778)	
y2016	-3.488 (2.221)		-4.188. (2.281)	
y2017	-2.756 (2.230)		-1.223 (2.201)	
y2018	-7.005** (2.398)		-6.191* (2.421)	
y2019	-15.610*** (2.760)		-14.682*** (2.843)	
m02	1.250* (0.535)		0.599 (0.545)	
m03	-3.722*** (0.604)		-3.924*** (0.585)	
m04	5.787*** (0.661)		5.909*** (0.598)	
m05	6.424*** (0.771)		4.608*** (0.671)	
m06	0.940 (0.698)		-0.881 (0.615)	
m07	1.019 (0.674)		-1.181* (0.560)	
m08	-0.233 (0.608)		-2.291*** (0.508)	
m09	0.942 (0.654)		-0.018 (0.515)	
m10	2.055*** (0.559)		1.022* (0.518)	
m11	3.053*** (0.550)		2.204*** (0.567)	
m12	4.623*** (0.481)		3.858*** (0.506)	

years of study - zero	48.959*** (1.674)	44.660*** (1.603)
years of study - 1 to 3 y	68.647*** (1.983)	63.461*** (1.899)
years of study - 4 to 7 y	89.446*** (2.305)	83.942*** (2.188)
years of study - 8 to 11 y	80.282*** (3.006)	70.473*** (3.049)
marital status - married	19.268*** (0.687)	18.362*** (0.750)
pre_appoint	57.434*** (0.749)	51.491*** (0.689)
une	-0.853. (0.498)	-1.102* (0.518)
mother_age	0.886*** (0.073)	0.977*** (0.070)
gest_age - 22 to 27 w	-1,028.522*** (24.913)	-896.718*** (25.289)
gest_age - 28 to 31 w	-1,069.162*** (17.656)	-1,048.226*** (19.442)
gest_age - 32 to 36 w	-236.620*** (16.137)	-277.644*** (15.390)
gest_age - 37 to 41 w	394.013*** (17.207)	319.139*** (15.528)
gest_age - more than 42 w	486.429*** (17.987)	399.336*** (15.846)
parity	30.100*** (0.317)	27.583*** (0.323)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,337,749	21,235,266
R2	0.18543	0.16862
Within R2	0.17665	0.15871

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 25 - Estimations of birthweight per daily deviations from seasonal means

Weather var.	Dependent variable – Birthweight (g)			
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.109*** (0.027)	-0.143*** (0.033)	-0.132*** (0.027)	-0.133*** (0.033)
-2 to -1.5	0.035 (0.048)	0.074 (0.050)	0.061 (0.049)	-0.037 (0.053)
-1.5 to -1	-0.025 (0.033)	-0.003 (0.046)	0.029 (0.035)	0.000 (0.046)
-1 to -0.7	-0.027 (0.042)	0.056 (0.050)	-0.023 (0.042)	0.067 (0.054)
0.7 to 1	-0.052 (0.049)	-0.073 (0.048)	-0.059 (0.047)	-0.089* (0.045)
1 to 1.5	0.051 (0.035)	-0.033 (0.035)	0.009 (0.033)	-0.029 (0.034)
1.5 to 2	-0.124*** (0.038)	-0.054 (0.033)	-0.114** (0.036)	-0.088** (0.030)
>2	-0.097*** (0.025)	0.006 (0.034)	-0.108*** (0.026)	-0.016 (0.030)
Precip.				
Neg.	-0.153*** (0.032)		-0.106*** (0.030)	
Pos.	-0.110*** (0.021)		-0.091*** (0.020)	
y2000	-7.912*** (1.358)		-7.622*** (1.340)	
y2001	-23.219*** (1.653)		-23.034*** (1.638)	
y2002	-35.420*** (1.762)		-33.261*** (1.896)	
y2003	-36.331*** (1.794)		-35.193*** (1.873)	
y2004	-24.594*** (1.735)		-22.555*** (1.733)	
y2005	-25.954*** (1.669)		-22.954*** (1.776)	
y2006	-29.421*** (1.654)		-27.333*** (1.680)	
y2007	-32.437*** (1.993)		-29.589*** (2.092)	
y2008	-31.316*** (1.912)		-28.909*** (2.010)	
y2009	-36.944*** (2.374)		-34.808*** (2.349)	
y2010	-26.625*** (1.899)		-25.665*** (1.949)	
y2011	-1.935 (1.964)		-3.816. (1.982)	
y2012	-5.946** (1.933)		-7.283*** (2.022)	
y2013	-7.035** (2.282)		-7.420** (2.312)	
y2014	-10.653*** (2.433)		-9.862*** (2.543)	
y2015	-11.290*** (2.746)		-11.424*** (2.697)	
y2016	-4.623* (2.222)		-4.350. (2.256)	
y2017	-3.282 (2.183)		-1.630 (2.151)	
y2018	-6.319** (2.425)		-5.780* (2.434)	
y2019	-0.358 (2.482)		-0.222 (2.554)	
y2020	38.893 (53.734)		66.412 (61.676)	
m02	0.353 (0.723)		-0.686 (0.644)	
m03	-4.796*** (0.808)		-5.428*** (0.795)	
m04	6.200*** (0.721)		6.059*** (0.640)	
m05	8.348*** (0.766)		6.894*** (0.679)	
m06	4.309*** (0.888)		3.604*** (0.796)	
m07	5.525*** (0.947)		4.508*** (0.887)	
m08	4.941*** (1.038)		3.740*** (1.026)	
m09	5.887*** (1.002)		5.515*** (1.023)	
m10	6.185*** (0.842)		5.831*** (0.807)	
m11	6.237*** (0.805)		6.024*** (0.826)	
m12	6.498*** (0.636)		6.161*** (0.636)	
years of study - zero	48.948*** (1.693)		44.758*** (1.612)	

years of study - 1 to 3 y	68.434*** (2.008)	63.398*** (1.910)
years of study - 4 to 7 y	89.438*** (2.320)	84.037*** (2.194)
years of study - 8 to 11 y	80.494*** (2.982)	70.709*** (2.983)
marital status - married	19.251*** (0.675)	18.327*** (0.738)
pre_appoint	57.549*** (0.748)	51.661*** (0.692)
une	-1.577*** (0.473)	-1.629*** (0.492)
mother_age	0.866*** (0.071)	0.963*** (0.068)
gest_age - 22 to 27 w	-1,014.430*** (25.130)	-882.247*** (25.437)
gest_age - 28 to 31 w	-1,060.043*** (17.828)	-1,041.745*** (19.523)
gest_age - 32 to 36 w	-225.884*** (16.182)	-269.229*** (15.519)
gest_age - 37 to 41 w	404.149*** (17.521)	327.576*** (15.879)
gest_age - more than 42 w	496.977*** (18.365)	408.582*** (16.266)
parity	30.320*** (0.317)	27.795*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,072,322	21,934,835
R2	0.18550	0.16868
Within R2	0.17691	0.15899

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 26 - Estimations of birthweight per weekly deviations from seasonal means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.137*** (0.025)	34.638 (31.291)	-0.150*** (0.024)	35.481 (30.153)
-2 to -1.5	-0.097** (0.037)	0.127 (1.859)	-0.065. (0.034)	1.319 (2.428)
-1.5 to -1	0.024 (0.024)	-0.608 (0.796)	0.022 (0.023)	-1.535. (0.801)
-1 to -0.7	-0.066** (0.023)	-0.089 (0.607)	-0.057* (0.024)	0.935 (0.614)
0.7 to 1	-0.002 (0.028)	-0.076 (0.094)	-0.026 (0.028)	-0.015 (0.092)
1 to 1.5	-0.051* (0.021)	-0.020 (0.068)	-0.076*** (0.020)	0.092 (0.060)
1.5 to 2	-0.090*** (0.025)	0.001 (0.062)	-0.111*** (0.025)	0.080 (0.058)
>2	-0.092*** (0.017)	-0.144** (0.045)	-0.110*** (0.018)	-0.057 (0.045)
Precip.				
Neg.	-0.108*** (0.029)		-0.062* (0.030)	
Pos.	-0.048*** (0.012)		-0.042*** (0.011)	
y2000	-7.950*** (1.333)		-7.455*** (1.279)	
y2001	-22.089*** (1.638)		-22.070*** (1.582)	
y2002	-34.107*** (1.789)		-31.917*** (1.925)	
y2003	-35.864*** (1.810)		-34.655*** (1.895)	
y2004	-24.287*** (1.751)		-22.315*** (1.751)	
y2005	-25.104*** (1.735)		-22.309*** (1.823)	
y2006	-28.273*** (1.707)		-26.361*** (1.727)	
y2007	-31.509*** (2.013)		-28.750*** (2.090)	
y2008	-30.606*** (1.960)		-28.014*** (2.049)	
y2009	-36.268*** (2.469)		-34.224*** (2.465)	
y2010	-25.956*** (2.001)		-24.923*** (2.052)	
y2011	-1.170 (2.014)		-3.039 (2.036)	
y2012	-4.702* (1.986)		-5.912** (2.112)	
y2013	-6.436** (2.371)		-6.852** (2.414)	
y2014	-9.011*** (2.517)		-8.171** (2.670)	
y2015	-10.109*** (2.837)		-10.266*** (2.842)	
y2016	-3.810. (2.286)		-3.693 (2.378)	
y2017	-1.748 (2.244)		-0.079 (2.248)	
y2018	-5.299* (2.442)		-4.513. (2.515)	
y2019	0.546 (2.510)		0.904 (2.624)	
y2020	40.501 (53.694)		68.028 (61.673)	
m02	-0.041 (0.591)		-0.847 (0.565)	
m03	-5.361*** (0.704)		-5.700*** (0.689)	
m04	5.805*** (0.698)		5.807*** (0.611)	
m05	8.006*** (0.807)		6.461*** (0.738)	
m06	4.444*** (0.872)		3.448*** (0.775)	
m07	6.225*** (0.980)		5.051*** (0.853)	
m08	6.390*** (1.042)		5.223*** (0.946)	
m09	7.420*** (1.007)		7.093*** (0.885)	
m10	7.432*** (0.831)		6.968*** (0.744)	
m11	7.051*** (0.710)		6.500*** (0.736)	
m12	6.840*** (0.536)		6.257*** (0.569)	

years of study - zero	48.905*** (1.692)	44.706*** (1.614)
years of study - 1 to 3 y	68.371*** (2.008)	63.332*** (1.910)
years of study - 4 to 7 y	89.385*** (2.319)	83.978*** (2.194)
years of study - 8 to 11 y	80.459*** (2.980)	70.666*** (2.981)
marital status - married	19.241*** (0.674)	18.322*** (0.737)
pre_appoint	57.549*** (0.748)	51.659*** (0.691)
une	-1.674*** (0.478)	-1.762*** (0.504)
mother_age	0.865*** (0.071)	0.963*** (0.069)
gest_age - 22 to 27 w	-1,012.699*** (25.196)	-882.621*** (25.495)
gest_age - 28 to 31 w	-1,054.148*** (18.052)	-1,040.991*** (19.821)
gest_age - 32 to 36 w	-216.354*** (16.548)	-267.767*** (16.241)
gest_age - 37 to 41 w	417.679*** (17.855)	329.856*** (16.800)
gest_age - more than 42 w	512.473*** (18.759)	411.261*** (17.406)
parity	30.325*** (0.317)	27.795*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,065,618	21,928,353
R2	0.18550	0.16869
Within R2	0.17692	0.15900

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 27 - Estimations of birthweight per monthly deviations from seasonal means

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-3.483*** (0.630)	-0.475 (0.672)	-2.991*** (0.612)	-0.969 (0.664)
-2 to -1.5	-1.038. (0.544)	-0.040 (0.526)	-1.244* (0.531)	-0.644 (0.531)
-1.5 to -1	-0.299 (0.335)	0.313 (0.476)	-0.094 (0.332)	-0.005 (0.507)
-1 to -0.7	0.517 (0.318)	-0.833. (0.499)	0.367 (0.341)	-0.344 (0.459)
0.7 to 1	-0.197 (0.303)	-0.512* (0.249)	-0.248 (0.287)	-0.565* (0.254)
1 to 1.5	0.087 (0.333)	-0.060 (0.338)	-0.458 (0.301)	-0.407 (0.296)
1.5 to 2	-1.085** (0.418)	-0.052 (0.492)	-1.318** (0.406)	-0.461 (0.452)
>2	-3.047*** (0.559)	1.173* (0.547)	-3.344*** (0.566)	0.640 (0.530)
Precip.				
Neg.	-3.351*** (0.758)		-2.392** (0.824)	
Pos.	-1.351*** (0.232)		-1.322*** (0.242)	
y2000	-7.672*** (1.404)		-7.623*** (1.353)	
y2001	-22.231*** (1.697)		-22.511*** (1.639)	
y2002	-34.300*** (1.841)		-32.559*** (1.981)	
y2003	-35.770*** (1.789)		-34.880*** (1.855)	
y2004	-24.398*** (1.754)		-22.500*** (1.757)	
y2005	-24.712*** (1.723)		-22.131*** (1.785)	
y2006	-28.488*** (1.696)		-26.759*** (1.699)	
y2007	-31.979*** (1.972)		-29.342*** (2.049)	
y2008	-30.290*** (1.930)		-27.992*** (1.980)	
y2009	-36.769*** (2.381)		-34.590*** (2.352)	
y2010	-25.927*** (1.946)		-25.095*** (1.983)	
y2011	-0.608 (1.973)		-2.921 (1.991)	
y2012	-5.076* (1.974)		-6.724** (2.071)	
y2013	-5.862* (2.294)		-6.755** (2.313)	
y2014	-9.265*** (2.454)		-8.977*** (2.574)	
y2015	-10.485*** (2.798)		-10.947*** (2.723)	
y2016	-4.157. (2.242)		-4.274. (2.269)	
y2017	-2.167 (2.217)		-0.638 (2.188)	
y2018	-4.769. (2.555)		-4.216 (2.596)	
y2019	-0.093 (2.490)		0.228 (2.575)	
y2020	38.846 (53.746)		66.891 (61.655)	
m02	1.006 (0.621)		-0.001 (0.573)	
m03	-4.312*** (0.694)		-4.857*** (0.677)	
m04	5.857*** (0.712)		5.558*** (0.626)	
m05	6.738*** (0.800)		5.193*** (0.687)	
m06	1.432. (0.834)		0.506 (0.731)	
m07	2.450** (0.822)		1.102 (0.716)	
m08	2.045* (0.848)		0.522 (0.778)	
m09	3.441*** (0.938)		2.840** (0.878)	
m10	4.123*** (0.705)		3.674*** (0.640)	
m11	4.396*** (0.641)		4.138*** (0.652)	
m12	5.517*** (0.610)		5.336*** (0.596)	

years of study - zero	48.891*** (1.691)	44.675*** (1.611)
years of study - 1 to 3 y	68.361*** (2.005)	63.279*** (1.908)
years of study - 4 to 7 y	89.380*** (2.313)	83.929*** (2.190)
years of study - 8 to 11 y	80.437*** (2.975)	70.609*** (2.980)
marital status - married	19.250*** (0.675)	18.330*** (0.737)
pre_appoint	57.550*** (0.748)	51.655*** (0.692)
une	-1.649*** (0.469)	-1.748*** (0.489)
mother_age	0.866*** (0.072)	0.963*** (0.069)
gest_age - 22 to 27 w	-1,016.120*** (25.185)	-884.023*** (25.474)
gest_age - 28 to 31 w	-1,063.429*** (17.840)	-1,045.186*** (19.542)
gest_age - 32 to 36 w	-230.833*** (16.114)	-274.176*** (15.399)
gest_age - 37 to 41 w	397.898*** (17.351)	321.645*** (15.561)
gest_age - more than 42 w	489.380*** (18.142)	401.162*** (15.863)
parity	30.319*** (0.317)	27.793*** (0.321)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	23,072,322	21,934,835
R2	0.18550	0.16868
Within R2	0.17692	0.15899

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 28 - Estimations of birthweight per bin of temperature and precipitation, controlling for El Niño and La Niña southern oscillations

Weather var.	Dependent variable - Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.234*** (0.027)	0.211*** (0.025)
15-18	0.150*** (0.034)	0.176*** (0.028)
18-21	0.062* (0.025)	0.081*** (0.023)
24-27	-0.147*** (0.024)	-0.141*** (0.024)
27-30	-0.350*** (0.043)	-0.336*** (0.041)
30-33	-0.426*** (0.064)	-0.422*** (0.063)
>33	-0.524 (0.689)	-0.212 (0.855)
Prec. (mm/m²)		
2.5 to 5	-0.077. (0.040)	-0.063 (0.040)
5 to 7.5	-0.106 (0.065)	-0.049 (0.060)
7.5 to 10	-0.266*** (0.063)	-0.303*** (0.061)
10 to 12.5	-0.085 (0.081)	-0.103 (0.079)
> 12.5	-0.140*** (0.030)	-0.091** (0.029)
y2000	-50.922 (53.483)	-57.206*** (5.189)
y2001	-62.610 (53.532)	-69.426*** (5.076)
y2002	-70.102 (53.573)	-75.283*** (5.063)
y2003	-77.287 (53.681)	-83.086*** (4.696)
y2004	-64.632 (53.650)	-69.782*** (4.632)
y2005	-65.005 (53.641)	-69.037*** (4.480)
y2006	-67.651 (53.712)	-72.720*** (4.332)
y2007	-75.059 (53.667)	-78.975*** (4.228)
y2008	-73.828 (53.710)	-77.973*** (4.110)
y2009	-71.603 (53.661)	-77.006*** (4.246)
y2010	-67.344 (53.714)	-73.203*** (3.859)
y2011	-45.241 (53.707)	-53.654*** (3.523)
y2012	-43.620 (53.622)	-51.969*** (3.694)
y2013	-45.381 (53.726)	-52.735*** (3.771)
y2014	-45.194 (53.700)	-51.731*** (3.727)
y2015	-40.720 (53.683)	-48.904*** (4.006)
y2016	-41.158 (53.652)	-48.351*** (3.507)
y2017	-43.555 (53.550)	-48.892*** (3.655)
y2018	-43.649 (53.472)	-50.037*** (3.971)
y2019	-36.400 (53.450)	-43.623*** (3.906)
y2020	(dropped)	17.647 (62.389)
m02	-0.573 (0.670)	-1.111* (0.560)
m03	-6.316*** (0.899)	-6.351*** (0.802)
m04	5.041*** (0.805)	5.216*** (0.677)
m05	9.530*** (0.788)	7.448*** (0.706)
m06	8.938*** (1.015)	7.114*** (0.940)
m07	14.060*** (1.564)	11.674*** (1.421)
m08	15.794*** (1.780)	13.063*** (1.698)
m09	16.279*** (1.575)	14.722*** (1.607)
m10	14.397*** (1.286)	13.001*** (1.264)

m11	11.198*** (0.972)	10.071*** (1.051)
m12	8.998*** (0.633)	7.897*** (0.687)
years of study - zero	50.872*** (1.748)	46.554*** (1.693)
years of study - 1 to 3 y	70.860*** (2.030)	65.615*** (1.961)
years of study - 4 to 7 y	91.715*** (2.329)	86.213*** (2.235)
years of study - 8 to 11 y	82.729*** (2.964)	72.770*** (2.988)
marital status - married	18.312*** (0.663)	17.405*** (0.723)
pre_appoint	58.414*** (0.766)	52.391*** (0.710)
une	-1.086* (0.469)	-1.195* (0.489)
ONI_index	-1.200** (0.391)	-0.932** (0.339)
mother_age	0.837*** (0.072)	0.942*** (0.068)
gest_age - 22 to 27 w	-993.053*** (25.024)	-868.511*** (25.479)
gest_age - 28 to 31 w	-1,039.664*** (17.941)	-1,030.490*** (19.941)
gest_age - 32 to 36 w	-204.203*** (16.389)	-257.520*** (15.893)
gest_age - 37 to 41 w	426.679*** (17.569)	340.005*** (16.064)
gest_age - more than 42 w	519.947*** (18.336)	421.348*** (16.352)
parity	30.785*** (0.327)	28.230*** (0.331)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,318,914	21,217,103
R2	0.18669	0.16979
Within R2	0.17821	0.16023

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. ONI_index – El Niño and La Niña index. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 29 - Estimations of birthweight per daily deviations from historical means, controlling for El Niño and La Niña southern oscillations

Weather var.	Dependent variable - Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.114 (0.279)	-0.009 (0.053)	-0.214 (0.207)	-0.064 (0.042)
-2 to -1.5	-0.089 (0.106)	-0.220** (0.078)	-0.227* (0.096)	-0.218*** (0.059)
-1.5 to -1	-0.038 (0.041)	0.084. (0.045)	-0.043 (0.043)	0.043 (0.038)
-1 to -0.7	0.020 (0.037)	0.001 (0.042)	0.014 (0.039)	-0.053 (0.036)
0.7 to 1	-0.112*** (0.022)	-0.034. (0.018)	-0.118*** (0.022)	-0.038. (0.023)
1 to 1.5	-0.027 (0.018)	-0.025. (0.014)	-0.066*** (0.016)	-0.036* (0.015)
1.5 to 2	-0.145*** (0.025)	-0.034 (0.024)	-0.152*** (0.024)	-0.028 (0.025)
>2	-0.106** (0.038)	-0.072** (0.024)	-0.112** (0.036)	-0.094*** (0.024)
Precip.				
Neg.	-0.017 (0.045)		0.024 (0.054)	
Pos.	-0.005 (0.019)		-0.010 (0.020)	
y2000	230.309*** (8.652)		-68.855 (61.670)	
y2001	213.926*** (8.966)		-81.674 (61.654)	
y2002	207.502*** (9.262)		-89.612 (61.607)	
y2003	204.471*** (9.126)		-93.881 (61.685)	
y2004	216.340*** (9.331)		-81.085 (61.763)	
y2005	214.877*** (9.276)		-81.717 (61.689)	
y2006	212.240*** (9.369)		-87.894 (61.719)	
y2007	206.423*** (9.331)		-92.867 (61.625)	
y2008	207.184*** (9.396)		-92.553 (61.703)	
y2009	206.999*** (9.695)		-93.618 (61.673)	
y2010	214.005*** (9.618)		-87.106 (61.770)	
y2011	238.904*** (9.843)		-65.798 (61.764)	
y2012	238.465*** (9.985)		-65.970 (61.734)	
y2013	236.390*** (10.010)		-67.386 (61.776)	
y2014	234.757*** (10.089)		-68.308 (61.748)	
y2015	238.682*** (10.134)		-65.251 (61.814)	
y2016	240.055*** (10.153)		-62.994 (61.786)	
y2017	236.908*** (10.420)		-64.493 (61.841)	
y2018	234.974*** (10.500)		-67.244 (61.827)	
y2019	242.275*** (10.422)		-60.450 (61.765)	
y2020	279.806*** (47.958)		(dropped)	
m02	1.252* (0.559)		0.704 (0.545)	
m03	-3.647*** (0.641)		-3.940*** (0.607)	
m04	6.288*** (0.678)		6.152*** (0.617)	
m05	6.923*** (0.818)		4.628*** (0.694)	
m06	1.324. (0.722)		-0.610 (0.610)	
m07	2.103** (0.680)		-0.403 (0.583)	
m08	1.936** (0.635)		-1.079* (0.525)	
m09	3.085*** (0.722)		1.490** (0.563)	
m10	4.251*** (0.609)		2.719*** (0.540)	
m11	4.746*** (0.583)		3.507*** (0.557)	

m12	6.081*** (0.487)	4.885*** (0.501)
years of study - zero	50.540*** (1.756)	46.574*** (1.732)
years of study - 1 to 3 y	70.553*** (2.045)	65.471*** (2.017)
years of study - 4 to 7 y	90.959*** (2.344)	85.988*** (2.285)
years of study - 8 to 11 y	81.334*** (2.976)	72.453*** (3.014)
marital status - married	17.914*** (0.666)	17.290*** (0.724)
pre_appoint	59.371*** (0.761)	52.216*** (0.702)
une	-0.833. (0.476)	-0.948. (0.498)
ONI_index	-0.886** (0.311)	-0.465. (0.278)
mother_age	0.742*** (0.073)	0.939*** (0.068)
gest_age - 22 to 27 w	-605.342*** (25.796)	-868.875*** (26.105)
gest_age - 28 to 31 w	-176.745*** (33.044)	-1,035.580*** (20.584)
gest_age - 32 to 36 w	715.360*** (41.156)	-264.894*** (15.910)
gest_age - 37 to 41 w	1,345.184*** (45.677)	330.472*** (15.840)
gest_age - more than 42 w	1,434.852*** (46.544)	409.873*** (16.063)
parity	31.170*** (0.329)	28.212*** (0.330)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,378,599	21,202,516
R2	0.21275	0.16990
Within R2	0.20436	0.16032

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. ONI_index – El Niño and La Niña index. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 30 - Estimations of birthweight per weekly deviations from historical means, controlling for El Niño and La Niña southern oscillations

Weather var.	Dependent variable - Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.081 (0.287)	-0.009 (0.048)	0.398 (0.282)	-0.078. (0.043)
-2 to -1.5	-0.090 (0.111)	-0.198** (0.074)	-0.089 (0.115)	-0.161* (0.063)
-1.5 to -1	-0.033 (0.042)	0.090* (0.045)	-0.052 (0.041)	0.058 (0.038)
-1 to -0.7	0.023 (0.036)	0.009 (0.039)	0.007 (0.036)	-0.055 (0.039)
0.7 to 1	-0.093*** (0.021)	-0.013 (0.017)	-0.092*** (0.024)	-0.035. (0.019)
1 to 1.5	-0.007 (0.017)	-0.021 (0.015)	-0.038* (0.017)	-0.029. (0.016)
1.5 to 2	-0.126*** (0.025)	-0.020 (0.023)	-0.148*** (0.025)	-0.022 (0.024)
>2	-0.104** (0.039)	-0.065** (0.023)	-0.101* (0.040)	-0.086*** (0.024)
Precip.				
Neg.	0.014 (0.045)		-0.002 (0.047)	
Pos.	0.009 (0.020)		0.009 (0.020)	
y2000	-35.045*** (2.479)		54.381 (44.395)	
y2001	-49.602*** (2.210)		34.737 (44.518)	
y2002	-57.476*** (1.915)		31.806 (44.500)	
y2003	-60.763*** (1.663)		29.099 (44.457)	
y2004	-49.024*** (1.732)		41.395 (44.444)	
y2005	-51.178*** (1.744)		40.632 (44.399)	
y2006	-53.907*** (1.997)		36.903 (44.372)	
y2007	-59.986*** (1.904)		32.303 (44.402)	
y2008	-59.041*** (1.979)		33.049 (44.442)	
y2009	-59.922*** (2.433)		30.748 (44.469)	
y2010	-52.984*** (2.475)		37.685 (44.370)	
y2011	-27.763*** (2.161)		59.817 (44.408)	
y2012	-28.923*** (2.180)		59.027 (44.413)	
y2013	-31.025*** (2.294)		57.721 (44.530)	
y2014	-32.786*** (2.457)		56.591 (44.500)	
y2015	-29.063*** (2.519)		58.656 (44.594)	
y2016	-25.560*** (2.384)		61.148 (44.429)	
y2017	-29.983*** (2.456)		59.928 (44.350)	
y2018	-33.073*** (2.753)		56.503 (44.362)	
y2019	-27.107*** (2.733)		62.708 (44.356)	
y2020	-162.889*** (39.294)		(dropped)	
m02	1.308* (0.540)		0.465 (0.561)	
m03	-3.506*** (0.615)		-4.204*** (0.619)	
m04	6.492*** (0.676)		6.343*** (0.632)	
m05	7.039*** (0.791)		4.733*** (0.694)	
m06	1.207 (0.746)		-0.370 (0.640)	
m07	2.173** (0.672)		-0.117 (0.582)	
m08	2.062** (0.636)		-0.691 (0.549)	
m09	3.279*** (0.764)		1.967*** (0.561)	
m10	4.243*** (0.636)		3.048*** (0.543)	
m11	4.729*** (0.590)		3.597*** (0.571)	

m12	5.839*** (0.487)	4.896*** (0.516)
years of study - zero	50.656*** (1.768)	46.583*** (1.786)
years of study - 1 to 3 y	70.551*** (2.037)	65.585*** (2.026)
years of study - 4 to 7 y	91.166*** (2.313)	85.980*** (2.279)
years of study - 8 to 11 y	82.904*** (2.927)	73.112*** (3.012)
marital status - married	18.308*** (0.669)	16.967*** (0.704)
pre_appoint	60.099*** (0.767)	54.568*** (0.737)
une	-0.931* (0.469)	-0.943. (0.488)
ONI_index	-1.421*** (0.300)	-0.588. (0.302)
mother_age	0.737*** (0.072)	0.820*** (0.068)
gest_age - 22 to 27 w	-361.922*** (28.972)	-423.347*** (27.740)
gest_age - 28 to 31 w	120.133*** (32.671)	40.611 (30.936)
gest_age - 32 to 36 w	1,018.975*** (36.132)	901.316*** (34.765)
gest_age - 37 to 41 w	1,648.056*** (39.550)	1,496.712*** (38.317)
gest_age - more than 42 w	1,737.547*** (40.517)	1,574.445*** (38.863)
parity	31.118*** (0.332)	28.807*** (0.345)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	22,118,986	20,774,583
R2	0.21665	0.20226
Within R2	0.20903	0.19382

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. ONI_index – El Niño and La Niña index. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 31 - Estimations of birthweight per monthly deviations from historical means, controlling for El Niño and La Niña southern oscillations

Weather var.	Dependent variable - Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-27.051* (13.391)	-0.382 (1.060)	-26.585*** (6.847)	-1.854. (1.080)
-2 to -1.5	1.039 (6.871)	-1.884 (1.595)	-3.604 (7.827)	-2.466. (1.398)
-1.5 to -1	4.622** (1.669)	-1.260 (0.805)	3.840* (1.534)	-0.290 (0.655)
-1 to -0.7	-1.082 (0.816)	0.428 (0.625)	-0.967 (0.800)	-0.184 (0.619)
0.7 to 1	-0.940*** (0.274)	-0.708*** (0.199)	-1.173*** (0.263)	-0.776*** (0.205)
1 to 1.5	-1.922*** (0.321)	-0.762** (0.257)	-2.054*** (0.322)	-0.691** (0.259)
1.5 to 2	-2.825*** (0.548)	-1.283** (0.471)	-3.102*** (0.533)	-1.062* (0.464)
>2	-2.069* (0.890)	-1.848** (0.587)	-2.408** (0.918)	-2.321*** (0.584)
Precip.				
Neg.	1.045 (3.093)		5.156. (2.739)	
Pos.	0.077 (0.473)		0.672. (0.391)	
y2000	24.379*** (2.211)		-58.320*** (5.175)	
y2001	12.538*** (1.837)		-70.211*** (5.074)	
y2002	3.637* (1.642)		-77.648*** (5.016)	
y2003	-0.504 (1.484)		-82.632*** (4.720)	
y2004	11.261*** (1.681)		-70.145*** (4.661)	
y2005	10.347*** (1.530)		-69.812*** (4.515)	
y2006	7.382*** (1.569)		-74.002*** (4.277)	
y2007	1.686 (1.359)		-78.711*** (4.300)	
y2008	2.954* (1.224)		-77.512*** (4.115)	
y2009	2.993** (1.131)		-78.521*** (4.130)	
y2010	8.884*** (1.363)		-73.121*** (3.869)	
y2011	33.081*** (1.335)		-51.659*** (3.623)	
y2012	32.549*** (1.250)		-51.858*** (3.792)	
y2013	30.404*** (0.976)		-53.196*** (3.849)	
y2014	29.106*** (1.177)		-53.425*** (3.769)	
y2015	33.855*** (1.214)		-50.069*** (3.907)	
y2016	34.690*** (1.359)		-48.411*** (3.546)	
y2017	31.617*** (2.544)		-49.719*** (3.757)	
y2018	29.140*** (2.943)		-53.087*** (3.962)	
y2019	36.544*** (2.880)		-46.462*** (3.869)	
y2020	45.179 (56.379)		13.303 (62.191)	
m02	1.391* (0.570)		0.691 (0.542)	
m03	-3.653*** (0.614)		-3.759*** (0.589)	
m04	6.436*** (0.677)		6.624*** (0.598)	
m05	7.004*** (0.810)		5.099*** (0.652)	
m06	1.577* (0.752)		-0.201 (0.606)	
m07	1.933** (0.732)		-0.171 (0.557)	
m08	1.379* (0.672)		-0.969. (0.516)	
m09	2.618*** (0.751)		1.647** (0.523)	
m10	3.546*** (0.636)		2.820*** (0.519)	
m11	4.485*** (0.607)		3.520*** (0.550)	

m12	5.676*** (0.519)	4.832*** (0.496)
years of study - zero	50.969*** (1.809)	46.603*** (1.711)
years of study - 1 to 3 y	70.971*** (2.117)	65.766*** (1.992)
years of study - 4 to 7 y	91.866*** (2.418)	86.362*** (2.266)
years of study - 8 to 11 y	82.795*** (3.059)	72.889*** (3.020)
marital status - married	18.186*** (0.668)	17.400*** (0.724)
pre_appoint	58.555*** (0.768)	52.438*** (0.706)
une	-0.807. (0.480)	-0.863. (0.491)
ONI_index	-1.130*** (0.296)	-0.869** (0.278)
mother_age	0.839*** (0.073)	0.939*** (0.068)
gest_age - 22 to 27 w	-988.958*** (25.720)	-873.068*** (25.830)
gest_age - 28 to 31 w	-1,041.745*** (18.524)	-1,040.683*** (20.195)
gest_age - 32 to 36 w	-210.123*** (16.613)	-271.085*** (15.675)
gest_age - 37 to 41 w	416.914*** (17.601)	323.351*** (15.693)
gest_age - more than 42 w	506.743*** (18.312)	401.640*** (15.953)
parity	30.787*** (0.333)	28.230*** (0.331)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	20,319,957	21,223,415
R2	0.18663	0.16971
Within R2	0.17817	0.16015

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. ONI_index – El Niño and La Niña index. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 32 - Estimations of birthweight per bin of temperature and precipitation, controlling by wildfires

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.193*** (0.031)	0.177*** (0.029)
15-18	0.161*** (0.048)	0.188*** (0.033)
18-21	0.051 (0.032)	0.071* (0.030)
24-27	-0.187*** (0.028)	-0.173*** (0.027)
27-30	-0.415*** (0.053)	-0.392*** (0.048)
30-33	-0.511*** (0.071)	-0.473*** (0.063)
>33	-0.689 (0.534)	-0.852 (0.549)
Prec. (mm/m²)		
2.5 to 5	-0.104* (0.045)	-0.094* (0.045)
5 to 7.5	-0.106 (0.065)	-0.053 (0.056)
7.5 to 10	-0.255*** (0.069)	-0.291*** (0.060)
10 to 12.5	-0.141 (0.089)	-0.168. (0.087)
> 12.5	-0.176*** (0.036)	-0.141*** (0.033)
y2003	-16.552 (57.823)	-6.935*** (1.749)
y2004	-4.641 (57.754)	5.779*** (1.712)
y2005	-4.161 (57.815)	7.309*** (1.489)
y2006	-7.476 (57.831)	2.664. (1.602)
y2007	-14.290 (57.809)	-2.904* (1.335)
y2008	-13.265 (57.953)	-1.988 (1.525)
y2009	-11.230 (57.672)	-0.775 (1.339)
y2010	-7.560 (57.918)	2.168 (1.375)
y2011	14.264 (57.920)	21.054*** (1.528)
y2012	15.392 (57.726)	22.952*** (1.125)
y2013	13.853 (57.888)	22.442*** (1.184)
y2014	13.728 (57.769)	23.183*** (1.297)
y2015	16.943 (57.595)	24.953*** (1.566)
y2016	17.902 (57.746)	26.395*** (0.990)
y2017	14.163 (57.580)	23.625*** (1.703)
y2018	14.563 (57.362)	22.731*** (2.354)
y2019	21.330 (57.251)	28.607*** (2.534)
y2020	(dropped)	58.787 (66.761)
m02	-0.760 (0.798)	-1.020 (0.668)
m03	-6.489*** (1.112)	-5.897*** (1.045)
m04	5.886*** (0.996)	6.296*** (0.828)
m05	11.168*** (0.956)	9.137*** (0.806)
m06	11.461*** (1.218)	9.210*** (1.162)
m07	16.717*** (1.940)	14.518*** (1.694)
m08	18.436*** (2.223)	16.174*** (1.957)
m09	19.016*** (1.861)	17.798*** (1.875)
m10	16.983*** (1.536)	16.240*** (1.411)
m11	13.582*** (1.149)	12.486*** (1.192)
m12	10.995*** (0.750)	10.012*** (0.797)

years of study - zero	59.755*** (2.322)	54.965*** (2.265)
years of study - 1 to 3 y	81.888*** (2.595)	75.059*** (2.558)
years of study - 4 to 7 y	103.204*** (2.903)	96.146*** (2.826)
years of study - 8 to 11 y	93.889*** (3.598)	82.233*** (3.669)
marital status - married	15.896*** (0.738)	14.859*** (0.779)
pre_appoint	61.411*** (0.887)	54.760*** (0.812)
une	-0.975* (0.474)	-0.811. (0.479)
wildfires	0.006* (0.002)	0.004 (0.003)
mother_age	0.739*** (0.079)	0.871*** (0.077)
gest_age - 22 to 27 w	-932.244*** (31.241)	-805.830*** (30.826)
gest_age - 28 to 31 w	-1,010.432*** (22.082)	-1,004.048*** (24.495)
gest_age - 32 to 36 w	-179.143*** (18.075)	-237.793*** (16.992)
gest_age - 37 to 41 w	432.319*** (19.602)	342.395*** (16.757)
gest_age - more than 42 w	521.723*** (20.389)	420.926*** (17.026)
parity	32.647*** (0.389)	29.942*** (0.416)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	16,571,433	15,755,906
R2	0.18417	0.16705
Within R2	0.17573	0.15754

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. wildfires – number of wildfires focus per locality/year. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 33 - Estimations of birthweight per daily deviations from historical means, controlling by wildfires

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.549. (0.303)	0.166. (0.096)	-0.232 (0.207)	0.033 (0.093)
-2 to -1.5	-0.244. (0.133)	-0.329*** (0.092)	-0.184 (0.116)	-0.150* (0.075)
-1.5 to -1	-0.082. (0.046)	0.082. (0.048)	-0.059 (0.051)	0.027 (0.044)
-1 to -0.7	0.012 (0.044)	0.001 (0.045)	-0.001 (0.046)	-0.045 (0.034)
0.7 to 1	-0.134*** (0.023)	-0.032 (0.021)	-0.102*** (0.023)	-0.025 (0.023)
1 to 1.5	-0.036. (0.020)	-0.017 (0.016)	-0.058*** (0.018)	-0.017 (0.016)
1.5 to 2	-0.107*** (0.026)	-0.032 (0.022)	-0.118*** (0.025)	-0.015 (0.021)
>2	-0.149*** (0.029)	-0.060** (0.022)	-0.133*** (0.031)	-0.068** (0.022)
Precip.				
Neg.	-0.002 (0.044)		0.035 (0.049)	
Pos.	-0.004 (0.024)		-0.004 (0.023)	
y2003	-16.010*** (2.547)		-57.451 (66.467)	
y2004	-5.571* (2.690)		-46.006 (66.579)	
y2005	-6.723** (2.183)		-45.541 (66.547)	
y2006	-9.708*** (2.182)		-52.599 (66.583)	
y2007	-14.309*** (2.099)		-56.257 (66.465)	
y2008	-14.044*** (1.711)		-55.782 (66.535)	
y2009	-15.203*** (1.541)		-58.065 (66.535)	
y2010	-8.284*** (1.598)		-51.946 (66.613)	
y2011	17.082*** (1.512)		-30.189 (66.626)	
y2012	14.843*** (1.447)		-31.813 (66.615)	
y2013	13.560*** (1.315)		-32.195 (66.624)	
y2014	11.329*** (1.379)		-33.511 (66.586)	
y2015	13.280*** (1.656)		-32.568 (66.678)	
y2016	16.154*** (1.463)		-29.055 (66.611)	
y2017	11.976*** (2.690)		-32.271 (66.609)	
y2018	9.424** (2.970)		-36.132 (66.567)	
y2019	16.056*** (3.002)		-30.173 (66.543)	
y2020	6.371 (50.671)		(dropped)	
m02	1.173. (0.621)		0.986. (0.599)	
m03	-3.636*** (0.740)		-3.181*** (0.752)	
m04	7.204*** (0.801)		7.453*** (0.720)	
m05	8.210*** (0.992)		6.132*** (0.841)	
m06	2.811** (0.905)		0.726 (0.786)	
m07	3.095*** (0.820)		1.008 (0.752)	
m08	2.765*** (0.767)		0.343 (0.667)	
m09	4.247*** (0.895)		3.038*** (0.720)	
m10	5.735*** (0.728)		4.884*** (0.639)	
m11	6.547*** (0.648)		5.316*** (0.612)	
m12	7.849*** (0.549)		6.701*** (0.562)	
years of study - zero	59.892*** (2.312)		55.137*** (2.290)	
years of study - 1 to 3 y	82.236*** (2.583)		75.257*** (2.585)	

years of study - 4 to 7 y	103.123*** (2.889)	96.321*** (2.856)
years of study - 8 to 11 y	93.138*** (3.573)	82.334*** (3.666)
marital status - married	15.499*** (0.745)	14.791*** (0.782)
pre_appoint	62.561*** (0.876)	54.606*** (0.804)
une	-0.589 (0.466)	-0.459 (0.461)
wildfires	0.006** (0.002)	0.005* (0.003)
mother_age	0.648*** (0.081)	0.869*** (0.077)
gest_age - 22 to 27 w	-631.876*** (26.873)	-808.862*** (31.541)
gest_age - 28 to 31 w	-228.192*** (35.619)	-1,014.090*** (25.438)
gest_age - 32 to 36 w	656.458*** (46.862)	-251.654*** (17.252)
gest_age - 37 to 41 w	1,264.350*** (53.546)	324.602*** (16.723)
gest_age - more than 42 w	1,349.230*** (54.480)	400.162*** (17.021)
parity	33.097*** (0.391)	29.896*** (0.413)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	16,603,685	15,738,563
R2	0.20856	0.16713
Within R2	0.20019	0.15760

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. wildfires – number of wildfires focus per locality/year. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 34 - Estimations of birthweight per weekly deviations from historical means, controlling by wildfires

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.386 (0.313)	0.163. (0.099)	-0.202 (0.284)	0.082 (0.089)
-2 to -1.5	-0.249. (0.139)	-0.290** (0.092)	-0.237. (0.138)	-0.151. (0.080)
-1.5 to -1	-0.072 (0.047)	0.069 (0.050)	-0.052 (0.044)	0.026 (0.047)
-1 to -0.7	0.023 (0.042)	0.020 (0.044)	-0.009 (0.043)	-0.069. (0.037)
0.7 to 1	-0.107*** (0.021)	-0.002 (0.019)	-0.107*** (0.025)	-0.036. (0.022)
1 to 1.5	-0.018 (0.020)	-0.008 (0.017)	-0.044* (0.019)	-0.016 (0.017)
1.5 to 2	-0.089*** (0.026)	-0.013 (0.022)	-0.107*** (0.026)	-0.013 (0.022)
>2	-0.145*** (0.029)	-0.047* (0.022)	-0.145*** (0.032)	-0.070** (0.023)
Precip.				
Neg.	0.033 (0.044)		-0.003 (0.047)	
Pos.	0.018 (0.024)		0.002 (0.022)	
y2003	-462.910*** (11.687)		34.010*** (2.155)	
y2004	-452.771*** (11.989)		45.037*** (2.304)	
y2005	-454.381*** (11.840)		44.494*** (2.154)	
y2006	-457.603*** (11.795)		40.087*** (2.523)	
y2007	-461.747*** (11.464)		36.715*** (2.167)	
y2008	-461.458*** (11.574)		37.180*** (2.040)	
y2009	-464.291*** (11.517)		34.057*** (2.022)	
y2010	-456.479*** (11.745)		40.934*** (2.232)	
y2011	-430.578*** (11.682)		63.302*** (2.146)	
y2012	-434.127*** (11.703)		61.216*** (2.090)	
y2013	-435.389*** (11.907)		60.703*** (1.679)	
y2014	-437.994*** (11.763)		59.045*** (1.565)	
y2015	-437.262*** (11.628)		59.267*** (1.672)	
y2016	-431.377*** (11.505)		62.966*** (1.809)	
y2017	-436.262*** (11.027)		60.059*** (2.894)	
y2018	-440.324*** (10.821)		55.987*** (3.344)	
y2019	-435.370*** (10.685)		61.360*** (3.186)	
y2020	-612.920*** (41.448)		17.728 (47.874)	
m02	1.173. (0.623)		0.736 (0.620)	
m03	-3.366*** (0.733)		-3.561*** (0.720)	
m04	7.348*** (0.800)		7.551*** (0.705)	
m05	8.277*** (0.979)		6.180*** (0.801)	
m06	2.596** (0.959)		0.773 (0.771)	
m07	3.239*** (0.830)		1.348. (0.729)	
m08	2.877*** (0.773)		0.788 (0.677)	
m09	4.278*** (0.965)		3.629*** (0.697)	
m10	5.669*** (0.783)		5.104*** (0.623)	
m11	6.534*** (0.660)		5.508*** (0.623)	
m12	7.575*** (0.548)		6.692*** (0.580)	
years of study - zero	59.640*** (2.325)		55.081*** (2.245)	
years of study - 1 to 3 y	81.888*** (2.576)		75.132*** (2.505)	

years of study - 4 to 7 y	102.902*** (2.861)	95.936*** (2.755)
years of study - 8 to 11 y	94.337*** (3.547)	82.808*** (3.574)
marital status - married	15.808*** (0.743)	14.783*** (0.773)
pre_appoint	63.357*** (0.886)	56.918*** (0.840)
une	-0.709 (0.464)	-0.534 (0.457)
wildfires	0.006* (0.002)	0.005. (0.003)
mother_age	0.639*** (0.081)	0.760*** (0.077)
gest_age - 22 to 27 w	-377.789*** (26.554)	-449.420*** (26.428)
gest_age - 28 to 31 w	100.114*** (29.648)	6.858 (28.167)
gest_age - 32 to 36 w	993.215*** (34.147)	861.603*** (32.664)
gest_age - 37 to 41 w	1,600.770*** (39.341)	1,439.854*** (37.488)
gest_age - more than 42 w	1,685.145*** (40.617)	1,514.343*** (38.229)
parity	33.035*** (0.397)	30.388*** (0.428)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	16,423,451	15,800,360
R2	0.21455	0.19961
Within R2	0.20699	0.19114

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. wildfires – number of wildfires focus per locality/year. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 35 - Estimations of birthweight per monthly deviations from historical means, controlling by wildfires

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-22.016 (16.679)	5.410* (2.268)	-26.150*** (5.425)	3.670 (2.604)
-2 to -1.5	-9.823 (9.636)	-5.752* (2.640)	-16.976 (11.626)	-6.173* (2.413)
-1.5 to -1	2.589 (2.069)	-1.268 (0.985)	2.233 (1.837)	0.722 (0.831)
-1 to -0.7	-1.049 (0.866)	0.274 (0.603)	-0.960 (0.806)	-0.318 (0.565)
0.7 to 1	-1.033*** (0.278)	-0.501. (0.263)	-1.198*** (0.240)	-0.607* (0.259)
1 to 1.5	-1.961*** (0.296)	-0.657* (0.306)	-2.031*** (0.278)	-0.623* (0.286)
1.5 to 2	-2.777*** (0.587)	-1.014* (0.416)	-2.935*** (0.571)	-0.830* (0.404)
>2	-2.655*** (0.669)	-1.567** (0.522)	-2.913*** (0.772)	-1.979*** (0.547)
Precip.				
Neg.	0.984 (3.065)		5.093* (2.493)	
Pos.	-0.150 (0.609)		0.235 (0.450)	
y2003	-8.596 (57.811)		-6.148*** (1.564)	
y2004	1.918 (57.791)		5.311*** (1.585)	
y2005	1.906 (57.857)		6.409*** (1.407)	
y2006	-1.982 (57.890)		1.145 (1.551)	
y2007	-6.565 (57.840)		-2.375. (1.232)	
y2008	-5.431 (57.916)		-1.314 (1.222)	
y2009	-6.762 (57.863)		-3.100* (1.237)	
y2010	-0.876 (57.996)		1.921 (1.368)	
y2011	24.054 (57.942)		23.538*** (1.290)	
y2012	21.796 (57.862)		22.475*** (1.164)	
y2013	20.182 (57.981)		21.748*** (1.189)	
y2014	18.523 (57.893)		21.135*** (1.231)	
y2015	21.073 (57.859)		22.689*** (1.296)	
y2016	23.680 (57.896)		25.567*** (1.007)	
y2017	19.933 (57.656)		22.514*** (1.692)	
y2018	16.985 (57.578)		18.496*** (2.120)	
y2019	23.799 (57.479)		24.445*** (1.999)	
y2020	(dropped)		53.434 (66.629)	
m02	1.264* (0.602)		0.932 (0.592)	
m03	-3.496*** (0.684)		-3.024*** (0.702)	
m04	7.518*** (0.746)		7.873*** (0.674)	
m05	8.467*** (0.934)		6.504*** (0.778)	
m06	3.018*** (0.900)		1.004 (0.773)	
m07	2.991*** (0.803)		1.192. (0.711)	
m08	2.245** (0.748)		0.504 (0.650)	
m09	3.917*** (0.851)		3.269*** (0.668)	
m10	5.309*** (0.703)		5.041*** (0.602)	
m11	6.178*** (0.630)		5.384*** (0.597)	
m12	7.542*** (0.540)		6.709*** (0.556)	
years of study - zero	59.940*** (2.322)		55.103*** (2.265)	
years of study - 1 to 3 y	82.273*** (2.583)		75.406*** (2.554)	

years of study - 4 to 7 y	103.592*** (2.891)	96.500*** (2.825)
years of study - 8 to 11 y	94.228*** (3.586)	82.535*** (3.666)
marital status - married	15.880*** (0.744)	14.841*** (0.782)
pre_appoint	61.472*** (0.884)	54.825*** (0.807)
une	-0.602 (0.462)	-0.442 (0.455)
wildfires	0.006** (0.002)	0.005. (0.003)
mother_age	0.736*** (0.080)	0.868*** (0.077)
gest_age - 22 to 27 w	-940.306*** (31.747)	-811.830*** (31.269)
gest_age - 28 to 31 w	-1,026.066*** (22.350)	-1,017.513*** (24.929)
gest_age - 32 to 36 w	-200.026*** (17.599)	-255.972*** (16.921)
gest_age - 37 to 41 w	406.180*** (18.928)	319.679*** (16.555)
gest_age - more than 42 w	491.318*** (19.767)	394.325*** (16.881)
parity	32.646*** (0.389)	29.941*** (0.417)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	16,572,126	15,756,506
R2	0.18406	0.16694
Within R2	0.17562	0.15743

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. wildfires – number of wildfires focus per locality/year. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 36 - Estimations of birthweight per bin of temperature and precipitation, for isolated areas subsample

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.313*** (0.050)	0.296*** (0.050)
15-18	0.208*** (0.049)	0.185*** (0.051)
18-21	0.047 (0.038)	0.038 (0.038)
24-27	-0.215*** (0.026)	-0.204*** (0.026)
27-30	-0.468*** (0.035)	-0.452*** (0.034)
30-33	-0.464*** (0.061)	-0.494*** (0.059)
>33	-0.061 (1.024)	0.756 (1.554)
Prec. (mm/m²)		
2.5 to 5	-0.286*** (0.066)	-0.285*** (0.064)
5 to 7.5	-0.188* (0.086)	-0.189* (0.085)
7.5 to 10	-0.460*** (0.100)	-0.280** (0.095)
10 to 12.5	-0.124 (0.117)	-0.163 (0.125)
> 12.5	-0.364*** (0.048)	-0.351*** (0.050)
y2000	-6.933** (2.502)	-10.149*** (2.382)
y2001	-27.536*** (2.841)	-25.945*** (2.658)
y2002	-36.643*** (3.109)	-36.733*** (3.003)

y2003	-45.081*** (3.010)	-45.878*** (2.923)
y2004	-35.510*** (3.175)	-34.581*** (3.064)
y2005	-37.303*** (2.976)	-37.850*** (2.931)
y2006	-43.238*** (3.122)	-41.794*** (3.059)
y2007	-52.962*** (3.113)	-54.328*** (3.041)
y2008	-51.445*** (3.203)	-52.814*** (3.158)
y2009	-55.885*** (3.359)	-53.476*** (3.192)
y2010	-45.713*** (3.301)	-47.953*** (3.310)
y2011	-29.668*** (3.394)	-36.919*** (3.215)
y2012	-35.023*** (3.457)	-39.208*** (3.291)
y2013	-34.860*** (3.521)	-38.248*** (3.323)
y2014	-39.757*** (3.479)	-41.787*** (3.325)
y2015	-40.415*** (3.628)	-43.332*** (3.360)
y2016	-39.791*** (3.546)	-44.273*** (3.383)
y2017	-45.529*** (4.200)	-45.643*** (4.016)
y2018	-47.330*** (4.727)	-46.795*** (4.613)
y2019	-42.332*** (4.635)	-44.924*** (4.542)
y2020	-70.978 (156.748)	29.174 (124.944)
m02	0.872 (1.327)	-0.221 (1.236)
m03	-2.912* (1.317)	-1.198 (1.262)
m04	8.581*** (1.327)	8.728*** (1.277)
m05	11.267*** (1.318)	10.464*** (1.300)
m06	9.782*** (1.395)	7.886*** (1.377)
m07	16.453*** (1.602)	14.264*** (1.566)
m08	19.097*** (1.698)	17.145*** (1.685)
m09	19.253*** (1.655)	16.685*** (1.646)
m10	14.316*** (1.484)	12.613*** (1.503)
m11	8.721*** (1.386)	6.109*** (1.394)
m12	5.084*** (1.256)	3.494** (1.233)
years of study - zero	58.238*** (2.569)	53.622*** (2.267)
years of study - 1 to 3 y	82.974*** (2.702)	77.120*** (2.435)
years of study - 4 to 7 y	100.073*** (2.911)	94.055*** (2.591)
years of study - 8 to 11 y	102.214*** (3.058)	94.578*** (2.795)
marital status - married	23.571*** (0.762)	23.348*** (0.748)
pre_appoint	51.507*** (0.692)	45.891*** (0.628)
une	-1.685** (0.547)	-1.509** (0.524)
mother_age	1.255*** (0.069)	1.261*** (0.068)
gest_age - 22 to 27 w	-799.217*** (31.131)	-690.087*** (31.701)
gest_age - 28 to 31 w	-860.067*** (29.694)	-821.209*** (28.228)
gest_age - 32 to 36 w	-124.337*** (28.933)	-159.294*** (27.401)
gest_age - 37 to 41 w	382.659*** (28.518)	310.614*** (26.997)
gest_age - more than 42 w	476.128*** (28.579)	394.339*** (27.192)
parity	28.314*** (0.292)	26.525*** (0.277)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	3,921,905	3,717,777

R2	0.13052	0.11731
Within R2	0.11836	0.10369

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 37 - Estimations of birthweight per daily deviations from historical means, for isolated areas subsample

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.552 (0.369)	0.142 (0.087)	0.058 (0.223)	-0.171 (0.104)
-2 to -1.5	-0.293. (0.166)	-0.426** (0.139)	-0.351* (0.166)	-0.088 (0.131)
-1.5 to -1	0.105 (0.072)	0.065 (0.082)	-0.023 (0.069)	-0.126. (0.076)
-1 to -0.7	0.197** (0.068)	0.039 (0.074)	0.131. (0.069)	0.008 (0.072)
0.7 to 1	-0.125*** (0.036)	0.022 (0.031)	-0.117** (0.036)	-0.019 (0.031)
1 to 1.5	0.046. (0.026)	-0.047* (0.021)	0.005 (0.026)	-0.057* (0.023)
1.5 to 2	-0.162*** (0.035)	-0.027 (0.025)	-0.183*** (0.035)	-0.031 (0.026)
>2	-0.081. (0.047)	-0.025 (0.029)	-0.059 (0.046)	-0.062. (0.033)
Precip.				
Neg.	0.126. (0.072)		-0.163* (0.076)	
Pos.	-0.042 (0.035)		-0.041 (0.036)	
y2000	-8.980*** (2.540)		-12.436*** (2.422)	
y2001	-32.865*** (2.932)		-28.480*** (2.763)	
y2002	-41.406*** (3.217)		-41.575*** (3.194)	
y2003	-47.728*** (3.074)		-48.017*** (3.003)	
y2004	-38.186*** (3.245)		-36.701*** (3.227)	
y2005	-40.990*** (3.039)		-41.476*** (3.073)	
y2006	-47.533*** (3.167)		-48.625*** (3.280)	
y2007	-55.334*** (3.125)		-61.001*** (3.229)	
y2008	-55.678*** (3.206)		-61.701*** (3.343)	
y2009	-61.531*** (3.351)		-62.004*** (3.378)	
y2010	-49.716*** (3.283)		-55.424*** (3.414)	
y2011	-29.194*** (3.367)		-40.559*** (3.327)	
y2012	-36.587*** (3.497)		-44.553*** (3.488)	
y2013	-38.067*** (3.539)		-46.077*** (3.543)	
y2014	-42.934*** (3.507)		-49.634*** (3.512)	
y2015	-43.610*** (3.749)		-49.982*** (3.622)	
y2016	-42.924*** (3.646)		-51.278*** (3.634)	
y2017	-49.135*** (4.228)		-53.117*** (4.187)	
y2018	-53.998*** (4.780)		-57.339*** (4.799)	
y2019	-49.350*** (4.683)		-55.992*** (4.751)	
y2020	-70.750 (151.459)		15.253 (124.955)	
m02	2.810* (1.327)		1.479 (1.242)	
m03	0.640 (1.300)		1.296 (1.269)	
m04	11.476*** (1.285)		10.496*** (1.279)	
m05	11.333*** (1.263)		9.501*** (1.270)	
m06	4.207*** (1.256)		1.897 (1.235)	
m07	4.837*** (1.278)		2.849* (1.242)	
m08	4.079** (1.280)		2.262. (1.251)	
m09	4.130** (1.303)		2.256. (1.234)	
m10	2.316. (1.256)		1.265 (1.260)	
m11	1.106 (1.298)		-0.931 (1.312)	

m12	1.540 (1.242)	0.245 (1.223)
years of study - zero	58.074*** (2.578)	53.635*** (2.272)
years of study - 1 to 3 y	82.879*** (2.706)	76.784*** (2.432)
years of study - 4 to 7 y	99.477*** (2.919)	93.698*** (2.590)
years of study - 8 to 11 y	101.053*** (3.064)	94.124*** (2.791)
marital status - married	23.350*** (0.763)	23.211*** (0.750)
pre_appoint	52.258*** (0.700)	45.785*** (0.634)
une	-1.494** (0.543)	-1.426** (0.527)
mother_age	1.187*** (0.069)	1.258*** (0.068)
gest_age - 22 to 27 w	-764.378*** (38.598)	-700.009*** (31.859)
gest_age - 28 to 31 w	-511.351*** (38.344)	-840.271*** (28.163)
gest_age - 32 to 36 w	246.333*** (38.741)	-185.575*** (27.281)
gest_age - 37 to 41 w	744.194*** (39.322)	275.662*** (26.911)
gest_age - more than 42 w	831.177*** (39.408)	354.556*** (27.054)
parity	28.549*** (0.293)	26.529*** (0.279)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	3,926,720	3,714,840
R2	0.14046	0.11738
Within R2	0.12831	0.10373

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 38 - Estimations of birthweight per weekly deviations from historical means, for isolated areas subsample

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.568 (0.380)	0.131 (0.090)	0.891** (0.336)	-0.030 (0.098)
-2 to -1.5	-0.328. (0.175)	-0.391** (0.142)	-0.288 (0.201)	-0.120 (0.145)
-1.5 to -1	0.071 (0.073)	0.059 (0.085)	-0.011 (0.075)	-0.074 (0.081)
-1 to -0.7	0.201** (0.068)	0.022 (0.074)	0.166* (0.067)	0.029 (0.074)
0.7 to 1	-0.126*** (0.035)	0.025 (0.030)	-0.087* (0.036)	-0.016 (0.031)
1 to 1.5	0.049. (0.026)	-0.045* (0.021)	0.039 (0.026)	-0.038. (0.022)
1.5 to 2	-0.155*** (0.035)	-0.018 (0.025)	-0.178*** (0.036)	-0.025 (0.026)
>2	-0.085. (0.047)	-0.020 (0.029)	-0.060 (0.047)	-0.058. (0.034)
Precip.				
Neg.	0.113 (0.074)		0.018 (0.072)	
Pos.	-0.055 (0.035)		-0.013 (0.035)	
y2000	-9.997*** (2.730)		-12.853*** (2.400)	
y2001	-33.783*** (3.243)		-34.873*** (3.320)	
y2002	-43.623*** (3.397)		-44.198*** (3.250)	
y2003	-49.587*** (3.250)		-49.573*** (2.989)	
y2004	-40.771*** (3.436)		-38.735*** (3.151)	
y2005	-44.217*** (3.241)		-43.660*** (3.012)	
y2006	-50.952*** (3.350)		-48.106*** (3.137)	
y2007	-58.927*** (3.333)		-58.874*** (3.075)	
y2008	-59.542*** (3.383)		-59.609*** (3.176)	
y2009	-65.474*** (3.511)		-62.506*** (3.214)	
y2010	-53.933*** (3.470)		-54.345*** (3.280)	
y2011	-32.546*** (3.559)		-38.808*** (3.206)	
y2012	-40.698*** (3.657)		-43.897*** (3.345)	
y2013	-42.753*** (3.731)		-45.025*** (3.375)	
y2014	-47.996*** (3.669)		-48.964*** (3.392)	
y2015	-48.562*** (3.920)		-49.776*** (3.488)	
y2016	-47.122*** (3.936)		-51.527*** (3.523)	
y2017	-53.929*** (4.397)		-53.210*** (4.062)	
y2018	-59.884*** (4.898)		-57.782*** (4.655)	
y2019	-55.572*** (4.794)		-57.766*** (4.610)	
y2020	-278.656* (113.125)		-0.147 (123.107)	
m02	3.127* (1.353)		0.805 (1.263)	
m03	0.386 (1.327)		1.165 (1.314)	
m04	12.145*** (1.310)		11.419*** (1.277)	
m05	11.497*** (1.291)		9.892*** (1.270)	
m06	4.256** (1.304)		2.430. (1.269)	
m07	5.305*** (1.297)		3.416** (1.258)	
m08	4.836*** (1.309)		2.893* (1.286)	
m09	4.837*** (1.339)		2.689* (1.253)	
m10	3.176* (1.303)		1.228 (1.286)	
m11	1.642 (1.340)		-1.206 (1.336)	

m12	1.952 (1.261)	0.170 (1.244)
years of study - zero	57.375*** (2.649)	53.592*** (2.321)
years of study - 1 to 3 y	82.073*** (2.771)	76.924*** (2.481)
years of study - 4 to 7 y	98.885*** (2.990)	93.314*** (2.638)
years of study - 8 to 11 y	101.081*** (3.128)	94.134*** (2.844)
marital status - married	23.375*** (0.773)	22.913*** (0.764)
pre_appoint	53.390*** (0.721)	47.938*** (0.653)
une	-1.453** (0.546)	-1.331* (0.522)
mother_age	1.114*** (0.070)	1.139*** (0.069)
gest_age - 22 to 27 w	-427.983*** (41.217)	-471.836*** (40.813)
gest_age - 28 to 31 w	41.897 (41.239)	-29.502 (40.247)
gest_age - 32 to 36 w	845.552*** (41.067)	716.259*** (40.146)
gest_age - 37 to 41 w	1,345.378*** (41.339)	1,177.753*** (40.350)
gest_age - more than 42 w	1,431.531*** (41.282)	1,255.042*** (40.409)
parity	28.694*** (0.299)	27.032*** (0.283)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	3,880,970	3,654,451
R2	0.15350	0.13944
Within R2	0.14246	0.12725

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 39 - Estimations of birthweight per monthly deviations from historical means, for isolated areas subsample

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-20.102 (29.145)	3.123 (2.630)	31.253 (22.561)	-3.081 (2.550)
-2 to -1.5	-3.070 (6.506)	-5.253* (2.664)	-4.992 (9.296)	-3.561 (3.073)
-1.5 to -1	4.715* (1.947)	-1.923 (1.275)	3.519. (2.029)	-0.600 (1.304)
-1 to -0.7	1.356 (1.077)	-0.757 (1.075)	0.878 (1.253)	-0.356 (1.142)
0.7 to 1	-0.919** (0.352)	-0.562. (0.315)	-0.995** (0.339)	-0.854** (0.316)
1 to 1.5	-1.703*** (0.361)	-0.856** (0.324)	-1.592*** (0.349)	-0.881** (0.338)
1.5 to 2	-2.396*** (0.571)	-1.259** (0.440)	-2.627*** (0.590)	-1.140* (0.466)
>2	-2.014. (1.115)	-0.664 (0.667)	-2.224. (1.143)	-1.714* (0.747)
Precip.				
Neg.	-0.126 (4.892)		3.200 (3.848)	
Pos.	-0.907 (0.702)		1.005 (0.687)	
y2000	-9.341*** (2.513)		-12.421*** (2.391)	
y2001	-30.793*** (2.908)		-28.740*** (2.733)	
y2002	-41.767*** (3.164)		-41.071*** (3.085)	
y2003	-47.736*** (3.054)		-48.700*** (2.979)	
y2004	-38.619*** (3.195)		-37.160*** (3.100)	
y2005	-40.435*** (2.984)		-40.430*** (2.936)	
y2006	-46.839*** (3.110)		-44.856*** (3.056)	
y2007	-54.562*** (3.108)		-55.642*** (3.015)	
y2008	-54.545*** (3.204)		-55.726*** (3.144)	
y2009	-60.109*** (3.323)		-57.131*** (3.166)	
y2010	-49.023*** (3.293)		-50.847*** (3.304)	
y2011	-29.195*** (3.360)		-36.560*** (3.184)	
y2012	-36.545*** (3.478)		-40.108*** (3.309)	
y2013	-38.779*** (3.517)		-41.614*** (3.340)	
y2014	-43.587*** (3.472)		-45.052*** (3.332)	
y2015	-43.467*** (3.730)		-45.403*** (3.477)	
y2016	-42.819*** (3.613)		-46.401*** (3.470)	
y2017	-48.797*** (4.195)		-48.471*** (4.033)	
y2018	-54.521*** (4.712)		-53.277*** (4.618)	
y2019	-50.332*** (4.639)		-52.018*** (4.581)	
y2020	-82.962 (156.066)		15.853 (124.933)	
m02	3.043* (1.321)		1.723 (1.229)	
m03	0.451 (1.278)		1.695 (1.241)	
m04	11.673*** (1.264)		11.231*** (1.246)	
m05	11.351*** (1.248)		10.074*** (1.242)	
m06	4.477*** (1.243)		2.458* (1.222)	
m07	5.053*** (1.268)		3.183** (1.224)	
m08	3.856** (1.266)		2.478* (1.232)	
m09	4.035** (1.290)		2.163. (1.203)	
m10	2.115. (1.244)		1.072 (1.248)	
m11	0.986 (1.278)		-1.019 (1.302)	

m12	1.470 (1.234)	0.202 (1.206)
years of study - zero	58.294*** (2.573)	53.657*** (2.264)
years of study - 1 to 3 y	83.152*** (2.704)	77.282*** (2.428)
years of study - 4 to 7 y	100.196*** (2.914)	94.177*** (2.584)
years of study - 8 to 11 y	102.259*** (3.060)	94.628*** (2.787)
marital status - married	23.605*** (0.762)	23.371*** (0.748)
pre_appoint	51.511*** (0.693)	45.899*** (0.630)
une	-1.484** (0.547)	-1.286* (0.522)
mother_age	1.248*** (0.069)	1.254*** (0.068)
gest_age - 22 to 27 w	-810.656*** (31.005)	-700.273*** (31.686)
gest_age - 28 to 31 w	-883.514*** (29.318)	-843.295*** (28.050)
gest_age - 32 to 36 w	-157.087*** (28.399)	-190.242*** (27.107)
gest_age - 37 to 41 w	339.934*** (27.908)	270.281*** (26.711)
gest_age - more than 42 w	426.930*** (27.861)	347.863*** (26.838)
parity	28.321*** (0.292)	26.536*** (0.277)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	3,921,905	3,717,777
R2	0.13033	0.11713
Within R2	0.11816	0.10351

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Precip. – Precipitation. Pos. – Positive shocks over 0.7 SD. Neg. – Negative shocks over 0.7 SD. Munic. – municipality. Max. – Maximum daily temperature. Min. – Minimum daily temperature.

Table S2. 40 - Estimations of birthweight per bin of temperature and precipitation, controlling for "Bolsa Família" program

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	0.222*** (0.029)	0.201*** (0.027)
15-18	0.148*** (0.044)	0.159*** (0.033)
18-21	0.074** (0.028)	0.085** (0.028)
24-27	-0.186*** (0.026)	-0.179*** (0.025)
27-30	-0.417*** (0.047)	-0.397*** (0.043)
30-33	-0.509*** (0.065)	-0.483*** (0.057)
>33	-0.132 (0.697)	0.183 (0.844)
Prec. (mm/m²)		
2.5 to 5	-0.080. (0.043)	-0.043 (0.041)
5 to 7.5	-0.098. (0.056)	-0.053 (0.050)
7.5 to 10	-0.229*** (0.064)	-0.279*** (0.056)
10 to 12.5	-0.180* (0.078)	-0.196** (0.075)
> 12.5	-0.168*** (0.032)	-0.124*** (0.030)
y2004	-13.888*** (2.193)	486.433*** (51.515)
y2005	-12.179*** (1.640)	489.501*** (51.585)
y2006	-13.823*** (1.484)	486.929*** (52.028)
y2007	-20.045*** (1.327)	481.911*** (51.959)
y2008	-19.200*** (1.709)	482.717*** (52.210)
y2009	-16.828*** (1.262)	484.349*** (51.613)
y2010	-11.910*** (1.733)	488.323*** (52.323)
y2011	9.109*** (1.610)	506.970*** (52.683)
y2012	11.117*** (1.023)	509.010*** (52.252)
y2013	9.456*** (1.346)	508.584*** (52.113)
y2014	9.457*** (1.201)	509.531*** (51.707)
y2015	13.012*** (1.536)	511.835*** (51.422)
y2016	13.432*** (0.881)	512.530*** (52.130)
y2017	10.101*** (1.278)	510.294*** (52.362)
y2018	10.333*** (1.618)	509.236*** (52.261)
y2019	17.310*** (1.618)	515.529*** (51.873)
y2020	8.771 (53.806)	526.313*** (75.871)
m02	-1.015 (0.714)	-1.498* (0.607)
m03	-6.686*** (0.992)	-6.598*** (0.924)
m04	5.211*** (0.887)	5.467*** (0.777)
m05	11.275*** (0.865)	8.788*** (0.751)
m06	11.363*** (1.168)	9.219*** (1.053)
m07	17.010*** (1.816)	14.160*** (1.570)
m08	19.116*** (2.096)	15.870*** (1.855)
m09	19.562*** (1.790)	17.627*** (1.721)
m10	18.110*** (1.420)	16.384*** (1.368)
m11	14.394*** (1.136)	12.788*** (1.125)
m12	11.708*** (0.755)	10.376*** (0.782)
years of study - zero	61.205*** (2.314)	57.178*** (2.281)
years of study - 1 to 3 y	83.318*** (2.559)	77.301*** (2.538)

years of study - 4 to 7 y	105.001*** (2.788)	98.421*** (2.739)
years of study - 8 to 11 y	95.339*** (3.315)	84.038*** (3.401)
marital status - married	14.545*** (0.602)	13.474*** (0.652)
pre_appoint	62.586*** (0.783)	55.899*** (0.710)
une	-0.961* (0.432)	-0.818. (0.435)
br_prog	-102.021*** (27.779)	-107.905*** (27.491)
mother_age	0.628*** (0.071)	0.778*** (0.069)
gest_age - 22 to 27 w	-928.949*** (27.500)	-797.221*** (28.415)
gest_age - 28 to 31 w	-1,016.990*** (19.975)	-1,007.308*** (22.747)
gest_age - 32 to 36 w	-188.734*** (16.720)	-243.765*** (16.368)
gest_age - 37 to 41 w	422.779*** (17.914)	337.213*** (15.951)
gest_age - more than 42 w	509.726*** (18.527)	413.973*** (16.126)
parity	33.562*** (0.370)	30.844*** (0.393)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,466,780	17,561,215
R2	0.18638	0.16902
Within R2	0.17848	0.16016

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 41 - Estimations of birthweight per daily deviations from historical means, controlling for “Bolsa Família” program

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.686* (0.289)	0.087 (0.102)	-0.115 (0.204)	-0.043 (0.100)
-2 to -1.5	-0.171 (0.123)	-0.329*** (0.092)	-0.199. (0.106)	-0.210** (0.072)
-1.5 to -1	-0.092* (0.041)	0.094* (0.044)	-0.061 (0.045)	0.045 (0.041)
-1 to -0.7	0.029 (0.039)	0.033 (0.043)	-0.010 (0.039)	0.009 (0.034)
0.7 to 1	-0.127*** (0.020)	-0.044* (0.019)	-0.101*** (0.021)	-0.051* (0.020)
1 to 1.5	-0.033* (0.016)	-0.031* (0.016)	-0.052*** (0.015)	-0.026. (0.014)
1.5 to 2	-0.104*** (0.022)	-0.069*** (0.020)	-0.123*** (0.022)	-0.041* (0.019)
>2	-0.108** (0.034)	-0.066** (0.021)	-0.095** (0.031)	-0.082*** (0.021)
Precip.				
Neg.	-0.009 (0.041)		0.008 (0.043)	
Pos.	0.003 (0.021)		0.000 (0.020)	
y2004	-17.650 (47.805)		-32.455 (61.869)	
y2005	-17.879 (47.864)		-30.780 (61.842)	
y2006	-19.582 (47.892)		-35.480 (61.891)	
y2007	-24.427 (47.844)		-39.213 (61.808)	
y2008	-24.277 (47.890)		-38.862 (61.883)	
y2009	-24.708 (47.924)		-40.290 (61.864)	
y2010	-17.010 (48.041)		-33.638 (61.944)	
y2011	7.044 (47.938)		-12.613 (61.941)	
y2012	6.504 (47.917)		-13.118 (61.917)	
y2013	4.499 (47.964)		-13.931 (61.969)	
y2014	2.540 (47.901)		-14.953 (61.928)	
y2015	5.128 (47.879)		-13.205 (61.999)	
y2016	7.477 (47.872)		-10.662 (61.935)	
y2017	4.325 (47.784)		-12.845 (61.914)	
y2018	2.274 (47.729)		-16.374 (61.863)	
y2019	9.133 (47.645)		-9.974 (61.812)	
y2020	(dropped)		(dropped)	
m02	1.140* (0.572)		0.599 (0.573)	
m03	-3.567*** (0.681)		-3.705*** (0.671)	
m04	6.765*** (0.736)		6.713*** (0.683)	
m05	8.306*** (0.901)		5.757*** (0.803)	
m06	2.602** (0.814)		0.608 (0.723)	
m07	3.291*** (0.757)		0.639 (0.703)	
m08	3.279*** (0.717)		0.061 (0.616)	
m09	4.540*** (0.813)		2.846*** (0.687)	
m10	6.552*** (0.717)		4.917*** (0.613)	
m11	6.991*** (0.625)		5.436*** (0.581)	
m12	8.262*** (0.556)		6.882*** (0.545)	
years of study - zero	61.153*** (2.316)		57.495*** (2.315)	
years of study - 1 to 3 y	83.324*** (2.572)		77.521*** (2.591)	
years of study - 4 to 7 y	104.540*** (2.805)		98.658*** (2.799)	

years of study - 8 to 11 y	94.267*** (3.322)	84.245*** (3.429)
marital status - married	14.120*** (0.604)	13.438*** (0.653)
pre_appoint	63.721*** (0.780)	55.734*** (0.706)
une	-0.768. (0.438)	-0.591 (0.432)
br_prog	-73.493* (28.797)	-99.698*** (28.738)
mother_age	0.532*** (0.073)	0.777*** (0.069)
gest_age - 22 to 27 w	-642.062*** (25.341)	-798.802*** (29.069)
gest_age - 28 to 31 w	-237.172*** (32.424)	-1,015.724*** (23.507)
gest_age - 32 to 36 w	644.964*** (41.951)	-255.769*** (16.536)
gest_age - 37 to 41 w	1,253.333*** (47.463)	321.647*** (15.900)
gest_age - more than 42 w	1,335.961*** (48.174)	395.689*** (16.080)
parity	34.040*** (0.371)	30.797*** (0.391)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,504,297	17,541,533
R2	0.21100	0.16911
Within R2	0.20319	0.16023

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 42 - Estimations of birthweight per weekly deviations from historical means, controlling for "Bolsa Família" program

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-0.522. (0.300)	0.083 (0.105)	-0.336 (0.258)	0.013 (0.100)
-2 to -1.5	-0.190 (0.128)	-0.306*** (0.092)	-0.194 (0.123)	-0.203* (0.081)
-1.5 to -1	-0.081* (0.042)	0.101* (0.046)	-0.073. (0.039)	0.065 (0.043)
-1 to -0.7	0.041 (0.037)	0.050 (0.042)	-0.003 (0.039)	-0.026 (0.037)
0.7 to 1	-0.096*** (0.019)	-0.014 (0.017)	-0.101*** (0.022)	-0.051** (0.019)
1 to 1.5	-0.014 (0.016)	-0.022 (0.016)	-0.045** (0.016)	-0.026 (0.016)
1.5 to 2	-0.086*** (0.023)	-0.052** (0.020)	-0.105*** (0.022)	-0.044* (0.020)
>2	-0.103** (0.034)	-0.052* (0.021)	-0.103** (0.034)	-0.079*** (0.022)
Precip.				
Neg.	0.023 (0.041)		0.009 (0.043)	
Pos.	0.021 (0.022)		0.013 (0.019)	
y2004	1,610.611*** (45.009)		63.794 (44.275)	
y2005	1,610.206*** (45.391)		64.604 (44.188)	
y2006	1,608.373*** (45.372)		62.050 (44.160)	
y2007	1,604.146*** (45.667)		58.656 (44.151)	
y2008	1,604.343*** (45.708)		59.000 (44.202)	
y2009	1,602.442*** (46.092)		56.728 (44.171)	
y2010	1,610.930*** (45.930)		64.171 (44.135)	
y2011	1,635.536*** (45.952)		85.705. (44.183)	
y2012	1,633.651*** (45.784)		84.676. (44.149)	
y2013	1,631.831*** (46.061)		83.713. (44.255)	
y2014	1,629.515*** (46.185)		82.470. (44.206)	
y2015	1,630.930*** (46.299)		83.399. (44.280)	
y2016	1,636.160*** (45.968)		86.181. (44.159)	
y2017	1,631.870*** (45.357)		84.330. (44.111)	
y2018	1,628.163*** (45.206)		80.493. (44.109)	
y2019	1,633.442*** (45.260)		86.406. (44.083)	
y2020	1,475.985*** (59.376)		(dropped)	
m02	1.101. (0.574)		0.360 (0.590)	
m03	-3.467*** (0.668)		-4.079*** (0.648)	
m04	6.773*** (0.739)		6.836*** (0.675)	
m05	8.251*** (0.887)		5.784*** (0.769)	
m06	2.337** (0.863)		0.677 (0.714)	
m07	3.287*** (0.762)		0.954 (0.690)	
m08	3.313*** (0.727)		0.525 (0.633)	
m09	4.611*** (0.877)		3.402*** (0.666)	
m10	6.387*** (0.770)		5.105*** (0.601)	
m11	6.848*** (0.635)		5.533*** (0.585)	
m12	7.897*** (0.557)		6.731*** (0.560)	
years of study - zero	61.133*** (2.331)		57.249*** (2.268)	
years of study - 1 to 3 y	83.250*** (2.571)		77.198*** (2.508)	
years of study - 4 to 7 y	104.606*** (2.785)		98.021*** (2.694)	

years of study - 8 to 11 y	95.766*** (3.295)	84.484*** (3.335)
marital status - married	14.479*** (0.606)	13.370*** (0.643)
pre_appoint	64.596*** (0.779)	58.090*** (0.737)
une	-0.786. (0.439)	-0.651 (0.434)
br_prog	-84.629** (29.396)	-86.786** (28.402)
mother_age	0.516*** (0.072)	0.663*** (0.069)
gest_age - 22 to 27 w	-363.488*** (28.505)	-427.487*** (28.730)
gest_age - 28 to 31 w	117.682*** (32.416)	30.100 (31.750)
gest_age - 32 to 36 w	1,009.862*** (36.055)	883.591*** (35.295)
gest_age - 37 to 41 w	1,617.761*** (39.962)	1,462.919*** (39.023)
gest_age - more than 42 w	1,699.870*** (40.887)	1,535.787*** (39.497)
parity	34.014*** (0.378)	31.325*** (0.405)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,294,489	17,613,044
R2	0.21772	0.20237
Within R2	0.21067	0.19452

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

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Table S2. 43 - Estimations of birthweight per monthly deviations from historical means, controlling for "Bolsa Família" program

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-22.016 (16.853)	2.917 (2.980)	-25.501*** (5.078)	0.042 (3.019)
-2 to -1.5	-7.790 (7.216)	-4.195 (2.783)	-12.351 (8.924)	-4.361. (2.579)
-1.5 to -1	3.578. (1.911)	-1.006 (0.973)	2.206 (1.716)	0.293 (0.797)
-1 to -0.7	-0.559 (0.755)	0.559 (0.633)	-0.688 (0.712)	0.005 (0.573)
0.7 to 1	-0.810** (0.274)	-0.604* (0.251)	-1.007*** (0.231)	-0.732** (0.245)
1 to 1.5	-1.779*** (0.271)	-1.117*** (0.291)	-1.880*** (0.262)	-0.969*** (0.269)
1.5 to 2	-2.289*** (0.499)	-1.730*** (0.380)	-2.522*** (0.478)	-1.465*** (0.360)
>2	-1.676* (0.759)	-1.682** (0.519)	-1.919* (0.780)	-2.124*** (0.531)
Precip.				
Neg.	0.556 (2.925)		4.426. (2.458)	
Pos.	-0.083 (0.557)		0.180 (0.413)	
y2004	-10.583*** (2.122)		596.545*** (45.099)	
y2005	-9.629*** (1.531)		598.784*** (45.311)	
y2006	-12.144*** (1.316)		595.359*** (45.745)	
y2007	-16.725*** (1.162)		591.912*** (45.479)	
y2008	-15.506*** (1.156)		593.101*** (45.693)	
y2009	-16.501*** (1.228)		591.730*** (45.709)	
y2010	-9.522*** (1.380)		597.626*** (45.989)	
y2011	14.250*** (1.057)		618.665*** (46.188)	
y2012	13.243*** (0.932)		618.077*** (46.112)	
y2013	11.154*** (1.238)		617.088*** (45.956)	
y2014	9.429*** (1.193)		616.515*** (45.622)	
y2015	12.420*** (1.335)		618.597*** (45.740)	
y2016	14.664*** (0.825)		620.915*** (46.031)	
y2017	12.060*** (1.241)		619.155*** (46.185)	
y2018	9.250*** (1.601)		615.282*** (46.389)	
y2019	16.356*** (1.455)		621.687*** (46.153)	
y2020	5.180 (53.908)		630.996*** (74.045)	
m02	1.185* (0.557)		0.577 (0.564)	
m03	-3.412*** (0.634)		-3.515*** (0.630)	
m04	7.084*** (0.688)		7.222*** (0.646)	
m05	8.644*** (0.855)		6.202*** (0.753)	
m06	2.800*** (0.818)		0.958 (0.719)	
m07	3.105*** (0.745)		0.819 (0.673)	
m08	2.626*** (0.705)		0.130 (0.607)	
m09	4.112*** (0.772)		2.969*** (0.637)	
m10	5.972*** (0.686)		4.908*** (0.582)	
m11	6.515*** (0.611)		5.344*** (0.567)	
m12	7.849*** (0.543)		6.738*** (0.542)	
years of study - zero	61.249*** (2.319)		57.183*** (2.289)	
years of study - 1 to 3 y	83.400*** (2.573)		77.336*** (2.559)	
years of study - 4 to 7 y	105.076*** (2.807)		98.450*** (2.764)	

years of study - 8 to 11 y	95.428*** (3.334)	84.071*** (3.425)
marital status - married	14.549*** (0.605)	13.475*** (0.654)
pre_appoint	62.598*** (0.782)	55.908*** (0.709)
une	-0.734. (0.436)	-0.584 (0.431)
br_prog	-78.574** (29.588)	-84.671** (29.209)
mother_age	0.622*** (0.071)	0.774*** (0.069)
gest_age - 22 to 27 w	-936.089*** (27.895)	-803.293*** (28.790)
gest_age - 28 to 31 w	-1,031.134*** (20.160)	-1,020.394*** (23.088)
gest_age - 32 to 36 w	-207.788*** (16.264)	-261.282*** (16.277)
gest_age - 37 to 41 w	398.918*** (17.260)	315.500*** (15.755)
gest_age - more than 42 w	481.719*** (17.892)	388.442*** (15.956)
parity	33.565*** (0.370)	30.843*** (0.394)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	18,468,163	17,562,449
R2	0.18627	0.16890
Within R2	0.17837	0.16005

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 44 - Estimations of birthweight per bin of temperature and precipitation, subsetted for “Bolsa Família” top most 80% receivers

Weather var.	Dependent variable – Birthweight (g)	
Temp. (ºC)	Boys	Girls
<15	-0.542 (0.757)	1.897* (0.824)
15-18	0.483 (0.300)	0.013 (0.238)
18-21	-0.115. (0.069)	-0.065 (0.077)
24-27	-0.081* (0.032)	-0.080* (0.033)
27-30	-0.242*** (0.039)	-0.237*** (0.038)
30-33	-0.193** (0.060)	-0.255*** (0.060)
>33	-0.456 (1.079)	1.426 (1.585)
Prec. (mm/m²)		
2.5 to 5	-0.173. (0.093)	-0.126 (0.088)
5 to 7.5	-0.164 (0.119)	-0.096 (0.123)
7.5 to 10	-0.355* (0.154)	-0.242 (0.162)
10 to 12.5	-0.129 (0.205)	-0.093 (0.205)
> 12.5	-0.306*** (0.088)	-0.325*** (0.080)
y2004	181.290 (183.060)	106.731 (126.803)
y2005	183.014 (183.061)	126.479 (125.417)
y2006	172.924 (182.319)	122.501 (125.254)
y2007	161.561 (182.180)	111.880 (125.220)
y2008	158.769 (182.157)	112.153 (125.288)
y2009	154.538 (182.258)	111.209 (125.177)
y2010	164.531 (182.151)	116.466 (125.322)
y2011	172.694 (182.095)	123.163 (125.254)
y2012	163.323 (182.239)	113.617 (125.229)
y2013	165.793 (182.204)	113.323 (125.246)
y2014	158.720 (182.205)	108.923 (125.324)
y2015	151.924 (182.414)	102.947 (125.302)
y2016	154.277 (182.350)	103.958 (125.180)
y2017	149.156 (182.507)	98.207 (125.213)
y2018	139.493 (182.530)	88.132 (125.411)
y2019	142.271 (182.475)	90.614 (125.374)
y2020	(dropped)	(dropped)
m02	-3.067 (2.116)	-3.483. (1.965)
m03	-5.343* (2.212)	-1.095 (2.020)
m04	10.637*** (2.246)	12.834*** (2.123)
m05	13.060*** (2.204)	12.425*** (2.062)
m06	6.030** (2.095)	4.228* (1.984)
m07	10.792*** (2.185)	6.709** (2.080)
m08	12.003*** (2.261)	9.647*** (2.199)
m09	11.822*** (2.301)	9.853*** (2.211)
m10	11.518*** (2.182)	7.884*** (2.152)
m11	7.342*** (2.155)	3.895. (2.101)
m12	3.699. (1.986)	2.412 (1.945)
years of study - zero	81.903*** (4.380)	74.857*** (3.991)
years of study - 1 to 3 y	114.108*** (4.207)	100.919*** (3.874)

years of study - 4 to 7 y	129.301*** (4.347)	117.042*** (3.983)
years of study - 8 to 11 y	129.830*** (4.588)	115.992*** (4.201)
marital status - married	14.132*** (1.073)	12.349*** (1.125)
pre_appoint	59.217*** (0.961)	53.902*** (0.914)
une	-0.456 (0.604)	0.359 (0.581)
mother_age	1.605*** (0.100)	1.714*** (0.095)
gest_age - 22 to 27 w	-509.662*** (38.867)	-440.009*** (39.393)
gest_age - 28 to 31 w	-620.531*** (36.064)	-662.374*** (36.177)
gest_age - 32 to 36 w	-21.638 (35.608)	-121.513*** (34.967)
gest_age - 37 to 41 w	410.747*** (35.728)	284.774*** (34.797)
gest_age - more than 42 w	496.412*** (36.050)	364.095*** (34.959)
parity	34.153*** (0.456)	31.448*** (0.460)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	1,516,664	1,441,565
R2	0.12179	0.10918
Within R2	0.11282	0.09954

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 45 - Estimations of birthweight per daily deviations from historical means, subsetted for "Bolsa Família" program top most 80% receivers

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.516 (0.489)	0.416*** (0.118)	-0.124 (0.504)	-0.034 (0.162)
-2 to -1.5	-0.087 (0.218)	-0.526** (0.187)	-0.215 (0.237)	-0.105 (0.184)
-1.5 to -1	-0.103 (0.117)	0.220. (0.122)	-0.014 (0.112)	-0.022 (0.116)
-1 to -0.7	0.260* (0.104)	-0.041 (0.112)	0.197. (0.108)	-0.016 (0.111)
0.7 to 1	-0.001 (0.045)	-0.046 (0.038)	0.016 (0.045)	-0.055 (0.037)
1 to 1.5	0.011 (0.031)	-0.077** (0.027)	0.008 (0.030)	-0.044. (0.025)
1.5 to 2	0.046 (0.035)	-0.032 (0.034)	0.005 (0.036)	-0.069* (0.033)
>2	-0.032 (0.032)	-0.055* (0.027)	-0.005 (0.030)	-0.059* (0.025)
Precip.				
Neg.	-0.090 (0.093)		-0.034 (0.085)	
Pos.	0.035 (0.046)		0.088. (0.047)	
y2000	145.373 (184.658)		112.069 (126.910)	
y2001	145.339 (184.692)		122.938 (125.643)	
y2002	133.269 (183.906)		126.286 (125.304)	
y2003	122.222 (183.777)		115.599 (125.288)	
y2004	118.186 (183.750)		113.950 (125.360)	
y2005	115.490 (183.804)		114.418 (125.239)	
y2006	123.781 (183.716)		119.313 (125.399)	
y2007	135.548 (183.687)		129.533 (125.327)	
y2008	127.200 (183.757)		119.689 (125.327)	
y2009	128.309 (183.723)		117.943 (125.300)	
y2010	120.525 (183.725)		113.658 (125.397)	
y2011	114.188 (183.837)		107.260 (125.447)	
y2012	116.288 (183.811)		108.406 (125.321)	
y2013	110.304 (183.917)		102.139 (125.318)	
y2014	99.060 (183.884)		90.374 (125.538)	
y2015	100.980 (183.812)		91.964 (125.493)	
y2016	-2.021 (2.070)		-2.307 (1.956)	
y2017	-2.975 (2.121)		0.892 (1.982)	
y2018	13.480*** (2.099)		15.237*** (2.042)	
y2019	15.181*** (2.057)		13.913*** (1.985)	
y2020	5.495** (2.020)		3.077 (1.901)	
m02	7.034*** (2.020)		2.548 (1.966)	
m03	6.459** (2.011)		3.427. (1.905)	
m04	5.849** (2.032)		3.399. (1.910)	
m05	6.305** (2.014)		2.431 (1.964)	
m06	3.849. (2.077)		0.307 (2.026)	
m07	1.760 (1.984)		0.569 (1.925)	
m08	81.998*** (4.362)		74.857*** (3.999)	
m09	114.005*** (4.181)		100.985*** (3.877)	
m10	128.949*** (4.328)		117.128*** (3.987)	
m11	128.563*** (4.563)		116.189*** (4.205)	

m12	13.757*** (1.071)	12.292*** (1.125)
years of study - zero	59.884*** (0.969)	53.948*** (0.915)
years of study - 1 to 3 y	-0.489 (0.603)	0.318 (0.584)
years of study - 4 to 7 y	1.549*** (0.101)	1.708*** (0.095)
years of study - 8 to 11 y	-528.548*** (44.487)	-442.143*** (39.567)
marital status - married	-500.308*** (41.617)	-669.085*** (36.302)
pre_appoint	102.917* (41.396)	-134.433*** (35.066)
une	528.804*** (41.721)	265.521*** (34.856)
mother_age	610.907*** (41.970)	341.684*** (34.986)
gest_age - 22 to 27 w	34.389*** (0.459)	31.474*** (0.460)
gest_age - 28 to 31 w	145.373 (184.658)	112.069 (126.910)
gest_age - 32 to 36 w	145.339 (184.692)	122.938 (125.643)
gest_age - 37 to 41 w	133.269 (183.906)	126.286 (125.304)
gest_age - more than 42 w	122.222 (183.777)	115.599 (125.288)
parity	118.186 (183.750)	113.950 (125.360)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	1,517,462	1,440,757
R2	0.12475	0.10913
Within R2	0.11584	0.09949

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

Table S2. 46 - Estimations of birthweight per weekly deviations from historical means, subsetted for "Bolsa Família" program top most 80% receivers

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	0.644 (0.517)	0.486*** (0.122)	0.151 (0.523)	-0.028 (0.160)
-2 to -1.5	-0.166 (0.245)	-0.642*** (0.194)	-0.280 (0.272)	-0.123 (0.190)
-1.5 to -1	-0.102 (0.119)	0.244. (0.128)	0.021 (0.113)	-0.025 (0.120)
-1 to -0.7	0.281** (0.108)	-0.012 (0.114)	0.219* (0.109)	-0.035 (0.114)
0.7 to 1	-0.007 (0.045)	-0.040 (0.039)	0.019 (0.045)	-0.060 (0.038)
1 to 1.5	0.021 (0.031)	-0.078** (0.027)	0.020 (0.030)	-0.043. (0.025)
1.5 to 2	0.056 (0.037)	-0.043 (0.035)	0.018 (0.037)	-0.080* (0.034)
>2	-0.023 (0.032)	-0.044 (0.027)	-0.006 (0.031)	-0.056* (0.026)
Precip.				
Neg.	-0.164. (0.093)		-0.052 (0.089)	
Pos.	0.045 (0.047)		0.089. (0.048)	
y2004	348.704** (128.258)		166.679 (138.490)	
y2005	348.067** (128.431)		182.969 (137.234)	
y2006	336.682** (127.360)		179.291 (136.997)	
y2007	325.032* (127.113)		169.001 (137.009)	
y2008	321.367* (127.158)		167.012 (136.966)	
y2009	319.058* (127.102)		166.450 (136.894)	
y2010	326.663* (127.008)		172.675 (137.037)	
y2011	340.056** (127.076)		184.197 (137.013)	
y2012	331.369** (127.080)		173.533 (137.012)	
y2013	331.671** (127.105)		171.147 (137.014)	
y2014	322.942* (127.040)		166.461 (137.088)	
y2015	316.399* (127.090)		159.413 (137.224)	
y2016	317.664* (127.052)		159.739 (137.123)	
y2017	312.028* (127.248)		153.764 (137.132)	
y2018	298.914* (127.190)		141.261 (137.262)	
y2019	300.462* (127.141)		141.179 (137.168)	
y2020	(dropped)		(dropped)	
m02	-2.267 (2.120)		-4.025* (1.994)	
m03	-3.572 (2.214)		-0.811 (2.018)	
m04	12.846*** (2.163)		14.277*** (2.080)	
m05	14.227*** (2.138)		13.415*** (2.024)	
m06	4.990* (2.103)		2.404 (1.954)	
m07	6.765** (2.090)		2.235 (2.013)	
m08	6.668** (2.117)		3.639. (1.952)	
m09	6.141** (2.071)		3.235. (1.946)	
m10	6.725** (2.078)		1.749 (2.050)	
m11	4.438* (2.139)		0.041 (2.083)	
m12	2.208 (2.046)		-0.102 (1.985)	
years of study - zero	81.854*** (4.444)		74.574*** (3.989)	
years of study - 1 to 3 y	113.901*** (4.247)		100.105*** (3.874)	
years of study - 4 to 7 y	128.400*** (4.404)		115.459*** (3.998)	

years of study - 8 to 11 y	128.835*** (4.663)	114.701*** (4.223)
marital status - married	13.524*** (1.093)	11.951*** (1.159)
pre_appoint	62.697*** (1.003)	57.535*** (0.955)
une	-0.191 (0.614)	0.482 (0.596)
mother_age	1.430*** (0.104)	1.479*** (0.098)
gest_age - 22 to 27 w	-288.329*** (50.323)	-355.135*** (53.166)
gest_age - 28 to 31 w	236.944*** (50.260)	92.799. (51.758)
gest_age - 32 to 36 w	919.892*** (50.921)	741.553*** (51.304)
gest_age - 37 to 41 w	1,347.624*** (51.315)	1,144.125*** (51.586)
gest_age - more than 42 w	1,427.786*** (51.407)	1,218.969*** (51.687)
parity	34.820*** (0.469)	32.350*** (0.477)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	1,497,470	1,446,839
R2	0.15109	0.13719
Within R2	0.14286	0.12832

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

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Table S2. 47 - Estimations of birthweight per monthly deviations from historical means, subsetted for "Bolsa Família" program top most 80% receivers

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	111.715*** (13.102)	5.856. (3.353)	77.764*** (10.303)	-1.538 (4.028)
-2 to -1.5	-14.091** (5.266)	0.842 (2.490)	-23.100*** (4.099)	1.207 (3.812)
-1.5 to -1	3.865. (2.112)	0.821 (1.755)	3.152 (2.301)	-2.892 (1.759)
-1 to -0.7	1.301 (1.747)	-1.572 (1.447)	1.584 (1.647)	-0.493 (1.275)
0.7 to 1	0.003 (0.439)	-0.777* (0.382)	-0.548 (0.416)	-1.169** (0.390)
1 to 1.5	-0.014 (0.391)	-1.572*** (0.378)	-0.205 (0.379)	-1.348*** (0.347)
1.5 to 2	-0.340 (0.504)	-1.251* (0.555)	-0.100 (0.498)	-1.558** (0.538)
>2	-0.453 (0.721)	-1.157. (0.644)	-1.210. (0.654)	-1.454* (0.601)
Precip.				
Neg.	-1.342 (4.251)		2.964 (3.648)	
Pos.	1.248 (1.005)		2.648** (0.999)	
y2004	187.929 (183.019)		114.115 (126.957)	
y2005	188.756 (183.021)		129.950 (125.541)	
y2006	178.130 (182.255)		125.941 (125.356)	
y2007	167.047 (182.124)		115.648 (125.340)	
y2008	162.654 (182.093)		114.453 (125.427)	
y2009	159.865 (182.178)		114.785 (125.289)	
y2010	168.798 (182.074)		119.136 (125.440)	
y2011	179.901 (182.026)		128.678 (125.359)	
y2012	171.088 (182.123)		119.907 (125.351)	
y2013	171.797 (182.130)		118.377 (125.342)	
y2014	164.487 (182.122)		113.832 (125.421)	
y2015	158.483 (182.276)		107.527 (125.470)	
y2016	160.808 (182.205)		109.094 (125.343)	
y2017	154.921 (182.395)		102.975 (125.343)	
y2018	143.370 (182.384)		91.004 (125.545)	
y2019	145.196 (182.315)		93.077 (125.510)	
y2020	(dropped)		(dropped)	
m02	-1.491 (2.076)		-2.209 (1.951)	
m03	-2.663 (2.097)		0.890 (1.975)	
m04	13.994*** (2.068)		15.204*** (2.030)	
m05	15.662*** (2.019)		13.962*** (1.958)	
m06	6.092** (1.995)		3.289. (1.892)	
m07	7.693*** (2.004)		2.706 (1.947)	
m08	6.589** (2.001)		3.470. (1.895)	
m09	5.774** (2.015)		3.357. (1.913)	
m10	6.122** (1.999)		2.370 (1.965)	
m11	3.503. (2.066)		0.454 (2.025)	
m12	1.646 (1.981)		0.835 (1.926)	
years of study - zero	81.925*** (4.378)		74.846*** (3.989)	
years of study - 1 to 3 y	114.175*** (4.205)		100.936*** (3.873)	
years of study - 4 to 7 y	129.381*** (4.346)		117.049*** (3.984)	

years of study - 8 to 11 y	129.937*** (4.585)	116.057*** (4.202)
marital status - married	14.112*** (1.071)	12.312*** (1.125)
pre_appoint	59.219*** (0.961)	53.928*** (0.914)
une	-0.436 (0.604)	0.346 (0.584)
mother_age	1.602*** (0.100)	1.711*** (0.095)
gest_age - 22 to 27 w	-514.760*** (38.747)	-441.768*** (39.493)
gest_age - 28 to 31 w	-632.455*** (35.826)	-670.264*** (36.248)
gest_age - 32 to 36 w	-39.361 (35.301)	-134.690*** (35.008)
gest_age - 37 to 41 w	386.951*** (35.306)	266.331*** (34.773)
gest_age - more than 42 w	469.030*** (35.532)	342.216*** (34.898)
parity	34.161*** (0.456)	31.445*** (0.460)
Fixed-Effects:		
Munic.	Yes	Yes
S.E.: Clustered	by: Munic.	by: Munic.
Observations	1,516,797	1,441,677
R2	0.12174	0.10915
Within R2	0.11277	0.09951

Source: author. y- years. m- months. pre_appoint – number of attended antenatal care appointments. une- state-level unemployment rates. br_prog- ratio of beneficiaries per municipality. mother_age- mother age in years. gest_age – gestational age in weeks. parity – number of previous children per mother. Munic. – municipality.

3 CAN FUTURE CLIMATE SHOCKS DEEPEN SOCIAL VULNERABILITIES IN BRAZIL?

Abstract

Background: Climate change effects can affect health outcomes via several channels. In a country with deep social inequalities, climate change effects on health are thought to contribute to deeper social vulnerabilities.

Methods: We used the estimates of birthweight effects from climate change so far in Brazil and applied them to this century's climate projections to identify the most vulnerable areas and most vulnerable populations while trying to ascertain whether these effects would be compensated or not by demographic changes.

Results: Our results suggest that climate change effects will not be homogenous for the whole country, and certain areas such as the Central-west and South are more in danger of experiencing a decrease in average birthweight than others. The effects will probably be compensated by the improvement of educational levels and demographic changes in mothers' characteristics, but the climate effects may decrease the society's gains as shocks intensify over time.

Conclusions: Climate change effects may affect birth outcomes for the next century, with increased damage for the most vulnerable populations, who are at a higher risk of getting trapped by poverty.

Keywords: Health economics, Climate change, Social vulnerability, Forecasted climate, Climate models.

3.1 INTRODUCTION

Future climate change estimates are alarming. According to the regional risks identified by the IPCC (2024) for this century, there is not a single world region that will remain unaffected by climate change. Increased risk of coastal and urban floods is expected in North America, Europe, Asia and Australasia, notably on the small islands. A higher possibility of facing water restrictions arises in Europe, Australasia, Africa, Central and South America. Wildfires are at increased risk of happening in North Europe and Europe and marine ecosystems are under threat in Polar regions and Australasia. Food production systems are menaced and the spread of vector-borne diseases is under intensification, particularly in Africa and Central and South America. However, health and economic risks are universal and are estimated to happen within all world regions (IPCC, 2024).

Brazil, in the heart of South America, will face these risks while still trying to overcome rooted social vulnerabilities such as poverty and income inequality. The Brazilian poor population (people who live with less than $6.85 a day) was 31.6% of the total population in 2022, while the population under extreme poverty (less than $2.15 a day) were 5.9% (IBGE, 2023). According to the World Bank (2022), although extreme poverty rates in Brazil are lower than few South America counterparts (Venezuela, 7.1%, Colombia, 6%), it is higher than most of its neighbours (Uruguay, 0.2%, Chile, 0.4%, Argentina, 0.6%, Paraguay, 1.3%, Ecuador, 3.2%, Bolivia, 2%). Pre-pandemic improvements were lost, and until 2022, were not retrieved again. In this meantime, the GINI index hints at the persistent failure to provide a better income distribution in the country: Brazil has ranked among the most unequal countries in the world for years (World Bank, 2022).

Under climatic risks, poverty persistence gets even more intense for several reasons. First, natural disasters such as droughts and floods may throw people into poverty. For the ones who are already poor, the material losses caused by the climatic change are a restriction to building wealth. Natural disasters compromise food security, work productivity, and educational attainment, which impacts human capital. The majority of the environmental risks affect the poorest more: people who live in abnormal housing conditions, have more exposed jobs, less savings and fewer assets. In rural areas, as agriculture productivity becomes more difficult to predict in a more unstable environment, people would likely engage less in crop investments that could pull them out of poverty to avoid the risk. Also, in rural areas affected by droughts, agricultural workers would switch to forest extractivist activities, thus compromising future income (Hallegatte et al., 2018).

Following the second essay of this thesis, weather shocks between 2000 and 2020 have imposed non-negligible impacts on Brazilian newborns' health. We argue in this essay that these effects are likely to increase due to the future climate projections for the Brazilian municipalities; where vulnerabilities and inequalities that exist nowadays will probably be deepened. Especially, the long-term impacts of the loss of human capital due to birthweight are likely to hinder the country's development and make it even more difficult for families to escape poverty. We estimate in this study the newborn birthweight changes in the future using long-term weather predictions for different scenarios while trying to take into account the changes in long-run demographic trends.

This chapter is organized as follows: in Section 2 we set out our methods and define the main model; in Section 3 we display the results, Section 4 contains the discussion, and Section 5 adds our conclusions.

3.2 METHODS

We rely on the estimates of the monthly deviations from the historical weather to identify the size and the direction of the climate change effects on birth weight and apply it to future weather predictions. The equation (1) is defined as follows:

$$Bw_{igtc} = \beta_1 \sum_{d=1}^{10} TminShock_{1c} + \beta_2 \sum_{d=1}^{10} TmaxShock_{1c} + \beta_3 \sum_{p>0} PrecShock_{1c} +$$

$$\beta_4 \sum_{p<0} PrecShock_{1c} + \beta_5 \sum_{d=1}^{10} TminShock_{2c} + \beta_6 \sum_{d=1}^{10} TmaxShock_{2c} +$$

$$\beta_7 \sum_{p>0} PrecShock_{2c} + \beta_8 \sum_{p<0} PrecShock_{2c} + \beta_9 \sum_{d=1}^{10} TminShock_{3c} +$$

$$\beta_{10} \sum_{d=1}^{10} TmaxShock_{3c} + \beta_{11} \sum_{p>0} PrecShock_{3c} + \beta_{12} \sum_{p<0} PrecShock_{3c} +$$

$$\theta_1 Gweek_i + \theta_2 \tau_{st} + \theta_3 \mu_m + y_t + m_t + c + \varepsilon_i$$

Where Bw_{igtc} is the birthweight of an individual i, gender g, born in a municipality c and a date t. $TempShock_{qc}$ represents the sum of shocks in temperature of intensity d observed during a given month, locality c and gestational trimester $q = \{1,2,3\}$. $PrecShock_{qc}$ represents the number of positive ($p > 1$) or negative shocks ($p < 1$) of any intensity beyond 0.7 SD that happened during each pregnancy. β_i for $i \in [1,12]$ are the parameters for weather variables, and θ_i for $i \in [1,3]$ are the remaining parameters. $Gweek_i$ represents a categorical variable indicating the gestational week of birth. μ_m is a vector of the mother's characteristics such as age, years of study, marital status, number of prenatal appointments and number of previous children to account for the fertility history.

τ_{st} is the unemployment rate at state and year level, y_t is fixed effect for the year of conception, which allows further socio-economic shocks that might have impacted pregnancies apart from climate issues and unemployment rates. m_t are fixed effects for the month of conception, which was included to deal with seasonality of date of conception[18]; and c is fixed effects per municipality, to account for locality characteristics such as region of the country, biome, and other non-observable factors more or less fixed in time. β_i for $i \in [1,6]$ are the parameters for weather variables, and θ_i for $i \in [1,3]$ are the remaining parameters. Only significant coefficients were used for calculation. They are also summarized at Table S3.1 at the supplementary material.

Future weather predictions were gathered from the pclima project, an initiative of the Brazilian Ministry of Science, Technology and Innovation developed by the INPE[19]. In their database, the estimates of the maximum and minimum monthly temperatures and precipitation are presented by geographical area in Brazil. The estimates are available for monthly data for three periods: proximal (2011-2040), medium (2041-2070) and distal (2071-2100). For instance, a map is shown on the platform for the maximum temperature by month for each of these timeframes. Besides these variables we gathered, there were also other variables available such as days with or without rain, radiation, relative humidity and others; however, we collected the variables that were present in our equation for consistency. The forecasted monthly

[18] To test whether there is any seasonality within our data, we checked the frequency of births according to the month of the year, available in Figure S2.1 on the Supplementary material. Even leaving out the year of 2020 (for which we only have data of the first semester), there is a seasonality pattern pointing to relative more frequent deliveries on the months of March, April and May.

[19] Available in: http://pclima.inpe.br/?page_id=183 (in Portuguese).

data gathered were then merged with our own historical weather database, to simulate an average number of shocks a regular pregnancy would suffer in the future compared to the baseline climate. For simplification, an average pregnancy was fixed in 9 months of consecutive exposition, considering the seasonality of conception by municipality present in the data between 2000-2020[20]. Thus, we are assuming that seasonality patterns are the same throughout the models.

On climate science, there are several global models using different assumptions and techniques to build their own predictions based on atmosphere, ocean, sea ice, land surface, marine biochemistry, ice sheets and the coupling between all those components (Goose et al., 2008). It is paramount to acknowledge that future climate depends on a different uncertainties – uncertainty on the level of future greenhouse gas emissions, uncertainty on the calibration of the nature variables – this is to say, a model can be less or more general than other - and, of course, the uncertainty regarding the aspects that are not fully understood by the present science (Cal-adapt, 2024).

On the Brazilian portal, the INPE institute have downscaled a regional model from the global models HADGEM2-ES, MIROC5, CANESM2 and BESM. HADGEM2-ES is the Hadley Centre Global Environment Model version 2, a family of models developed by UK meteorological service who considers the earth systems such as the carbon cycles, atmospheric and ocean variables ensemble (Met Office UK, 2024), what is called a coupled model (Goose et al., 2008). MIROC5 stands for Model for Interdisciplinary Research on Climate version 5. It is another coupled model comprised of an atmospheric, oceanic, land surface and a coupling algorithm, developed by the University of Tokio, Japan (Watanabe et al., 2010). CANESM2 is the Canadian Earth System Model, another coupled system, who considers the interrelationships between atmosphere-ocean, terrestrial carbon model and an ocean carbon model (Canadian Centre for Climate Modelling and Analysis, 2020). Finally, BESM (Brazilian Earth System Model) is a coupled model and the only South American initiative that is part of the Coupled Model Intercomparison Project 6 (CMIP6), the international project that exchanges best practices and continuous development in climate projections (Veiga et al., 2019; Veiga et al., 2023; WGCM, 2024). All models have been continuously evaluated in their performance of representing Brazilian weather by the literature, still,

[20] It was retrieved the average seasonality of conception for each municipality between 2000-2020, which then was used as weights for a weighted average to get an average pregnancy exposition.

some models are more accurate for specific Brazilian subregions than the others, and generally, HADGEM2-ES is the one who performs the best (Brito et al., 2019; Almagro et al., 2020; Silva et al., 2021; Ferreira et al., 2023). HADGEM2-ES is used to cover better warmer and drier simulations, CANESM2 uses to have an average simulation, and MIROC-5 tries to cover the best combination of possibilities (Cal-Adapt, 2024). We gathered estimates for all of them to compare the estimates across models and allow for a comprehensive set of estimates.

Besides having different models, the data also contain two categories of Representative Concentration Pathways (RCP's) for this century, representing two different scenarios of future gas emissions. RCP 4.5 is an estimated intermediate scenario, in which the measures for controlling the emissions are done but are not completely stringent. This RCP assumes emissions of CO_2, CH_4 and N_20 will peak around 2040 and then will decrease. RCP 8.5, in turn, assumes emissions are growing high and will peak around 2100, without additional efforts to control emissions (IPCC, 2024). Descriptive statistics for the models are presented in Table 3.1 below. It is noteworthy to mention that for all climate models, the estimates point to a general increase in temperatures, with the RCP 8.5 forecasting a higher rise. Also, most of the scenarios on the 8.5 report a decrease in the precipitation levels.

Although the data by municipality were not promptly available, we managed to extract them from the maps provided by the platform using an R package we developed specifically for this task. The R package is now publicly available containing the estimates for each model, time frame, weather variable and scenario by municipality[21].

Apart from the weather data, we also must derive the estimates for the demographic variables that pertain to the original model and are not weather-related. For this, we relied on the projection of our data from SINASC database. Average mother age has been increasing worldwide (OECD family database, 2024), and also in Brazil. On the SINASC database, the average mother age at the beginning of the 2000s was 25.04 years while in 2020 the average has risen to 25.88. We gathered the linear trend for the available data and extrapolated until 2100. Although it is a strong assumption that the average mother age will increase linearly for the whole century, updated statistics from developed countries (OECD family database, 2024) point to an average mother age above 30 years growing in the last few years. It is important to

[21] The R package is called projclimbr and is available in https://github.com/tallysfeldens/projclimbr

acknowledge that as evidence of health risks of the offspring of older mothers starts to be highlighted and discussed (Barclay et al, 2016), these trends may change. However, we do not have any information on a country where this trend started to be reversed so far and we chose to keep the assumptions the simple and conservative as possible. Information on the averages by period is depicted in Table 3.2.

Table 3. 1 - Descriptive statistics for forecasted weather variables by model, timeframe and RCP scenario

Timeframe	Scenario	Weather variable (mean)	BESM	CANESM2	HADGEM2-ES	MIROC5
2011-2040						
	RCP4.5					
		Precipitation	120.4	118.49	83.95	122.59
		Max	29.41	30.02	29.4	26.03
		Min	19.27	19.44	18.42	16.13
	RCP8.5					
		Precipitation	121.9	115.63	84.63	116.67
		Max	29.59	30.19	30.19	26.2
		Min	19.49	19.5	18.91	16.19
2041-2070						
	RCP4.5					
		Precipitation	121.15	110.83	97.37	128.09
		Max	30.00	31.18	30.15	26.64
		Min	19.84	20.19	19.39	16.69
	RCP8.5					
		Precipitation	110.5	99.71	89.14	123.38
		Max	31.17	32.3	31.6	27.33
		Min	20.54	20.78	20.3	17.22
2071-2100						
	RCP4.5					
		Precipitation	124.59	109.26	94.05	123.6
		Max	30.21	31.82	30.84	27.03
		Min	20.1	20.66	19.94	17.03
	RCP8.5					
		Precipitation	93.97	69.01	81.63	122.31
		Max	32.97	35.34	34.00	28.69
		Min	21.75	22.27	22.28	18.48

Source: author. RCP – Representative Concentration Pathways. Max – Maximum temperature. Min – Minimum temperature.

From SINASC data, it is noticeable that there is also an increasing trend regarding the number of years of study per mother. At the beginning of the 2000s, the share of mothers without any level of schooling was 4.7%; while in 2019 this share dropped to 0.30%. We extrapolated the improvement of these estimates for all educational levels from the SINASC until 2100. Our estimates point that around 2032 all women giving birth will at least have completed four to seven years of schooling; with the rate of higher levels of education rising throughout the century. Using this estimate, around 2100, virtually all mothers will have completed upper secondary education[22]. These assumptions are also in line with the most recent Brazilian National Education Plan[23], a report that establishes the short and medium-term government aims for population educational achievements; and the World Bank post-COVID perspectives on the demand for higher education (Murthi and Bassett, 2022).

According to the SINASC data and IBGE estimates for the next century, not only mothers have been giving birth later in life and preferring to get more years of study but are also having fewer children than before. Henceforth, we accounted for the forecasted demographic changes in fecundity rates. IBGE estimates for future children per woman were available until 2060, from where we extrapolated until 2100 using a linear trend. Averages are available in Table 3.2.

In Brazil, also the number of antenatal appointments taken by mothers have increased during the period between 2000 and 2020. At the beginning of the series, the average number of visits was around four and six visits; and by the end of the series most of the mothers were having at least six visits. The WHO recommends that each mother should attend at least eight visits to ensure a healthy pregnancy (WHO, 2016). Therefore, we set the best-case scenario where all pregnancies follow the WHO recommendations and assume that Brazilian coverage of health supply and mothers' preferences will converge to this guideline in the future.

Lastly, for simplicity, we assume there is no change in the trends for marital status in the average population.

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[22] Brazilian compulsory school starts at 6 years old. Eleven years of study or more is equivalent to at least upper secondary school finished.
[23] At the moment, the last PNE was available in https://pne.mec.gov.br/. Page in Portuguese.

Table 3. 2 – Mother characteristics by period

	Mother age	Years of study	Fecundity (children per woman)	Antenatal appointments	Marital status
2011-2040	28.78	10.34	1.73	8	60% married and 40% non-married
2041-2070	34.36	11.75	1.66	8	60% married and 40% non-married
2071-2100	39.91	12.47	1.59	8	60% married and 40% non-married

Source: authors, based on information from linear projections of the SINASC database, IBGE predictions and WHO guidelines.

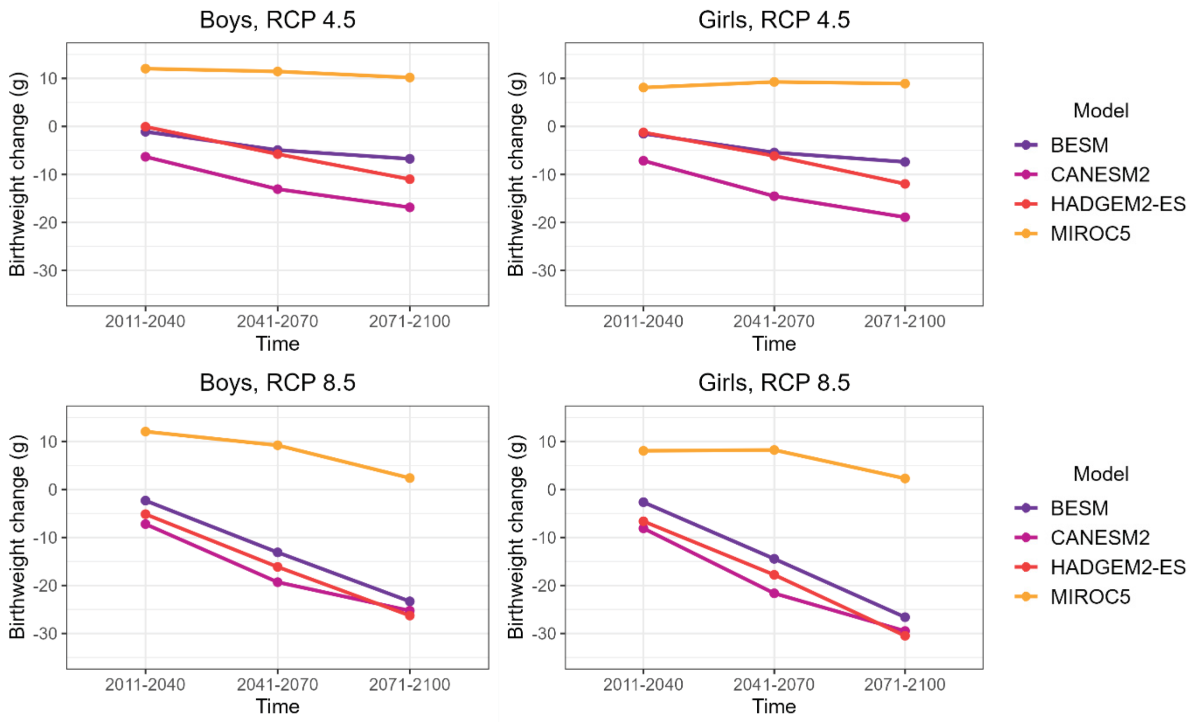
3.3 RESULTS

3.3.1 Main estimation

Our results are depicted for each gender (boys and girls), time frames (2011-2040, 2041-2070, 2071-2100), scenarios (RCP4.5 and RCP8.5) and weather models (HADGEM2-ES, MIROC5, CANESM2 and BESM). Point values are available in the Supplementary material (Table S3.2). In Figure 3.1, we present the results in terms of net change in birthweight in case the weather variables assume the forecasted values and no demographic changes take place. In other words, Figure 3.1 presents the overall changes due to weather only, holding all other variables unchanged.

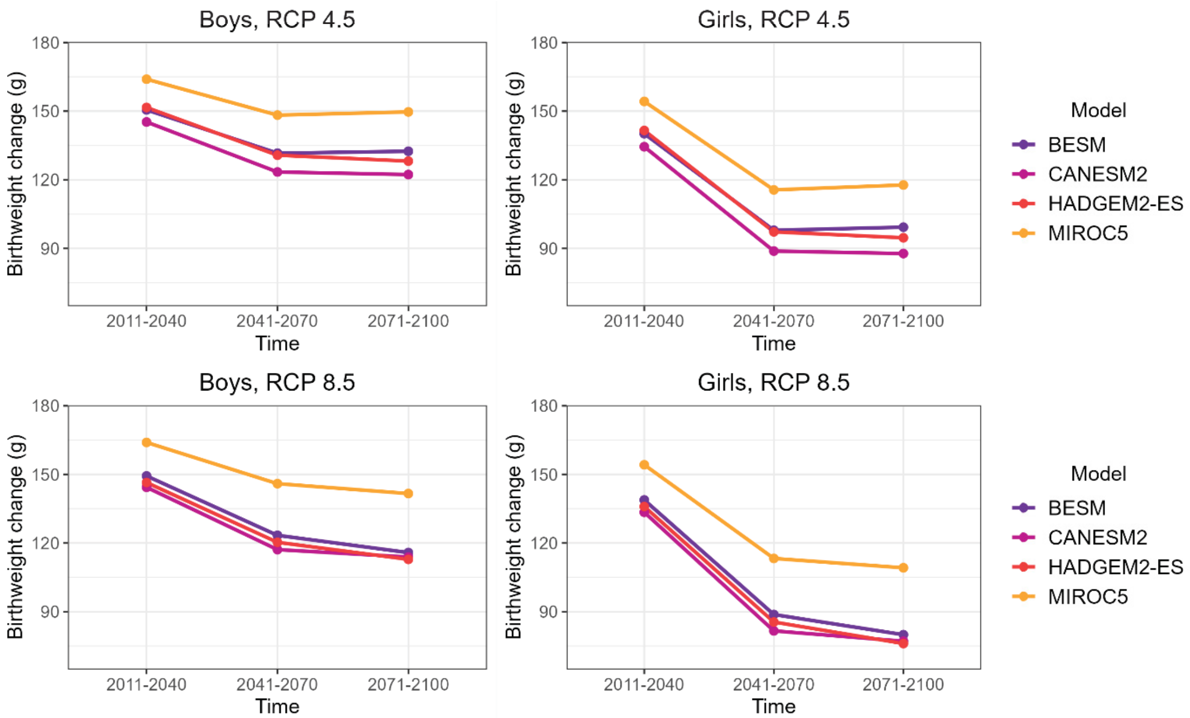
The results displayed in Figure 3.1 show that birthweight would decrease due to the increased frequency of climatic shocks according to most of the models, reaching up to an average 30g loss. Only model MIROC5 forecasts an amelioration of the climatic patterns and thus reflects a gain in birthweight. From the ones that indicate a negative effect on birthweight, CANESM2 is the model that displays the biggest impact on the Brazilian population, while BESM is the one that produces the lowest impact. Results on the RCP 4.5 depict a change in the slope of birthweight losses around 2041-2070, which agrees with the assumptions of the RCP 4.5 of moderate interventions to prevent climate change from worsening. Results for RCP 8.5, instead, reflect a scenario of low-effort interventions. Henceforth, the forecasted birthweight losses are more prominent across the models, reaching the peak loss by the end of the century. Results for boys and girls are similar, but girls' losses are a bit more pronounced.

Figure 3. 1 - Estimates for birthweight changes, without demographics



Source: authors

Figure 3. 2 - Estimates for birthweight changes, with demographics

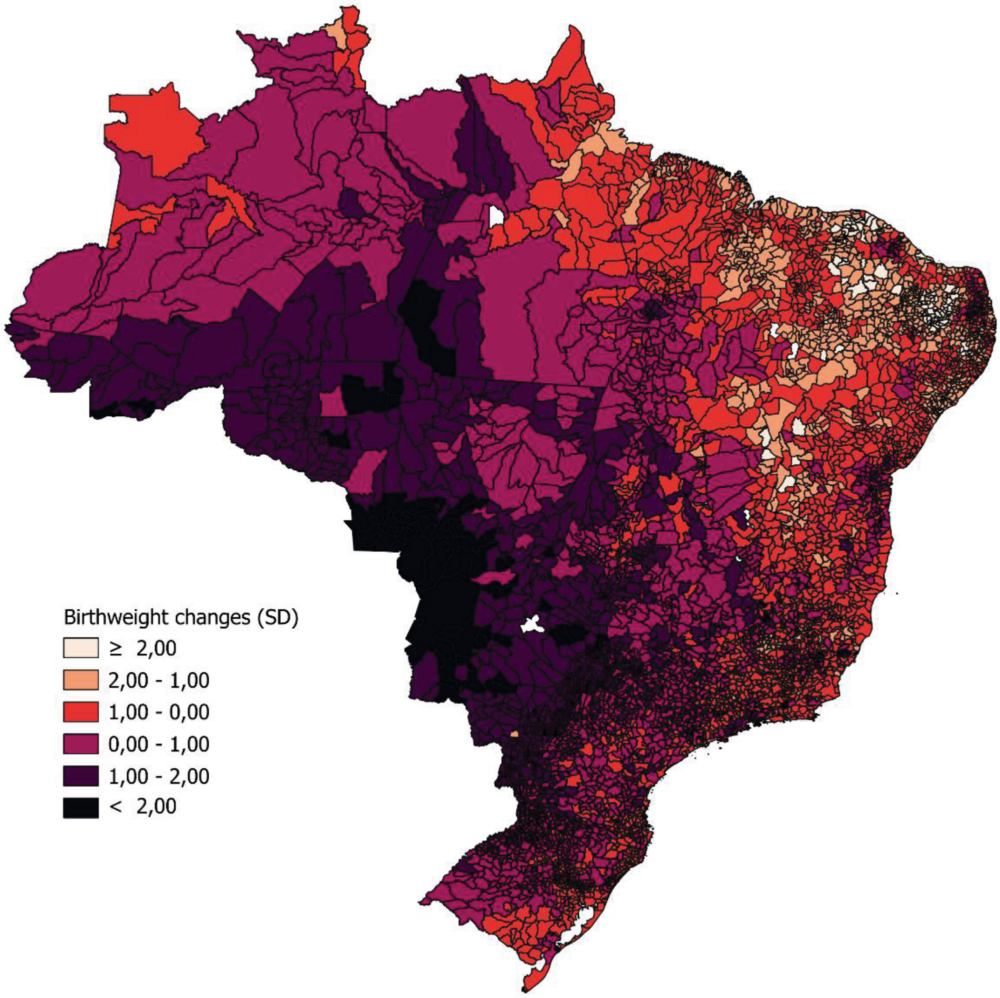


Source: authors

Figure 3.2 replicates the results considering altogether the effects from the weather side and the changes in the demographical trends on the mother's characteristics such as a rise in education levels, a rise in the frequency of antenatal appointments, a rise in the average age to have children and a decrease on the fecundity rates. We can notice that now most of the models converge to a rise in birthweight for boys and girls, which indicates the demographic changes will likely compensate for the decrease in birthweight caused by the climate. However, as time goes by, the level of compensation decreases and some of the benefits from these demographic changes are lost due to the occurrence of climatic shocks, especially under the scenario of RCP 8.5 and for young girls.

Figure 3.3 below shows the geographical distribution of the effects over the country territory excluding the demographic trends averaged by all models, RCP’s and timeframes. It is noticeable that the continental areas of the country are the most affected by birthweight losses, especially the areas corresponding to the North and Central-west regions of the country. The biggest reason behind this is the exposure to heavier and longer heat waves that are forecasted for these regions for all the models. In Table 3.3 we present in detail the average birthweight loss by Brazilian region. Central-west region is the most severely affected, followed by the South and the North regions.

Figure 3. 3 - Geographical distribution of the estimated birthweight changes, averaged by all models, genders, RCP's and timeframes



Source: authors

Table 3. 3 – Mean birthweight losses by Brazilian region (g) averaged by all models, genders, RCP's and timeframes

Central-west	17.56
South	11.75
North	10.44
Southeast	9.77
Northeast	0.13

Source: authors

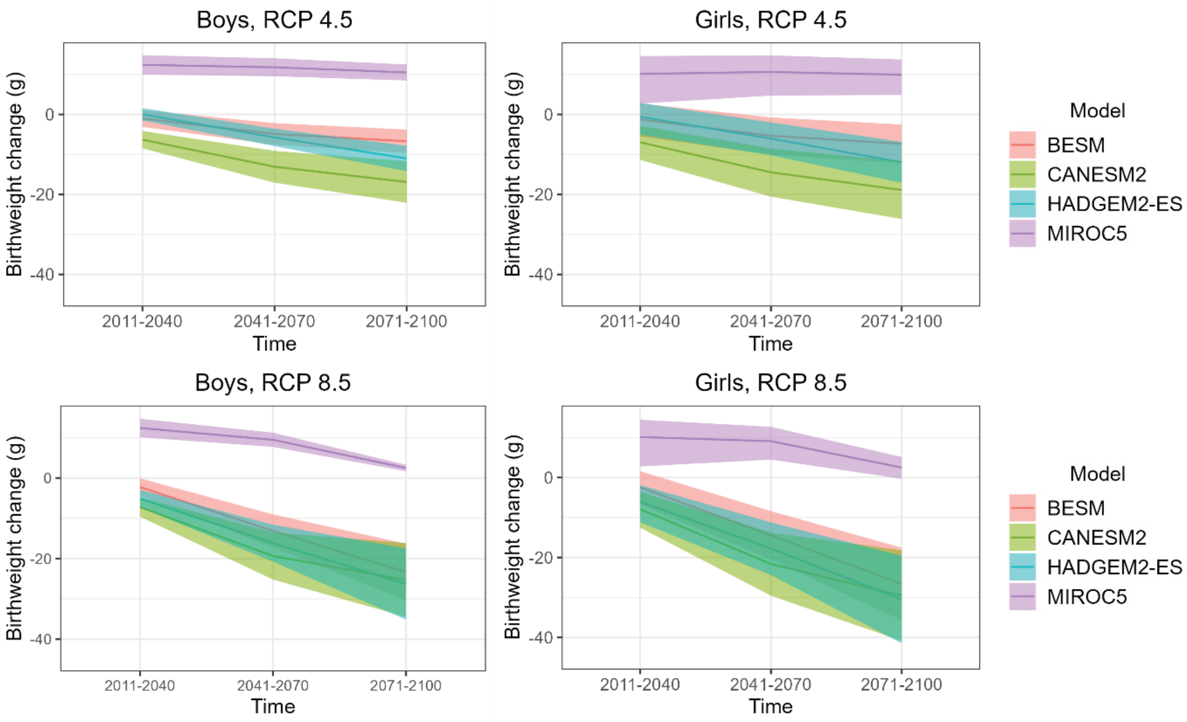
3.3.2 Sensitivity analysis

Models of climate projections are affected by several types of uncertainties. For instance, the relationship between the weather variables is complex and projections may be drawn from models more or less realistic; or more or less accurate to mimic a given region. The assumptions underlying the models, for example, are subject to human choice, which generates judgement uncertainty and model uncertainty. Besides, the estimations themselves carry the statistical uncertainty.

Thus, we estimated the confidence interval of the models using the original upper and lower bound of the coefficients of the equation (1) to account for statistical uncertainty. The results for the estimation without demographic variables and with demographic variables are depicted in Figures 3.4 and 3.5 respectively. From the images, we may identify that most of the models not considering the demographic changes project a birthweight loss of around 0g and 20g in scenario 4.5 and around 0g to 40g in scenario 8.5. When we consider the demographic changes, instead, the change in the birthweight lay around 70g and 170g in both scenarios.

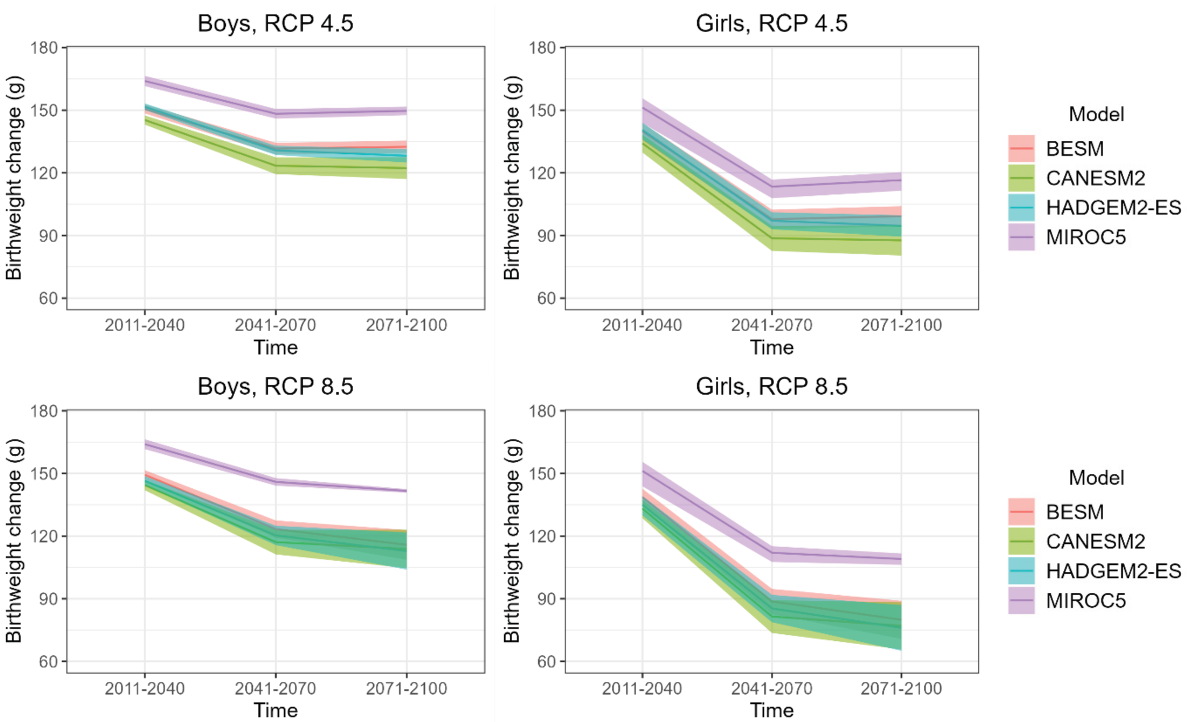
To account for the uncertainty of the demographic characteristics we assumed, thus controlling partially for the judgement uncertainty, we also estimated three versions of the equation (1) considering that: a) there is no change in the mother's age, b) there is no change on the educational level of the mothers, c) there is no change on the fertility trends. Figures 3.6, 3.7 and 3.8 display those exercises below. These results show that projections of educational achievement take the lead in the demographic part of weight gain and that fertility rates raise the birthweight on the hypothesis of stopping decreasing. However, controlling for each of those assumptions, there is still a sizeable impact on all weather models.

Figure 3. 4 - Estimates for birthweight changes, without demographics, with confidence intervals



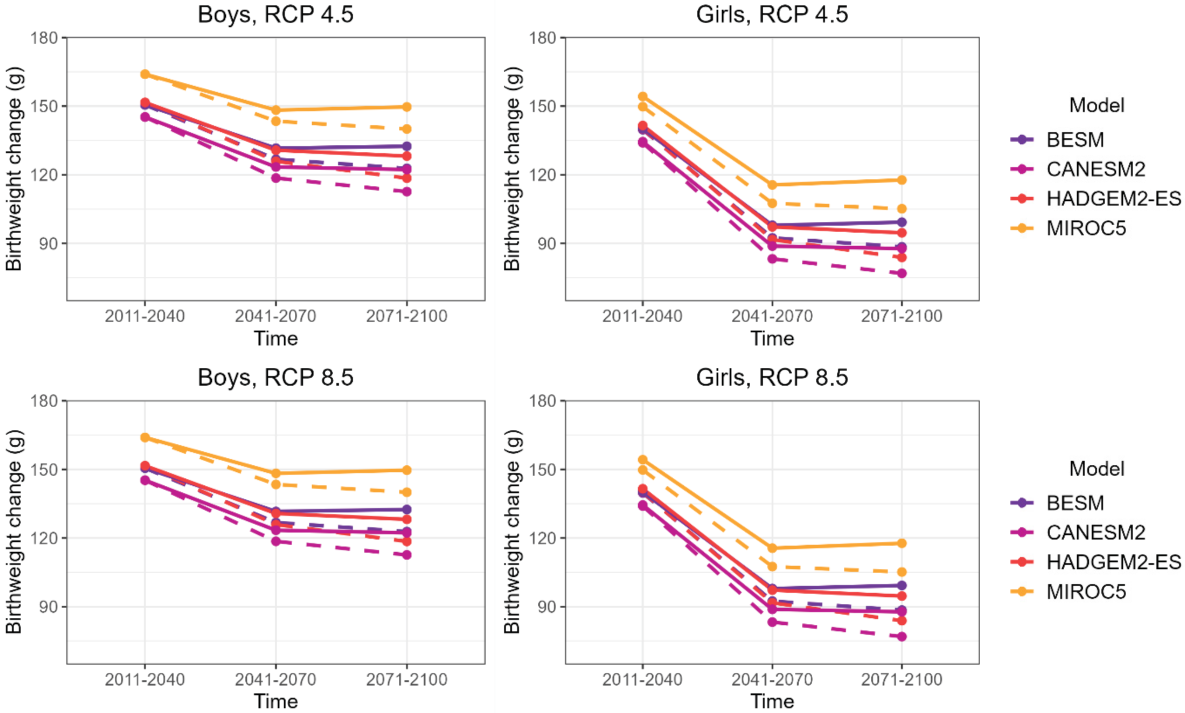
Source: authors

Figure 3. 5 - Estimates for birthweight changes, with demographics, with confidence intervals



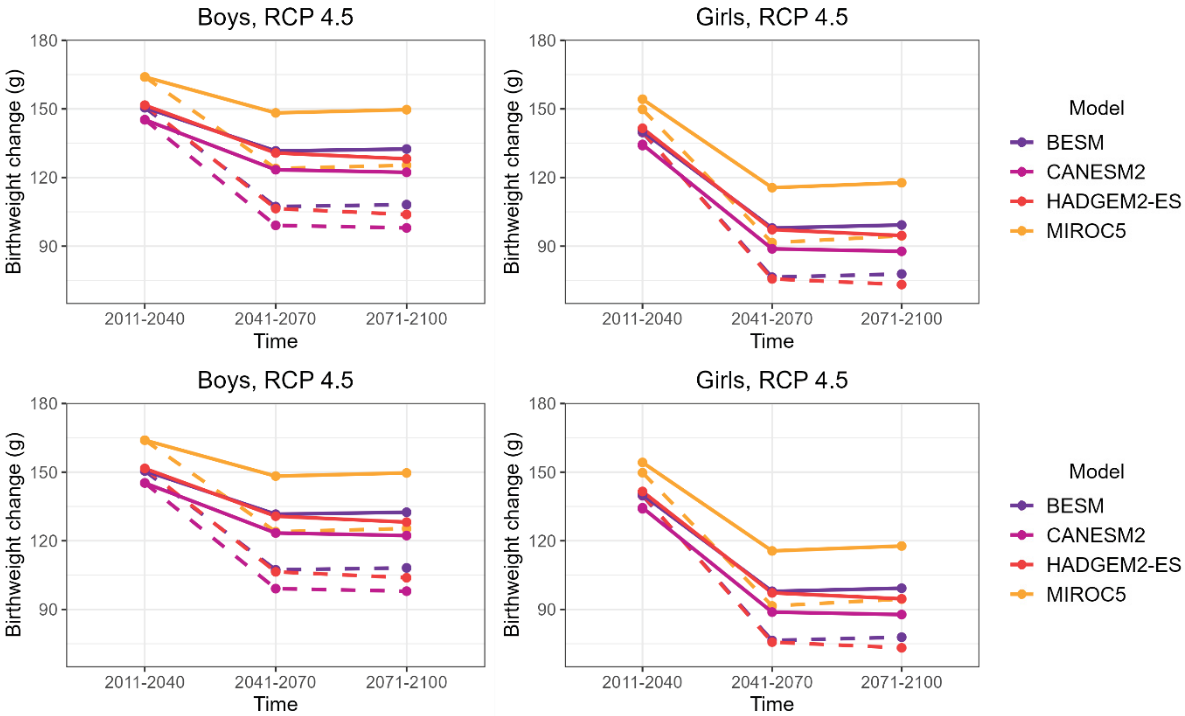
Source: authors

Figure 3. 6 - Estimates for birthweight changes, with demographics, assuming mother age is unchanged



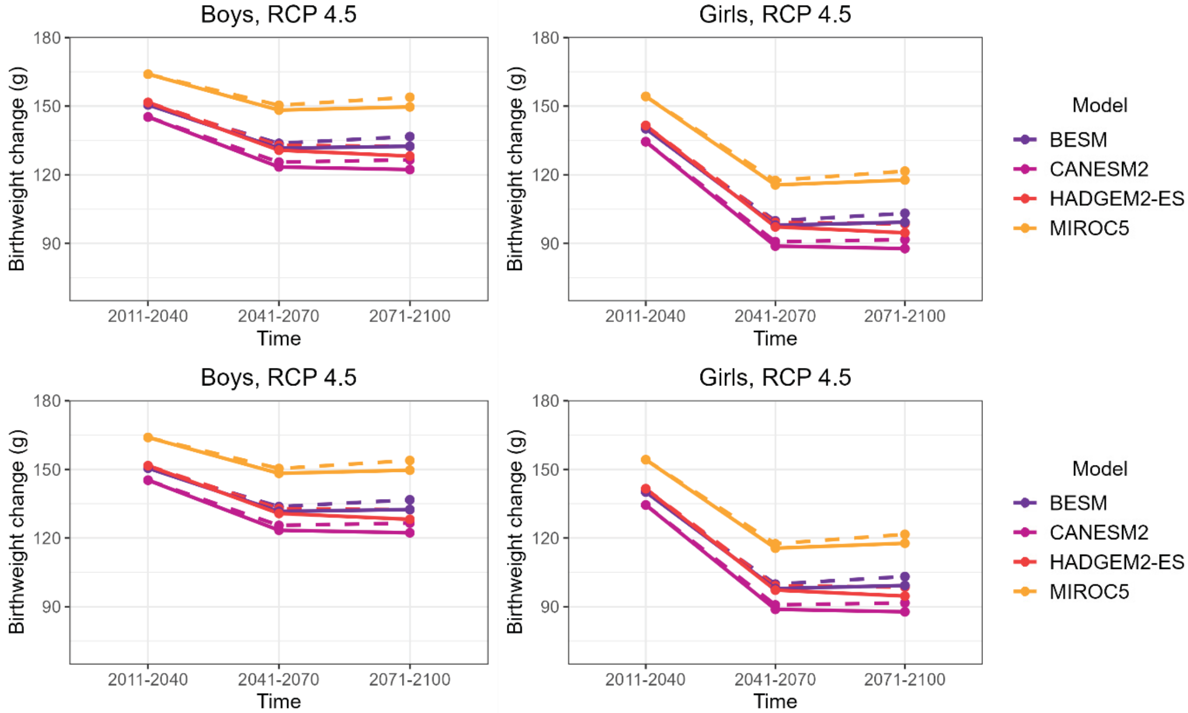
Hashed lines represent the hypothesis of the mother's age unchanged. Source: authors.

Figure 3. 7 - Estimates for birthweight changes, with demographics, assuming education unchanged



Hashed lines represent the hypothesis of education unchanged. Source: authors.

Figure 3. 8 - Estimates for birthweight changes, with demographics, assuming fertility rates unchanged



Hashed lines represent the hypothesis of fertility rates unchanged. Source: authors.

3.4 DISCUSSION

In this study, we took advantage of the previous estimations on the impacts of climate shocks on the birthweight of Brazilian newborns and extrapolated for the forecasted climate until the end of the century. According to our estimations, effects are going to be deepened as the year approaches 2100 and if the worst-case scenario RCP 8.5 concretizes itself. Most models coincide with little differentiation, only the model MIROC5 projections point to a gain in birthweight. This model has the characteristic of both assuming a decrease in the level of detrimental effects and trying to cover the best set of possibilities (Cal-Adapt, 2024); thus, acting as a powerful reference point.

When we consider the demographic changes such as an increase in women's education, a decrease in fecundity levels, an increase in the mother’s age and an increase in antenatal visits, the effects of climate change are compensated and for all the models there is an expected raise on the birthweight. However, gains from these changes in demographic characteristics are at risk of being partially lost as time goes by and climate shocks intensify.

Our study points out that there is no homogeneity in the areas affected by future climatic shocks. Areas on the continental part of Brazil are more exposed to higher temperatures and will bear the burden of the higher losses on birthweight. In the Central-West, the most affected area, the population will face increased temperatures in an already warm region, which also has been affected by desertification advances and wildfires in the last years (De Moraes et al., 2023). In Southern Brazil, the second biggest impact, the results are probably driven by the increase in the temperature of this traditionally colder area.

The expansions of climatic shocks in the Brazilian countryside are concerning as the most urbanized areas are concentrated along the coast, leaving an interior with low population density (IBGE, 2019). As suggested by the second essay of this thesis, isolated areas are particularly prone to experience deeply the effects of climatic change. We theorize that barriers to adaptation measures and the reliance on agricultural subsistence may play a significant role in striking this population, who will be more affected by the intensification of the climate changes and at the same time will probably be less prepared, cultivating a cycle of the climatic trap with relevant health losses. This concern is in line with Hallegatte et al. (2018), who claim that climatic shocks may worsen poverty-scaping strategies by difficulty wealth resilience over natural disasters and affecting more intensely the ones living under abnormal housing conditions.

Birthweight losses also contribute to perpetuating poverty traps as it affect human capital formation. According to previous literature, birthweight losses can affect schooling achievements later in life, which suggests the occurrence of long-term cognitive effects (Figlio et al., 2014; Torche and Echevarría, 2017). Henceforth, by limiting cognition achievements in school, human capital formation will be affected in the long run, deepening the poverty trap. When taking into account the vulnerability caused by the climate itself, it becomes evident that the most vulnerable populations are to be thrown into disadvantaged contexts and will likely suffer barriers to overcome and escape from it. Regional poles of poverty and inequality may become more common.

This study has several limitations. Firstly, projected climates are models derived from uncertainty and depend on assumptions more or less adequate to the regional context. We utilized four of the models available for the Brazilian territory to achieve a comprehensive set of projections validated by the official institutes. Secondly, we are assuming that the coefficients from equation (1) are fixed in time and the relationships between birthweight and monthly weather shocks will be the same for the period between 2011-2100. Although it is a strong assumption, imposing that this relationship is fixed is a way of simplifying the model for ease of interpretation and keeping it conservative. We also assumed demographic changes for education, fecundity, behaviour towards pregnancy and mother age and did sensitivity analysis showing how slightly different assumptions affect our results. Despite our attempts to be the most consistent and coherent with the actual trends, it is a difficult task to guarantee that all these assumptions will concretize themselves. Access to health care, for instance, cannot be taken for granted, as income distribution and geographical disparities are important barriers to the convergence of the quality of care. Therefore, our choices are not free from criticism.

Furthermore, we could not take into consideration the consequences of migration patterns for the Brazilian population. Several studies have considered that climate change is going to cause relevant migration across the territory (Delazeri et al., 2021; Delazeri et al., 2022), which will probably alter our results in uncertain directions. Due to the lack of forecasted climate-related migration data for the whole country, we preferred to assume that the composition of the population is unchanged.

Lastly, adaptation strategies against climate shocks will likely be developed and improved over time, but we could not account for this in this analysis. In particular, adaptation capabilities may also be mediated by socioeconomic status and initial conditions. Henceforth, our results should be seen as the lower bound estimates.

3.5 CONCLUSION

In this study, we estimated the birthweight effects of the future climate shocks in Brazil until 2100. The results point out a decrease in the birthweight because of the intensification of the climatic shocks, notably for the Brazilian countryside. However, thanks to demographic changes in Brazil concerning mother characteristics, these effects will probably be compensated. Still, the effects are non-negligible and can counterforce the advances made by society by deepening social vulnerabilities and raising the risk of poverty traps.

Further works should improve the estimates found in this study by including migration and adaptation measures and understanding regional dynamics between Brazilian municipalities.

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SUPPLEMENTARY MATERIAL

Table S3. 1 Estimations of birthweight per monthly deviations from historical means (summarized)

Weather var.	Dependent variable – Birthweight (g)			
	Boys		Girls	
Shock size (SD)	Max.	Min.	Max.	Min.
<-2	-19.590 (13.142)	-0.870 (0.945)	-11.075 (13.274)	-2.119* (0.911)
-2 to -1.5	-0.477 (5.909)	-1.494 (1.389)	-3.019 (6.943)	-2.287. (1.296)
-1.5 to -1	4.404** (1.560)	-2.180** (0.693)	3.962** (1.480)	-1.307* (0.599)
-1 to -0.7	-0.706 (0.787)	-0.019 (0.564)	-0.732 (0.782)	-0.492 (0.563)
0.7 to 1	-1.076*** (0.281)	-0.623** (0.209)	-1.231*** (0.270)	-0.701** (0.217)
1 to 1.5	-1.978*** (0.328)	-0.738** (0.275)	-2.114*** (0.337)	-0.714* (0.280)
1.5 to 2	-2.980*** (0.561)	-1.367** (0.503)	-3.239*** (0.545)	-1.178* (0.505)
>2	-2.182* (0.918)	-1.931** (0.596)	-2.506** (0.949)	-2.393*** (0.610)
Precip.				
Neg.	0.768 (3.188)		5.197 (2.857)	
Pos.	0.091 (0.466)		0.771 (0.395)	

Source: authors

Table S3. 2 - Point estimates of birthweight changes by model, timeframe, RCP, population and inclusion of demographics

Timeframe	Model	Demographics	RCP	Population	Change on birthweight (g)
2011-2040	BESM	0	45	Boys	-1.104
2011-2040	CANESM2	0	45	Boys	-6.315
2011-2040	HADGEM2-ES	0	45	Boys	-0.059
2011-2040	MIROC5	0	45	Boys	12.039
2041-2070	BESM	0	45	Boys	-4.923
2041-2070	CANESM2	0	45	Boys	-13.057
2041-2070	HADGEM2-ES	0	45	Boys	-5.762
2041-2070	MIROC5	0	45	Boys	11.451
2071-2100	BESM	0	45	Boys	-6.748
2071-2100	CANESM2	0	45	Boys	-16.856
2071-2100	HADGEM2-ES	0	45	Boys	-10.989
2071-2100	MIROC5	0	45	Boys	10.19
2011-2040	BESM	1	45	Boys	150.569
2011-2040	CANESM2	1	45	Boys	145.277
2011-2040	HADGEM2-ES	1	45	Boys	151.612
2011-2040	MIROC5	1	45	Boys	163.973
2041-2070	BESM	1	45	Boys	131.621
2041-2070	CANESM2	1	45	Boys	123.409
2041-2070	HADGEM2-ES	1	45	Boys	130.748
2041-2070	MIROC5	1	45	Boys	148.272
2071-2100	BESM	1	45	Boys	132.465
2071-2100	CANESM2	1	45	Boys	122.286
2071-2100	HADGEM2-ES	1	45	Boys	128.170
2071-2100	MIROC5	1	45	Boys	149.666
2011-2040	BESM	0	85	Boys	-1.104

2011-2040	CANESM2	0	85	Boys	-6.315
2011-2040	HADGEM2-ES	0	85	Boys	-0.059
2011-2040	MIROC5	0	85	Boys	12.039
2041-2070	BESM	0	85	Boys	-4.923
2041-2070	CANESM2	0	85	Boys	-13.057
2041-2070	HADGEM2-ES	0	85	Boys	-5.762
2041-2070	MIROC5	0	85	Boys	11.451
2071-2100	BESM	0	85	Boys	-6.748
2071-2100	CANESM2	0	85	Boys	-16.856
2071-2100	HADGEM2-ES	0	85	Boys	-10.989
2071-2100	MIROC5	0	85	Boys	10.19
2011-2040	BESM	1	85	Boys	149.331
2011-2040	CANESM2	1	85	Boys	144.369
2011-2040	HADGEM2-ES	1	85	Boys	146.464
2011-2040	MIROC5	1	85	Boys	163.986
2041-2070	BESM	1	85	Boys	123.365
2041-2070	CANESM2	1	85	Boys	117.127
2041-2070	HADGEM2-ES	1	85	Boys	120.320
2041-2070	MIROC5	1	85	Boys	145.955
2071-2100	BESM	1	85	Boys	115.824
2071-2100	CANESM2	1	85	Boys	113.875
2071-2100	HADGEM2-ES	1	85	Boys	112.860
2071-2100	MIROC5	1	85	Boys	141.642
2011-2040	BESM	0	45	Girls	-1.507
2011-2040	CANESM2	0	45	Girls	-7.147
2011-2040	HADGEM2-ES	0	45	Girls	-1.25
2011-2040	MIROC5	0	45	Girls	8.109
2041-2070	BESM	0	45	Girls	-5.44
2041-2070	CANESM2	0	45	Girls	-14.525
2041-2070	HADGEM2-ES	0	45	Girls	-6.138
2041-2070	MIROC5	0	45	Girls	9.278
2071-2100	BESM	0	45	Girls	-7.391
2071-2100	CANESM2	0	45	Girls	-18.903
2071-2100	HADGEM2-ES	0	45	Girls	-11.962
2071-2100	MIROC5	0	45	Girls	8.927
2011-2040	BESM	1	45	Girls	140.155
2011-2040	CANESM2	1	45	Girls	134.447
2011-2040	HADGEM2-ES	1	45	Girls	141.539
2011-2040	MIROC5	1	45	Girls	154.248
2041-2070	BESM	1	45	Girls	97.914
2041-2070	CANESM2	1	45	Girls	88.828
2041-2070	HADGEM2-ES	1	45	Girls	97.233
2041-2070	MIROC5	1	45	Girls	115.569
2071-2100	BESM	1	45	Girls	99.260
2071-2100	CANESM2	1	45	Girls	87.755
2071-2100	HADGEM2-ES	1	45	Girls	94.640
2071-2100	MIROC5	1	45	Girls	117.720
2011-2040	BESM	0	85	Girls	-2.654

2011-2040	CANESM2	0	85	Girls	-8.106
2011-2040	HADGEM2-ES	0	85	Girls	-6.634
2011-2040	MIROC5	0	85	Girls	8.053
2041-2070	BESM	0	85	Girls	-14.451
2041-2070	CANESM2	0	85	Girls	-21.641
2041-2070	HADGEM2-ES	0	85	Girls	-17.785
2041-2070	MIROC5	0	85	Girls	8.222
2071-2100	BESM	0	85	Girls	-26.608
2071-2100	CANESM2	0	85	Girls	-29.492
2071-2100	HADGEM2-ES	0	85	Girls	-30.479
2071-2100	MIROC5	0	85	Girls	2.286
2011-2040	BESM	1	85	Girls	138.818
2011-2040	CANESM2	1	85	Girls	133.446
2011-2040	HADGEM2-ES	1	85	Girls	135.951
2011-2040	MIROC5	1	85	Girls	154.204
2041-2070	BESM	1	85	Girls	88.734
2041-2070	CANESM2	1	85	Girls	81.597
2041-2070	HADGEM2-ES	1	85	Girls	85.465
2041-2070	MIROC5	1	85	Girls	113.260
2071-2100	BESM	1	85	Girls	79.924
2071-2100	CANESM2	1	85	Girls	77.065
2071-2100	HADGEM2-ES	1	85	Girls	76.048
2071-2100	MIROC5	1	85	Girls	109.176

Source: authors