Assessing developmental predictions of life history theory in psychology using census data

**ASSESSING DEVELOPMENTAL PREDICTIONS OF LIFE HISTORY THEORY IN PSYCHOLOGY USING CENSUS DATA**

**By VINICIUS BETZEL KOEHLER, M.Sc.**

**A Thesis Submitted to the School of Graduate Studies in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy (PhD)**

**McMaster University © Copyright by Vinicius B. Koehler, September 2025**

# Descriptive Note

McMaster University DOCTOR OF PHILOSOPHY (2025) Hamilton, Ontario

(Psychology, Neuroscience, and Behaviour)

TITLE: Assessing developmental predictions of life history theory in psychology using census data

AUTHOR: Vinicius Betzel Koehler, M.Sc. (Universidade Federal do Espírito Santo)

SUPERVISOR: Dr. M.D. Rutherford

PAGES: xx (total preliminary pages), 259 (total pages)

# Lay Abstract

Life history theory (LHT) is grounded in natural selection and evolution and predicts that one’s early environment can influence how one lives and reproduces. Evidence supporting this idea has been found in many species, including humans. LHT research in psychology explains why children who experience harsh and unpredictable environments, are, years later, more likely to reproduce earlier and more often than those who grew up in more bountiful and stable environments. Even though this relation is assumed to be a human adaptation, studies assessing this process in entire human populations are lacking. In this dissertation we assessed LHT using data from three countries (Brazil, US, and Canada) and five geographic levels (municipalities (Brazil), counties (US), dissemination areas, census divisions and provinces and territories (Canada)). Because this is a developmental phenomenon, we used a longitudinal approach: predictors and outcomes were separated by 10-15 years. We found that the predicted associations between harshness and reproduction patterns were strongest in Brazil in Canadian Indigenous populations, and that the proportion of visible minorities were also significant predictors of reproductive patterns in the US and Canada. This result may indicate that the associations predicted by LHT may be stronger in populations exposed to a greater range of harshness early in development.

# Abstract

Life history theory in psychology (LHT-P) posits that early harshness and unpredictability levels influence one’s life history strategy (LHS), a suit of traits and developmental milestones that can include reproduction, risky behaviour, aggression and violence, attachment, and more. Perhaps the strongest association studied is that proposed by psychosocial acceleration theory (PAT), which predicts that higher levels of harshness and unpredictability (especially father absence) is associated with earlier puberty and sexual debut, especially in females. However, recent criticisms have questioned whether LHS differs across humans, whether PAT’s assumptions are exaggerated, and whether any observed association is causal. Surprisingly, country-wide populational studies testing LHT-P and PAT’s assumptions, especially studies using longitudinal designs, are lacking. This dissertation used a mix of exploratory and confirmatory analytical approaches to determine if harshness and unpredictability early in life predict earlier and frequent reproduction using publicly available governmental data from the Brazilian Census, the American Community Survey, the Canadian Census and other Statistics Canada sources. We separated predictors and outcomes by 10 to 15 years across the different studies and tested models using cross-sectional and inverted timeline (i.e., harshness and unpredictability “predicting” earlier reproduction) methods. We used five geographic levels to assess predictions: Brazilian municipalities, US counties, and Canadian dissemination areas, census divisions, and provinces and territories. We also tested whether the proportion of visible minorities (i.e., Brazilian Black population, American Black and Hispanic or Latino population, and Canadian visible minorities and Indigenous population) are significant predictors of earlier and frequent reproduction. Results from Chapter 3 suggest that the proportion of the population that lacks resources, has bigger family sizes, and are young married mothers in Brazil predicted the proportion of young mothers and percentage of children 10 years later. We observed a similar finding in US counties data with a 14-year separation between predictors and outcomes. The percentage of Blacks in Brazil was not a significant predictor, but percentage of Blacks and of Hispanic or Latino in US populations was a negative and significant predictor of frequent reproduction. Chapter 4 showed that census divisions data yielded better results than dissemination areas, which indicates that geographical and populational stability results in a better model performance than larger sample sizes. The prevalence of children in low-income families and the percentage of children predict family size of one-parent families and more frequent reproduction 15 years later. However, contrary to LHT-P assumptions, higher unemployment and higher rents relative to income were predictive of *smaller* family size of one-parent families and *less frequent* reproduction. The proportion of Indigenous people was also predictive family size of one-parent families. The longitudinal model performed better than the model with reversed timeline. Results from Chapter 5 show that the interaction between the proportion of Indigenous people and the cost of living to income ratio was also predictive of earlier and more frequent reproduction in Canadian provinces and territories 15 years later, but the main effect of the proportion of Indigenous people was negatively associated with earlier and frequent reproduction. Overall, the analyses of population data support some assumptions of LHT-P and PAT literature, and suggest that visible minorities, especially in US and Canada, probably encounter sources of harshness and unpredictability that are generally not captured in LHT-P literature. Therefore, future studies could explore new measures of harshness and unpredictability to these different sources of environmental harshness and unpredictability to fully characterize environments experienced by visible minorities.

# Acknowledgements

It’s a unique feeling to be sitting by myself at the desk I spent the past four years at, looking back at it all. So many people, so many moments, and transformations. It has made me think about how much, whether intently or not, we change the lives of the people around us. You have definitely changed mine in ways I can’t express. Yet, here is my attempt.

Mel. Thank you for taking me in. Thank you for your guidance and support. It’s been five years, and I still can’t believe how fast and efficient you are in reading and editing, solving problems and giving me direction. Also, thank you for always giving me freedom to explore my interests and for believing in my ideas, even the failed ones! Thank you for properly introducing me to life history theory. I think I could truly keep working on it for life. For showing me that there is an evolutionary lens to developmental psychology. Thank you for being a good friend from the beginning. There are literally no words to express how much we’re thankful for your help in settling us in, during COVID and all. In this last leg, thank you for your patience and encouragement.

Pat and Paul, my supervisory committee. You have always been truly supportive and have always encouraged me to have a deeper understanding of the research. You played a key role in my formation during this doctorate. The way you shaped my comprehensive exam was one of those key moments. In doing that, you shaped the form of this dissertation. Throughout these years, you have raised my understanding of stats and of this research to a level that I didn’t think I would reach.

My lab friends. Victoria, the first person who made me feel welcomed and at home, even helping me settle in the new apartment and all. Hasan, thank you for all the laughs, for teaching me squash and for being a shining example in so many ways. Maheen, I totally resonate with the lab-twin vibe. Thanks for going through that with me, for the sharing of feelings, struggles and the kind of group therapy chats that we would go on time and again. Esin, thank you for your energy, for shared feelings and struggles, and for the fun. Catherine, thank you for your support and encouragement. You somehow knew when to give me some boosts in motivation in the moments I really needed them. To all of you, thank you for the true friendship and for creating the most fun, supportive and engaging work environment I have ever had. Mel, this is thanks to you, too. I hope we continue to be friends for life.

Xiaomei and Sonia were two post-docs who always encouraged me and believed in me and in my research, maybe more than I did at that time. Thank you for that! Sophia, this dissertation would not be happening if it weren’t for you, too. Thank you for the partnership, for being a model of dedication, hard work, passion, and efficiency. Above all, thank you for being a great friend.

I want to thank my cohort, especially Kiah and Maya, who truly helped me in the beginning. I will never forget stats! And also, Jamie and Max, who were friendly company throughout. To the undergrads I worked with. Thank you for the help, learning, and for accepting to work on this somewhat awkward, offbeat, project.

Friends outside the department. I want to thank Lucas. I don’t think I would be here if it weren’t for you. Thank you for being my partner through the whole process. From planning to apply to grad studies together to this day. Moving to a different country is always challenging. Moving with family during a global pandemic adds some extra spice. In this process, I want to thank Andre, the first friendly Brazilian face at McMaster who also helped a lot early on. Lisandra and Jefferson, partners in starting a Ph.D. at Mac, at moving during a pandemic, and now partners in parenting. Rhayner, thank you for being a true friend even thousands of miles apart and for giving me an occasional self-esteem boost. Ricardo, thank you also for being a friend and a partner at the end of this Ph.D. and for being a model of dedication, hard work and planning. Thank you all for the friendship.

I need to thank my sister, Kymberle (yeah, that’s the spelling). She has always had that kind of big brother admiration. Because of that, she has always encouraged me to meet such exaggerated expectations. She, however, was the one who encouraged me to pursue a graduate degree by pursuing hers. Thank you, sis. And my parents, who always valued education and sacrificed themselves to offer us better opportunities. They taught me the values I have and helped make me the person I am today. Thank you for always encouraging me in my endeavors – even the ones you didn’t agree with or understand.

Michelle, my life partner. You have been with me through all the ups and downs of this journey. All the struggles. You gave up everything you had in our home country to embark on this journey with me. You have always believed in it and believed in me; way more than I do. I love you and I cannot say how thankful I am to have you.

And João. Thank you for making me like developmental psychology. My experience as an undergrad certainly didn’t help with that. Thank you for being such a wonderful son and child. And now I’m so emotional that I can barely write. Thank you for being my great little partner. You brighten our days every day. You have given this journey, and my life, a whole new greater meaning.

You have all transformed a young little boy who would lie down on his sandy front yard to talk to the clouds into someone who is about to defend his Ph.D. in psychology. This achievement is just as much yours. Thank you.

# Table of Contents

[Descriptive Note ii](#_Toc209610099)

[Lay Abstract iii](#_Toc209610100)

[Abstract iv](#_Toc209610101)

[Acknowledgements vi](#_Toc209610102)

[Table of Contents ix](#_Toc209610103)

[List of Figures xv](#_Toc209610104)

[List of Tables xvi](#_Toc209610105)

[List of Abbreviations and Symbols xviii](#_Toc209610106)

[Declaration of Academic Achievement xx](#_Toc209610107)

[Chapter 1: Introduction 21](#_Toc209610108)

[Reproduction and fertility issues 21](#_Toc209610109)

[Explanations for fertility decline 22](#_Toc209610110)

[Life history theory 24](#_Toc209610111)

[The origins and principles of life history theory 24](#_Toc209610112)

[Fast-slow continuum 25](#_Toc209610113)

[Application to humans and the transition to psychology 26](#_Toc209610114)

[Developmental timing and interaction with other factors 27](#_Toc209610115)

[Challenges to LHT-P 29](#_Toc209610116)

[Populational studies 30](#_Toc209610117)

[Visible minorities 31](#_Toc209610118)

[The next chapter 33](#_Toc209610119)

[References 34](#_Toc209610120)

[Chapter 2: Secondary data processing and analysis 43](#_Toc209610121)

[Preface 43](#_Toc209610122)

[References 45](#_Toc209610123)

[Abstract 47](#_Toc209610124)

[Secondary and big data 48](#_Toc209610125)

[What is secondary and Big data? 48](#_Toc209610126)

[Advantages and challenges of using secondary data in psychology 49](#_Toc209610127)

[Census 51](#_Toc209610128)

[Methodological considerations and limitations of using Census data 51](#_Toc209610129)

[The empirical chapters 52](#_Toc209610130)

[Life history theory considerations 53](#_Toc209610131)

[Data processing 55](#_Toc209610132)

[Overview of each chapter 58](#_Toc209610133)

[References 61](#_Toc209610134)

[Chapter 3: Harshness predicts reproduction in Brazilian municipalities and US counties: a life history theory approach 80](#_Toc209610135)

[Preface 80](#_Toc209610136)

[References 83](#_Toc209610137)

[Abstract 86](#_Toc209610138)

[Introduction 87](#_Toc209610139)

[Young parenthood in Brazil 91](#_Toc209610140)

[Methods 91](#_Toc209610141)

[Data selection and transformation 91](#_Toc209610142)

[Partial Least Squares Structural Equation Modeling (PLS-SEM) 93](#_Toc209610143)

[Models 95](#_Toc209610144)

[Results 96](#_Toc209610145)

[Measurement model 97](#_Toc209610146)

[Reflective measurement model 97](#_Toc209610147)

[Formative measurement model 97](#_Toc209610148)

[Structural model 98](#_Toc209610149)

[Model comparisons 98](#_Toc209610150)

[Discussion 99](#_Toc209610151)

[Caveats 103](#_Toc209610152)

[Frequent Reproduction in the United States 108](#_Toc209610153)

[Methods 108](#_Toc209610154)

[Data selection and transformation 108](#_Toc209610155)

[Results 110](#_Toc209610156)

[Discussion 112](#_Toc209610157)

[General discussion 115](#_Toc209610158)

[Conclusion 121](#_Toc209610159)

[References 122](#_Toc209610160)

[Chapter 4: Proportion of young children, rates of indigeneity in the population, and socioeconomic factors predict reproduction frequency and single parenting 15 years later in Canadian census divisions 152](#_Toc209610161)

[Preface 152](#_Toc209610162)

[Abstract 155](#_Toc209610163)

[Introduction 156](#_Toc209610164)

[Life history theory 156](#_Toc209610165)

[Indigenous people and visible minorities in Canada 158](#_Toc209610166)

[Current study 159](#_Toc209610167)

[Methods 160](#_Toc209610168)

[Data selection and transformation 160](#_Toc209610169)

[Partial Least Squares Structural Equation Modeling (PLS-SEM) 161](#_Toc209610170)

[Model 162](#_Toc209610171)

[Study 4.1: Are Dissemination Areas or Census Divisions 163](#_Toc209610172)

[the best geographical level for analysis? 163](#_Toc209610173)

[Results 164](#_Toc209610174)

[Discussion 167](#_Toc209610175)

[Study 4.2: Is it a developmental phenomenon or just statistical artifacts? 168](#_Toc209610176)

[Method 169](#_Toc209610177)

[Results 169](#_Toc209610178)

[Discussion 171](#_Toc209610179)

[Study 4.3: Is there a sensitive period 172](#_Toc209610180)

[to experience harsh and unpredictable environments? 172](#_Toc209610181)

[Method 173](#_Toc209610182)

[Results 173](#_Toc209610183)

[Discussion 174](#_Toc209610184)

[Study 4.4: Do Indigenous people and visible minorities face different circumstances? 175](#_Toc209610185)

[Method 176](#_Toc209610186)

[Results 176](#_Toc209610187)

[Discussion 176](#_Toc209610188)

[General discussion 178](#_Toc209610189)

[Caveats 182](#_Toc209610190)

[Conclusion 183](#_Toc209610191)

[References 185](#_Toc209610192)

[Chapter 5: Proportion of Indigenous Populations Predicts Teen Pregnancy and Birth Rates Only When the Cost of Living is High 205](#_Toc209610193)

[Preface 205](#_Toc209610194)

[References 208](#_Toc209610195)

[Abstract 212](#_Toc209610196)

[Introduction 213](#_Toc209610197)

[Indigenous Populations in Canada 213](#_Toc209610198)

[Life history theory 215](#_Toc209610199)

[The current study 218](#_Toc209610200)

[Methods 219](#_Toc209610201)

[Data selection and transformation 219](#_Toc209610202)

[Analytical approach 220](#_Toc209610203)

[Results 222](#_Toc209610204)

[Discussion 224](#_Toc209610205)

[Limitations 225](#_Toc209610206)

[Conclusion 227](#_Toc209610207)

[References 228](#_Toc209610208)

[Chapter 6: General Discussion 241](#_Toc209610209)

[Findings in Brazil and in the US 242](#_Toc209610210)

[Findings in Canada 246](#_Toc209610211)

[Findings in Canada – Indigenous people 248](#_Toc209610212)

[Limitation and future directions 249](#_Toc209610213)

[Final conclusions 251](#_Toc209610214)

[References 253](#_Toc209610215)

# List of Figures

**Chapter 2**

Figure 1. Model predicting early reproduction in Brazil …………..………………………...79

**Chapter 3**

Figure 1. Model predicting early reproduction in Brazil …………..……………………….150

Figure 2. Model predicting early reproduction in Brazil excluding lack of resources…...…151

**Chapter 4**

Figure 1. Proportion of young children, rates of visible minorities in the population, and socioeconomic factors predict early reproduction in Canadian Census Divisions……....…202

Figure 2. Proportion of young children, rates of indigeneity in the population, and socioeconomic factors predict early reproduction in Canadian Dissemination Areas.......…203

Figure 3. Later harshness an unpredictability are poor predictors of previous measures of early reproduction.………………………………… …………………………………….…204

**Chapter 5**

Figure 1. When the cost of living is high, the proportion of indigeneity predicts birth rates…………………………………………………………………………………………240

# List of Tables

**Chapter 2**

Table 1. Variables fed into the first model of Chapter 2.……………………………….…....68

Table 2. Variables in the Model Using Brazilian Census and Similar Variables Using US American Community Survey.………………………………………………………….…....72

Table 3. Variables fed into the first models of Chapter 3...………………………...…….….76

**Chapter 3**

Table 1. Variables in the Brazilian model and inferred concepts..........................................133

Table 2. Assessment of Brazilian Formative latent variables ...............................................135

Table 3. Assessment of Brazilian Structural model……………………………………...…136

Table 4. Variables in the Model Using Brazilian Census and Similar Variables Using US American Community Survey………………………………………………………………137

Table 5. Variables predicting percent of 0 to 4-years olds in United States counties………141

Table 6. Variables predicting percent of 5 to 9-years olds in United States counties……....142

Table 7. Variables predicting percent of 15 to 19 Years of Age Who Had Given Birth…...143

Table 8. Multivariate Linear Regression Model of Women Who Had Given Birth in the Past 12 Months…………………………………………………………………………………...144

Table 9. Explanatory Power of the Four Models……………………………………….…..145

Table 10. Percent of Age Group - 0 to 4 Years of Age by Low, Medium, and High Tertile of Predictors………………………………………………………………………………..…..146

Table 11. Percent of Age Group - 5 to 9 Years of Age by Low, Medium, and High Tertile of Predictors……………………………………………………………………………….…...147

Table 12. Percent of Women 15 to 19 Years of Age Who Had Birth by Low, Medium, and High Tertile of Predictors……………………………………………………….…………..148

Table 13. Percent of Women Who Had Birth in the Past 12 Months by Low, Medium, and High Tertile of Predictors…………………………………………………………………...149

**Chapter 4**

Table 1. Variables fed into the first models in Study 1……………………………………..194

Table 2. Formative Latent Variables Assessment of Dissemination Areas Model in Study 1……………………………………………………………………………………………..197

Table 3. Structural Model Assessment in Study 1………………………………………….198

Table 4. Structural Model Assessment of the Tertiles of Children Aged 0-4 years in Study 3……………………………………………………………………………………………..199

Table 5. Structural Model Assessment of the Tertiles of Children Aged 5-9 years in Study 3……………………………………………………………………………………………..200

Table 6. Structural Model Assessment of the Tertiles of Visible Minorities in Study 4…...201

**Chapter 5**

Table 1. Proportion of Indigenous people is highly correlated with proportions of single-parent households and of violent crime, but not with cost of living.…………………….…237

Table 2. Longitudinal interaction between proportion of Indigenous people and cost of living predicts teenage pregnancy and birth rates better than cross-sectional interaction…………238

# List of Abbreviations and Symbols

ACE, Addictive genetic; shared environment, and non-shared environment modelling

ACS, American Community Survey

*Adj. R²*, adjusted R-squared

*α,* Cronbach’s alpha

ANOVA, analysis of variance

APGAR, Appearance, Pulse, Grimace, Activity, and Respiration test

API, Application Programming Interface

AVE, average variance extracted

*β,* standardized beta coefficients

CARE, Collective benefit, Authority to control, Responsibility, and Ethics

CB-SEM, covariance based structural equation modeling

CD, census division

CI, confidence interval

DA, dissemination area

*F,* F ratio

*f,* Cohen’s *f*

HTML, HyperText Markup Language

HTMT, Heterotrait-Monotrait Ratio

*λ*, factor loading

LHS, life history strategies

LHT, life history theory

LHT-E, life history theory in evolutionary biology and behavioural ecology

LHT-P, life history theory in evolutionary psychology

LM, linear model

M, mean

MAE, mean absolute error

N, number of participants, number of variables

NA, not applicable, not available, not assessed, or no answer

OCAP®, Ownership, Control, Access, and Possession

OSF, the open science framework

*p,* p value

PAT, psychosocial acceleration theory

PLS-SEM, partial least squares structural equation modeling

R, programming language

*r,* correlation coefficient

RMSE, root mean square error

*ρC,* composite reliability

*ρA,* reliability coefficient

SD, standard deviation

SE, standard error

SIDRA, Sistema IBGE de Recuperação Automática

SP, São Paulo

*t,* t-statistics

US, United States of America

VIF, variance inflation factor

WEIRD, Western, Educated, Industrialized, Rich and Democratic

*z,* z-score

# Declaration of Academic Achievement

Chapter 3: Dr. M.D. Rutherford and I designed the study. I collected the data. I conducted the analyses. I created all figures and prepared the manuscript for publication, which was edited by Dr. M.D. Rutherford.

Chapter 4: Dr. M.D. Rutherford and I designed the study. I collected the data. I conducted the analyses. I created all figures and prepared the manuscript for publication, which was edited by Dr. M.D. Rutherford.

Chapter 5: Dr. Sophia Melanson Ricciardone, Dr. M.D. Rutherford and I designed the study. Dr. Sophia Melanson Ricciardone collected the data. I conducted the analyses. Dr. Sophia Melanson Ricciardone and I collaborated on all figures and preparation of the manuscript for publication, which was edited by Dr. M.D. Rutherford.

# Chapter 1: Introduction

## Reproduction and fertility issues

Reproduction is an essential function of all living organisms. To be adapted to the environment, all species must survive and reproduce (Buss, 2024; Darwin, 1859). Reproducing does not come without risks and costs, though. For humans, reproduction usually means many years of investment in raising offspring. In addition, there are several biological and health risks associated with reproduction, especially for females.

Early and frequent reproducing is associated with risks for both the mother and the offspring. The risks of teenage pregnancy include maternal anemia, eclampsia, postpartum depression among the risks for the mother and low birth weight, respiratory distress syndrome and autism as the risks for the children of teenage mothers (Jeha et al., 2015). These risks have been identified in both developing and developed countries. Assessing 932 births from teenage mothers in a hospital in Ethiopia, Abebe and colleagues (2020) found that teenage mothers were more likely to give birth to low birth weight, to give birth prematurely and with adverse obstetric and perinatal outcomes than adult mothers. In Canada, a rich and developed country, a study with 1080 teenage pregnant women found that they were more likely to have depression and use substances than adult pregnant women (Wong et al., 2020). Another study tracking more than 2 million teenage females in Ontario for 20 years found that teenage pregnancies was associated with premature death of the mother, with risk increasing for those with more than one pregnancy (Ray et al., 2024).

Multiparity has also been associated with higher risks for the mother and the child such as more obstetric complications and higher morbidity and mortality (Bai et al., 2002). Shorter inter-birth intervals also are associated with unhealthy and risky outcomes low-birth weight, preterm birth, low APGAR score and maternal anemia (Beyene et al., 2025). Using data from the US National Survey of Family Growth, Gemmill and Lindberg (2013) found that females aged 15-19 years old was one of the groups that were more likely to have a short interpregnancy interval.

On the other hand, a lack of reproduction, aside from not meeting the adaptedness aspect as mentioned above, has profound societal aspects. A global decline in fertility rate (Roser, 2014) has been associated with future societal problems. Lower fertility means a transition in the demographic pyramid which results in an increase of the average age of the population. It has been hypothesized that low fertility rates and population aging will result in a reduction in available labor, economic stagnation and strain on pensions, and healthcare and emergency systems (Aitken, 2024; Ha, 2025). Addressing population fertility rates and creating public policies for reproduction have been of increasing governmental concern (Stone & Wingerter, 2024).

## Explanations for fertility decline

Many factors have been proposed to influence pregnancy and fertility rates. These include equitable access to resources, reductions in child mortality, institutional support parents and youth, socialization and cultural factors. Perhaps the most common explanation for the decline in global fertility in the second half of the of the 20th century is the increased access of females to education, employment and health care (Aitken, 2024; Roser, 2014). As females have more equitable access to socioeconomic means and health care and medicine, they are more in control of their reproduction (e.g., use of contraceptives) and have the choice of whether to invest in having and raising children or to delay reproduction and invest in their education and career.

Another related explanation for reduced fertility is the decline in infant and child mortality (Aitken, 2024; Roser, 2014). As couples become more certain that their child will live until adulthood, there is less incentive to having multiple children. Advances in nutrition and in access to primary health care (e.g., vaccines) have resulted in infant mortality reduction. This increased survival certainty, associated with urbanization (Aitken, 2024), increases the costs of life and of raising children, further reducing incentives to having children.

All of these factors – urbanization, greater access and more years of education, higher costs of living – also result in delays in marriage and family formation (Aitken, 2024; Roser, 2014; Stone & Wingerter, 2024), which shortens the reproductive window, especially for females. A report about fertility in Southern Europe has identified that among married couples, fertility has become quite stable (Stone & Wingerter, 2024). There has been, however, a postponing of marriage until a later age, and this delay explains in great part the fertility decline. France has been an exception among these countries and its policies towards tax benefits, maternity leaves and other governmental support were attributed to be reasons for its comparatively higher fertility.

Institutional support then, is another explanation for when and how often people have children (Stone & Wingerter, 2024; Wodtke, 2013). The lack of affordable childcare, parental leave, or work flexibility have been proposed as reasons for reduced fertility (Ha, 2025). On the other hand, poor institutional support also has been suggested as an explanation for increased or earlier reproduction. On a smaller scale, residents of socially isolated neighbourhoods and communities that lack good schools, recreational facilities, childcare and after-school programs have earlier and, often unwanted, pregnancies (Wilson, 1987; Wodtke, 2013). In these impoverished communities, unstable employment conditions may reduce parents’ availability and monitoring on early or unsafe sexual activity. Economic hardship can also increase fatalism, which reduces the perceived costs of having children. Over time, peer group socialization and a local culture can normalize or even incentivize early parenting.

## Life history theory

Life history theory (LHT) offers a framework for explaining when and how often people have children. The theory posits that resources invested in one function (e.g., reproduction) cannot be invested in other functions (e.g., acquiring food). The environment cues organisms to select a pattern of investments – both the amount and timing – that is most adaptive (Del Giudice et al., 2015; Ellis et al., 2009).

### The origins and principles of life history theory

LHT originated from evolutionary biology, and it was first used to explain differences between species (Stearns, 1992). Its tenets say that: 1. resources are limited; 2. species need to trade-off resources allocation to different areas; 3. the environment selects (and cue species) optimal resource allocations (Del Giudice et al., 2015). Energy and time are limited resources. Investing them in parenting (e.g., feeding, monitoring) reduces availability for other functions like foraging, mating, or somatic growth (Del Giudice et al., 2015; Ellis et al., 2009).

Environmental characteristics select for different resource allocations. Population density and environmental harshness and unpredictability have been hypothesized to be particularly important for determining which pattern of resource allocation is most adaptive. In environments where there is a high level or mortality due to predation, lack of resources, or disease, an organism is unlikely to survive for an extended period of time, so it may not have an opportunity to reproduce in the future. Therefore, it would be more advantageous for species in this niche to reach sexual maturity fast, reproduce fast and early, and not invest much in any particular offspring (Ellis et al., 2009; Griskevicius et al., 2011). This strategy would result in better chances of reproduction and the spread of genes that, even in the event of high mortality, some of the offspring would survive and reproduce.

LHT also predicts that unpredictable environments with high fluctuations of sources of morbidity and mortality should be associated with faster sexual maturity. By contrast, resource-rich and stable environments should be associated with slower sexual maturity. Where organisms can be more certain of their chances of survival and future reproduction, acquiring resources and investing more in growth and body maintenance (e.g., calories, body size, status) for an extended period would be an optimal strategy. At a later age, these resources can be invested in generating fewer and higher *quality* offspring that can outcompete others. This suite of adaptive changes that covary depending on the environment has been coined life history strategies (LHS; Del Giudice et al., 2015; Ellis et al., 2009).

### Fast-slow continuum

Earlier workers on these different strategies originated in biology the *r* and *K* selection. strategies (Stearns, 1992). Placing species along a continuum depending on the rate and timing of their investments in earlier and faster reproduction or in body maintenance and growth would result in a *continuum* (Belsky et al., 2012; Ellis et al., 2009; Hartman et al., 2018). Classical examples of species near the *r* and *K* poles of the continuum are the mouse and the elephant, respectively (Griskevicius et al., 2011; Sear, 2020). Mice, which are *r-strategists*, do not grow much, develop and reach puberty quickly, and have large litters with short inter-litter intervals. Elephants, *K-strategists*, grow to a far greater body size over several years, a process that requires more calories. They also, reproduce later, and give birth to one calf that requires considerable investment from its parents. LHS attributes the differences between the developmental and reproductive behaviours of mice and elephants to differences in the harshness and unpredictability of the environments experienced by these two species (Stearns, 1992). Higher populational density is another variable that would usually favour the slower LHS because it would help offspring in outcompeting conspecifics (Ellis et al., 2009).

Even though the theory was developed to explain between-species variation, it has also been applied to within-species variation. Environmental change can, to a smaller degree, shift resource allocation and timing of growth and reproduction in bacteria (Stone et al., 2023), fish (Malone et al., 2022), and reptiles, birds and mammals (Albaladejo‐Robles et al., 2023). Unsurprisingly, it has also been applied to humans (Webster et al., 2014; Xu et al., 2018).

### Application to humans and the transition to psychology

This notion of the environment shaping and selecting for species different investments and reproduction timing were adapted to psychology. In doing so, it became much more focused on within-species variation, which obviously claimed for species plasticity in reacting to the environment. Chisholm and colleagues (1993) argued that early environmental adversity (e.g., lack of resources or marital discord) can result in inadequate child rearing by the parents, which results insecure or avoidant attachment. This process would later on manifest in an early somatic maturation (e.g., early puberty) and earlier reproductive strategy with reduced investment in offspring that is comparable the *r-strategy*. On the other hand, individuals raised in more resource rich and stable environments would develop with the opposite development characteristics: secure attachment, later puberty and reproduction and more investment in offspring. The field in psychology started to refer to these developmental paths as the *fast-slow LHS continuum*. This rationale has been supported by other researchers (see Del Giudice & Belsky, 2010). This line of research resulted in two related fields of study, one in evolutionary biology and behavioural ecology (LHT-E) and the other in evolutionary psychology (LHT-P; Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Sear, 2020). Among LHT-P, a great deal of attention has been given to psychosocial acceleration theory (PAT), which posits that early environmental adversity can alter the onset of puberty (most studies measure time of menarche), and other developmental milestones such as sexual debut and the age of having children (Belsky et al., 1991; Ellis, 2004).

A considerable amount of these psychological studies have focused on how environmental harshness and unpredictability is related to faster or earlier reproductive markers (Webster et al., 2014), but applications of LHT-P also have examined associations with other outcome variables such as attachment styles (Del Giudice, 2009; Del Giudice & Belsky, 2010), risk and aggressiveness (Ellis et al., 2021; Lu & Chang, 2019), and academic achievement (Chang et al., 2019). Harshness is usually assessed through socioeconomic status (Copping et al., 2013; Ellis et al., 2009). Unpredictability is a much harder concept to measure (Young et al., 2020) because a core assumption is that the individual should not able to anticipate the environmental change that occurred. Nevertheless, a considerable amount of the literature has been using parental transitions (i.e., changes in family configuration such as in divorce and remarriage), parental availability or parental employment change and residential changes as measures of unpredictability (Belsky et al., 1991, 2012; Chang et al., 2019; Copping et al., 2013; Doom et al., 2016; Ellis et al., 2003; Hartman et al., 2018; Lu & Chang, 2019; Nolin & Ziker, 2016; Simpson et al., 2012; Webster et al., 2014). Father absence has been found to be one of the strongest predictors of faster LHS (Ellis et al., 2003; Hartman et al., 2018; Webster et al., 2014).

### Developmental timing and interaction with other factors

It is worth noting that this association between the environment and reproduction is a developmental phenomenon. Early exposure to different levels of harshness and unpredictability would cue individuals into shifting a suite of traits that develop over one’s life course. Therefore, a key assumption of this theory is that there is a particular time of environmental exposure that would create such tendency. Findings in LHT-P suggest that the first 5 years of life (Copping et al., 2013; Doom et al., 2016; Ellis et al., 2003; Simpson et al., 2012; Szepsenwol et al., 2019) or the first 7 years of life are the most critical for shaping LHS (Belsky et al., 1991; Del Giudice et al., 2015; Nettle & Frankenhuis, 2020).

It also is worth noting that LHT-P and the other explanations of these developmental phenomena are not mutually exclusive. More access to health care, standardized education, and nutrition, which ultimately decrease infant and child mortality, could represent a reduction in environmental harshness and unpredictability. Furthermore, applications of LHT-P must deal with the fact that the contemporary environment certainly is dissimilar from our environment of evolutionary adaptedness. This is particularly true in developed countries, where individuals face smaller threats with regard to predation, death and disease, and where most of LHT-P studies have been conducted (Sear, 2020; Volk, 2023; Webster et al., 2014).

Insufficient institutional support could also mean elevated levels of harshness and unpredictability, which would cue individuals into a faster LHS. This effect can become even more salient if these poorly serviced neighborhoods experience more violence, mortality or homicide (Griskevicius et al., 2011; Wilson & Daly, 1997). In addition, a cyclical component has been hypothesized in which father absence creates the expectation in the children that relationships do not last (and consequently investment in offspring), which in turn could cue these children into seeking short-term relationships and lower investments in offspring later in life (Del Giudice et al., 2015; Stearns, 1992; Volk, 2023). This cyclical effect could have some similarity or some influence in the emergence of a local culture in which short-term relationships, earlier or more frequent reproduction are more accepted or supported.

### Challenges to LHT-P

Recent critiques of LHT-P and PAT center on their conceptual drift from evolutionary biology and the limited empirical support for key assumptions. Perhaps the strongest of such criticisms is its departure from its parent theory in biology (Nettle & Frankenhuis, 2020; Sear, 2020; Stearns & Rodrigues, 2020). For example, the fast-slow continuum, as a suite of covarying trait, has been rejected by LHT-E and replaced by research in which traits adaptability to the environment have been measured more independently. LHT-E research often uses more formal models which tend to make more explicit assumptions and to quantify trade-offs and how these trade-offs impact fitness in different conditions (Sear, 2020; Stearns & Rodrigues, 2020). These models – more similarly to current LHT-P – also tend to use many variables and track their complex interactions. These differences resulted in some conceptual divergences and inconsistencies between the two theories.

The hypothesized causal relationship between harshness and unpredictability to early puberty and to earlier and frequent reproduction has also been under scrutiny (Frankenhuis & Nettle, 2020; Richardson et al., 2024). A meta-analysis by Webster and colleagues (2014) found that the association between father absence and menarche was smaller in studies with bigger samples. Richardson and colleagues (2024) used ACE modeling and found little evidence for a causal link between early adversity and reproductive timing, suggesting that prior associations may reflect genetic and shared environmental confounds.

The definition of the variables involved in LHS change lacks specificity. Harshness has been defined as the level of death and disease outside of one’s control (Ellis et al., 2009), but usually it is measured using socioeconomic indicators; however, how much low socioeconomic status correlates with higher extrinsic death and disease levels is debatable (Stearns & Rodrigues, 2020; Volk, 2023, 2025). Unpredictability refers to the stochastic variation of harshness, but it also remains poorly defined, with debates over whether it reflects sudden changes, increased variance, or shifts in autocorrelation with harshness (Young et al., 2020). The literature has also not yet explored the effects of an increase of unpredictability that is coupled with a decrease of harshness (e.g., changes of residence and of parental availability due to parents’ better employment conditions; migration to more favourable conditions).

Critics also argue that PAT claims (e.g., the *fast-slow continuum* as a suit of traits) are over generalized (Richardson et al., 2024; Volk, 2025) and that using the fast-slow LHS continuum as a construct is predictive of little actual behaviour (Frankenhuis & Nettle, 2020; Stearns & Rodrigues, 2020). In sum, LHT-P and PAT proponents have been called to considerably revise the theory’s assumptions, become stricter in its use and predictions and to move back towards its parent in evolutionary biology and behavioural ecology.

## Populational studies

Originally developed to explain variation across species, LHT, especially LHT-P, has since been applied to individual-level differences. However, most LHT-P studies rely on cross-sectional data from Western populations, limiting their ability to test developmental predictions (Chang et al., 2019; Sear, 2020; Webster et al., 2014). Using a cross-sectional design to investigate a developmental phenomenon requires one to either ask participants to generate retrospective reports or to describe their expectations of future events. Retrospective reports can be affected by memory retrieval processes and presentation bias (Richardson et al., 2024), while the latter method, aside from presentation bias, is susceptible to many sorts of noise. Longitudinal studies have mostly focused on qualitative associations instead of testing predictions based in more formal models (Stearns & Rodrigues, 2020). Many also rely on a few long-term longitudinal studies, which means that many results are based on the same data sources (Young et al., 2020).

Several studies have tested LHT-P or PAT assumptions with populational data (e.g., Copping et al., 2013; Copping & Campbell, 2015; Wilson & Daly, 1997) or very large, cross-sectional samples (e.g., Chang et al., 2019; Richardson et al., 2024). The use of governmental data, and especially of census data, may be a great source to test such predictions (Copping, 2017), so the lack of studies using such data is surprising. To date, no study has used longitudinal, population-wide data to test whether early environmental harshness and unpredictability predict reproductive outcomes. This dissertation addresses that gap by analyzing census and governmental data from Brazil, the U.S., and Canada. Across three empirical studies, we examine whether early-life conditions forecast reproductive patterns, assess the suitability of this method for LHT-P research, and identify predictive variables across contexts. For the purposes of this dissertation, we are using concepts of harshness and unpredictability as they are usually measured in LHT-P. Harshness will be understood as having lower socioeconomic status and reduced access to resources, whereas unpredictability will be understood as having fluctuations of parental availability, of parental employment and geographical moves. Because we expect that children will be mostly affected by these environmental conditions, we will also use the proportion of children as a measure.

## Visible minorities

Visible minorities are usually exposed to particularly harsh and unpredictable environments. For example, Brazil has a long history of slavery and racism that exist to this day (Pimentel, 2022). Black people in Brazil have unequal access to education, health care (IBGE (Instituto Brasileiro de Geografia e Estatística), 2022), employment and income than other groups. They are also more likely to be victims of homicide and most of these victims are young men (Cerqueira & Bueno, 2024). Similarly in the US, another country with a long history of slavery and discrimination, Black people are more likely than other ethnical groups to be in disadvantageous neighbourhood and unequally exposed to crime (Browning et al., 2017). They are more likely to experience food insecurity and discrimination in access to health care (Bleich et al., 2019). Indigenous people, another visible minority in Canada, also have long history of repression, confinement of its culture and ways of living (Neu & Graham, 2006; Romaniuk, 2008). In 2021, the homicide rates of Indigenous victims was six times than that of non-Indigenous victims in Canada (David & Jaffray, 2022).

Following LHT-P rationale, it would be reasonable to assume that these especially harsh and unpredictable circumstances could also interact with common measures of harshness and unpredictability (i.e., socioeconomic status and parental transitions) and affect reproduction patterns. Supporting this argument, Indigenous people in Canada are younger and faster growing than non-Indigenous people (Government of Canada, 2022), which maybe indicate more frequent reproduction. Teenage pregnancy is also disproportionately high among Indigenous people in comparison to non-Indigenous populations (Reading & Wien, 2009; Sheppard et al., 2017). Black women also have higher fertility rates than non-Black women in the US (Pew Research Center, 2015).

We hypothesized that visible minorities populations are likely to be exposed to especially harsh and unpredictable environments from early childhood and that these circumstances can affect their reproductive trajectory. Because of that, we are also using the proportion of visible minorities as a predictor of reproductive outcomes throughout this dissertation.

## The next chapter

The next chapter discusses several characteristics of secondary data research, its advantages and potential challenges. We end the next chapter with an overview of the empirical studies in this dissertation. The three empirical studies use data from three countries (Brazil, US and Canada) in different geographical levels and different year ranges. We primarily explore if harshness and unpredictability measures in one year can predict future reproduction indicators. In doing so, we assess: 1. If this method is suitable to LHT-P research; 2- Which variables will be predictive of reproductive patterns in these different countries; and 3- If this developmental phenomenon shows in populational data. We hope that these studies can inform LHT-P and PAT proponents to move towards more specific and formal models that can be tested with more confirmatory approaches and individual level data.

## References

Abebe, A. M., Fitie, G. W., Jember, D. A., Reda, M. M., & Wake, G. E. (2020). Teenage Pregnancy and Its Adverse Obstetric and Perinatal Outcomes at Lemlem Karl Hospital, Tigray, Ethiopia, 2018. *BioMed Research International*, *2020*, 1–8. https://doi.org/10.1155/2020/3124847

Aitken, R. J. (2024). Population decline: Where demography, social science, and biology intersect. *Reproduction*, *168*(1), e240070. https://doi.org/10.1530/REP-24-0070

Albaladejo‐Robles, G., Böhm, M., & Newbold, T. (2023). Species life‐history strategies affect population responses to temperature and land‐cover changes. *Global Change Biology*, *29*(1), 97–109. https://doi.org/10.1111/gcb.16454

Bai, J., Wong, F. W. S., Bauman, A., & Mohsin, M. (2002). Parity and pregnancy outcomes. *American Journal of Obstetrics and Gynecology*, *186*(2), 274–278. https://doi.org/10.1067/mob.2002.119639

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Belsky, J., Steinberg, L., & Draper, P. (1991). Childhood Experience, Interpersonal Development, and Reproductive Strategy: An Evolutionary Theory of Socialization. *Child Development*, *62*(4), 647–670. https://doi.org/10.1111/j.1467-8624.1991.tb01558.x

Beyene, F. Y., Wudineh, K. G., Bantie, S. A., & Tesfu, A. A. (2025). Effect of short inter-pregnancy interval on perinatal and maternal outcomes among pregnant women in SSA 2023: Systematic review and meta-analysis. *PLOS ONE*, *20*(1), e0294747. https://doi.org/10.1371/journal.pone.0294747

Bleich, S. N., Findling, M. G., Casey, L. S., Blendon, R. J., Benson, J. M., SteelFisher, G. K., Sayde, J. M., & Miller, C. (2019). Discrimination in the United States: Experiences of black Americans. Health Services Research, 54(S2), 1399–1408. https://doi.org/10.1111/1475-6773.13220

Browning, C. R., Calder, C. A., Ford, J. L., Boettner, B., Smith, A. L., & Haynie, D. (2017). Understanding Racial Differences in Exposure to Violent Areas: Integrating Survey, Smartphone, and Administrative Data Resources. The ANNALS of the American Academy of Political and Social Science, 669(1), 41–62. https://doi.org/10.1177/0002716216678167

Buss, D. M. (2024). *Evolutionary psychology: The new science of the mind* (Seventh edition). Routledge.

Cerqueira, D., & Bueno, S. (2024). Atlas da violência 2024. Ipea; FBSP.

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. *Developmental Psychology*, *55*(4), 890–903. https://doi.org/10.1037/dev0000655

Chisholm, J. S., Ellison, P. T., Evans, J., Lee, P. C., Lieberman, L. S., Pavlik, Z., Ryan, A. S., Salter, E. M., Stini, W. A., & Worthman, C. M. (1993). Death, Hope, and Sex: Life-History Theory and the Development of Reproductive Strategies [and Comments and Reply]. Current Anthropology, 34(1), 1–24. https://doi.org/10.1086/204131

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), *Encyclopedia of Evolutionary Psychological Science* (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Copping, L. T., & Campbell, A. (2015). The environment and life history strategies: Neighborhood and individual-level models. *Evolution and Human Behavior*, *36*(3), 182–190. https://doi.org/10.1016/j.evolhumbehav.2014.10.005

Copping, L. T., Campbell, A., & Muncer, S. (2013). Violence, teenage pregnancy, and life history: Ecological factors and their impact on strategy-driven behavior. *Human Nature (Hawthorne, N.Y.)*, *24*(2), 137–157. https://doi.org/10.1007/s12110-013-9163-2

Darwin, C. (1859). *On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life*. John Murray.

David, J.-D., & Jaffray, B. (2022). Homicide in Canada, 2021. Juristat, 85-002–X(1209–6393).

Del Giudice, M. (2009). Sex, attachment, and the development of reproductive strategies. *Behavioral and Brain Sciences*, *32*(1), 1–21. https://doi.org/10.1017/S0140525X09000016

Del Giudice, M., & Belsky, J. (2010). The Development of Life History Strategies: Toward a Multi-Stage Theory. In D. M. Buss & P. H. Hawley (Eds.), *The Evolution of Personality and Individual Differences* (pp. 154–176). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195372090.003.0006

Del Giudice, M., Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), *The Handbook of Evolutionary Psychology* (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

Doom, J. R., Vanzomeren-Dohm, A. A., & Simpson, J. A. (2016). Early unpredictability predicts increased adolescent externalizing behaviors and substance use: A life history perspective. *Development and Psychopathology*, *28*(4pt2), 1505–1516. https://doi.org/10.1017/S0954579415001169

Ellis, B. J. (2004). Timing of Pubertal Maturation in Girls: An Integrated Life History Approach. *Psychological Bulletin*, *130*(6), 920–958. https://doi.org/10.1037/0033-2909.130.6.920

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? *Child Development*, *74*(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Ellis, B. J., Shakiba, N., Adkins, D. E., & Lester, B. M. (2021). Early external‐environmental and internal‐health predictors of risky sexual and aggressive behavior in adolescence: An integrative approach. *Developmental Psychobiology*, *63*(3), 556–571. https://doi.org/10.1002/dev.22029

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. *Evolution and Human Behavior*, *41*(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Gemmill, A., & Lindberg, L. D. (2013). Short Interpregnancy Intervals in the United States. *Obstetrics & Gynecology*, *122*(1), 64–71. https://doi.org/10.1097/AOG.0b013e3182955e58

Government of Canada. (2022). The Daily—Indigenous population continues to grow and is much younger than the non-Indigenous population, although the pace of growth has slowed. https://www150.statcan.gc.ca/n1/daily-quotidien/220921/dq220921a-eng.htm

Griskevicius, V., Delton, A. W., Robertson, T. E., & Tybur, J. M. (2011). Environmental contingency in life history strategies: The influence of mortality and socioeconomic status on reproductive timing. *Journal of Personality and Social Psychology*, *100*(2), 241–254. https://doi.org/10.1037/a0021082

Ha, K.-M. (2025). Population decline, political economy, and emergency management—Qualitative descriptive research. *Humanities and Social Sciences Communications*, *12*(1), 541. https://doi.org/10.1057/s41599-025-04868-y

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

IBGE (Instituto Brasileiro de Geografia e Estatística). (2022). Desigualdades sociais por cor ou raça no Brasil (2nd ed.). IBGE.

Jeha, D., Usta, I., Ghulmiyyah, L., & Nassar, A. (2015). A review of the risks and consequences of adolescent pregnancy. *Journal of Neonatal-Perinatal Medicine*, *8*(1), 1–8. https://doi.org/10.3233/NPM-15814038

Lu, H. J., & Chang, L. (2019). Aggression and risk‐taking as adaptive implementations of fast life history strategy. *Developmental Science*, e12827. https://doi.org/10.1111/desc.12827

Malone, E. W., Perkin, J. S., Keith Gibbs, W., Padgett, M., Kulp, M., & Moore, S. E. (2022). High and dry in days gone by: Life‐history theory predicts Appalachian mountain stream fish assemblage transformation during historical drought. *Ecology of Freshwater Fish*, *31*(1), 29–44. https://doi.org/10.1111/eff.12606

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Nolin, D. A., & Ziker, J. P. (2016). Reproductive Responses to Economic Uncertainty: Fertility Decline in Post-Soviet Ust’-Avam, Siberia. *Human Nature*, *27*(4), 351–371. https://doi.org/10.1007/s12110-016-9267-6

Pew Research Center. (2015). Childlessness Falls, Family Size Grows Among Highly Educated Women [Report]. Pew Research Center. https://www.pewresearch.org/social-trends/2015/05/07/family-size-among-mothers/

Pimentel, R. (2022). “Equal Before the Law,” But Not in Practice: Brazil’s Social Inequality Crisis—Harvard Political Review. https://harvardpolitics.com/brazil-social-inequality/

Ray, J. G., Fu, L., Austin, P. C., Park, A. L., Brown, H. K., Grandi, S. M., Vandermorris, A., Boblitz, A., & Cohen, E. (2024). Teen Pregnancy and Risk of Premature Mortality. *JAMA Network Open*, *7*(3), e241833–e241833. https://doi.org/10.1001/jamanetworkopen.2024.1833

Richardson, G. B., Bates, D., Ross, A., Liu, H., & Boutwell, B. B. (2024). Is reproductive development adaptively calibrated to early experience? Evidence from a national sample of females. *Developmental Psychology*, *60*(2), 306–321. https://doi.org/10.1037/dev0001681

Roser, M. (2014). The global decline of the fertility rate. *Our World in Data*.

Sear, R. (2020). Do human ‘life history strategies’ exist? *Evolution and Human Behavior*, *41*(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Sheppard, A. J., Shapiro, G. D., Bushnik, T., Wilkins, R., Perry, S., Kaufman, J. S., Kramer, M. S., & Yang, S. (2017). Birth outcomes among First Nations, Inuit and Métis populations. Health Reports, 28(11), 11–16.

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. *Developmental Psychology*, *48*(3), 674–686. https://doi.org/10.1037/a0027293

Stearns, S. C. (1992). *The evolution of life histories*. Oxford University Press.

Stearns, S. C., & Rodrigues, A. M. M. (2020). On the use of “life history theory” in evolutionary psychology. *Evolution and Human Behavior*, *41*(6), 474–485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Stone, B. W. G., Dijkstra, P., Finley, B. K., Fitzpatrick, R., Foley, M. M., Hayer, M., Hofmockel, K. S., Koch, B. J., Li, J., Liu, X. J. A., Martinez, A., Mau, R. L., Marks, J., Monsaint-Queeney, V., Morrissey, E. M., Propster, J., Pett-Ridge, J., Purcell, A. M., Schwartz, E., & Hungate, B. A. (2023). Life history strategies among soil bacteria—Dichotomy for few, continuum for many. *The ISME Journal*, *17*(4), 611–619. https://doi.org/10.1038/s41396-022-01354-0

Stone, L., & Wingerter, E. (2024). *Is There Hope for Low Fertility? “Demographic Rearmament” in Southern Europe*.

Szepsenwol, O., Zamir, O., & Simpson, J. A. (2019). The effect of early-life harshness and unpredictability on intimate partner violence in adulthood: A life history perspective. *Journal of Social and Personal Relationships*, *36*(5), 1542–1556. https://doi.org/10.1177/0265407518806680

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. *Evolution and Human Behavior*, *44*(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Volk, A. A. (2025). Pumping the Brakes on Psychosocial Acceleration Theory: Revisiting its Underlying Assumptions. *Evolution and Human Behavior*, *46*(1), 106657. https://doi.org/10.1016/j.evolhumbehav.2025.106657

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. *Evolutionary Psychology*, *12*(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. *BMJ*, *314*(7089), 1271–1271. https://doi.org/10.1136/bmj.314.7089.1271

Wilson, W. J. (1987). *The truly disadvantaged: The inner city, the underclass, and public policy*. University of Chicago press.

Wodtke, G. T. (2013). Duration and timing of exposure to neighborhood poverty and the risk of adolescent parenthood. *Demography*, *50*(5), 1765–1788. https://doi.org/10.1007/s13524-013-0219-z

Wong, S. P. W., Twynstra, J., Gilliland, J. A., Cook, J. L., & Seabrook, J. A. (2020). Risk Factors and Birth Outcomes Associated with Teenage Pregnancy: A Canadian Sample. *Journal of Pediatric and Adolescent Gynecology*, *33*(2), 153–159. https://doi.org/10.1016/j.jpag.2019.10.006

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. *Evolution and Human Behavior*, *39*(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005

Young, E. S., Frankenhuis, W. E., & Ellis, B. J. (2020). Theory and measurement of environmental unpredictability. *Evolution and Human Behavior*, *41*(6), 550–556. https://doi.org/10.1016/j.evolhumbehav.2020.08.006

# Chapter 2: Secondary data processing and analysis

## Preface

Large secondary data sets are available at unprecedented scales. Increased use of such data could inform and complement more traditional methods in psychology (Andersen et al., 2011; Johnston, 2017; Trzesniewski et al., 2011). These large data sets may have higher ecological validity (Andersen et al., 2011; Jones, 2010; Kievit et al., 2022) than data sets collected in traditional, lab-based research. For example, secondary data can be more diverse and representative of a population than samples of undergraduate students from Western and developed countries that are common in Psychology experiments (Henrich et al., 2010). In addition, many secondary datasets are offered periodically (e.g., annual governmental surveys or daily posts on social media), which make them useful for studying longitudinal phenomena and to conduct replications.

There are, nonetheless, several constraints that arise when using secondary data sets. The most obvious one is that the researcher must work with the data that is available: there is no possibility of tailoring measures to fit a research question (Andersen et al., 2011; Johnston, 2017). Another inherent limitation is that it is non-experimental, therefore it makes it difficult to infer causality (Weston et al., 2019). Other limitations and criticisms include the reduced control over data collection, which can create inconsistencies such as missing data or noise (Trzesniewski et al., 2011; Weston et al., 2019), and data complexity, which usually necessitates substantial data wrangling and complex methods of analysis (Chen et al., 2020; Drovandi et al., 2017; Walkup & Yanos, 2005).

This chapter describes the processes used to select, process and analyze Census data to test life history theory predictions (Belsky et al., 2012; Ellis et al., 2009; Hartman et al., 2018). We describe how we decided which variables, among all data available, would be selected. This process mainly included selecting the variables that most closely matched measures commonly used in life history theory research. We then discuss how skewness in data distributions was treated with data transformation, how differences in variance can affect our analyses, and how we established ruler for dealing with missing data and outliers. We also describe how our analyses used beta coefficients, *R*², and effect sizes to complement statistical inferences based on *p* values.

We conclude with an overview of the empirical chapters in the dissertation. Chapter 3 describes a study that found that indicators of harshness and of living with young parents in larger family sizes can predict reproduction more frequently and at an earlier in Brazilian municipalities. We had a similar finding with US data. In Chapter 4, I show that some indicators of harshness and of the proportion of Indigenous people and visible minorities can predict more frequent reproduction in Canadian census divisions and dissemination areas. Finally, in Chapter 5 I show that the interaction between the proportion of Indigenous people and cost of living to income ratio predicts birth and teenage pregnancy rates in Canadian provinces and territories, but that the main effect of the proportion of Indigenous people is negatively associated with birth and teenage pregnancy rates. Although the current chapter does not include any empirical studies and therefore report no findings, it is an important piece for the reader to have a more comprehensive understanding of the research described in the empirical chapters.

### References

Andersen, J. P., Prause, J., & Silver, R. C. (2011). A Step-by-Step Guide to Using Secondary Data for Psychological Research: Using Secondary Data. *Social and Personality Psychology Compass*, *5*(1), 56–75. https://doi.org/10.1111/j.1751-9004.2010.00329.x

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Chen, R., Sun, C., Chen, J., Jen, H., Kang, X. L., Kao, C., & Chou, K. (2020). A Large‐Scale Survey on Trauma, Burnout, and Posttraumatic Growth among Nurses during the COVID‐19 Pandemic. *International Journal of Mental Health Nursing*, inm.12796. https://doi.org/10.1111/inm.12796

Drovandi, C. C., Holmes, C. C., McGree, J. M., Mengersen, K., Richardson, S., & Ryan, E. G. (2017). Principles of Experimental Design for Big Data Analysis. *Statistical Science*, *32*(3). https://doi.org/10.1214/16-STS604

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature*, *466*(7302), 29–29. https://doi.org/10.1038/466029a

Johnston, M. (2017). Secondary Data Analysis: A Method of which the Time Has Come. *Qualitative and Quantitative Methods in Libraries*, *3*(3), 619–626.

Jones, C. (2010). Archival Data: Advantages and Disadvantages for Research in Psychology: Archival Data. *Social and Personality Psychology Compass*, *4*(11), 1008–1017. https://doi.org/10.1111/j.1751-9004.2010.00317.x

Kievit, R. A., McCormick, E. M., Fuhrmann, D., Deserno, M. K., & Orben, A. (2022). Using large, publicly available data sets to study adolescent development: Opportunities and challenges. *Current Opinion in Psychology*, *44*, 303–308. https://doi.org/10.1016/j.copsyc.2021.10.003

Trzesniewski, K. H., Donnellan, M. B., Lucas, R. E., & American Psychological Association (Eds.). (2011). *Secondary data analysis: An introduction for psychologists* (1st ed). American Psychological Association.

Walkup, J. T., & Yanos, P. T. (2005). Psychological Research With Administrative Data Sets: An Underutilized Strategy for Mental Health Services Research. *Professional Psychology: Research and Practice*, *36*(5), 551–557. https://doi.org/10.1037/0735-7028.36.5.551

Weston, S. J., Ritchie, S. J., Rohrer, J. M., & Przybylski, A. K. (2019). Recommendations for Increasing the Transparency of Analysis of Preexisting Data Sets. *Advances in Methods and Practices in Psychological Science*, *2*(3), 214–227. https://doi.org/10.1177/2515245919848684

## Abstract

This chapter outlines the benefits and challenges of using secondary data, especially census data and other publicly available governmental data, for research in psychology. It begins by defining Secondary and Big Data and describing their increasing relevance due to availability, affordability, and higher ecological validity compared to traditional methods of research. The rationale for using such data, as well as methodological and statistical considerations that arise in the context of life history theory in psychology (LHT-P), are discussed. I discuss several challenges that occur when using secondary data, such as the lack of experimental control, missing or imperfect measures, non-normal distributions, and the need for data transformation. Also, limitations of inferential statistics, particularly the overpowered nature of *p*-values in population-level datasets, are presented

***Keywords:*** *Secondary data, advantages, challenges, methods.*

## Secondary and big data

This chapter aims to describe the process, advantages and limitations of using secondary data – especially census and other government publicly available data – for research in psychology. We highlight methodological considerations and offer an overview of the studies presented in this dissertation.

### What is secondary and Big data?

Secondary data, in research contexts, is any data that exists before a researcher has formulated their research questions and/or hypotheses (Weston et al., 2019) or data that has been collected by a primary source that is now being used for a different, secondary purpose (Andersen et al., 2011; Johnston, 2017). Secondary data includes archival data (e.g., medical reports, newspapers), large electronic data (e.g., shopping habits, social media use), government surveys (e.g., Censuses, economic and community reports), and data from previous longitudinal research projects. One can re-utilize and re-purpose data that has been collected many years before with a novel research question.

The exponential growth of electronically accessible information has resulted in the coining of the term Big Data, which has been defined as data characterized by the three Vs: high volume, velocity, and variety (Albattah, 2016; Bareinboim & Pearl, 2016; Chen & Wojcik, 2016). These three Vs result in data that often cannot be processed using commonly available hardware or software (Chen & Wojcik, 2016; Drovandi et al., 2017) or analysed by standard statistical methods (Drovandi et al., 2017). While high velocity (i.e., data that is generated and updated with high frequency or instantly) does not characterize most of national surveys, volume and variety does. With ever expanding data from many different sources, national surveys can offer varied data about millions of individuals (e.g., public use microdata samples; see Ruggles, 2025). There has been a call for researchers to leverage and benefit from these sources of data in psychological research (Chen & Wojcik, 2016; Copping, 2017; Johnston, 2017).

### Advantages and challenges of using secondary data in psychology

As secondary data sets becomes larger, more varied and more available, they have become a valuable source of data for psychological research. Using secondary data also has some advantages over traditional methods of psychological research. The first is that it is often cheaper to use secondary data because it is publicly available or available at a minimal cost (Johnston, 2017; Jones, 2010), which is important for research in developing countries. Another advantage is that secondary data often provides sample sizes that cannot be achieved in research labs (Andersen et al., 2011; Kievit et al., 2022).

Furthermore, these samples usually are more representative of populations than samples comprised of university students in Western and developed countries (Henrich et al., 2010), common in psychological research. In addition, secondary data has high external validity because it measures people’s actual behaviour (e.g., their shopping habits, when they had children, what content they interact with in social media). Also, with some familiarity with this source of data, researchers can conduct research much faster compared to collecting participant data in an experimental laboratory. Finally, the relative low cost and availability of secondary data make it easier to replicate studies, which is a recent and growing concern in psychology and social sciences (Korbmacher et al., 2023; Open Science Collaboration, 2015).

However, using secondary data has several disadvantages. Perhaps the most important one is that the researcher is limited to the data that is available (Andersen et al., 2011; Johnston, 2017). Instead of tailoring the measures to collect exactly the variables of interest, the researcher working with secondary data needs to work with data that has been collected before he designed his research project. Also, secondary data is not experimental (Andersen et al., 2011; Jones, 2010): The researcher is dealing with already collected data and is not manipulating any of the variables. Therefore, it is limited with respect to making causality inference (Weston et al., 2019).

In addition, some have criticized secondary data as being too complex. The data requires some effort to be understood (Jones, 2010), which will often require examining long documentation and protocols (Johnston, 2017). Also, there may be unknown issues about data collection (Trzesniewski et al., 2011) or data could have been collected using a variety of procedures (e.g., compiled reports from many smaller jurisdictions) which could affect reliability of the measures (Weston et al., 2019). Lastly, the complexity of the data often means that researchers need to use alternative or unfamiliar statistical methods (Chen & Wojcik, 2016; Drovandi et al., 2017, Walkup & Yanos, 2005).

It is important to note that methods that address research questions using secondary data and more traditional research are not mutually exclusive (Andersen et al., 2011; Chen & Wojcik, 2016; Jones, 2010). Secondary data is a rich source of information that complements more traditional approaches. A researcher can use secondary data to test initial hypothesis and associations between variables and then use more traditional research methods that allow for causal inference. Conversely, secondary data can also be helpful in confirming results from more traditional research findings with larger and more diversified samples.

## Census

Most countries in the world conduct a census periodically (World Health Organization, 2020). The census is the official count of the population, and it is usually accompanied by several other demographic and socioeconomic measures (Cambridge Dictionary, 2025; Statistics Canada, 2022). As such, it is the most comprehensive description of a population. Even though the variables measured by each census differ between countries, it is possible to make cross-cultural comparisons. Its periodicity also facilitates comparisons across time.

Census data is usually reported as total count, average or percentage of variable (e.g., females or males) in a given area. Countries’ statistical departments and even some international organizations (e.g., World Health Organization; see Athena API, n.d.) and initiatives (e.g., ourworldindata.org) offer public access to their data through their websites. Generalized and usually simpler compilations can be directly accessed through the websites while more complex and tailored queries can be accessed through portals or Application Programming Interface (APIs) that usually require a user account.

### Methodological considerations and limitations of using Census data

The characteristics of census data require some considerations regarding statistical testing. Frequentist statistical tests rely on significance tests (e.g., *p*-values) to inform whether the null or the alternative hypothesis is supported (Gelman & Loken, 2016; Lakens, 2022). This is problematic when using the Census as a source of data for two reasons. These tests are more suitable for traditional research, in which the researcher works with a sample and tests the effect of an independent variable on a dependent variable. Then the *p*-value is the probability of obtaining an effect of the dependent variable (e.g., a difference between group means) given that the null hypothesis is true. It can also be interpreted as the information that the association measured between variables is or is not greater than what would be observed by chance. A country’s census, however, is not a sample of a larger population. Rather, it is the best possible probe of an entire population. Therefore, any association that we find would be the best description of such association in the population and we argue that it should be considered, regardless of it being statistically significant.

In addition, traditional inferential statistics tests may be overpowered by census data. *P*-values are sensitive to sample size, so with a large sample size even a very small effect may be statistically significant (Gelman & Weakliem, 2009; Lakens, 2022). In these circumstances it may be more appropriate to focus on effect sizes rather than *p*-values (Andersen et al., 2011; Gelman & Weakliem, 2009; Kievit et al., 2022).

Another issue regards the distributions of census data. A common assumption of statistical tests is that data follow a normal distribution (Grimm & Yarnold, 2010), but many census variables are percentages that are not normally distributed. Often, census variables (e.g., people living below poverty line) are right skewed (i.e., near zero on the x axis). Researchers working with such data sets should be cautious in choosing statistical tests when the data does not meet the test’s assumptions and in applying data transformations.

## The empirical chapters

This section provides an overview of the studies in this dissertation. We discuss the methodological and theoretical considerations that were necessary to conduct the research.

### Life history theory considerations

The first step to discover whether census data can be used to test LHT-P assumptions was to narrow the outcome that we were interested in measuring. LHT-P posits that life history strategies can affect many developmental outcomes including time and frequency of reproduction (Ellis et al., 2003; Webster et al., 2014), a lower threshold for risk-taking and violence (Copping & Campbell, 2015; Doom et al., 2016; Wilson & Daly, 1997), attachment (Del Giudice, 2009; Del Giudice & Belsky, 2010), and academic performance (Chang et al., 2019). We chose reproduction as our outcome measure because it is one of the most common and well-stablished associations in LHT-P and because it was the most likely measure to be consistently reported in the Census. A secondary question we were exploring in these studies is whether the proportion of visible minorities in the population was significant predictor of early and more frequent pattern of reproduction. Therefore, measures of the percentage of visible minorities (e.g., Black, Hispanic and Indigenous) minorities were added in different studies.

The second step was to determine what data was available at each country and create a subset of the data that more closely fits what has been used in LHT-P. Most studies assessing early or frequent reproduction strategies in LHT-P literature use harshness and unpredictability as predictors (Belsky et al., 2012; Ellis et al., 2009; Hartman et al., 2018; Webster et al., 2014; Xu et al., 2018). Therefore, we aimed to include variables that serve as proxies for harshness, such as economic status and access to resources, and proxies for unpredictability, such as measures of parental transitions (e.g., marital status, single-parent households), parental employment change (e.g., being unemployed or precariously employed), and geographic move (e.g., moving within the last year or migrating from a different country). Reproduction indicators included measures of the percentage of children in a given geography, parenting by age of the mother, and of single-parent households. LHT-P research does not often consider the effect of population density, which may also be a relevant predictor (Ellis et al., 2009), therefore it was not included in the studies in this dissertation.

As stated above, when dealing with secondary, the researcher has to work with the variables that are available. This means that a variable of interest is often not available in the data or that the variable available is not the best measure to observe some effect. Some variables that are commonly used in LHT-P studies were not available in the census data. The most notable case is the time of menarche (Webster et al., 2014), which is simply not assessed in censuses. Parental employment transitions were consistently a case in which the variables available were not the best measure of *employment transitions* and we collected many variables that might have been indicative of that (e.g., being unemployment, being self-employed (unincorporated), time commuting to and from work, or using public transit to go to work). The measures of *frequent reproduction* were also a common case of the variables available not being the best measure of what was intended. To measure *frequent reproduction*, the most closely fitting measures we found were the percentage of children and measures of family size.

The variables that we interpreted to be indicative of each concept (e.g., frequent reproduction, employment transitions, income, access to resources, etc.) se variables were grouped into their respective concept. Table 1 shows the variables used in the study with data from the Brazil census (Chapter 3) and links each variable with its corresponding LHT-P concept and the factor in which they were loaded. After selecting the data that would be used, we used generally accepted methodological and statistical guidelines for including or excluding variables and factors. The abbreviations in Table 1 indicate variables that were maintained in the final statistical models. The data in Chapters 3 and 4 were analyzed with partial least squares structural equation modelling (Hair et al., 2021, 2022), whereas the data in the second study of Chapters 3 and in the data in Chapter 5 were analyzed with stepwise linear regression (Field et al., 2014; Harrell, 2015). A complete description of these steps can be found in the methods section of each chapter.

### Data processing

Secondary data is almost never organized and ready for analysis. Instead, secondary data usually exists in a raw and unstructured format, so data processing or data wrangling is a necessary step between acquiring data and analysing it (Andersen et al., 2011; Chen & Wojcik, 2016). This step usually involves removing variables that will not be useful in the research project, structuring it in a format that will be ready for analysis, and merging multiple data sets that can be ready for the intended statistical software or statistical technique (Andersen et al., 2011; Chen & Wojcik, 2016; Grimm & Yarnold, 2010).

In our studies, data processing involved reading all data acquired and subsequently removing data that we did not intend to use. Examples of what data that has been removed in this data wrangling process include different geographical levels (e.g., average value of a variable in the whole country), codes for geomapping, repeated variables (e.g., counts of the total population or the total number of households), and obviously variables that were not of interest. In the case of Brazil entire data frames were removed (e.g., birth rates for women in many age intervals) because the data source would not allow selecting and accessing only variables of interest. Due to the different sizes of the population in different geographies, all measures were transformed to either a percentage of the total population or the total number of households. This transformation reduced a bias in which more populous geographies would appear with higher of many of the variables of interest simply because it was more populous.

A third concern was the difference in the scale and in the variance across variables. A large (i.e., more than 10-fold) difference in variables scales can result in an ill-scaled covariance matrix in the case of structural equation modelling analysis (Kline, 2016) or result in bias and lack of reliability in other analyses (Trzesniewski et al., 2011). In our studies these differences were most apparent when comparing certain percentages of the population (e.g., percentage of mothers aged 15 to 19 years old), typically small values with limited variance, with income variables, which have values in the tens of thousands and correspondingly more variance.

The distributions of percentages in census data often are strongly skewed. Some of our analyses assumed the data were distributed normally, therefore we used square root and logarithmic transformation of the data. This transformation would aid analysis by reducing skewness and transforming the distribution to closer to normal distribution. Most of the studies in this dissertation, however, make use of partial least structural equation modelling which is robust in processing non-normal data (Hair et al., 2022).

Missing data is another common issue when dealing with secondary data. Different methods of dealing with missing data will involve deleting cases or variables with missing data, weighing methods (common when dealing with surveys) and data imputation methods (Trzesniewski et al., 2011). The optimal approach to deal with missing data depends on whether data is missing due to random or non-random factors (Ranganathan & Hunsberger, 2024; Trzesniewski et al., 2011). The approach used for studies described in Chapters 3 and 4 was to delete variables with missing values above 5%.

We considered this approach to missing data appropriate because the data was extracted from governmental census and statistical departments. The census data often was expressed as means or total counts calculated from individual participants. Therefore, the data included in the census already incorporated some technique to deal with missing data. In addition, variables with more than 5% of missing values were rare. Again, this is a result of the variables being the total count or means value of a given geography. Finally, many of our variables had alternative variables that would serve as proxies of the same construct. For example, a measure of the percentage of people living with a minimum wage or less in Brazil, was used as a proxy of a harsher life. Alternatively, a plausible proxy measure of a harsher life – a life with fewer opportunities due to low socioeconomic status – could be the percentage of families who do not own a refrigerator, or the percentage of people without access to sanitation. Having to remove one of these variables due to missing data would not impact our ability to test our hypotheses.

My approach to deal with outliers was to remove all cases in which any of the variables had a *z*-score > |3|. We relied on the fact that the data was representative of an entire population, so removing outliers would improve the model's predictiveness without reducing power. In Chapter 3 and in Chapter 4 I used partial least squares structural equation modelling analysis (PLS-SEM). PLS-SEM is an exploratory analytical approach composed of a measurement model, which has similarities with exploratory factor analysis, and a structural model, which has similarities with path analysis. Figure 1 describes the decision making process during these analyses and the full description of the analysis can be found in the *Methods* sections of Chapter 3 and Chapter 4.

### Overview of each chapter

The overall aim of my studies was to make use of publicly available data to test predictions of LHT-P. Specifically, we tested whether indicators of harshness and unpredictability used in LHT-P can predict indicators of reproduction. Another aim was to determine if higher percentages of visible minorities and marginalized populations also are good predictors of these indicators of reproduction. The first study in this dissertation was exploratory: it attempts to determine if census data can be used to test hypotheses based on LHT-P and to discover the patterns of relationships among variables. The subsequent studies are assessing similar questions, but with small variations in the data source or the analytical approach. Future research with more specific models and more strict statistical testing is encouraged.

The study in Chapter 3 used census data from Brazil, a developing country with a large population that it is marked by a long history of slavery, racism and economic inequality (Couto & Brenck, 2024; Pimentel, 2022). We used Brazilian municipalities as the level of analysis and included the percentage of Black and Asian ethnicities in these municipalities to assess if these would be significant predictors of indicators reproduction. Data from a sample of households of the Brazilian census was used. The data is available through the SIDRA portal (*Sistema IBGE de Recuperação Automática - SIDRA*, 2024). The portal offers many different tables ranging from characteristics of the population to characteristics of the individuals. We assessed 26 different tables, each comprised of a diverse range of subtabs.

Many of the census variables are nested within higher-level variables. For example, the portal offers the count of males in a municipality, then it offers the number of males that are employed (a variable nested within the prior one), and then the number of males, employed, that are within certain age ranges (nested with the prior). Whenever possible, the higher-level variables were selected (e.g., sex) in an attempt to isolate the effect of that variable independently from others. This process was repeated for the subsequent studies and chapters: US comparison (Chapter 3), and in the studies using Canadian census divisions and dissemination areas data (Chapter 4).

A second comparison in Chapter 3 uses data from the American Community Survey 5-year detailed tables (ACS; U.S. Census Bureau, 2016). In this study we tested if relevant predictors and outcome using data from Brazil would be relevant predictors of reproduction different country. We were still interested to see how visible minorities and ethnicities could be associated in this phenomenon, so we used these variables, even though they were not relevant predictors. The US is a developed country with a much different human development index (*Human Development Index | Human Development Reports*, 2022), but both Brazil and the US are large countries with large populations (United Nations, 2025) and comparable economic inequality (Our World in Data, 2025), which we assumed to be associated with variance in harshness and unpredictability experience by their population.

The geographical level of analysis was US counties, which are defined as the “primary legal divisions of most states” (U.S. Census Bureau, 2025, Counties (and equivalents) section). Counties can be constituted of independent cities, parishes or boroughs, but most counties encompass a larger geographical area that can include cities, towns and villages in both urban and rural areas. ACS data is available through US Bureau of Statistics API (*Census Data API: /Data*, 2025). Around 64,000 variables are available in different ACS years. Table 2 reports the variables that were relevant predictors or outcomes in Brazil and the most similar variable that we could find available in the ACS.

The fourth chapter was an attempt to use the same method we used with Brazilian data in Chapter 3, but using Canadian data this time. We also assessed whether findings would be similar between the two studies. We selected variables from the Canadian Census Analyser (Statistics Canada, 2024) in a process similar to the one performed with Brazilian data. Table 3 shows the variables that were used in the first iteration of the model in this chapter. Differently from the second chapter, though, we used two geographical level of analyses: census divisions and dissemination areas. A dissemination area is a small, relatively stable, geographical unit composed of an average of 400 to 700 people whereas the census division is a much more stable geographical unit usually composed of neighbouring municipalities (*Dictionary, Census of Population, 2021*, 2023). The analyses of two models were ran independent using these two geographical units.

The fifth chapter used a different approach. We utilized variables that aren’t included in the census (e.g., violent crime index) to predict birth rates and teenage parenting rates, the latter is a variable not present in the Canadian Census Analyser, but reported by Statistics Canada in the provincial level. Therefore, we utilized Canadian provinces and territories as the level of analysis and because that yielded a data frame with only 13 cases, we utilized a forward stepwise linear regression analysis. We also included variables that are akin to what is usually included in the LHT-P literature, but slightly better than what is available in the Canadian census analyser. These are cost of living to income ratio and the single-parenting ratio. Similarly to the other studies, we also tested if the percentage of indigenous populations in Canadian provinces and territories were a predictor of birth rates and teenage pregnancies.

## References

Albattah, W. (2016). The Role of Sampling in Big Data Analysis. *Proceedings of the International Conference on Big Data and Advanced Wireless Technologies*, 1–5. https://doi.org/10.1145/3010089.3010113

Andersen, J. P., Prause, J., & Silver, R. C. (2011). A Step-by-Step Guide to Using Secondary Data for Psychological Research: Using Secondary Data. *Social and Personality Psychology Compass*, *5*(1), 56–75. https://doi.org/10.1111/j.1751-9004.2010.00329.x

Bareinboim, E., & Pearl, J. (2016). Causal inference and the data-fusion problem. *Proceedings of the National Academy of Sciences*, *113*(27), 7345–7352. https://doi.org/10.1073/pnas.1510507113

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Cambridge Dictionary. (2025). *CENSUS | English meaning—Cambridge Dictionary*. https://dictionary.cambridge.org/dictionary/english/census

*Census Data API: /data*. (2025). https://api.census.gov/data.html

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. *Developmental Psychology*, *55*(4), 890–903. https://doi.org/10.1037/dev0000655

Chen, E. E., & Wojcik, S. P. (2016). A practical guide to big data research in psychology. *Psychological Methods*, *21*(4), 458–474. https://doi.org/10.1037/met0000111

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), *Encyclopedia of Evolutionary Psychological Science* (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Copping, L. T., & Campbell, A. (2015). The environment and life history strategies: Neighborhood and individual-level models. *Evolution and Human Behavior*, *36*(3), 182–190. https://doi.org/10.1016/j.evolhumbehav.2014.10.005

Couto, P., & Brenck, C. (2024). Monetary Policy and the Gender and Racial Employment Dynamics in Brazil. *Review of Political Economy*, 1–25. https://doi.org/10.1080/09538259.2023.2294306

Del Giudice, M. (2009). Sex, attachment, and the development of reproductive strategies. *Behavioral and Brain Sciences*, *32*(1), 1–21. https://doi.org/10.1017/S0140525X09000016

Del Giudice, M., & Belsky, J. (2010). The Development of Life History Strategies: Toward a Multi-Stage Theory. In D. M. Buss & P. H. Hawley (Eds.), *The Evolution of Personality and Individual Differences* (pp. 154–176). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195372090.003.0006

*Dictionary, Census of Population, 2021*. (2023). Statistics Canada = Statistique Canada.

Doom, J. R., Vanzomeren-Dohm, A. A., & Simpson, J. A. (2016). Early unpredictability predicts increased adolescent externalizing behaviors and substance use: A life history perspective. *Development and Psychopathology*, *28*(4pt2), 1505–1516. https://doi.org/10.1017/S0954579415001169

Drovandi, C. C., Holmes, C. C., McGree, J. M., Mengersen, K., Richardson, S., & Ryan, E. G. (2017). Principles of Experimental Design for Big Data Analysis. *Statistical Science*, *32*(3). https://doi.org/10.1214/16-STS604

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? *Child Development*, *74*(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Field, A., Miles, J., & Field, Z. (2014). *Discovering statistics using R* (Repr). Sage.

Gelman, A., & Loken, E. (2016). *The Statistical Crisis in Science* (M. Pitici, Ed.; pp. 305–318). Princeton University Press. https://doi.org/10.1515/9781400873371-028

Gelman, A., & Weakliem, D. (2009). Of Beauty, Sex and Power: Too little attention has been paid to the statistical challenges in estimating small effects. *American Scientist*, *97*(4), 310–316. JSTOR.

Grimm, L. G., & Yarnold, P. R. (Eds.). (2010). *Reading and understanding more multivariate statistics* (6. print). American Psychological Association.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Third edition). SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Harrell, F. E. (2015). *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*. Springer International Publishing. https://doi.org/10.1007/978-3-319-19425-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature*, *466*(7302), 29–29. https://doi.org/10.1038/466029a

*Human Development Index | Human Development Reports*. (2022). https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

Johnston, M. (2017). Secondary Data Analysis: A Method of which the Time Has Come. *Qualitative and Quantitative Methods in Libraries*, *3*(3), 619–626.

Jones, C. (2010). Archival Data: Advantages and Disadvantages for Research in Psychology: Archival Data. *Social and Personality Psychology Compass*, *4*(11), 1008–1017. https://doi.org/10.1111/j.1751-9004.2010.00317.x

Kievit, R. A., McCormick, E. M., Fuhrmann, D., Deserno, M. K., & Orben, A. (2022). Using large, publicly available data sets to study adolescent development: Opportunities and challenges. *Current Opinion in Psychology*, *44*, 303–308. https://doi.org/10.1016/j.copsyc.2021.10.003

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (Fourth edition). The Guilford Press.

Korbmacher, M., Azevedo, F., Pennington, C. R., Hartmann, H., Pownall, M., Schmidt, K., Elsherif, M., Breznau, N., Robertson, O., Kalandadze, T., Yu, S., Baker, B. J., O’Mahony, A., Olsnes, J. Ø.-S., Shaw, J. J., Gjoneska, B., Yamada, Y., Röer, J. P., Murphy, J., … Evans, T. (2023). The replication crisis has led to positive structural, procedural, and community changes. *Communications Psychology*, *1*(1), 3. https://doi.org/10.1038/s44271-023-00003-2

Lakens, D. (2022). Why P values are not measures of evidence. *Trends in Ecology & Evolution*, *37*(4), 289–290. https://doi.org/10.1016/j.tree.2021.12.006

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716. https://doi.org/10.1126/science.aac4716

Our World in Data. (2025). *Economic Inequality—Our World in Data*. https://ourworldindata.org/economic-inequality

Pimentel, R. (2022). *“Equal Before the Law,” But Not in Practice: Brazil’s Social Inequality Crisis—Harvard Political Review*. https://harvardpolitics.com/brazil-social-inequality/

Ranganathan, P., & Hunsberger, S. (2024). Handling missing data in research. *Perspectives in Clinical Research*, *15*(2), 99–101. https://doi.org/10.4103/picr.picr\_38\_24

Ruggles, S. (2025). The shortcomings of synthetic census microdata. *Proceedings of the National Academy of Sciences*, *122*(11), e2424655122. https://doi.org/10.1073/pnas.2424655122

*Sistema IBGE de Recuperação Automática—SIDRA*. (2024). https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2022/universo-populacao-por-cor-ou-raca

Statistics Canada. (2022). *Guide to the Census of Population, 2021, Chapter 1 – Introduction*. https://www12.statcan.gc.ca/census-recensement/2021/ref/98-304/2021001/chap1-eng.cfm

Statistics Canada. (2024). *Canadian census analyser* [Dataset]. Computing in the Humanities and Social Sciences at the University of Toronto (CHASS). https://datacentre.chass.utoronto.ca/census/

Trzesniewski, K. H., Donnellan, M. B., Lucas, R. E., & American Psychological Association (Eds.). (2011). *Secondary data analysis: An introduction for psychologists* (1st ed). American Psychological Association.

United Nations. (2025). *Home Page | Data Portal*. https://population.un.org/dataportal/home?df=399c47a5-aef4-4a21-ae4d-66eed3b383c5

U.S. Census Bureau. (2016). *2015 American Community Survey 1-year* [API]. https://api.census.gov/data/2005/acs/acs1/profile.html

U.S. Census Bureau. (2025). *Terms and Definitions*. https://www.census.gov/programs-surveys/popest/guidance-geographies/terms-and-definitions.html

Walkup, J. T., & Yanos, P. T. (2005). Psychological Research With Administrative Data Sets: An Underutilized Strategy for Mental Health Services Research. *Professional Psychology: Research and Practice*, *36*(5), 551–557. https://doi.org/10.1037/0735-7028.36.5.551

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. *Evolutionary Psychology*, *12*(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Weston, S. J., Ritchie, S. J., Rohrer, J. M., & Przybylski, A. K. (2019). Recommendations for Increasing the Transparency of Analysis of Preexisting Data Sets. *Advances in Methods and Practices in Psychological Science*, *2*(3), 214–227. https://doi.org/10.1177/2515245919848684

Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. *BMJ*, *314*(7089), 1271–1271. https://doi.org/10.1136/bmj.314.7089.1271

World Health Organization. (2020, June 23). *Proportion of countries that have conducted at least one population and housing census in the last 10 years (%)*. https://apps.who.int/gho/athena/data/GHO/SG\_REG\_CENSUS?format=html&profile=filter&x-format=html&x-profile=xtab&x-title=table&x-topaxis=GHO;&x-sideaxis=UNSDGREGION;YEAR&filter=UNSDGREGION:\*;

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. *Evolution and Human Behavior*, *39*(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005

**Table 1**

*Variables fed into the first model of Chapter 2.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor in the model** | **Variables present in the Census** | **Variable abbreviationa** |
| Harshness | SES measures | Low income and lack of resources | Lack of recycling or garbage collection | No recycling service |
|  | Lack of electrical power serviceb | No electrical power |
|  |  |  | Lack of a fridge or freezer c |  |
|  |  |  | Lack of a TV |  |
|  |  |  | People with income of 1 minimum wage or less | 1 minimum wage or less |
|  |  |  | People with income of 1 – 2 minimum wages |  |
|  |  |  | People with income of 2 – 3 minimum wages |  |
|  |  | Family/house size (Lack of resources) | Number of people in the family – 6 people | Families with 6 people |
|  |  | Number of people in the family – 7 – 1 0 people |  |
|  |  |  | Number of people in the family – 11 people or more |  |

**Table 1** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | Resident density per bedroom - More then 2 up to 3 residents | 2-3 residents / bedroom |
|  |  |  | Resident density per bedroom – More than 3 residentsc | >3 residents / bedroom |
|  |  |  | Number of rooms – 2 rooms c | 2 rooms in the house |
|  |  | Low Education | Age group 20 – 24 with 1 year of education or lessc |  |
|  |  |  | Age group 20 – 24 with 1 – 3 years of educationc |  |
|  |  |  | Age group 20 – 24 with 4 – 7 years of education |  |
| Unpredictability | Parental transitions | Youth and married with children (parental transitions + having a young mother) | Divorcedc | Separated |
|  | Judicially separatedc | Divorced |
|  |  | Age group 10 – 14 living with spouse or partner |  |
|  |  | Age group 15 – 19 living with spouse or partner | 15-19yo living w. partner |
|  |  |  | Women age group 10 – 14 with children |  |
|  |  |  | Women age group 15 – 19 with childrenc | Mothers 15 to 19yo |
|  |  |  | Women age group 20 – 24 with children | Mothers 20 to 24yo |
|  | Parental occupation transitions | Unemployed or precariously employed | Males 25 – 29 economically active |  |
|  | Males 30 – 34 economically active |  |
|  | Males 25 – 29 not economically active |  |
|  |  |  | Males 30 – 34 not economically active |  |

**Table 1** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | Females 25 – 29 economically active |  |
|  |  |  | Females 30 – 34 economically active |  |
|  |  |  | Females 25 – 29 not economically active |  |
|  |  |  | Females 30 – 34 not economically active |  |
|  |  |  | Occupation position – Self employed – not contributing for retirement/pension |  |
|  |  |  | Occupation position – production for their own consumption |  |
|  |  |  | Age group 25 – 29 – working up to 14 hours weekly |  |
|  |  |  | Age group 25 – 29 – working 15 – 29 hours weekly |  |
| - | - | Percentage of childrend | Age group 0 – 4 |  |
|  |  |  | Age group 5 – 9 |  |
| - | - | Skin colour | Colour or ethnicity – Black |  |
|  |  |  | Colour or ethnicity – South Asian |  |
|  |  |  | Colour or ethnicity - Indigenous |  |
| Reproduction | Menarche, Number of partners, | Early reproduction | Age group 0 – 4 | Children 0 to 4yo |
|  |  | Age group 5 – 9 | Children 5 to 9yo |
|  |  | Women age group 10 – 14 with children |  |
|  |  | Women age group 15 – 19 with children | Mothers 15 to 19yo |

**Table 1** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | Women age group 20 – 24 with children | Mothers 20 to 24yo |
|  |  | Youth Married | Age group 10 – 14 living with spouse or partner |  |
|  |  |  | Age group 10 – 14 married but not living together |  |
|  |  |  | Age group 15 – 19 living with spouse or partner c |  |
|  |  |  | Age group 20 – 24 living with spouse or partner |  |
|  |  |  | Age group 20 – 24 married but not living together |  |

*Note*. Harshness and Unpredictability variables collected from Census in 2000 and Reproduction variables collected from 2010. aVariable abbreviation if retained in the final model. bLog transformation and ² Square root transformation applied to the variables. dIncluded in early models but planned to be used to compare model performance.

**Table 2**

*Variables in the Model Using Brazilian Census and Similar Variables Using US American Community Survey.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables in Brazilian Census**  **Geographic level: Municipalities** | **Variables found in the American Community Survey (ACS)**  **Geographic level: Counties** | **Classification**  Equivalent (E)  Similar (S)  Not found (N) | **ACS code** |
| **Predictors: 2000** | **Predictors: 2005-2009** |  |  |
| (lacking) Existence of services and durable goods - recycling or waste collection | Lacking complete plumbing facilitiesb; Plumbing Facilities for Occupied Housing Units | S | B25048\_003E |
| (lacking) Existence of services and durable goods - electric lights | Lacking complete kitchen facilitiesb; Kitchen Facilities for Occupied Housing Units | S | B25052\_003E |
| People with income of 1 minimum wage or less | Income in the past 12 months below poverty levelc | S | B17001\_002E |
| Separated - judicially separated | Separatedab: Male; Now married; Married, spouse absent; Separated +  Female; Now married; Married, spouse absent; Separated | E | B12001\_007E  B12001\_016E |
| Divorced | Divorcedac: Male; Divorced +  Female; Divorced | E | B12001\_010E  B12001\_019E |

**Table 2** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Age group - 15 to 19 years of age - Living with a spouse or partner | Women who did not have a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years oldc | S | B13002\_013E |
| Age group - 15 to 19 years of age - with children | Women who had a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years old +  Women who had a birth in the past 12 months; Unmarried (never married, widowed, and divorced); 15 to 19 years oldac | S | B13002\_004E  B13002\_008E |
| Age group - 20 to 24 years of age - with children | Women who had a birth in the past 12 monthsb | S | B13002\_002E |
| Number of family members - 6 people |  | N |  |
| Residents’ density per dormitory - more than 2,0 to 3,0 residents | Complete plumbing facilities; 1.01 or more occupants per roomc | S | B25050\_007E |
| Residents’ density per dormitory - more than 3,0 residents |  | N |  |
| Number of rooms - 2 rooms | Median number of rooms | S | B25018\_001E |

**Table 2** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Black ethnicity | Sex by age (Black or African American alone)b | E | B01001B\_001E |
| Indigenous ethnicity | Sex by age (Hispanic or Latino)b | N | B01001I\_001E |
| Age group - 0 to 4 years of age | Age group - 0 to 4 years of agea: Male; Under 5 years +  Female; Under 5 years | S | B01001\_003E  B01001\_027E |
| Age group - 5 to 9 years of age | Age group - 5 to 9 years of agea: Male; 5 to 9 years +  Female; 5 to 9 years | S | B01001\_004E  B01001\_028E |
| **Outcomes: 2010** | **Outcomes: 2018-2023** |  |  |
| Age group - 0 to 4 years of age | Age group - 0 to 4 years of agea: Male; Under 5 years +  Female; Under 5 years | S | B01001\_003E  B01001\_027E |
| Age group - 5 to 9 years of age | Age group - 5 to 9 years of agea: Male; 5 to 9 years +  Female; 5 to 9 years | S | B01001\_004E  B01001\_028E |
| Women 15 to 19 years of age with children | Women who had a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years oldc | S | B13002\_004E |

**Table 2** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Women 20 to 24 years of age with children | Women who had a birth in the past 12 months | S | B13002\_002E |

*Note*. a: Manually calculated the sum of the variables to come up with a single variable representative of both groups; b: log transformed variables; c: square root transformed variables.

**Table 3**

*Variables fed into the first models of Chapter 3.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
| Harshness | SES measures | Income | Median family income | DA |
|  |  | Prevalence children 6 years of age or less living with low income before tax | CD |
|  |  | Lack of resources | Occupied private dwellings needing minor repairs | DA |
|  |  | Occupied private dwellings needing major repairs | DA |
|  |  |  | Tenant occupied households spending more than 30% on rent | CD; DA |
|  |  |  | Employed labour force 15 years of age and over using public transit |  |
|  |  | Low schooling | Population 25 – 64 with no certificate, diploma or degree |  |
| Unpredictability | Parental transitions | Female lone parent | Female lone parent |  |
|  | Median of female lone-parent income |  |
|  |  |  | Percentage of female lone-parent income coming from other sources (i.e., neither employment nor government transfers) |  |
|  |  | Male lone parent | Male lone parent |  |

**Table 3** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
|  |  |  | Median of male lone-parent income |  |
|  |  |  | Percentage of male lone-parent income coming from other sources (i.e., neither employment nor government transfers) |  |
|  |  | Separated | Divorced | DA |
|  |  | Widowed | DA |
|  |  |  | Separated, but still legally married |  |
|  | Parental occupation transitions | Precariously labour | Unemployment rate of population 25 years and over | CD |
|  | People 15 years and over who worked in different census subdivision |  |
|  | Unemployment rate of population 15 years and over with children at home |  |
|  | People 15 years and over self-employed (unincorporated) without paid help |  |
|  |  |  | People 15 years and over who worked part year or part time |  |
|  | Geographical transitions | Migrants and speaking foreign languages | Movers 1 year ago |  |
|  | Movers 5 years ago |  |
|  |  | Neither English nor French as first official language spoken |  |
|  |  |  | Non-official language spoken in single responses |  |
|  |  |  | English and non-official language in multiple responses |  |
|  |  |  | French and non-official language in multiple responses |  |

**Table 3** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
| - | - | Indigenous | Total aboriginal ancestry population | CD |
|  |  | Visible minority | Total visible minority population | DA |
|  |  | Non-official language spoken in single responses | DA |
| - | - | Young children | Age group 0 – 4 years of age | CD; DA |
|  |  | Age group 5 – 9 years of age | DA |
| Reproduction | Age of menarche, number of partners, number of children, and interbirth interval | Frequent reproduction | Average size of families | CD; DA |
|  | Average number of children in families with children | CD; DA |
|  |  | Families with 4 persons | CD; DA |
|  |  | Families with 5 or more persons | CD; DA |
|  | Single parenting | Average family size of one-parent families | CD |
|  | Big families | Private households with 4 persons |  |
|  |  | Private households with 5 or more persons |  |
|  |  | Recent reproduction | Age group 0 – 4 years of age | CD |

*Note*. Harshness and Unpredictability variables collected from Census 2006 and Reproduction variables collected from 2021. Final model indicates whether the variable was a relevant and significant in the models using Census division (CD) or Dissemination area (DA) sample.

**Figure 1**

*Decision making process in the PLS-SEM analysis*

A screenshot of a flowchart

AI-generated content may be incorrect.

# Chapter 3: Harshness predicts reproduction in Brazilian municipalities and US counties: a life history theory approach

## Preface

Life history theory in psychology (LHT-P) posits that a child’s early environment predicts later reproductive behaviour (Belsky et al., 2012; Ellis et al., 2009; Stearns, 1992). Specifically, the theory predicts that the levels of harshness and unpredictability that a child encounters influences the age of sexual maturity, the age of first childbearing, and the frequency of reproduction (Ellis et al., 2009; Webster et al., 2014; Xu et al., 2018). Harsher environments, which have a higher level of death and disease outside of the individual’s control, and more unpredictable environments, which exhibit a higher level of random variation of harshness, usually favor earlier puberty and first childbearing and more frequent reproduction. On the other hand, less harsh and more stable environments usually favor a longer investment in growth, acquiring resources and status at the cost of reproducing later and less often (Belsky et al., 2012; Hartman et al., 2018; Simpson et al., 2012).

These effects of the early environment are thought to be an adaptive response. In harsh, unpredictable conditions, individuals are less certain of their chances of reproducing later in life and less certain of their children’s chances to reach maturity and reproduce themselves (Kaplan & Gangestad, 2015; Stearns, 1992). This uncertainty favors a strategy of reproducing earlier and more often because i) one may not have the chance to reproduce later; and ii) not all children may reach an age for reproduction. Coming from an evolutionary perspective, this theory – with some modifications – is applicable across different species and should be applicable to virtually all human populations (Buss, 2024; Chang et al., 2019; Del Giudice & Belsky, 2010). This broad applicability of the theory, in addition to the fact that public governmental data often includes measures of environmental harshness and unpredictability, means that such data can have remarkable value in evaluating the application of LHT-P to human behaviour (Copping, 2017). Not only that, but LHT-P has been under serious criticisms. Critics urge LHT-P to include more formal modelling in its approach, which will bring LHT-P closer to its related theory in biology, and to better specify which outcomes are actually measurable by certain early environments (Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Sear, 2020). Surprisingly, research leveraging public governmental data to approach LHT-P assumptions has been lacking. Addressing this is the first goal of this chapter.

This chapter had four aims: 1. Assess whether an exploratory structural equation modelling (SEM) approach would have an acceptable performance at using harshness and unpredictability indicators to predict subsequent measures of reproductive behaviour; 2. Assess which indicators would best predict reproduction; 3. Assess whether this analysis using a confirmatory approach and a different data set would yield similar findings with the first study; and 4. Assess whether percentage of visible minorities in the population is a significant predictor of reproduction patterns.

To address the first two aims, we used 50 predictor variables from 5507 Brazilian municipalities and utilized a partial least square structural equation modelling approach (Hair et al., 2021, 2022). All variables were expressed as a percentage or an average of a municipal population, making it a populational approach. The outcome measure was a factor composed of the percentage of young mothers and of young children taken from the same municipalities 10 years later. The analysis found that 12 predictor variables that indicated a lack of resources, a prevalence of young married mothers, and large family size explained 84% of the variance of the outcome measure. This result supported the first two hypothesis of this paper: that the analytical approach and model performance would be acceptable and that indicators of harshness and unpredictability would be significant predictors of reproduction.

To attempt to have findings that were as similar as possible with the first study, we analyzed data from 3,209 US counties using variables that were similar to the significant variables that were identified using Brazil’s data. An initial attempt to analyze the data with covariance-based SEM because the confirmatory factor analysis did not converge to a solution that met usual criteria. Therefore, the US data were analyzed with stepwise multiple regression. As was found with the analysis of the Brazil data, variables indicative of harsh early environments were significant predictors of the percentage of young children in US counties. However, the explanatory power of such variables was considerably lower than the one found in the study with Brazil census data.

Finally, to address the fourth aim, we included the percentage of visible minorities as predictors of reproduction. The percentage of Black people in Brazil and the percentage of Black and of Hispanic people in the US were used. Black people were neither a good predictor nor a mediator of early reproduction in Brazil. Results in the US were different. The percentage of Black and Hispanic people were significant predictors of the percentage of children aged 0-4 years old around 14 years later and the percentage of Black people were significant predictors of the percentage of children aged 5-9 years.

These findings support the claim that public governmental data is a useful source to test LHT-P and that some measures of harshness are good predictors of subsequent reproduction. They also support the developmental and longitudinal assumption that early environment predicts future patterns of reproduction. However, the differences between the results obtained with the Brazil and US data suggest that the effects of early environmental harshness depend on cultural and environmental factors.

### References

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Buss, D. M. (2024). *Evolutionary psychology: The new science of the mind* (Seventh edition). Routledge.

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. *Developmental Psychology*, *55*(4), 890–903. https://doi.org/10.1037/dev0000655

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), *Encyclopedia of Evolutionary Psychological Science* (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Del Giudice, M., & Belsky, J. (2010). The Development of Life History Strategies: Toward a Multi-Stage Theory. In D. M. Buss & P. H. Hawley (Eds.), *The Evolution of Personality and Individual Differences* (pp. 154–176). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195372090.003.0006

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. *Evolution and Human Behavior*, *41*(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Third edition). SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), *The Handbook of Evolutionary Psychology* (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Sear, R. (2020). Do human ‘life history strategies’ exist? *Evolution and Human Behavior*, *41*(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. *Developmental Psychology*, *48*(3), 674–686. https://doi.org/10.1037/a0027293

Stearns, S. C. (1992). *The evolution of life histories*. Oxford University Press.

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. *Evolutionary Psychology*, *12*(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. *Evolution and Human Behavior*, *39*(1), 40–51. <https://doi.org/10.1016/j.evolhumbehav.2017.08.005>

## Abstract

Harsh and unpredictable environments early in childhood can cue humans into developing earlier and more frequent reproduction in adulthood. This study tested whether variables measuring harsh and unpredictable circumstances in Brazilian municipalities and in US counties would predict reproductive behaviour 10 to 14 years later. Predictor data were extracted from the Brazilian census and American Community Survey. A secondary analysis assessed whether the percentage of visible minorities (black and indigenous population) would also be a predictor or mediator of reproductive behaviour. Partial least squares structural equation modelling and covariance based structural equation modelling were used in the analysis of Brazil and US data, respectively. Brazilian municipalities with higher rates of lack of resources, with young mothers both married or separated, and with large families with many residents per room had higher rates of teenage and young-adult mothers and of young children. A similar pattern was found in the US, where harshness predicted the percentage of young children. Higher rates of perceived minorities were not a relevant predictor in Brazil, and they were a negative predictor of the percentage of Children in the US. These findings suggest that harsh environments in the first years of life can lead to different patterns of reproduction.

***Keywords:*** *Life History Theory, Teen Pregnancy, Harshness, Unpredictability, Reproduction, Perceived Minorities.*

## Introduction

Life history theory in psychology (LHT-P; Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Sear, 2020) describes factors that influence the allocation of resources to reproduction or to body growth and maintenance (Ellis et al., 2009; Stearns, 1992; Xu et al., 2018). LHT-P originated from life history theory in evolutionary biology (LHT-E), which initially was used to account for variation between species (Del Giudice, 2009). However, the theory also accounts for within-species variation (Albaladejo‐Robles et al., 2023; Malone et al., 2022; Stone et al., 2023), including humans (Dinh et al., 2022; Richardson et al., 2020; Stearns et al., 2008).

Depending on their pattern of investments in reproduction or body growth and maintenance, species or individuals can be classified as lying on a continuum from fast to slow life history strategies (LHS; Copping & Campbell, 2015; Sear, 2020; Stearns & Rodrigues, 2020) Species or individuals on the fast LHS end favour investments in reproduction earlier in life and focus on offspring *quantity* whereas those on the slow LHS end would prioritize body-growth and maintenance and offspring *quality* (Ellis et al., 2009). The fast-slow continuum has been criticized on a number of grounds, which we discuss below, but it continues to be a common feature of LHT-P research (e.g., Chang et al., 2019; Wang et al., 2022; Zhu & Chang, 2020).

In LHT-P research, harsh and unpredictable ecologies have been associated with fast LHS (Copping & Campbell, 2015; Griskevicius et al., 2011; Webster et al., 2014). In LHT-P, harshness is defined as the rates of extrinsic morbidity and mortality in the environment whereas unpredictability is defined as stochastic variation of such rates (Ellis et al., 2009). If resources are scarce or unpredictable, or if there are high levels of predation, reproducing fast (i.e., at a young age) and creating numerous offspring may be advantageous because it maximizes the probability of passing on genes and spreading them in the environment.

In practice, research with humans has used socio-economic measures as a proxy for harsh conditions whereas unpredictability has been typically measured with measures of parental absence or transitions, parental employment change, and geographical moves (Belsky et al., 2012; Ellis et al., 2003; Hartman et al., 2018; Xu et al., 2018). Early reproduction is typically measured as time of menarche (Webster et al., 2014), time of sexual debut, and age at marriage and at giving birth to a firstborn child (Copping & Campbell, 2015; Ellis et al., 2003; Xu et al., 2018). Among the usual unpredictability measures, parental absence the first 5-7 years of life seems to be the best predictor of early reproduction (Ellis et al., 2003; Simpson et al., 2012; Webster et al., 2014; Xu et al., 2018).

Recently, the assumptions and even the findings of LHT-P have been criticized. These criticisms include questioning the existence of a single fast-slow LHS continuum in humans (Nettle & Frankenhuis, 2020) and its utility in explaining variation in adopted traits (Stearns & Rodrigues, 2020). This continuum has been mainly abandoned in LHT-E (Nettle & Frankenhuis, 2020) where researchers have been using formal mathematical models to make predictions that are typically focused on a limited number of traits (Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020). In LHT-P, a few studies have failed to find the expected results derived from the theory (e.g., Nolin & Ziker, 2016; Richardson et al., 2020; Wells et al., 2019).

Other critics hypothesize that mortality, morbidity and resource scarcity may no longer be present in modernized environment as much as they would be present in the environment of evolutionary adaptedness (Volk, 2023). As a result, this milder degree? of harshness and/or unpredictability would be insufficient to promote faster LHS development in humans (Nolin & Ziker, 2016; Volk, 2023). This problem likely is even greater in developed countries, where most of LHT-P studies have been conducted (Sear, 2020; Volk, 2023; Webster et al., 2014; Xu et al., 2018).

A longitudinal design would be ideal to test hypothesis between environmental conditions and a life trajectory of prioritizing investments in either reproduction or growth and maintenance, particularly considering the developmental aspect of a critical time of exposure (0-7 years of age) to the environmental predictors and the later appearance of the outcomes. When considering the measures that are typically used (e.g., socioeconomic status, family structure and marital relationships), census and other governmental surveys would make a valuable data source for this field (Copping, 2017). Most countries conduct censuses or other surveys periodically and measure variables similar to the variables of interest in this field. Moreover, utilizing such data sources would allow for cross-country comparisons including non-western and developing populations, which is more representative of the majority of human population (Henrich et al., 2010). However, the use of census data to test LHT-P hypothesis has not been well explored. To the best of our knowledge, LHT-P research utilizing the census or surveys of entire populations has only been done in England and Wales (Copping, 2017; Copping & Campbell, 2015). Most studies predicting human life history strategies are derived from surveys with convenience samples (Sear, 2020), with either adults (e.g., Wang et al., 2022) or adolescent participants (e.g., Lordelo et al., 2011), and with many longitudinal studies relying on just two samples: the Minnesota study of risk and adaptation, and the Study of Early Childcare and Youth Development (Young et al., 2020).

There are four aims in the studies in this chapter. The first is to determine if an exploratory analytical method using both LHT-P as a theoretical frame of work and using governmental surveys could be useful in predicting reproductive patterns in an entire country’s population. To do this we will investigate whether variables extracted from the Brazilian Census that are akin to the constructs of harshness and unpredictability usually present in LHT-P literature can predict earlier reproduction 10 years later. Following LHT-P literature, we hypothesize that socio-economic stressors — typically indicative of harshness — and that family configuration stressors – typically indicative of parental absence – will be the best predictors of earlier reproduction.

This manuscript will be using demographic variables descriptive of people residing in a given municipality, but make interpretations based on an evolutionary psychology theory, a field in which research is usually conducted with participant data. This approach will limit the validity and breadth of inferences we can make from the studies in the manuscript. On the other hand, testing this theory using a country’s population as the “sample size” is important considering how valuable cross-cultural or universal traits findings are for evolutionary psychology (Buss, 2024).

The second aim of this manuscript is to identify the best predictors of earlier reproduction. Among all potential indicators of harshness and unpredictability present in the Brazilian census, which ones are the most significant and relevant predictors to our outcome variables? We have no specific hypothesis about which variables will be selected, but we aim to discuss potential explanations for variables that are, or are not, significant and relevant predictors.

The third aim of this manuscript is to test if the findings in a different country’s population (the US) and using a different data source (the American Community Survey; ACS) would be similar to the findings observed with Brazilian census. We will use a more confirmatory analytical approach in this analysis. Considering the evolutionary background of LHT-P, we hypothesize that, in general, the results using US data will be in the same direction as they were with Brazilian data, although we expect to find some differences due to socioeconomic and or cultural differences between the two countries.

The last aim of the study is to assess whether a higher percentage of visible minorities groups in a given geography in both countries is predictive of earlier reproduction. Since both countries have a long history of Black and indigenous communities facing discrimination in education, employment, health access, justice system and many other settings (Aliverti et al., 2023; Bleich et al., 2019; Couto & Brenck, 2024; Serchen et al., 2022; Silva et al., 2024), and the US observes a somewhat more recent history of racism against and discrimination against Hispanic or Latinos (Canizales & Vallejo, 2021), a secondary question is whether these ethnicities will be either predictors of earlier reproduction or mediating variables in our primary prediction. We hypothesize that geographies with higher percentages of visible minorities ethnicities will be associated with higher percentages of reproduction indicators.

## Young parenthood in Brazil

## Methods

### Data selection and transformation

We accessed publicly available Census data from 5507 municipalities from the 2000 census and 5565 municipalities from the 2010 census from Instituto Brasileiro de Geogragia e Estatística (IBGE; Brazilian Institute of Geography and Statistics). Brazilian municipalities differ a lot in population size (M = 30,849, SD = 186,746), with the biggest city, São Paulo (SP), having more than 10 million habitants in 2000, and the smallest, Borá (SP), counting only 795 habitants.

We selected a subset of variables that are publicly available online in the *Amostra - Tabulação Avançada* (“Sample - Advanced Tabulation” in free translation) at SIDRA (*Sistema IBGE de Recuperação Automática - SIDRA*, 2024). This subset was selected based on the variables available in the Census that best map onto the variables frequently measured in studies in LHT-P (i.e., socioeconomic status and parental change and earlier or frequent reproduction). Variables that did not resemble these frequent measures in LHT-P literature were ignored (e.g., living in a rented or owned dwelling with or without mortgage). One clear case in which it was not possible to include a frequent measure in LHT-P literature was the measure of menarche, a common measure to indicate different LHS that is not present in Census data.

We then merged 40 variables from the 2000 census with 10 outcome variables from the 2010 census and used them in an initial model. These variables from the 2000 census were initially grouped into the following predictors: *Low income and lack of resources, Family/house size, Low Education,* *Youth and married with children, Unemployed or precariously employed, Children aged 0 to 9 years old,* and *Black skin colour*. The 10 variables from the 2010 census were grouped into the following outcomes: *Early reproduction* and *Youth married.* Table 1 includes the variables that were used in the two models in the first study. SM\_Table 1 in supplementary materials include the initial 40 variables extracted from the 2000 census. Both tables describe the factor variables the census variables were assigned into; and the analogous variables typically used in LHT-P research they are intended to represent. Refer to *SM\_Variables* for compilation of the raw data collected and how they were initially categorized.

We also used usual statistical treatments related to missing data, outliers and data transformation. A cut-off criterion for missing values of 5% was established: any variable with 5% or more of missing values would be removed from the model. Four of the outcome variables were removed for this reason (Women age group 10 – 14 with children; Age group 10 – 14 living with spouse or partner; Age group 10 – 14 married but not living together; and Age group 20 – 24 married but not living together). None of the predictors were above the cut-off criterion. We also removed municipalities which had any variables more than 3 z-scores from the mean value. These criteria were used to reduce the likelihood that missing data or outliers would affect our analyses.

Lastly, the square root and log transformations were applied to all variables. For each measure, we then selected the values (i.e., original, square root transformed, or log-transformed) whose distribution was closest to normality based on visual inspection of histograms and boxplots. Log transformation of two *Unemployed or precariously employed* variables transformed cases to infinity, which were then replaced by NA and ended up being above the 5% cut-off criterion. *Unemployed or precariously employed* variables were tested but not included in the model (see more details in the result section). After merging and z-score removal, 4135 municipalities remained to be used in analysis.

### Partial Least Squares Structural Equation Modeling (PLS-SEM)

Structural equation modeling (SEM) combines factor analysis and path analysis (i.e., a series of multiple regression analysis) to examine relationships between observed and latent variables (Hair et al., 2022; Kline, 2016). It has the advantage of describing complex relationships between several variables in a single model. It has been utilized in social sciences, business, and psychology to evaluate hypothesized causal relationships and make predictions of an outcome variable that is usually a construct that cannot be directly measured (Hair et al., 2022; Kline, 2016; Maruyama, 1997).

Covariance-based structural equation modeling (CB-SEM) is the most widely used version of SEM, and it is primarily used in confirmatory analyses (Hair et al., 2022; Kline, 2016). Partial Least squares structural equation modeling (PLS-SEM) is used primarily in exploratory analyses that are not based on goodness-of-fit measures (Hair et al., 2022). Whereas CB-SEM relies on fit indices that are based on comparisons of the covariance matrix implied in the model with the observed covariance matrix (Kline, 2016), PLS-SEM relies on several statistics for the evaluation of its measurement (factor analysis) and its structural (path analysis) model (Hair et al., 2022).

PLS-SEM is a nonparametric analysis, and it is more robust than CB-SEM with formative latent variables (i.e., where items are understood to be forming the latent variable instead of the latent variable being the assumed common cause for the items), which is true for all of our predictors. It also allows single-item measures to be included in the structural model. PLS-SEM performs similarly to CB-SEM in a wide range of cases, especially with larger sample sizes or for simple mediation models (Hair et al., 2022; Willaby et al., 2015). All of the above factors suggest that PLS-SEM, as opposed to CB-SEM, is a better analytical approach for this study.

However, we acknowledge that PLS-SEM has been criticized as being merely a weighting system in its measurement model; because (unlike CB-SEM) it lacks a theoretical bases to integrate measurement and structural models; therefore, it does not allow for overidentification tests. PLS-SEM also has been criticized for using significance tests that are more suitable for normally distributed data when it is mostly used with non-normal distribution data. (Rönkkö et al., 2015). We are mindful of these limitations and of the exploratory nature of this analysis when interpreting our findings. All analyses were conducted in R using the seminr package (Ray et al., 2018).

Considering the large sample size, it would be very likely that we would find significant p-values in nearly all the evaluation statistics. In addition, considering that the census is the description of virtually the whole population in a given country, *p*-values are not very informative. Regardless of statistical significance, the associations found with this data will be the description of an association found in a country’s population. Due to that and to the criticisms of PLS-SEM analysis, we stablished significance of ≤ .01 for our analysis but also examined whether confidence intervals included zero – which results in a null path or loading null – and on thresholds recommended by Hair et al. (2021) for accepting the measurement and structural models. We used the following thresholds to characterize explanatory power: Adj. *R*² < .2 = negligible; From .2 - .5 = weak; From .5 - .7 = moderate; Above >.7 = Strong (Nau, 2020). The threshold for paths to be included in the model were *β* > |0.1| because low *β* are at risk of the CI crossing 0, rendering the path null.

### Models

Predictors were set as formative latent variables (i.e., a group of items that sufficiently describe them) whereas outcomes were set as reflective latent variables (i.e., when the group of items are understood to be caused by them). We argue that it is not the case that a latent variable such as low income or big family size are constructs that are causing the variables measured, but we argue that different LHS are the common cause for our outcome latent variables, therefore making them reflective latent variables.

To reach the final selected model, we started with the assessment of measurement model. Collinearity, weights, and loadings of formative latent variables were used for assessment of its significance and importance, and loadings, reliability, internal consistency, and discriminant validity were used for reflective factors. The recommended convergent validity analysis for formative factors was not possible with our data, an issue that has been known to occur in research using secondary data (Hair et al., 2019). After deriving the set of latent variables, the collinearity, relevance and significance of paths was assessed. The factors that passed these assessments and had explanatory power greater than 0.2 were retained. The final model was bootstrapped (nboot = 10,000) and findings are summarized in the result section. The raw and wrangled data, all materials and model outputs used in this study are openly available on OSF at https://osf.io/akqxn/?view\_only=65fb56165b9b48e18d170213493b934d. See *SM03 R files* and *SM04 model iterations output* for the full analytical report and results.

Two model comparisons were planned. One tested whether the ethnicity latent variable would be a significant and relevant predictor or mediator. The other was a test of the selected model; however, the model was tested with the top and bottom quartiles of the sample based on the percentage of children 0-4 years old and 5-9 years old. We hypothesized that ethnicity would be a significant mediator and that paths and explanatory power of the top quartiles would be higher than the bottom quartiles. See *SM04 model iterations output* for the full analytical report and results of the different models tested. The studies in this manuscript were not preregistered.

## Results

The selected model used three variables (i.e., *Youth and married with children, Family/house size*, *Low income and lack of resources*) to predict the outcome variable *Early reproduction* (Fig. 1). The paths from two predictors, *Unemployed or precariously employed* and *Low Education,* were negligible (*β* < 0.1) and the explanatory power of *Youth Married* was also negligible (Adj. *R²* < .01), so these three variables were dropped from the model. The path from *Low Education* to *Early reproduction* was low (*β* = 0.06) but remained significant (*p* < .001) whereas the path from *Unemployed or precariously employed* to *Early reproduction* was not (*p* > .05). Maintaining these two variables in the model to predict *Early reproduction* did not significantly increase the explanatory power (increase in Adj. *R*² < .01). They were, therefore, dropped from the model in accordance with the analytical plan. For a comparison of the models including and excluding these variables, see Analyses3 and Analyses4 HTML files in sm04\_model\_iterations\_output and their associated output CSV files in the supplementary materials.

### Measurement model

#### Reflective measurement model

*Early reproduction* was defined as a reflective latent variable. In this step, we are assessing which variables load into a factor to determine what that factor represents. Alternatively, a variable can be assigned as a single-item factor if it is an important measure for the research question but does not load onto any factor. Guidelines for assessing reflective latent variables in the measurement model (Hair et al., 2019, 2021) include the loadings (*λ* >.7), indicators reliability (loading² > .05), internal consistency (α, ρC, ρA > .7), reliability (Average variance extracted; AVE > .5), discriminant validity (Heterotrait-Monotrait Ratio; HTMT < .9 and Fornell-Larcker criterion, in which the constructs correlations should be lower than the square root of the AVE). The loadings obtained were *Children 0 to 4yo* = .96, *Children 5 to 9yo* = .94*, Mothers 15 to 19yo* = .86, *Mothers 20 to 24yo* = .93. Indicator reliability obtained were *Children 0 to 4yo* = .92, *Children 5 to 9yo* = .88*, Mothers 15 to 19yo* = .74, *Mothers 20 to 24yo* = .86. Internal consistency (α = .94, ρC = .96, ρA = .95) and reliability (AVE = .85) were also above the threshold. HTMT did not pass the recommended threshold (For *Family/house size* HTMT was = .93, for *Low income and lack of resources* it was = .90 and for *Youth and married with children* it was = .96), but Fornell-Larcker criterion did (√AVE = .92 and correlations with *Family/house size* = .83, *Low income and lack of resources* = .89 and *Youth and married with children* = .81). Implications of the HTMT and Fornell-Larcker different reports about variable’s discriminant validity are discussed in the discussion section.

#### Formative measurement model

*Youth and married with children, Family/house size* and *Low income and lack of resources* were defined as formative latent variables. The assessment included collinearity (Variance inflation factor; VIF < .5), weights and loadings for significance and relevance of indicators. Table 2 reports these indices. All indicators were significant (*p* < .01), and confidence interval did not cross 0*.*

### Structural model

The structural model was also assessed for collinearity (VIF < .5), paths significance and relevance, explanatory power (Adj. *R²* ≥ .25), and effect size (*f²* ≥ .02). The results are summarized in Table 3. Variables in the model met all three criteria, meaning they were considered to be not colinear, significant (*p* < .01) and relevant predictors of *Early reproduction*. Paths confidence intervals did not cross 0.

Predictive power was assessed with k-fold cross-validation model (k = 10) with RMSE out-of-sample between the PLS-SEM model and a naive linear regression model ignoring the latent variables. The performance was similar, but the naive linear regression model performed better than the PLS-SEM (*Children 0 to 4yo* = 0.638, *Children 5 to 9yo* = 0.532, *Mothers 15 to 19yo* = 0.659, *Mothers 20 to 24yo* = 1.126, and *Children 0 to 4yo* = 0.666, *Children 5 to 9yo* = 0.559, *Mothers 15 to 19yo* = 0.669, *Mothers 20 to 24yo* = 1.160, respectively). MAE out-of-sample statistics were similar, with linear model performing slightly better than the PLS-SEM model.

### Model comparisons

To test whether ethnicity was a predictive factor of early reproduction we collected data of the percentage of Black, Indigenous and South Asian people in municipalities. The percentage of Indigenous and South Asian people was mostly absolute zeros in almost half of the municipalities (> 2,000 cases) and these measures were removed. Percentage of Black people was then included as a single-item both as a predictor and as a mediator in our most restricted model between *Youth and married with children* and *Family/house* and *Early reproduction.* Based on our cut-off criteria, Black ethnicity was neither a relevant predictor (𝛽 < .01), nor a mediator (i.e., direct paths being greater than the multiplication of mediated paths) of *Early reproduction*. The path from *Youth and married with children* to *Early reproduction* was𝛽 =.47*,* whereas the mediated path was𝛽 = - .09 to Black ethnicity and 𝛽 < .01 to *Early reproduction,* which results in a mediated path lower than - .001*.* The *Family/house size* path to *Early reproduction* was𝛽 =.51*,* whereas the mediated path was𝛽 = - .44 to Black ethnicity and 𝛽 < .01 to *Early reproduction,* which results in a mediated path lower than - .001. The path from Black ethnicity to *Early reproduction* was also non-significant.

The second planned comparison was to divide the sample between the lowest and highest quartiles of percentage of children aged 0-4 and of children aged 5-9 and compare how the model would predict the outcome measures in each of these subsamples. There were minor issues with some indices in some of the subsamples (i.e., *Mothers 15 to 19yo* loading: *λ* < .7 in the lowest quartiles and *Low income and lack of resources* and HTMT crossing 1 in the highest quartile of percentage of children aged 5-9). An optimal model (i.e., passing all criteria) was not sought for these comparisons because we intended to maximize the similarity between these and the first model. Paths, effect sizes and predictive values were similar between the different subsamples, but the *R²* was different between the quartiles with highest percentage of children aged 0-4 and 5-9 (Adj. *R*² = .64 and .69, respectively) and the quartiles with the lowest percentage of children in this age period (Adj. *R*² = .53 and .59, respectively).

## Discussion

The first aim of this study was to test if an exploratory analytical approach using LHT-P as the theoretical approach to data selection and interpretation and using the census could successfully predict reproductive patterns in an entire country’s population. To do this we tested whether census measures associated with familial socio-economic stressors, young marriage, and living in a poorly resourced area could predict early reproduction as reported in the census 10 years later. The explanatory power for *Early reproduction* was remarkable (Adj. *R*² = .84). The model was useful in discriminating between factors that were significant and relevant predictors and factors that were not. The model was also able to discriminate between outcome factors that had acceptable explanatory power and effect sizes from those that did not. We found that the factors *Low income and lack of resources*, *Youth and married with children* and *Family/house size* were predictive of *Early reproduction,* whereas other factors (e.g., *Low education*) were not. In addition, some outcomes (e.g., *Youth married*)were not predicted by any factor*.* Thus, this approach to study LHT-P has been supported and further research could test these findings further by using a similar analysis (e.g., PLS-SEM, exploratory factor analysis) with different data sets or by using a more confirmatory approach.

The second aim was to identify which indicators of harshness and unpredictability in the 2000 census would best predict measures of earlier reproduction in the 2010 census. Both the percentage of children aged 0 to 9 years in a Brazilian municipality, and the percentage of women 15-24 years old with children, were predicted by the percentage of 1) families with low resources (i.e., no electrical power or garbage collection service, and living with 1 minimum wage or less); 2) women 15-24 years old with children, teenagers with a spouse, and people divorced or separated; and 3) large families with more than 1 person per bedroom. Considering that linear models performed better than PLS-SEM in the predictive power step, it is worth noting that these variables these were the most successful predictors of earlier reproduction in Brazilian municipalities regardless of they being properly grouped into factors.

Notably, these effects were measured across a 10-year gap with predictors measured in 2000 and outcomes measured in 2010. This time delay allowed us to test the hypothesis that this relationship is a developmental phenomenon (Ellis et al., 2003; Simpson et al., 2012; Szepsenwol et al., 2019). Based on LHT-P, our hypothesis was that children experiencing harsh and unpredictable conditions in the first years of life are likely to develop a “faster” LHS, experience puberty earlier, and start reproducing earlier. Our findings in addition with findings from previous research support the assumption that there is a critical period of development (0 - 7 years old) in which exposure to harsher and unpredictable environments is likely to cue individuals into reproducing more frequently or earlier. Other findings in the literature also support this assumption by showing that sudden or current change in harsh life conditions does not impact reproductive behaviour (Richardson et al., 2020) or is associated with reproductive decline (Nolin & Ziker, 2016).

To further support the hypothesis that the correlation is a developmental phenomenon and not due to some spatial association or some statistical artifact, we repeated the analyses using the quartiles with highest and lowest percentage of children aged 0-4 and the quartiles with highest and lowest percentage of children 5-9. The paths from predictors to outcome remained similar across the 4 subsamples (ranging from .35 to .48) and comparable to the main model, indicating a stability in the association between these variables. Crucially, the municipalities with the most children had greater explanatory power than those with fewer children, consistent with the idea that this is a developmental phenomenon.

Because we are using census data, our analyses used municipal populations, not just samples of the populations. Therefore, conclusions can and should be drawn regarding non-predictive variables, especially when there is strong prediction that these variables will be associated with *Early reproduction*. Two variables were worth noting: *Unemployed or precariously employed* and *Low Education*. *Unemployed or precariously employed* was not a relevant nor significant predictor of *Early reproduction.* The variables composing the factor indexed youth who were not economically active, and those who were precariously employed or not employed full time, so we intended it to be a factor indicative of parental employment change, which is in the LHT-P literature as a common measure of unpredictability (Belsky et al., 2012; Ellis et al., 2003; Hartman et al., 2018). In the third iteration of the model, the confidence interval of the variable’s weights (i.e., indicator of variable significance) included 0, suggesting that they may not be statistically significant to describe the factor, according with our analytical plan. In addition, the paths from *Unemployed or precariously employed* to both *Married* and *Early reproduction* were below 0.1, suggesting that it was not a relevant predictor for either outcome variable. This result is surprising given that Brazil faces a social security problem of informality in work (i.e., workers not legally registered with the employer and often not eligible to pensions or social security benefits). Depending on classification criteria, between 45 and 55% of Brazilian employees were working informally in 2004 and informality was negatively associated with age (Henley et al., 2009). The fact that a higher percentage of young males and females not economically active or precariously employed was not a relevant predictor of teenage or young adults with children is contrary tosome previous reports (Belsky et al., 2012; Simpson et al., 2012), but consistent with results reported by Hartman and colleagues (2018).

*Low Education*, which could be an indicator of lack of access to resources, was a significant predictor, but not a relevant predictor of *Early reproduction*. In Brazil, education attainment has also been negatively and significantly associated with informal employment in the 90s and 2000s (Henley et al., 2009). Using England and Wales census data, Copping and colleagues (Copping et al., 2013; Copping & Campbell, 2015) found an association between education and family instability and LHS. In addition, women’s access to education has been associated with global fertility decline (Roser, 2014). One possible explanation for why *Unemployed or precariously employed* and *Low Education* were not relevant or significant predictors of *Early reproduction* may be the presence of other variables that better explain the phenomenon (e.g., *Low income and lack of resources)*. Lower education attainment and employment precariousness are expected to be associated with lower pay and reduced access to resources. The absence of such variables in previous research may explain the difference between them being significant predictors of LHS.

### Caveats

This research has been conducted using Brazilian municipalities data. Therefore, any conclusion or inference about individuals should be done with careful consideration. Two other reasons for careful consideration are the lack of manipulation and random assignment of participants (characteristics of experimental research), which then increase the chances of confounding variables. Many variables that are not available in the census (e.g., mortality, disease, use of contraceptive or family planning) could be equal or better predictors of our outcome variables and can be covarying with any of our predictors.

Some parameters in the model required theory-informed interpretation. One of our discriminant validity measures (HTMT) was not attained for the three predictors. Nevertheless, we decided to retain it because the other measure (Fornell-Lacker) passed the criteria and because the issue with a high HTMT is the risk of it being above 1 in the population (Hair et al., 2022). Bootstrapped measures did not reach 1, therefore, it is very unlikely that the HTMT is 1 in the population, which suggests that the variables attained discriminant validity.

Secondly, *Low income and lack of resources* was substantially collinear with *Early reproduction* (VIF = 5.14), which would favor removing the variable. There is an association between harshness, typically measured as socio-economic status (Chang et al., 2019; Doom et al., 2016) and faster life history strategy (Ellis et al., 2009) and subject matter knowledge should be applied to model selection (Harrell, 2015), especially in exploratory research. We argue that the variables here are conceptually different. For example, not having electrical power nor garbage collection services and having a low-income are conceptually different from being a young mother or living in a large family (the other predictors), and also differ from our *Early reproduction* measures. Therefore, we decided to retain the variable in the model. The explanatory power between the model including *Low income and lack of resources* and the model excluding it were similar (R² = .84 and .80, respectively).

It also helps in the interpretation that the observed collinearity – or a high degree of association – did not occur between our measures of *Youth and married with children* variable and the measures in *Early reproduction,* which are conceptually similar to each other and the path between them was not closest to 1. A Pearson correlation analysis also did not show very high correlation (i.e., r > 0.85) between women 15 - 24 years old with children in 2000 with the same variable in 2010 (*r* = .58, *p* < .001). The percentage of women 15 – 19 years old in 2010, for example, were more highly correlated with predictors *No recycling service*, the percentage of children 0 – 4 years old, and the percentage of children 5 – 9 years old (*r* > .68, *p* < .001), but the latter two were not included in the model. If the data was only observing a geographical correlation across time, one would expect collinearity and a very high correlation among variables that are conceptually the same variable but that were measured in two time points. This also suggests that we are not observing a mere geographical correlation. It is likely that certain municipalities with a higher percentage of children aged 5-9 years old living in harsh conditions and with larger families then see these children to grow up and become young parents. Future research may repeat this study with census data in different years or make some changes in the variables composing the factors to assess whether this collinearity persists.

This study relies on the assumption that most children from one municipality will grow up and remain in the same municipality 10 years later. If this were not true, we would be just measuring geographical correlations or some statistical artifact. The census in 2010 reports that 62.8% of Brazilians were born in the municipality they live in (*Sistema IBGE de Recuperação Automática - SIDRA*, 2024) and the National Household Sample Survey indicated that in 2011 59.9% of Brazilians lived in the municipality they were born in (Goularti, 2016). The age range of most mobility is between 25 and 29 years. In comparison to the most mobile age range, the population between 15 and 19 years old was 74% as likely to move in the 2000 census and 69% as likely to move in the 2010 census (Nascimento et al., 2016). In addition, if the national average is around 60% of the population, it is reasonable to assume that this percentage will be negatively associated with age until the age range of most mobility. In other words, for people younger than 25 years of age, the younger the person the more likely it is that she is in the municipality where she was born. This association between age and mobility will not be true only if one is expecting a considerable migration back to the municipality of birth at a later age. We can then expect that among people 24 and younger, which is the population relevant to our outcome variable, 59.9% or more will be residing in the municipality they were born in.

It is worth noting that the factor *Youth and married* *with children* was not a relevant predictor of *Youth Married*, an outcome factor dropped in the model. These two factors are composed of the same variables, only with the 10-year gap. This observation goes in line with the finding that *Youth and married with children* was not collinear with *Early reproduction*. All this supports the hypothesis that our results reveal a developmental phenomenon.

For the comparison of ethnicity, we removed the variable *Low income and lack of resources* and tested whether Black ethnicity would be a relevant predictor or mediator of *Early reproduction*. As stated above, we expected nearly all variables to be significant because of the large sample size, even when adopting a criterion of *p* < .01, and therefore we used *β* > .1 as a threshold for considering a variable relevant. Surprisingly, even though Brazil has both historical and institutional anti-Black racism (Couto & Brenck, 2024; Pimentel, 2022), the percentage of Black people was not a relevant predictor nor a mediator of *Early reproduction*, which was contrary to our fourth hypothesis. We believe that this result may be due to the low percentage of people in Brazilian municipalities identifying as Black (mean = 5.8), which reduces its usefulness as a measure of variation of across municipalities. In fact, most Brazilians self-identify as “Pardos” (roughly translated to Brown). Adding “Pardos” and Blacks as a variable or racial visible minority could have increased the percentage of the population under this criterion but could also reduce variability across municipalities and introduce noise, so we decided not to add them in this study. Future studies could explore this further by using the percentage of specific ethnicities as a predictor variable.

Assessing the predictive value of the model is a recommended step of PLS-SEM (Hair et al., 2019, 2022). In this step, the prediction of each of the directly observed variables (i.e., the four variables indicating *Early reproduction*) of our PLS-SEM model is compared to a naive linear regression model (which does not group variables into factors). The linear regression model performed better than the PLS-SEM model in every model we have tested. We believe this is because the factors included in our analyses were derived from measures that are not sufficiently correlated to capture our hypothesized constructs. The variables measuring any of our factors were not originally intended to measure *Early reproduction, Low income and lack of resources, Family/house size,* nor *Youth and married with children.* In this study, they were grouped into factors because of a hypothesized association derived from LHT-P literature, and statistically, derived from the PLS-SEM Measurement model measures, to justify such groupings. In this case, they are illustrative of the common harshness of unpredictability conditions that can predict a faster life history strategy (Ellis et al., 2009). Should a linear model be a better predictor of such process, it is of little harm to our hypotheses.

In addition, the predictive value assessment is meant to be indicative of the capacity of the model to predict out-of-sample outcomes (Hair et al., 2022; Shmueli et al., 2016). However, because this study is using census data, there is no alternative sample where this model can be replicated. We are not estimating what would be the association between predictors and outcomes in a population, we are describing what they are. This is another reason why we did not rely much on statistical significance when choosing the optimal model. Moreover, previous research has not reported predictive value of PLS-SEM models (Kazár, 2014) or has tested the predictive value of PLS-SEM models with different approaches (Shmueli et al., 2016; see Riou et al., 2016 for an example).

Municipalities likely have higher correlations between variables when those municipalities are nearer geographically. It is possible that the predictive value has been affected by this spatial relationship. In addition, characteristics specific to a region, community, or the differences between urban and rural communities could confound the interaction between the variables studied, increasing error in the model prediction. Future studies using spatial cross-validation (Pohjankukka et al., 2017) or stratified cross validation (Diamantidis et al., 2000) approaches could address this issue.

A final limitation of this study is its exploratory nature (Szollosi & Donkin, 2021). We used LHT-P to inform variables selection and, to the extent possible, the time frame of a phenomenon. However, after this initial selection that was theory based, decisions about maintaining or removing variables in the model were mainly made for statistical reasons. Therefore, this study is descriptive, and not ideal for hypothesis testing. Future studies could attempt to use more confirmatory approaches, CB-SEM for example. When supported by theoretical background, CB-SEM allow for hypothesized causal inferences (Kline, 2016; Maruyama, 1997). Indeed, there has been a claim for more formal and more refined models in LHT in psychology (Nettle & Frankenhuis, 2020; Stearns & Rodrigues, 2020). Study 2 in this manuscript attempted to use CB-SEM with a different data set (ACS). Future studies could test whether this pattern is representative of a more longitudinal/developmental phenomenon or mere geographical correlation by using same year (i.e., predictors and outcomes extracted in the same census year) or reverse (i.e., predictors extracted in the most recent census and outcomes extracted in the past) models. These comparisons, however, are not in the scope of this manuscript.

In sum, this study tested whether growing up in an unpredictable and harsh environment predicts the development of a “faster” LHS using data from the census of a developing country. A model utilizing variables measuring lack of resources, larger families, parental transition and young parents substantially predicted a variable measuring early reproduction in both the overall sample and in the geographic areas with the highest percentages of children.

## Frequent Reproduction in the United States

In this study we used a confirmatory method of analysis to determine if the variables that were significant predictors of reproduction patterns in Brazilian municipalities would be significant predictors of reproductive indicators in a new data set. We chose a different country for this test (US) and a different year range. We hypothesized that most of the variables would be significant predictors of reproduction.

## Methods

### Data selection and transformation

We utilized the variables that were relevant and significant predictors or outcomes in the Brazil data (Fig. 1) to select potential variables for this study. Publicly available data was collected from the American Community Survey: 5-Year Estimates aggregate tables (U.S. Census Bureau., 2020) using the Census Bureau of Statistics API. Predictors were extracted from the ACS 5-year aggregate table in 2009 (i.e., aggregate estimates from 2005-2009) and outcomes in 2023 (i.e., aggregate estimates from 2019-2023). Thus, there was a time difference of around 14 years between predictors and outcomes. The ACS produces its estimates by collecting data from approximately 3.5 million addresses in the US and Puerto Rico every year. These data are reported as estimates of geographies with at least 65,000 people (e.g., census tracts or counties). The five-year aggregate combines data from five consecutive years to produce estimates of geographies with fewer than 65,000 people (U.S. Census Bureau., 2020).

We decided to use US counties as the geographic level of data collection. Counties or equivalents are the primary divisions of American states and they usually include multiple cities or towns (U.S. Census Bureau, 2022). We chose to use counties instead of smaller geographies to reduce the likelihood of a high percentage of the population moving during the 14-year the time span in which data was collected.

Data from ACS 2009 included 3,221 counties and data from ACS 2023 included 3,222 counties of US mainland, Alaska, Hawaii and Puerto Rico. Table 4 reports the 25 variables that were collected for this study and how they compare to the variables that were used in the model in study 1. As was done with the Brazil census data, variables were square-root and log transformed, and the boxplots of these variables were used to choose the transformation (or non-transformed variable) that most closely resembled a normal distribution. Outliers (z-score > |3|) and missing values (NA ≥ 5%) were also removed as they were in the previous study.

Merging the data from 2009 and 2023 resulted in 3,209 counties. The reduction from 3221 counties in 2009 is due primarily to the division or redefinition of a county, which produced a different code for the new geographical division. Outlier removal reduced the data merged data set to 2763 counties, which represents a reduction of around 15%. No variable had a NA count higher than 5%, therefore no variables were removed due to this process. Therefore, the final data set consisted of 19 predictor and 6 outcome variables and 2763 counties. All scripts and a full report of data curation and transformation is available in supplementary materials.

## Results

Covariance-based structural equation modelling (CB-SEM) analysis was planned for this data. CB-SEM is an alternative to PLS-SEM that encompass a more confirmatory approach (Hair et al., 2022; Kline, 2016). The measurement model is tested in confirmatory factor analysis and in a subsequent step structural model is tested with the paths between factors. In both steps of CB-SEM, fit indices measure how well the covariance matrix generated from the data match the covariance matrix hypothesized from the model (CFI and TLI > .9 and SRMR and RMSEA < 0.1). Models that exhibit good fit are accepted as properly describing the data (Kline, 2016).

We attempted different methods of loading the variables into factors in the confirmatory factor analysis steps. These steps included different combinations of variables provided there was theoretical support in LHT-P and using ACS variables that ACS reports separated by sex both as separate variables loading into a factor or the as combined across sexes. However, the CFA indicated that these variables were not converging into factors. Often, one variable would load highly (e.g., *λ* > 1) and the others would load lowly (e.g., *λ* < 0.3). See supplementary materials for a full report of these steps. This result was not surprising considering that CB-SEM does not allow a factor to be composed of less than 3 variables and to deal with formative factors (Hair et al., 2021, 2022). When removing the factors in the measurement model, CB-SEM is only a series of multivariate linear regressions. Particularly when there is no mediation or other interaction between outcome variables. Therefore, the analytical approach of US data was switched to multivariate linear regressions.

Different multivariate linear regression models utilized the outcome and predictor variables described in Table 2. Given the non-normal characteristic of the data and the arguably large sample size, we utilized Heteroskedasticity-consistent degrees of freedom correction (HC1) to inflate residuals and make the analysis more reliable (Long & Ervin, 2000; MacKinnon & White, 1985). The robust standard error correction used in the regression analyses[?] was an addition intended to deal with heteroskedasticity which. This was a concern because our data expressed population units that differed in size and because data was always expressed as a rate or percentage and the population units differed in size. It is expected that variables or areas with percentages near the middle (50%) will vary more than those near the pole’s extremes (i.e., 0 or 100%), and it is also expected that larger areas (e.g., big cities) will be more homogenous than smaller areas. Both of these factors would result in unequal error variance.

We assessed collinearity with Variance Inflation Factor (VIF > 3), but no predictor was removed because none was above this criterion. Non-significant variables were removed from the model until only significant variables were left, a process similar to stepwise linear regression analysis (Harrell, 2015). Tables 4 – 7 report the models for each outcome variable and Table 8 reports the explanatory power of these four models. The models predicted a substantial proportion of variance of *Age Group - 0 to 4 Years of Age* (*R²* = 0.49, *F*(11, 2733) = 240.91, *p* < .001, Adj. *R²* = 0.49) and of *Age Group - 5 to 9 Years of Age* (*R²* = 0.39, *F*(6, 2738) = 291.82, *p* < .001, Adj. *R*² = 0.39) and a weak or negligible proportion of variance of *Women 15 to 19 Years of Age Who Had Birth* (*R²* = 0.07, *F*(5, 2739) = 43.71, *p* < .001, Adj. *R²* = 0.07) and of *Women Who Had Birth in the Past 12 Months* (*R*² = 0.10, *F*(3, 2741) = 98.28, *p* < .001, Adj. *R*² = 0.10). Frequency tables showing the mean of each outcome variable, expressed without a log or square root transformation, for each tertile of the predictor variables were also compiled to provide a better visualization of the models (Tables 9 – 12).

## Discussion

This study aimed to assess whether an analysis with US data would have similar findings with the Brazil census analysis, but this time with a confirmatory analysis. There were a few similarities. Linear regression models that used predictors that were identified in our analysis of the Brazil data that are similar to measures of harshness and unpredictability in LHT-P (Belsky et al., 2012; Ellis et al., 2003; Hartman et al., 2018; Xu et al., 2018), accounted for a substantial proportion of the variance across US counties of the percentage of children aged 0-4 and 5-9 years in US counties. A higher percentage of children in a county can be understood as more frequent reproduction that is caused by 1. A higher percentage of women are having children in these counties; or 2. A subset of women in these counties are having multiple children.

The outcome variables of young motherhood (*Women 15 to 19 Years of Age Who Had Birth*) and recent reproduction (*Women Who Had Birth in the Past 12 Months*) also had significant predictors, but the explanatory power of these variables were weak or negligible. Some considerations can help understand this poor performance. First, there is a global trend toward the decline and delay in fertility (Roser, 2014; Volk, 2023). Access to education and health care, especially among women, are understood to be the lead causes of this decline and delay. Observing the frequency tables, we can see that the non-transformed percentage of Women 15 to 19 Years of Age Who Had Birth is always smaller than 0.1 % and of Women Who Had Birth in the Past 12 Months is never above 2%, and this global trend could explain the small percentage found in our data.

Secondly, the notably small percentages, particularly in the first case, mean that outlier cases potentially resulting from confounding variables would exert a disproportionately large influence on the variance of these variables. This noise would likely have a reduced impact if these outcome variables encompassed a greater proportion of the population. Lastly, the considerable right-skewness observed (i.e., values clustering near zero) increases the likelihood of the model being impacted by the violation of distributional assumptions required for linear regression analyses. Future studies could repeat this analysis with a subset of the population in which there are higher percentages of young or recent parents or making use of a more robust analysis.

The model predicting the percentage of *Age Group - 0 to 4 Years of Age* in 2023 contained 11 significant predictors and the one predicting *Age Group - 5 to 9 Years of Age* contained 6 predictors. Out of these, the outcome variable (i.e., the percentage of children in these age ranges) was also a predictor. This brings up the discussion about whether these variables represent merely a geographical correlation across time. However, predictors and outcomes are separated by roughly 14 years, therefore, one can also argue that the process is that US counties with a higher percentage of children (0-9 years old) in 2009 had these children becoming of reproductive age 14 later and a subset of these people had children in 2023, maintaining the higher percentage of children in comparison with other US counties. Interestingly, the percentage of children aged 0-4 years had the highest t-values and standardized *β* for both of the outcomes: children aged 0-4 years and children aged 5-9 years. If we were observing merely geographical correlation over time, one would expect the same variables to have the highest associations, which didn’t happen for children aged 5-9 years.

Having fewer resources in 2009 – indicated by not having a complete kitchen, having income below poverty level, and having more than 1 occupant per room in the household – were positively associated with *Age Group - 0 to 4 Years of Age* in 2023. This result is consistent with the literature showing that harsher environments favor having children more frequently (Belsky et al., 2012; Ellis et al., 2009; Stearns, 1992). Contrary to this literature, our analysis found that not having complete plumbing or the median number of rooms in the household were in the opposite direction. Lack of complete plumbing was negatively associated whereas median number of rooms was positively associated with the percentage of children. It may be the case that not having complete plumbing in the household is related to geographical location (e.g., rural vs. urban) rather than harshness *per se*. The association between household density (occupants per room) and young children could be due to multiple generations co-habiting: Some young children may be the grandchildren of the primary occupants. For instance, households with more children may also be households with more rooms, but the increase may not be one-to-one (i.e., children sharing bedrooms). The median number of rooms was a significant predictor of the percentage of children aged 5-9 years, but having one or more occupants per room was not.

The percentage of *women who had births in the past 12 months* and of *divorced* people were also significant predictors of the percentage of children both aged 0-4 and aged 5-9 years. The former may support the claim that the phenomenon being observed is of more frequent reproduction in harsher environment while the latter is contrary to what has been observed in the literature. According to LHT-P, experiencing parental transitions during the childhood favors faster and more frequent reproductive strategies because it alters the expectation that the parental figure (usually the father) will remain in the relationship and invest in children (Belsky et al., 2012; Volk, 2023). However, our data shows that counties that had more divorced people in 2009 had a *lower* percentage of children aged 0-9 years in 2023.

Unlike what was found in the previous study, a high percentage of Blacks in 2009 was a significant predictor of the percentage of children aged 0 – 9 years in 2023 and the percentage Hispanic people was a significant predictor of the percentage of children aged 0 – 4 years. These associations were all negative, meaning that once you remove the effect of socioeconomic predictors, ethnicity is a significant predictor in the *opposite* direction of the common perception that these ethnicities have larger families (Pew Research Center, 2015).

This study suffers from similar limitations as the study with Brazil data. Considering that we are describing an observation made with aggregate values of large geographical areas (US counties), one should be very careful when considering how our results apply to individual behaviours. There is the possibility that confounding variables are present and that, if observed or measured, would result in a different interpretation of the phenomenon at the individual level.

Data in both studies were transformed, therefore, *β* values cannot be directly interpreted as a multiplier to convert a change in a predictor variable to a change in the outcome variable. Future studies could use subsamples that would not require such transformations and develop models that would allow for such interpretation. Even after transformation, data was not normal, and linear regressions assume normality of residuals. We utilized HC1 correction, but this data skewness could still influence the precision of the linear models. Finally, our sample consisted of more than 2,700 cases and p-values are sensitive to sample size (Gelman & Weakliem, 2009; Lakens, 2022). The significance level reported for most variables were below .001 but they should still be interpreted with caution as they could be merely reflecting an overpowered analysis. Future studies should seek to confirm the results in this study and refine model predictions.

## General discussion

Our first study determined if predictions derived from LHT-P could account for measures of reproductive behaviours contained in Brazil census data. Studies with a similar approach have been conducted before in the United Kingdom (Copping et al., 2013; Copping & Campbell, 2015), but to our knowledge our study is novel in a few characteristics. First, the analysis of the Brazil census was the first study to utilize population data from a developing country to assess LHT-P hypotheses. Second, our analyses used a longitudinal approach - using data from one year to predict data collected a decade or more later - to assess the developmental prediction proposed by LHT-P (Ellis et al., 2003; Simpson et al., 2012; Webster et al., 2014). Third, this project is the first to compare the results obtained from two countries with very large populations (more than 200 million people). Fourth, the study is the first to assess whether ethnicity, along with common predictors in LHT-P literature, is predictive of reproduction.

These two studies were designed to answer several research questions. The first was whether an exploratory version of structural equation modelling analysis would converge and perform well using secondary data. This question is interesting because secondary data tend to be suboptimal for variable selection (Andersen et al., 2011; Johnston, 2017; Jones, 2010) and are unlikely to achieve model fit (Hair et al., 2022) because data collection was not designed for that purpose. This analysis is even more challenging because we used variable measured in one year to predict outcomes a decade later.

PLS-SEM analyses of the Brazilian data worked reasonably well. We found some variables converged into satisfactory factors (e.g., *Low income and lack of resources)* but others did not (e.g., *Early reproduction* was initially tested with variables of married youth) and some were good predictors (e.g., *Low income and lack of resources)* but others were not (*Unemployed or precariously employed)*. The structural assessment was also satisfactory, and the explanatory power of *Early reproduction* was substantial to a level that is rarely found in the social sciences. The cross-validation predictive power of the PLS-SEM model was similar to what would be achieved by linear models. We believe that PLS-SEM is suitable for analyzing this type of data and encourage future studies to use it to analyze data from different countries.

The second aim of the study was to assess which predictors, among the ones that were akin to those frequently used in LHT-P, would best predict variables that index early reproduction. In contrast to studies that identified unpredictability (Belsky et al., 2012; McLaughlin et al., 2021; Simpson et al., 2012), especially parental transitions (Hartman et al., 2018), as the strongest predictor of faster LHS, our study found that measures of marital status (akin to parental transitions) and labour quality (akin to parental availability) were *poorer* predictors of *Early reproduction* than measures of harshness (i.e., *Low income and lack of resource*). Most LHT-P studies have been conducted in developed countries. Such populations may have both lower levels of harshness and less variance in measures of harshness (not having access to electricity being rare, for example). The variance in harshness in our data set may explain why harshness was the best predictor of early reproduction in our study but not in studies relying on data from developed countries.

The variance of the measures of unpredictability could be obscured by other variables. For example, the same variance or even the same regions in which there is a high level of unemployment (*Unemployed or precariously employed*, intended to measure parental availability) could covary with *Low income and lack of resources*, which would obscure the predictive power of one of the variables. Our analyses did not find that these measures were collinear, which is an outcome that we would expect if they were strongly correlated. However, this assessment only measures collinearity among factors not the directly observed variables. It is possible that a different arrangement of the observed variables would reveal such collinearity.

The third aim of this study was to assess whether an analysis of survey data from a developed country would yield similar findings to the ones obtained from an analysis of census data from a developing country. Results from the Brazil data indicated that people living in harsher environments are – 10 years later – more likely to have children and are more likely to have children at a younger age. In addition, the percentage of mothers aged 15 – 24 years and of people 15 – 19 years old living with a partner were predictive of a higher percentage of children and of younger mothers. We argue that this is a developmental phenomenon: it is likely that many children living in those municipalities in 2000 grew up to become young mothers in 2010. The results from the United States were comparable. For models predicting the percentage of children aged 0 -4 and children 5 – 9 years, indicators of harshness (e.g., lacking a complete kitchen, low income, more rooms per dwelling, more than one occupant per room), and a higher percentage of women who had births in past 12 months and the percentage of children aged 0 – 9 years old were predictive of the percentage of young children (0 – 4 years) 14 years later. As in the Brazil data, the analysis of the US data supports the developmental hypothesis that children living in counties with higher levels of harshness in 2009 grew up to become parents in 2021.

In both studies, the percentage of divorced people in a municipality or county was a negative predictor of the percentage of children in the same area 10-14 years later. This result was surprising because “parental transitions” is a common measure associated with a faster LHS in LHT-P (Belsky et al., 2012; Ellis et al., 2009; Hartman et al., 2018). Parental transitions are assumed to signal to children that relationships do not last, so one should expect these children to become adults with lower expectations of partner investment in raising children (Volk, 2023). Our result is inconsistent with this prediction. It can be interpreted, though, in light of the recent shifts of marriage and divorce statistics (Herre et al., 2020; Kennedy & Ruggles, 2014). Marriage has been in a slight decline and there is an increase in conjugal relationships and parenting without marriage, which in turn lowers divorce rates. Marriage and divorce are also happening at later age. If divorces are decoupled or less representative of parental availability to children, this change can impact the predictive power of divorce rates. In addition, if divorces are happening at a later age, the time frame of this longitudinal analysis will not allow for this variable to be predictive of a faster LHS.

Cross-country comparisons are of interest. Results from the Brazilian census indicated that lack of access to recycling service and to electrical power was associated with a higher percentage of children and of early parenting. However, lacking plumbing in the US was associated with a *lower* percentage of children 14 years later. This different association found in the US data may be due to a reduced prevalence of a lack of plumbing or due to it being an indicator of geographical location (e.g., urban vs. rural environments) instead of a harsher environment.

Harshness indicators in the ACS were not significant predictors of the percentage of children aged 5 – 9 years. The variables that were positively associated with the percentage of children were the percentage of children between 2005 and 2009, of women who had births in the previous year, and the median number of rooms. The percentage of children and of women who had births in the previous year being significant predictors may be due to the similarity in the variables. Geographies with a higher number of children in a given year are more likely to have higher number of children 14 years later. A possibility for harshness variables not being predictive of the percentage of children aged 5- 9 years is that the age range and the time difference between predictors and outcomes were not aligned. The middle point of our predictors using US data was 2007, and of the outcomes it was 2021. The outcome variable being children who were 5 – 9 years old in 2021 means that they were born between 2012 to 2016 and means that the children who were 0 – 4 years old in 2007 would still not be in reproductive age then. Therefore, the time spam does not allow for the phenomenon described by LHT-P to be found with this outcome variable.

With all these considerations, we suggest that results found with US data were somewhat similar to the ones found with the Brazil census. The US and Brazil are two of the biggest countries in land mass and both countries have population counting in the hundreds of millions. Finding similar results between the two countries is a valuable contribution to LHT-P literature. Moreover, findings that are common among different environments and that are found among a large sample size are invaluable to evolutionary psychology because of its claims of adaptations that have been selected in our evolutionary history (Buss, 2024).

Finally, we assessed whether the percentage of visible minorities, which historically have faced and still face harsher circumstances, would be a significant and relevant predictor of our reproduction measures. They were not. Having a high percentage of Black people in Brazilian municipalities had a negligible effect on early reproduction and the Black or Hispanic and Latino percentages in US counties had a significant *negative* effect on reproduction rates. Previous studies have established an association between Black ethnicity in the US and early parenthood (Wilson, 1987; Wodtke, 2013) and both Hispanic/Latino and Black women have higher fertility rates than White women in the US (Pew Research Center, 2015). We suggest that the relationship between these previous findings and our results demonstrate the different circumstances and the history of racism and discrimination that visible minorities face (Bleich et al., 2019; Canizales & Vallejo, 2021; Couto & Brenck, 2024). The effect of reduced socioeconomic resources, not a general effect of ethnicity, explains reproductive behaviour in our model, and our analysis of the US data shows that Black and Hispanics or Latinos are actually having *fewer* children when the effects of socioeconomic resources are removed.

Several other factors could help explaining the phenomenon described in this study, but they were out of our scope here. For example, genetic variation may have a role in the different LHS developed by humans (Buss, 2016; Del Giudice, 2009). It could be that genes select for or shape environmental conditions and both would impact on LHS factors such as time of puberty (Volk, 2025). Cultural or institutional factors could help explain the association between poverty and early parenting (Wilson, 1987; Wodtke, 2013). For example, parents who experience a longer commute to work or who work longer hours to provide necessary income may not have as much time as parents from more affluent conditions to support or supervise their children in their sex and reproductive decisions. In addition, poorer areas are frequently the ones that lack institutions that aid parents in such tasks. These alternative explanations could interact with LHT-P claims to explain the association between poor communities and early and frequent parenting.

In sum, the usual LHT-P hypothesis that harshness is associated with early or more frequent reproduction was supported by a study using populational level data from a developing country and partially supported by data from a developed country. The effects of environmental unpredictability were inconsistent, and the percentage of visible minorities was either a non-relevant predictor or was a significant predictor of reproduction that was in the opposite direction to what has been commonly observed in the literature. Future research could aim to confirm such results with different data sets.

### Conclusion

Using Brazilian census data, we showed that harshness early in childhood in a municipality predicts early reproduction in that municipality, consistent with the prediction of LHT-P. In the United States, harshness early in childhood in a county predicts higher reproduction rate in the same county, a finding that is similar to the findings in Brazil. Ethnicity predicted reproduction in the United States but not Brazil, suggesting that our dataset cannot completely account for the effect of ethnicity on reproduction.

## References

Albaladejo‐Robles, G., Böhm, M., & Newbold, T. (2023). Species life‐history strategies affect population responses to temperature and land‐cover changes. Global Change Biology, 29(1), 97–109. https://doi.org/10.1111/gcb.16454

Aliverti, A., Carvalho, H., Chamberlen, A., & Sozzo, M. (Eds.). (2023). Decolonising the criminal question: Colonial legacies, contemporary problems (1st ed.). Oxford university press.

Andersen, J. P., Prause, J., & Silver, R. C. (2011). A Step-by-Step Guide to Using Secondary Data for Psychological Research: Using Secondary Data. Social and Personality Psychology Compass, 5(1), 56–75. https://doi.org/10.1111/j.1751-9004.2010.00329.x

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. Developmental Psychology, 48(3), 662–673. https://doi.org/10.1037/a0024454

Bleich, S. N., Findling, M. G., Casey, L. S., Blendon, R. J., Benson, J. M., SteelFisher, G. K., Sayde, J. M., & Miller, C. (2019). Discrimination in the United States: Experiences of black Americans. Health Services Research, 54(S2), 1399–1408. https://doi.org/10.1111/1475-6773.13220

Buss, D. M. (Ed.). (2016). The handbook of evolutionary psychology (2nd edition). Wiley.

Buss, D. M. (2024). Evolutionary psychology: The new science of the mind (Seventh edition). Routledge.

Canizales, S. L., & Vallejo, J. A. (2021). Latinos & Racism in the Trump Era. Daedalus, 150(2), 150–164. https://doi.org/10.1162/daed\_a\_01852

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. Developmental Psychology, 55(4), 890–903. https://doi.org/10.1037/dev0000655

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), Encyclopedia of Evolutionary Psychological Science (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Copping, L., T., & Campbell, A. (2015). The environment and life history strategies: Neighborhood and individual-level models. Evolution and Human Behavior, 36(3), 182–190. https://doi.org/10.1016/j.evolhumbehav.2014.10.005

Copping, L. T., Campbell, A., & Muncer, S. (2013). Violence, teenage pregnancy, and life history: Ecological factors and their impact on strategy-driven behavior. Human Nature (Hawthorne, N.Y.), 24(2), 137–157. https://doi.org/10.1007/s12110-013-9163-2

Couto, P., & Brenck, C. (2024). Monetary Policy and the Gender and Racial Employment Dynamics in Brazil. Review of Political Economy, 1–25. https://doi.org/10.1080/09538259.2023.2294306

Del Giudice, M. (2009). Sex, attachment, and the development of reproductive strategies. Behavioral and Brain Sciences, 32(1), 1–21. https://doi.org/10.1017/S0140525X09000016

Diamantidis, N. A., Karlis, D., & Giakoumakis, E. A. (2000). Unsupervised stratification of cross-validation for accuracy estimation. Artificial Intelligence, 116(1–2), 1–16. https://doi.org/10.1016/S0004-3702(99)00094-6

Dinh, T., Haselton, M. G., & Gangestad, S. W. (2022). “Fast” women? The effects of childhood environments on women’s developmental timing, mating strategies, and reproductive outcomes. Evolution and Human Behavior, 43(2), 133–146. https://doi.org/10.1016/j.evolhumbehav.2021.12.001

Doom, J. R., Vanzomeren-Dohm, A. A., & Simpson, J. A. (2016). Early unpredictability predicts increased adolescent externalizing behaviors and substance use: A life history perspective. Development and Psychopathology, 28(4pt2), 1505–1516. https://doi.org/10.1017/S0954579415001169

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? Child Development, 74(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. Human Nature, 20(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. Evolution and Human Behavior, 41(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Gelman, A., & Weakliem, D. (2009). Of Beauty, Sex and Power: Too little attention has been paid to the statistical challenges in estimating small effects. American Scientist, 97(4), 310–316. JSTOR.

Goularti, J. G. (2016). Migrações e urbanização em Santa Catarina. Desenvolvimento Socioeconômico Em Debate, 1(2), 85. https://doi.org/10.18616/rdsd.v1i2.2398

Griskevicius, V., Delton, A. W., Robertson, T. E., & Tybur, J. M. (2011). Environmental contingency in life history strategies: The influence of mortality and socioeconomic status on reproductive timing. Journal of Personality and Social Psychology, 100(2), 241–254. https://doi.org/10.1037/a0021082

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (Third edition). SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Harrell, F. E. (2015). Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis. Springer International Publishing. https://doi.org/10.1007/978-3-319-19425-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. Development and Psychopathology, 30(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Henley, A., Arabsheibani, G. R., & Carneiro, F. G. (2009). On Defining and Measuring the Informal Sector: Evidence from Brazil. World Development, 37(5), 992–1003. https://doi.org/10.1016/j.worlddev.2008.09.011

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. Nature, 466(7302), 29–29. https://doi.org/10.1038/466029a

Herre, B., Samborska, V., Ortiz-Ospina, E., & Roser, M. (2020). Marriages and Divorces. Our World in Data.

Johnston, M. (2017). Secondary Data Analysis: A Method of which the Time Has Come. Qualitative and Quantitative Methods in Libraries, 3(3), 619–626.

Jones, C. (2010). Archival Data: Advantages and Disadvantages for Research in Psychology: Archival Data. Social and Personality Psychology Compass, 4(11), 1008–1017. https://doi.org/10.1111/j.1751-9004.2010.00317.x

Kazár, K. (2014). PLS Path Analysis and its Application for the Examination of the Psychological Sense of a Brand Community. Procedia Economics and Finance, 17, 183–191. https://doi.org/10.1016/S2212-5671(14)00893-4

Kennedy, S., & Ruggles, S. (2014). Breaking Up Is Hard to Count: The Rise of Divorce in the United States, 1980–2010. Demography, 51(2), 587–598. https://doi.org/10.1007/s13524-013-0270-9

Kline, R. B. (2016). Principles and practice of structural equation modeling (Fourth edition). The Guilford Press.

Lakens, D. (2022). Why P values are not measures of evidence. Trends in Ecology & Evolution, 37(4), 289–290. https://doi.org/10.1016/j.tree.2021.12.006

Long, J. S., & Ervin, L. H. (2000). Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. The American Statistician, 54(3), 217–224. https://doi.org/10.1080/00031305.2000.10474549

Lordelo, E. da R., Seidl-de-Moura, M. L., Vieira, M. L., Bussab, V. S. R., Oliva, A. D., Tokumaru, R. S., & Britto, R. C. S. (2011). Ambiente de desenvolvimento e início da vida reprodutiva em mulheres brasileiras. Psicologia: Reflexão e Crítica, 24(1), 116–125. https://doi.org/10.1590/S0102-79722011000100014

MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics, 29(3), 305–325. https://doi.org/10.1016/0304-4076(85)90158-7

Malone, E. W., Perkin, J. S., Keith Gibbs, W., Padgett, M., Kulp, M., & Moore, S. E. (2022). High and dry in days gone by: Life‐history theory predicts Appalachian mountain stream fish assemblage transformation during historical drought. Ecology of Freshwater Fish, 31(1), 29–44. https://doi.org/10.1111/eff.12606

Maruyama, G. (1997). Basics of structural equation modeling. Sage Publications.

McLaughlin, K. A., Sheridan, M. A., Humphreys, K. L., Belsky, J., & Ellis, B. J. (2021). The Value of Dimensional Models of Early Experience: Thinking Clearly About Concepts and Categories. Perspectives on Psychological Science, 16(6), 1463–1472. https://doi.org/10.1177/1745691621992346

Nascimento, T. C. L. do, Silva, R. P. da, & Lucas, L. A. P. (2016). Tendência das migrações brasileiras: Diferenciais de sexo, idade, distância e volume dos migrantes intermunicipais para 1995-2000 e 2005-2010. 18. https://files.alapop.org/congreso7/files/pdf/349-250.pdf

Nau, R. (2020). What’s a good value for R-squared? https://people.duke.edu/~rnau/rsquared.htm

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? Philosophical Transactions of the Royal Society B: Biological Sciences, 375(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Nolin, D. A., & Ziker, J. P. (2016). Reproductive Responses to Economic Uncertainty: Fertility Decline in Post-Soviet Ust’-Avam, Siberia. Human Nature, 27(4), 351–371. https://doi.org/10.1007/s12110-016-9267-6

Pew Research Center. (2015). Childlessness Falls, Family Size Grows Among Highly Educated Women [Report]. Pew Research Center. https://www.pewresearch.org/social-trends/2015/05/07/family-size-among-mothers/

Pimentel, R. (2022). “Equal Before the Law,” But Not in Practice: Brazil’s Social Inequality Crisis—Harvard Political Review. https://harvardpolitics.com/brazil-social-inequality/

Pohjankukka, J., Pahikkala, T., Nevalainen, P., & Heikkonen, J. (2017). Estimating the prediction performance of spatial models via spatial k-fold cross validation. International Journal of Geographical Information Science, 31(10), 2001–2019. https://doi.org/10.1080/13658816.2017.1346255

Ray, S., Danks, N. P., & Calero Valdez, A. (2018). seminr: Building and Estimating Structural Equation Models (p. 2.3.3) [Dataset]. https://doi.org/10.32614/CRAN.package.seminr

Richardson, G. B., Placek, C., Srinivas, V., Jayakrishna, P., Quinlan, R., & Madhivanan, P. (2020). Environmental stress and human life history strategy development in rural and peri-urban South India. Evolution and Human Behavior, 41(3), 244–252. https://doi.org/10.1016/j.evolhumbehav.2020.03.003

Riou, J., Guyon, H., & Falissard, B. (2016). An introduction to the partial least squares approach to structural equation modelling: A method for exploratory psychiatric research. International Journal of Methods in Psychiatric Research, 25(3), 220–231. https://doi.org/10.1002/mpr.1497

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat emptor. Personality and Individual Differences, 87, 76–84. https://doi.org/10.1016/j.paid.2015.07.019

Roser, M. (2014). The global decline of the fertility rate. Our World in Data.

Sear, R. (2020). Do human ‘life history strategies’ exist? Evolution and Human Behavior, 41(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Serchen, J., Mathew, S., Hilden, D., Southworth, M., Atiq, O., Health and Public Policy Committee of the American College of Physicians\*, Mathew, S., Hilden, D., Beachy, M., Curry, W., Hollon, M., Jumper, C., Mellacheruvu, P., Parshley, M., Sagar, A., Slocum, J., Tan, M., Van Doren, V., & Yousef, E. (2022). Supporting the Health and Well-Being of Indigenous Communities: A Position Paper From the American College of Physicians. Annals of Internal Medicine, 175(11), 1594–1597. https://doi.org/10.7326/M22-1891

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. Journal of Business Research, 69(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Silva, K. K. R., Lima, M. E. O., & Silva, P. D. (2024). Racism and Indigenous Peoples in Brazil: A Scoping Review. Psicologia - Teoria e Prática, 26(1). https://doi.org/10.5935/1980-6906/ePTPSP15944.en

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. Developmental Psychology, 48(3), 674–686. https://doi.org/10.1037/a0027293

Sistema IBGE de Recuperação Automática—SIDRA. (2024). https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2022/universo-populacao-por-cor-ou-raca

Stearns, S. C. (1992). The evolution of life histories. Oxford University Press.

Stearns, S. C., Allal, N., & Mace, R. (2008). Life history theory and human development. In Foundations of evolutionary psychology. (pp. 47–69). Taylor & Francis Group/Lawrence Erlbaum Associates.

Stearns, S. C., & Rodrigues, A. M. M. (2020). On the use of “life history theory” in evolutionary psychology. Evolution and Human Behavior, 41(6), 474–485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Stone, B. W. G., Dijkstra, P., Finley, B. K., Fitzpatrick, R., Foley, M. M., Hayer, M., Hofmockel, K. S., Koch, B. J., Li, J., Liu, X. J. A., Martinez, A., Mau, R. L., Marks, J., Monsaint-Queeney, V., Morrissey, E. M., Propster, J., Pett-Ridge, J., Purcell, A. M., Schwartz, E., & Hungate, B. A. (2023). Life history strategies among soil bacteria—Dichotomy for few, continuum for many. The ISME Journal, 17(4), 611–619. https://doi.org/10.1038/s41396-022-01354-0

Szepsenwol, O., Zamir, O., & Simpson, J. A. (2019). The effect of early-life harshness and unpredictability on intimate partner violence in adulthood: A life history perspective. Journal of Social and Personal Relationships, 36(5), 1542–1556. https://doi.org/10.1177/0265407518806680

Szollosi, A., & Donkin, C. (2021). Arrested Theory Development: The Misguided Distinction Between Exploratory and Confirmatory Research. Perspectives on Psychological Science, 16(4), 717–724. https://doi.org/10.1177/1745691620966796

U.S. Census Bureau. (2020). Understanding and Using American Community Survey Data: What All Data Users Need to Know. U.S. Government Publishing Office. https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs\_general\_handbook\_2020.pdf

U.S. Census Bureau. (2022). Glossary. https://www.census.gov/programs-surveys/geography/about/glossary.html?utm\_source=chatgpt.com#par\_textimage\_13

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. Evolution and Human Behavior, 44(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Volk, A. A. (2025). Pumping the Brakes on Psychosocial Acceleration Theory: Revisiting its Underlying Assumptions. Evolution and Human Behavior, 46(1), 106657. https://doi.org/10.1016/j.evolhumbehav.2025.106657

Wang, X., Zhu, N., & Chang, L. (2022). Childhood unpredictability, life history, and intuitive versus deliberate cognitive styles. Personality and Individual Differences, 184, 111225. https://doi.org/10.1016/j.paid.2021.111225

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. Evolutionary Psychology, 12(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Wells, J. C. K., Cole, T. J., Cortina-Borja, M., Sear, R., Leon, D. A., Marphatia, A. A., Murray, J., Wehrmeister, F. C., Oliveira, P. D., Gonçalves, H., Oliveira, I. O., & Menezes, A. M. B. (2019). Low Maternal Capital Predicts Life History Trade-Offs in Daughters: Why Adverse Outcomes Cluster in Individuals. Frontiers in Public Health, 7, 206. https://doi.org/10.3389/fpubh.2019.00206

Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what Partial Least Squares (PLS) can offer differential psychology. Personality and Individual Differences, 84, 73–78. https://doi.org/10.1016/j.paid.2014.09.008

Wilson, W. J. (1987). The truly disadvantaged: The inner city, the underclass, and public policy. University of Chicago press.

Wodtke, G. T. (2013). Duration and timing of exposure to neighborhood poverty and the risk of adolescent parenthood. Demography, 50(5), 1765–1788. https://doi.org/10.1007/s13524-013-0219-z

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. Evolution and Human Behavior, 39(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005

Young, E. S., Frankenhuis, W. E., & Ellis, B. J. (2020). Theory and measurement of environmental unpredictability. Evolution and Human Behavior, 41(6), 550–556. https://doi.org/10.1016/j.evolhumbehav.2020.08.006

Zhu, N., & Chang, L. (2020). An evolutionary life history explanation of sexism and gender inequality. Personality and Individual Differences, 157, 109806. <https://doi.org/10.1016/j.paid.2019.109806>

**Table 1**

*Variables in the Brazilian model and inferred concepts.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT-P** | **Factor in the model** | **Variables present in the Census** | **Variable abbreviationa** |
| Harshness | SES measures | Low income and lack of resources | Lack of recycling or garbage collection | No recycling service |
|  | Lack of electrical power serviceb | No electrical power |
|  |  |  | People with income of 1 minimum wage or less | 1 minimum wage or less |
|  |  | Family/house size (Lack of resources) | Number of people in the family – 6 people | Families with 6 people |
|  |  |  | Resident density per bedroom - More then 2 up to 3 residents | 2-3 residents / bedroom |
|  |  |  | Resident density per bedroom – More than 3 residentsc | >3 residents / bedroom |
|  |  |  | Number of rooms – 2 rooms c | 2 rooms in the house |
| Unpredictability | Parental transitions | Youth and married with children (parental transitions + having a young mother) | Divorcedc | Separated |
|  | Judicially separatedc | Divorced |
|  |  | Age group 15 – 19 living with spouse or partner | 15-19yo living w. partner |
|  |  | Women age group 15 – 19 with childrenc | Mothers 15 to 19yo |

**Table 1** *(Continued)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | Women age group 20 – 24 with children | Mothers 20 to 24yo |
| - | - | Percentage of childrend | Age group 0 – 4 |  |
|  |  |  | Age group 5 – 9 |  |
| - | - | Skin colourd | Colour or ethnicity – Black |  |
| Reproduction | Menarche, Number of partners, number of children. | Early reproduction | Age group 0 – 4 | Children 0 to 4yo |
|  |  | Age group 5 – 9 | Children 5 to 9yo |
|  |  | Women age group 15 – 19 with children | Mothers 15 to 19yo |
|  |  | Women age group 20 – 24 with children | Mothers 20 to 24yo |

*Note*. Harshness and Unpredictability variables collected from Census in 2000 and Reproduction variables collected from 2010.

aVariable abbreviation if retained in the final model; bLog transformation and cSquare root transformation applied to the variables; dIncluded in first iteration of the model but planned to be used in model comparisons.**Table 2**

*Assessment of Brazilian Formative latent variables.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Latent variables** | | **VIF** | **Weights** | **Loadings** |
| Youth and married with children | |  |  |  |
|  | Separated | 1.90 | -.25 | -.51 |
|  | Divorced | 1.87 | -.17 | -.41 |
|  | 15-19yo living w. partner | 2.31 | .10 | .73 |
|  | Mothers 15 to 19yo | 2.50 | .39 | .81 |
|  | Mothers 20 to 24yo | 1.69 | .488 | .84 |
| Family/house size | |  |  |  |
|  | Families with 6 people | 1.94 | .25 | .80 |
|  | 2-3 residents / bedroom | 2.80 | .37 | .90 |
|  | >3 residents / bedroom | 2.80 | .47 | .92 |
|  | 2 rooms in the house | 1.36 | .07 | .43 |
| Low income and lack of resources | |  |  |  |
|  | No recycling service | 1.37 | .91 | .99 |
|  | No electrical power | 1.86 | .08 | .59 |
|  | 1 minimum wage or less | 1.71 | .10 | .54 |

*Note*. VIF: collinearity assessment. Bootstrapped weights and loadings were all significant (p. < .01) and confidence intervals did not cross zero.

**Table 3**

*Assessment of Brazilian Structural model.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Predictors** | **Early reproduction** | | |
|  | VIF | Paths | f² |
| Youth and married with children | 2.74 | .27 | .16 |
| Family/house size | 3.48 | .24 | .11 |
| Low income and lack of resources | 5.14 | .48 | .28 |
| Adj. R² | .84 | | |

*Note*. VIF: collinearity assessment. Bootstrapped paths were all significant (p. < .01) and confidence intervals did not cross zero.

**Table 4**

*Variables in the Model Using Brazilian Census and Similar Variables Using US American Community Survey.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables in Brazilian Census**  **Geographic level: Municipalities** | **Variables found in the American Community Survey (ACS)**  **Geographic level: Counties** | **Classification**  Equivalent (E)  Similar (S)  Not found (N) | **ACS code** |
| **Predictors: 2000** | **Predictors: 2005-2009** |  |  |
| (lacking) Existence of services and durable goods - recycling or waste collection | Lacking complete plumbing facilitiesb; Plumbing Facilities for Occupied Housing Units | S | B25048\_003E |
| (lacking) Existence of services and durable goods - electric lights | Lacking complete kitchen facilitiesb; Kitchen Facilities for Occupied Housing Units | S | B25052\_003E |
| People with income of 1 minimum wage or less | Income in the past 12 months below poverty levelc | S | B17001\_002E |
| Separated - judicially separated | Separatedab: Male; Now married; Married, spouse absent; Separated +  Female; Now married; Married, spouse absent; Separated | E | B12001\_007E  B12001\_016E |
| Divorced | Divorcedac: Male; Divorced +  Female; Divorced | E | B12001\_010E  B12001\_019E |

**Table 4** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Age group - 15 to 19 years of age - Living with a spouse or partner | Women who did not have a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years oldc | S | B13002\_013E |
| Age group - 15 to 19 years of age - with children | Women who had a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years old +  Women who had a birth in the past 12 months; Unmarried (never married, widowed, and divorced); 15 to 19 years oldac | S | B13002\_004E  B13002\_008E |
| Age group - 20 to 24 years of age - with children | Women who had a birth in the past 12 monthsb | S | B13002\_002E |
| Number of family members - 6 people |  | N |  |
| Residents density per dormitory - more than 2,0 to 3,0 residents | Complete plumbing facilities; 1.01 or more occupants per roomc | S | B25050\_007E |
| Residents density per dormitory - more than 3,0 residents |  | N |  |
| Number of rooms - 2 rooms | Median number of rooms | S | B25018\_001E |

**Table 4** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Black ethnicity | Sex by age (Black or African American alone)b | E | B01001B\_001E |
| Indigenous ethnicity | Sex by age (Hispanic or Latino)b | N | B01001I\_001E |
| Age group - 0 to 4 years of age | Age group - 0 to 4 years of agea: Male; Under 5 years +  Female; Under 5 years | S | B01001\_003E  B01001\_027E |
| Age group - 5 to 9 years of age | Age group - 5 to 9 years of agea: Male; 5 to 9 years +  Female; 5 to 9 years | S | B01001\_004E  B01001\_028E |
| **Outcomes: 2010** | **Outcomes: 2018-2023** |  |  |
| Age group - 0 to 4 years of age | Age group - 0 to 4 years of agea: Male; Under 5 years +  Female; Under 5 years | S | B01001\_003E  B01001\_027E |
| Age group - 5 to 9 years of age | Age group - 5 to 9 years of agea: Male; 5 to 9 years +  Female; 5 to 9 years | S | B01001\_004E  B01001\_028E |
| Women 15 to 19 years of age with children | Women who had a birth in the past 12 months; Now married (including separated and spouse absent); 15 to 19 years oldc | S | B13002\_004E |

**Table 4** *(Continued)*

|  |  |  |  |
| --- | --- | --- | --- |
| Women 20 to 24 years of age with children | Women who had a birth in the past 12 months | S | B13002\_002E |

*Note*. a: Manually calculated the sum of the variables to come up with a single variable representative of both groups; b: log transformed variables; c: square root transformed variables.**Table 5**

*Variables predicting percent of 0 to 4-years olds in United States counties.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Effect** | **β** | ***SE*** | ***t-value*** | ***p-value*** | **Std.β** |
| Intercept | 0.38 | 0.48 | 0.80 | .426 |  |
| Lacking complete plumbing facilities | -0.34 | 0.09 | -3.81 | ≤ .001\*\*\* | -0.08 |
| Lacking complete kitchen facilities | 0.38 | 0.08 | 4.57 | ≤ .001\*\*\* | 0.10 |
| Income in the past 12 months below poverty level | 0.16 | 0.03 | 5.21 | ≤ .001\*\*\* | 0.12 |
| Divorced | -0.35 | 0.06 | -5.88 | ≤ .001\*\*\* | -0.11 |
| Women who had a birth in the past 12 months | 0.31 | 0.11 | 2.75 | .006\*\* | 0.06 |
| 1.01 or more occupants per room | 0.19 | 0.06 | 3.09 | .002\*\* | 0.08 |
| Age group - 0 to 4 years of age | 0.43 | 0.03 | 14.11 | ≤ .001\*\*\* | 0.51 |
| Age group - 5 to 9 years of age | 0.13 | 0.03 | 5.20 | ≤ .001\*\*\* | 0.14 |
| Black or African American alone | -0.08 | 0.01 | -6.32 | ≤ .001\*\*\* | -0.10 |
| Hispanic or Latino | -0.10 | 0.02 | -4.21 | ≤ .001\*\*\* | -0.09 |
| Median number of rooms | 0.32 | 0.06 | 5.11 | ≤ .001\*\*\* | 0.13 |

*Note*. \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 6**

*Variables predicting percent of* *5 to 9-years olds in United States counties.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Effect** | **β** | ***SE*** | ***t-value*** | ***p-value*** | **Std.β** |
| Intercept | 0.59 | 0.42 | 1.43 | .154 |  |
| Divorced | -0.17 | 0.07 | -2.63 | .009\*\* | -0.05 |
| Women who had a birth in the past 12 months | 0.27 | 0.13 | 2.15 | .031\* | 0.05 |
| Age group - 0 to 4 years of age | 0.43 | 0.03 | 14.79 | ≤ .001\*\*\* | 0.45 |
| Age group - 5 to 9 years of age | 0.19 | 0.03 | 6.27 | ≤ .001\*\*\* | 0.18 |
| Black or African American alone | -0.13 | 0.02 | -8.41 | ≤ .001\*\*\* | -0.14 |
| Median number of rooms | 0.35 | 0.05 | 6.94 | ≤ .001\*\*\* | 0.12 |

*Note*. \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 7**

*Variables predicting percent of 15 to 19 Years of Age Who Had Given Birth.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Effect** | **β** | ***SE*** | ***t-value*** | ***p-value*** | **Std.β** |
| Intercept | -0.17 | 0.03 | -5.79 | < .001\*\*\* |  |
| Lacking complete kitchen facilities | 0.03 | 0.01 | 2.97 | .003\* | 0.06 |
| Divorced | 0.03 | 0.01 | 3.95 | < .001\*\*\* | 0.08 |
| Women 15 to 19 years of age who had birth | 0.05 | 0.02 | 3.25 | .001\*\*\* | 0.07 |
| Age group - 0 to 4 years of age | 0.02 | 0.00 | 8.91 | < .001\*\*\* | 0.18 |
| Black or African American alone | 0.01 | 0.00 | 4.33 | < .001\*\*\* | 0.09 |

*Note.* \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 8**

*Multivariate Linear Regression Model of Women Who Had Given Birth in the Past 12 Months.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Effect** | **β** | ***SE*** | ***t-value*** | ***p-value*** | **Std.β** |
| Intercept | 0.13 | 0.06 | 2.25 | .024\* |  |
| 1.01 or more occupants per room | 0.03 | 0.01 | 2.42 | .016\* | 0.06 |
| Age group - 0 to 4 years of age | 0.04 | 0.00 | 9.76 | < .001\*\*\* | 0.18 |
| Median number of rooms | 0.06 | 0.01 | 6.38 | < .001\*\*\* | 0.09 |

*Note*. \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 9**

*Explanatory Power of the Four Models*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Outcome variable** | ***R*²** | **Adj. *R*²** | ***F* statistic** | ***p-value*** |
| Age Group - 0 to 4 Years of Age | 0.49 | 0.49 | F(11, 2733) = 240.91 | < .001 |
| Age Group - 5 to 9 Years of Age. | 0.39 | 0.39 | F(6, 2738) = 291.82 | < .001 |
| Women 15 to 19 Years of Age Who Had Birth. | 0.07 | 0.07 | F(5, 2739) = 43.71 | < .001 |
| Women Who Had Birth in the Past 12 Months | 0.1 | 0.1 | F(3, 2741) | < .001 |

*Note*. All regression models were statistically significant at *𝑝* < .001

**Table 10**

*Percent of Age Group - 0 to 4 Years of Age by Low, Medium, and High Tertile of Predictors*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Outcome variable** | **Low Tertile** | **Middle Tertile** | **High Tertile** | ***p* -value** |
| Lacking complete plumbing facilities | 5.48 | 5.54 | 5.56 | \*\*\* |
| Lacking complete kitchen facilities | 5.39 | 5.51 | 5.52 | \*\*\* |
| Income in the past 12 months below poverty level | 5.40 | 5.52 | 5.50 | \*\*\* |
| Separated | 5.54 | 5.44 | 5.43 |  |
| Divorced | 5.78 | 5.46 | 5.17 | \*\*\* |
| Now married - 15 to 19 years old | 5.38 | 5.45 | 5.60 |  |
| Women 15 to 19 years of age who had birth | 5.23 | 5.49 | 5.70 |  |
| Women who had a birth in the past 12 months | 4.98 | 5.42 | 6.03 | \*\* |
| 1.01 or more occupants per room | 5.13 | 5.46 | 6.00 | \*\* |
| Age group - 0 to 4 years of age | 4.76 | 5.41 | 6.25 | \*\*\* |
| Age group - 5 to 9 years of age | 4.88 | 5.49 | 6.06 | \*\*\* |
| Black or African American alone | 5.56 | 5.33 | 5.52 | \*\*\* |
| Hispanic or Latino | 5.36 | 5.47 | 5.58 | \*\*\* |
| Median number of rooms | 5.30 | 5.55 | 5.61 | \*\*\* |

*Note*. \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 11**

*Percent of Age Group - 5 to 9 Years of Age by Low, Medium, and High Tertile of Predictors*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Outcome variable** | **Low Tertile** | **Middle Tertile** | **High Tertile** | ***p* -value** |
| Lacking complete plumbing facilities | 6.01 | 5.96 | 6.02 |  |
| Lacking complete kitchen facilities | 5.93 | 5.91 | 6.04 |  |
| Income in the past 12 months below poverty level | 6.00 | 5.96 | 5.92 |  |
| Separated | 6.08 | 5.98 | 5.81 |  |
| Divorced | 6.27 | 5.93 | 5.67 | \*\* |
| Now married - 15 to 19 years old | 5.90 | 5.91 | 6.07 |  |
| Women 15 to 19 years of age who had birth | 5.77 | 5.93 | 6.18 |  |
| Women who had a birth in the past 12 months | 5.44 | 5.93 | 6.51 | \* |
| 1.01 or more occupants per room | 5.66 | 5.91 | 6.42 |  |
| Age group - 0 to 4 years of age | 5.24 | 5.92 | 6.72 | \*\*\* |
| Age group - 5 to 9 years of age | 5.30 | 5.98 | 6.61 | \*\*\* |
| Black or African American alone | 6.14 | 5.84 | 5.90 | \*\*\* |
| Hispanic or Latino | 5.80 | 5.93 | 6.15 |  |
| Median number of rooms | 5.76 | 5.97 | 6.19 | \*\*\* |

*Note.* \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 12**

*Percent of Women 15 to 19 Years of Age Who Had Birth by Low, Medium, and High Tertile of Predictors*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Outcome variable** | **Low Tertile** | **Middle Tertile** | **High Tertile** | ***p* -value** |
| Lacking complete plumbing facilities | 0.039 | 0.035 | 0.042 |  |
| Lacking complete kitchen facilities | 0.035 | 0.037 | 0.047 | \* |
| Income in the past 12 months below poverty level | 0.026 | 0.034 | 0.057 |  |
| Separated | 0.030 | 0.037 | 0.051 |  |
| Divorced | 0.039 | 0.037 | 0.041 | \*\*\* |
| Now married - 15 to 19 years old | 0.040 | 0.033 | 0.044 |  |
| Women 15 to 19 years of age who had birth | 0.034 | 0.032 | 0.051 | \*\*\* |
| Women who had a birth in the past 12 months | 0.035 | 0.036 | 0.047 |  |
| 1.01 or more occupants per room | 0.027 | 0.037 | 0.052 |  |
| Age group - 0 to 4 years of age | 0.032 | 0.036 | 0.050 | \*\*\* |
| Age group - 5 to 9 years of age | 0.031 | 0.037 | 0.050 |  |
| Black or African American alone | 0.033 | 0.036 | 0.048 | \*\*\* |
| Hispanic or Latino | 0.035 | 0.037 | 0.046 |  |
| Median number of rooms | 0.049 | 0.039 | 0.027 |  |

*Note*. \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Table 13**

*Percent of Women Who Had Birth in the Past 12 Months by Low, Medium, and High Tertile of Predictors*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Outcome variable** | **Low Tertile** | **Middle Tertile** | **High Tertile** | ***p* -value** |
| Lacking complete plumbing facilities | 1.19 | 1.20 | 1.17 |  |
| Lacking complete kitchen facilities | 1.18 | 1.18 | 1.17 |  |
| Income in the past 12 months below poverty level | 1.19 | 1.18 | 1.16 |  |
| Separated | 1.21 | 1.16 | 1.16 |  |
| Divorced | 1.25 | 1.16 | 1.12 |  |
| Now married - 15 to 19 years old | 1.17 | 1.17 | 1.19 |  |
| Women 15 to 19 years of age who had birth | 1.16 | 1.16 | 1.21 |  |
| Women who had a birth in the past 12 months | 1.08 | 1.18 | 1.28 |  |
| 1.01 or more occupants per room | 1.10 | 1.19 | 1.28 | \* |
| Age group - 0 to 4 years of age | 1.06 | 1.17 | 1.31 | \*\*\* |
| Age group - 5 to 9 years of age | 1.05 | 1.20 | 1.28 |  |
| Black or African American alone | 1.20 | 1.14 | 1.19 |  |
| Hispanic or Latino | 1.15 | 1.18 | 1.20 |  |
| Median number of rooms | 1.12 | 1.19 | 1.24 | \*\*\* |

*Note.* \*: *p* ≤ .05; \*\*: *p* ≤ .01; \*\*\*: *p* ≤ .001.

**Figure 1**

*Model predicting early reproduction in Brazil*

A diagram of a family

AI-generated content may be incorrect.

*Note.* Figure created in R using seminr package. Hexagons represent latent variables and rectangles represent items from Census. Predictors are formative latent variables using Census data in 2000 and outcomes are reflective latent variables using Census data in 2010.

**Figure 2**

*Model* predicting early reproduction in Brazil *excluding lack of resources*

A diagram of a child development

AI-generated content may be incorrect.

*Note*. Figure created in R using seminr package. Hexagons represent latent variables and rectangles represent items from Census. Predictors are formative latent variables using Census data in 2000 and outcomes are reflective latent variables using Census data in 2010.

# Chapter 4: Proportion of young children, rates of indigeneity in the population, and socioeconomic factors predict reproduction frequency and single parenting 15 years later in Canadian census divisions

## Preface

In the previous study of Brazilian municipalities we found that measures of environmental harshness and unpredictability (i.e., places with a high percentage of younger mother large families in poor resourced areas) were predictive of early parenting and high percentage of children 10 years later. A few similar findings were observed in a study using US counties data, although the effects were smaller than in the one with Brazil data. On the other hand, we found that the percentage of Black people was not a relevant variable in Brazil but was an important one in the US. Importantly, this second analysis used a straight-forward confirmatory approach, with no consideration of between-country differences.

There were still many unanswered questions from the previous study. For example, would a method like the one used to analyze the Brazil census data yield similar results when applied to data from a developed country? Are the significant associations between predictor and outcome measures caused by a longitudinal and developmental phenomenon or are they just geographical correlations or some other statistical artifact? Do visible minorities face different environmental circumstances that would make the percentage of visible minorities significant predictors of earlier or frequent reproduction? The current chapter addresses these questions by applying the method and analysis used the Brazil study to 43 variables from the Canadian census in 2006 and 2021. We assessed whether dissemination areas (N = 48,867) or census divisions (N = 286) results in a better model performance. We also inverted the timeline of the model using predictors in 2021 and outcomes in 2006 to investigate the directionality of the association. Finally, we included the percentage of visible minorities and of Indigenous people as predictors in the model and subsampled the data into quantiles with the highest and lowest percentage of visible minorities and of Indigenous people.

The results showed that models that based on the census division were better at predicting reproduction than models using dissemination areas. Unemployment, the percentages of young children, young children in low-income families, and people spending a high amount of their income on rent, and the percentage of Indigenous people all predicted the percentage of young children, family sizes, and family sizes of one-parent families. When we inverted the timeline of the model, it performed worse. The percentage of female single parents was significantly associated with itself 15 years earlier, and the percentage of young children in low-income families was associated with the past percentage of larger family sizes and the percentage of young children.

These findings provide partial support of the LHT-P developmental claim that harsher and more unpredictable environments promote frequent reproduction strategies and that early environments are particularly critical in shaping such strategies. For instance, census divisions with more children and more children in low-income families in 2006 predicted frequent reproduction and single parenting in 2021. On the other hand, unemployment and people spending a high amount of income on rent, which are plausible measures of harshness and predictability, were negatively associated with reproductive measures in the future.

When using subsamples based on the percentage of young children, the communities with the highest percentage of children explained more variance of *family size of one-parent families*, but there was no difference when explaining the other reproductive measures. There was also no difference when using subsamples of visible minorities. We argue that Canada offers a more stable and resourceful environment, and therefore a lower variation in environmental harshness and unpredictability, than Brazil. Our results are consistent with the view that Indigenous people and visible minorities face *different* harsh and unpredictable circumstances that are not usually captured in LHT-P research.

## Abstract

Life history theory in Psychology (LHT-P) posits that experiencing harsh and unpredictable environments during childhood cue development of earlier and more frequent reproductive behaviours. However, this developmental association has not been tested in large human populations. This study examines this developmental hypothesis with an exploratory analytical approach to determine if measures of harshness and unpredictability from census data of a developed country (Canada) are relevant predictors of measures of reproduction 15 years later. We also assess if the proportion of Indigenous people and of visible minorities are relevant predictors. We found that a higher percentage of children in low-income households was predictive of higher percentage of single parent households in Canadian census divisions, but measures indicative of lower access to resources and unpredictable parental availability were *negatively* predictive of reproduction. The percentage of Indigenous people was also predictive of higher single parenting. Our findings can help inform public policies around early pregnancy and family planning.

***Keywords:*** *Life History Theory, Harshness, Unpredictability, Reproduction, Census, Indigenous people.*

## Introduction

### Life history theory

Life history theory proposes that the optimal allocation of resources to different functions varies among species and across diverse environmental contexts (Del Giudice et al., 2015; Stearns, 1992). Resources such as energy and time are limited, and an organism must allocate these resources across many functions. An organism needs to maintain its body functioning or, depending on their time of development, grow its body. It also needs to seek food and mates, build or acquire resources (e.g., find or defend territory, a nest or mound, tools), heal from wounds or fend off pathogens, reproduce and, for many species, invest some resources in offspring. Depending on the environment and an organism's niche, different patterns of investments are more adaptive (Ellis et al., 2009). For example, for a species under considerable predation, investing in acquiring resources is unlikely to pay off. It may be more adaptive to invest in reaching sexual maturity earlier and reproducing faster, reducing the chances of being predated before passing on its genes. Differences in the optimal level of investment for each body function at each time of development leads to the development of different life history strategies (LHS). Life history theory had its origins in biology (LHT-B) and it started describing differences between species (Del Giudice, 2009; Stearns, 1992), but it has also been used to describe differences within species (Albaladejo‐Robles et al., 2023; Stearns et al., 2008; Stone et al., 2023), including humans (Del Giudice & Belsky, 2010; Dinh et al., 2022), which started the related field of life history theory in evolutionary psychology (LHT-P; Nettle & Frankenhuis, 2020).

A considerable amount of research in LHT-P has focused on assessing how environments high in harshness (i.e., the level of death and disease outside of one’s control) and unpredictability (i.e., random variation of harshness) influence the likelihood of humans developing a faster LHS (Ellis et al., 2009; Frankenhuis & Nettle, 2020; Volk, 2023). This faster strategy includes a suite of adaptations and behaviours such as earlier puberty (Webster et al., 2014; Xu et al., 2018), earlier and more frequent reproduction (Dinh et al., 2022; M. Wilson & Daly, 1997), and higher risk-taking (Chang et al., 2019; Simpson et al., 2012). A faster LHS would be more adaptive in harsh and unpredictable environments because an individual would be less certain of their future chances of reproduction. The early environment, particularly during the first seven years of life, is critical in shaping one’s LHS (Ellis et al., 2003; Simpson et al., 2012; Webster et al., 2014; Xu et al., 2018).

LHT-P has been criticized for departed considerably from LHT-B, which uses more formal modelling and more specific predictions (Nettle & Frankenhuis, 2020). Another criticism is that LHT-P uses a vague and imprecise definition of LHS that often includes an array of behaviours that lack proper measures of how different environments shape different strategies (Frankenhuis & Nettle, 2020; Sear, 2020). For example, unpredictability lacks a clear statistical definition (Young et al., 2020) and may refer to harshness undergoing a sudden change or having a high variance across time. Furthermore it is unclear whether unpredictability that increases harshness leads to the development of faster LHS or if unpredictability that decreases the mean level of harshness also leads to a faster LHS. Finally, the existence or utility of LHS, conceptualized as a suite of correlated behaviours, has been questioned (Sear, 2020; Stearns & Rodrigues, 2020; Volk, 2023). Many have argued that LHT-P should revise its assumptions and in a way that harmonizes it with LHT-B (Nettle & Frankenhuis, 2020; Sear, 2020; Stearns & Rodrigues, 2020; Volk, 2025).

In practice, LHT-P research has used socioeconomic indicators as a measure of resource access and therefore a measure of harshness (Copping & Campbell, 2015; Hartman et al., 2018; Simpson et al., 2012), and measures of parental transitions (e.g., household configuration change and employment change) and geographical moves as a measures of unpredictability (Belsky et al., 2012; Young et al., 2020). Earlier or faster reproduction has been measured as time of menarche (Xu et al., 2018) – because it is a direct and memorable puberty marker – and as the first time having sex or first time having children (Ellis et al., 2003; Webster et al., 2014).

Census and other public records frequently provide measures of socioeconomic status, employment, migration, marital status and fertility (Statistics Canada, 2024). These measures are also often publicly available and reported periodically. These characteristics make censuses an invaluable asset for research (Copping, 2017; Johnston, 2017; Trzesniewski et al., 2011), particularly for research testing the LHT-P claims (Copping, 2017) because it fits well with LHT-P developmental description and because populational findings – and more importantly cross cultural findings – are especially important in the argument that results observed may be adaptations (Buss, 2024).

### Indigenous people and visible minorities in Canada

The current project examines the association between the percentage of Indigenous people and LHS. We want to acknowledge that the use of *Indigenous people* is not sufficient to reference the heterogeneity of the cultural groups expressed by this term (Statistics Canada, 2017). In Canada, this term refers to First Nations, Métis, and Inuit communities; each with their own cultural identity, governance and history. The choice to use *Indigenous people* in this study aims to reflect the terminology adopted by Statistics Canada (*Dictionary, Census of Population, 2021*, 2023), which reported the counts of *Aboriginal ancestry population* in 2006 and *Indigenous identity* in 2021 (Statistics Canada, 2024).

Indigenous people are more likely to be subject to harsh circumstances compared to non-Indigenous people in Canada (*Honouring the Truth, Reconciling for the Future*, 2015). Colonial history, confinement of its culture and ways of living to “reservations” and other structural inequities (Neu & Graham, 2006; Romaniuk, 2008) cause Indigenous people to experience harsher environments, on average. According to LHT-P, these circumstances may be part of the cause for Indigenous people to be younger (Statistics Canada, 2023), faster growing (Statistics Canada, 2017), and to have disproportionately high rates of teenage pregnancy (Reading & Wien, 2009) than non-Indigenous people.

Visible minorities are also socially disadvantaged in Canada. They are often target of discrimination and trauma (Williams et al., 2022) including unequal access to employment (Henry et al., 1985; Intungane et al., 2024) and health care (Husbands et al., 2022). Similarly to the case of Indigenous people, immigrants, which are often from non-White ethnicities, are also having more children than the non-immigrant population (Bélanger et al., 2006).

### Current study

This study assesses five research questions:

1. Will an exploratory analytical approach informed by LHT-P and using Census generate a model significantly predictive of reproduction indicators 15 later?
2. Will a smaller or larger geography level of analysis generate better results.
3. Is it likely to be a developmental and longitudinal phenomenon?
4. Will the model perform better in geographies with more children?
5. Are the proportions of Indigenous and visible minorities relevant predictors of reproduction?

We hypothesize that our statistical model will account for a significant amount of variance of reproduction indicators in Canada. However, we are not sure whether models using data from smaller or larger geographical regions will perform better. Data from smaller geographies will yield higher statistical power and more variance because of its smaller convergence to mean values. On the other hand, data from larger geographies will be more stable and less susceptible to noise due to migration between regions.

Our main predictions are that harshness and unpredictability measures will be predictive of higher reproduction 15 years later, but that such an association will not hold in a model that uses an inverted timeline. Geographies with a higher proportion of children and with higher proportions of Indigenous people and visible minorities will reach more explanatory power of reproduction measures than geographies with a smaller proportion of these groups.

## Methods

### Data selection and transformation

We accessed census data through the Canadian Census Analyzer (Statistics Canada, 2024). Data was extracted from 52973 dissemination areas (DA) and 288 census divisions (CD) in the 2006 census and 57936 DA and 293 CD in the 2021 census. Statistics Canada defines a dissemination area as a “small, relatively stable geographic unit composed of one or more adjacent dissemination blocks with an average population of 400 to 700 persons” (*Dictionary, Census of Population, 2021*, 2023, p.86). Census divisions are larger geographies composed of groups “of neighbouring municipalities joined together” and “are the most stable administrative geographic areas” (*Dictionary, Census of Population, 2021*, 2023, p.68) next to provinces or territories. After merging 2006 and 2021 data, 48867 DA and 286 CD remained. This reduction in the number of cases is due to geographical redefinition or recoding between 2006 and 2021.

We extracted 120 variables from the 2006 census and 235 variables from the 2021 census that we considered of any relevance to the research question. These variables comprised information about age and sex, family and dwelling characteristics, income, immigration, labour, education, and indigenous and visible minorities. From this set, 105 variables were thematically grouped to create the factors used in this analysis. Table 1 describes the 43 variables and the factors used in the first model and *Variable index* provides a full list of variables extracted and how they were classified.

We assessed NAs next with a 5% cut-off stablished (i.e., if more than 5% of the values were NAs, the variable would be excluded), but no variables met such cut-off. Most of the variables were right skewed. Square root and log transforms were applied to all variables. The distributions of the original and transformed variables were inspected with boxplots. In cases where there was a notable difference between distributions (i.e., median closer to the center of the quartiles, whiskers of relatively equal lengths, and fewer outliers) the transformation that was closest to normal was used in subsequent analyses. When the distributions did not differ, the order of preference was to use the variable with no transformation, the square-root transformation, followed by the log transformation (Table S1).

In the transformation process, we found that more than 75% of the values in four variables (i) median male lone parent income; ii) percentage of male lone parent income coming from other sources; iii) prevalence of low income; and iv) people speaking French and a non-official language) were zeros. These variables were removed from the model because they could distort the relationship between variables. Finally, we defined outliers in as values with a z-score absolute value greater than 3 and cases with outliers were also removed. Therefore, the final data used for the model had 38 variables and 39,481 cases in the DA sample and 240 cases in the CD sample (See Table 1).

### Partial Least Squares Structural Equation Modeling (PLS-SEM)

PLS-SEM is an exploratory and predictive analysis focused on explaining the variance in the dependent variables (Hair et al., 2021). It combines a measurement model (factor analysis) and a structural model (path analysis) and relies on several statistics for the evaluation of model's quality (Hair et al., 2022). PLS-SEM is a nonparametric analysis, and it is more robust with formative factors, in which the latent variable is defined as the combination of measures rather than the measures being an expression of the latent variable (Hair et al., 2021), which is true for all the factors we used as predictors. PLS-SEM also allows for single-item factors, which is an advantage when working with secondary data.

Large samples generate low p-values even when the effect size is small. Considering the dissemination area sample size in this study, it is likely that we would interpret results in the analysis as significant merely due to the sample size. Because the census is the best description of a population, any obtained results is descriptive of Canadian the population, regardless of statistical significance. In addition, PLS-SEM has been criticized for how it calculates statistical significance (Rönkkö et al., 2015), but many evaluations of a model's quality in PLS-SEM are assessed using p-values. To deal with this issue, we stablished significance of ≤ .01 (T. Stat ≥ 2.576) for our analysis and we also assessed whether confidence intervals included zero and on thresholds recommended by Hair and colleagues (2019, 2021) for accepting the measurement and structural models. A criteria in which we differed slightly from Hair and colleagues (2019, 2021) was the use of the following R² criteria: <.2 = negligible; From .2 - .5 = weak; From .5 - .7 = moderate; Above >.7 = Strong (Nau, 2020).

### Model

All the models in this paper had formative factors as predictors and reflective factors as outcomes. The biggest difference between these two types of variables is that in a formative factor the items are understood as describing the factors instead of being an expression of such factor. For example, *lack of resources* is a formative factor that is described by the measures of people living in households in need of minor repairs, major repairs, or spending more than 30% of their income on rent. On the other hand, an outcome measure such as the percentage of families with two or more children is thought to be caused by the reflective factor *faster LHS.*

Following guidelines proposed by Hair and colleagues (2019, 2021), we assessed the reflective factors loadings (>.7), indicators reliability (loading² > .05), internal consistency (α, ρC, ρA > .7) and reliability (AVE > .5). Discriminant validity was assessed with heterotrait-monotrait ratio (HTMT; < .9) and Fornell-Larcker criterion, in which the constructs correlations should be lower than the square root of the AVE. Formative factors were assessed with collinearity (VIF < .5), and weights and loadings for significance and relevance of indicators. Convergent validity analysis was not possible because there would not be alternative measures of the variables used, nor would it be possible to re-sample participants who responded to the census. Finally, we assessed collinearity (VIF < .5), relevance and significance of paths (bootstrapped *β*, T. Stat, and CI), explanatory power (Adj. *R*²) in the structural model. Paths that were above criteria in these assessments and outcome variables with an explanatory power of above 0.3 were selected. We also assessed predictive power using a k-fold cross-validation model (k = 10) with RMSE and MAE out-of-sample between the PLS-SEM models and a naïve linear regression model. This analysis is intended to check if the grouping the variables into factors outperforms linear regressions that draw direct paths between observed predictors and outcomes. See Supplementary materials “Building the model” for the full analytical report”. The materials, raw data and transformed data for both phases of this experiment are available on OSF. This study was not pre-registered.

## Study 4.1: Are Dissemination Areas or Census Divisions

## the best geographical level for analysis?

In the first study we aimed to build the model using DA and build a second one using CD. Our goal was to offer insight to the hypothesis of population mobility. We hypothesized that measures akin to the common measures of harshness, unpredictability used in research would predict measures of reproduction present in both data sets. We established a *R²* > 0.1 difference to consider that the models are performing differently, but we did not have a specific hypothesis whether the model using CD data would have a higher R² than the one using DA data. The method followed the steps described in the *Partial Least Squares Structural Equation Modeling* and *Model* sections above (page 157 and 158).

### Results

Figure 1 illustrates the model with DA and figure 2 illustrates the model with CD data. Squares represent the variables extracted from the census and hexagons represent the factors they were loaded into. The arrows represent the paths between factors and between observed variables and factors. Arrows pointing from observed variables to the factors represent formative factors and arrows pointing from the factors to observed variables represent reflective factors. In the case of single-item factors, the arrows convey no meaning other than indicating that the factor is composed of that single observed variable. Arrow’s width represents the path’s strength and dashed lines indicate a negative association. All the variables present in the models on both DA and CD samples were above criteria of model quality. In the reflective model assessment, loadings were *Average size of families* = .97, *Average number of children in families with children* = .86, *Families with 4 people* = .73, *Families with 5 or more people* = .95, *Children aged 0-4 years* = .93 on the CD model and *Average size of families* = .94, *Average number of children in families with children* = .79, *Families with 4 people* = .78, *Families with 5 or more people* = .81 on the DA model. Reliability were *Average size of families* = .93, *Average number of children in families with children* = .74, *Families with 4 people* = .53, *Families with 5 or more people* = .90, *Children aged 0-4 years* = .87 and *Average size of families* = .88, *Average number of children in families with children* = .62, *Families with 4 people* = .61, *, Families with 5 or more people* = .66; internal consistency were α = .93, ρC = .95, ρA = .94 and α = .86, ρC = .90, ρA = .88; reliability were AVE = .79 and AVE = .70 on both CD and DA models respectively. Considering the confidence upper limit, HTMT discriminant validity criterion did not pass criterion between the variables of *Young children* and *Frequent reproduction* (.91) on the CD sample, but passed the criteria on the DA sample. However, the correlations between variable were below the AVE on the assessment Fornell-Larcker criterion on both samples, which indicates they achieved discriminant validity. Table 2 reports the formative measurement model assessments of the DA model. Since all predictors in the CD models were single-item variables, the measurement model assessment of such variables is not applicable. See the *Selected model* in *Study 1* for Pearson’s r correlation tables, means and standard deviations of the variables used in both DA and CD models.

Both models contained variables that were not colinear and that were significant and relevant predictors of *frequent reproduction*. The explanatory power (r²) of *frequent reproduction* in both samples was above the pre-determined criteria. The explanatory power in the DA sample was weak (Adj. *R²* = .49) but in the CD sample it was strong (Adj. *R²* = .81). The explanatory power of the variance of female single parenting was moderate (Adj. *R²* = .64) in the model built using the CD sample. The model using the CD sample was also a more parsimonious model, utilizing only 5 single-item variables. All of these factors support the hypothesis that the CD data represent a more stable geographic organization and are less affected by population mobility. Most effect sizes were medium and large in the CD sample but were small in the DA sample. Due to these results, the subsequent analyses will be either conducted using the CD sample or, in the cases where we use both samples, we will focus discussion on the model using the CD sample. Table 3 reports the structural model assessment of both models.

A few distinctions are worth noting (Fig. 1 and Fig. 2). In the CD sample, only the variables of young children aged 0-4 years (*Young children)* and the unemployment rate of people aged 25 and over (*Unemployed*) are relevant in predicting *Frequent reproduction*. However, *Young children* was negatively associated with *Frequent reproduction*, and *Unemployed* was a negatively associated with both *Frequent reproduction* and *Single parenting*. Households spending more than 30% of their income on rent (*High rents*) also was a relevant and significant predictor, but it was negatively associated with *Single parenting*. *Young children* is the same variable as FR5 in *Frequent reproduction*, only separated by 15 years. In the DA samples, *Frequent reproduction* was positively associated with median family income (*Income*) and negatively associated with *Lack of resources* and the percentage of households with *Divorced or Widowed* parents. All of these associations in both models are contrary to the predictions of LHT-P. On the other hand, the variables positively associated with *Frequent reproduction* were *Young children* and *Visible minority*. The variables composing *Young children*, however, were not included in the variables in the *Frequent reproduction* factor, as it was in the model with the CD sample. Therefore, it is not the case of a geographical correlation of the same variable across time. *Visible minority* was a relevant predictor of *Frequent reproduction* on the DA sample and *Indigenous* was a relevant predictor of the average family size of one-parent families (*Single parenting*).

The effect sizes on the CD sample of the variables predicting *Frequent reproduction* were large and the variables predicting *Single parenting* were small to medium. On the other hand, on the DA sample, the effect sizes of the variables predicting *Frequent reproduction* were mostly small, with the exception of the effect of *Young children* on it being medium. The RMSE out-of-sample metrics predictive values were lower on the naive linear model (CD: *Average size of families* = .06, *Average number of children in families with children* = .07, *Families with 4 people* = .51, *Families with 5 or more people* = .27, *Children aged 0-4 years* = .49, *Family size of one-parent families* = .07; DA: *Average size of families* = .05, *Average number of children in families with children* = .06, *Families with 4 people* = .30, *Families with 5 or more people* = .43) than on the PLS-SEM (CD: *Average size of families* = .06, *Average number of children in families with children* = .08, *Families with 4 people* = .55, *Families with 5 or more people* = .34, *Children aged 0-4 years* = .52, *Family size of one-parent families* = .08; DA: *Average size of families* = .05, *Average number of children in families with children* = .06, *Families with 4 people* = .32, *Families with 5 or more people* = .44). The MAE out-of-sample metrics predictive values were also lower than the PLS-SEM values. This indicates that the linear model performed better (i.e., its predictions incurred in lower errors) if such models were tested with unseen data.

### Discussion

The model on CD was the most parsimonious model (i.e., using the smallest number of predictive variables) and was able to predict more variables with both higher explanatory power and effect sizes. This suggests that using CD is the most reliable geographic level to predict frequent reproduction in Canada. Indeed, CD is the most stable administrative geographic area (*Dictionary, Census of Population, 2021*, 2023) with yearly interprovincial migration rates of 47.1 and 45.3 per 1,000 among Canadians aged 18 to 24 and 25 to 44, respectively (*Internal Migration: Overview, 2016/2017 to 2018/2019*, 2021). Considering that some of internal migrants will migrate again, and that it is likely that migration is less among children and older adults. It is arguable that over the span of 15 years (the time difference in our data), more than half of Canadians will remain in the same CD.

Naïve linear models had fewer errors than the PLS-SEM in predicting the outcome variables. This has been a consistent observation in the multiple model iterations in this and in past studies and it probably indicates that the factors we are using to describe the measures are not in fact functioning as factors. This would be an expected or common result when dealing with secondary data, because the measures were not designed to be grouped as factors. On the other hand, both the naïve linear model and the PLS model incurred considerably low errors. The errors RMSE varied between 2.06% and 15.4% of the mean value and between 41.9% and 71.9% of the standard deviation of the variables in *frequent reproduction*. This indicates that both models’ errors were only a fraction of the mean value and lower than 1 standard deviation of any of the variables. Therefore, both models had errors smaller than the natural variability of the data, which is something remarkable given the reduced sample for the census divisions and the expected noisy characteristics of such data set.

A smaller issue regards the discriminant validity between the variables (HTMT). Indeed, the measure used in *Young Children* (i.e., % of children between 0-4 years of age) is one of the measures loading into *Frequent reproduction*, only with the 15-year gap difference. The HTMT not meeting criteria was only the case in the bootstrapped confidence interval upper limit, though, and the Fornell-Lacker criterion was within recommended values. Therefore, we decided to keep *Young Children* in the model. Further interpretation of this issue and of the paths between predictors and outcome will be approached in the main discussion. For Studies 2, 3 and 4, we decided to used CD geographical level as our main level of analysis.

## Study 4.2: Is it a developmental phenomenon or just statistical artifacts?

In this study we were interested in testing the hypothesis that the results found were a mere correlational stability of our variables across time. Whether the findings of Study 1 likely describe a developmental association or merely statistical artifacts. To achieve that we reversed the years of predictor and outcomes variables. We set the variables of harshness and unpredictability in 2021 to predict reproduction variables in 2006. Since our primary hypothesis is that harsh and unpredictable environments would predict faster LHS in Canadian geographies, we expected that the hypothesis of mere correlational stability would not be supported. Therefore, we hypothesized that the longitudinal model in Study 1 will have a better performance and a higher explanatory power than the reversed one.

### Method

We used the Census Division data frame because it had higher predictive power in Study 1. The model in this study started with the first iteration of the Census Division model in the previous study. However, the predictor variables were selected from 2021 Census and the outcome variables were selected from Census 2006. Similar to the previous study, we established a *R²* >.1 difference to consider that the models are performing differently in their explanatory power. By following the same methods, we attempted to make a fair comparison between the longitudinal, with the proper direction of time between predictors and outcomes, and this reversed model, with the future predicting variables in the past. We expected that random variations in the data would result in the models being slightly different, but we argue that their performances would be more comparable because we found the same methods.

### Results

Only two single-item predictors and two outcome variables were kept in the reversed model. *Low-income children* had a positive path to predict *Frequent reproduction* and a negative one to predict *Female lone-parents* and *Female lone-parents* also had a positive path to predict *Female lone-parents* 15 years in the past (Fig. 3). Since the predictors were all single-item variables, formative model assessment does not apply to this model.

The reflective model assessment of *Frequent reproduction* resulted in acceptable measures of factor quality and indicated a cohesive factor. The loadings were *Average size of families* = 0.93, *Families with 5 or more people* = 0.90, *Children aged 0-4 years* = 0.95, and *Children aged 5-9 years* = 0.96. Indicator’s reliability were *Average size of families* = .87, *Families with 5 or more people* = .80, *Children aged 0-4 years* = .91, *Children aged 5-9 years* = .93; and the factor internal consistency indices were α = .95, ρC = .97, ρA = .94; and reliability was AVE = .88. The 99.5% confidence interval of HTMT discriminant validity criterion also did not pass 1 with any of the other factors, but it was above .9 with Low-income children. The Fornell-Larcker criterion showed a higher correlation between *Frequent reproduction* than the square root of the AVE with the other factors, which indicates discriminant validity.

Figure 3 reports the structural model in Study 4.2. The model assessment indicated no collinearity between the predictors of *Female lone-parents* (VIF = 1.00), all paths were relevant and significant (*β* > |.1|, *p* ≤ .01) with CI not crossing 0. The explanatory power of *Frequent reproduction* and *Female lone-parents were* moderate (Adj. *R²* = .70 and .72, respectively). The analysis revealed large effect sizes from *Female lone-parents* to *Female lone-parents* (*f²* = 2.40) and from *Low-income children* to *Frequent reproduction* (*f²* = 2.30), and medium effect sizes from *Low-income children* to *Female lone-parents* (*f²* = 0.15).

Both out-of-sample metrics of predictive values were lower on the linear model than on the partial least squares model. RMSE LM: *Average size of families* = .080, *Families with 5 or more people* = .420, *Children aged 0-4 years* = .538, *Children aged 5-9 years* = .498, *Lone-parent families (female parent)* = .302; RMSE PLS : *Average size of families* = .084, *Families with 5 or more people* = .471, *Children aged 0-4 years* = .569, *Children aged 5-9 years* = .570, *Lone-parent families (female parent)* = .359; MAE LM: *Average size of families* = .062, *Families with 5 or more people* = .317, *Children aged 0-4 years* = .411, *Children aged 5-9 years* = .393, *Lone-parent families (female parent)* = .232; and MAE PLS model *Average size of families* = .066, *Families with 5 or more people* = .370, *Children aged 0-4 years* = .427, *Children aged 5-9 years* = .448, *Lone-parent families (female parent)* = .291. This indicates that a naïve LM performs better at predicting *Female lone- parents* and *Frequent reproduction* regardless of the data distribution.

One predictor that was excluded from the model is worth noting. The percentage of children aged 0-4 years was removed because it was highly colinear with other predictors (VIF = 21.0). This finding was dissimilar to the models in Study 4.1. Several other predictors were removed because they were not relevant or not significant (*β* ≤ .1, *p* ≥ .01, and/or CI crossing 0). They were *Low schooling, Male lone-parents*, *Indigenous peoples*, *Precarious labour*, and *Visible minorities*. The eighth iteration of the model in *SM\_Study2* reports these results. *SM\_Study2* provides a full report on the iterations to reach the model.

### Discussion

The reversed model had only two directly observed variables predicting two factors: *Female lone-parents,* being a single-item factor, and *Frequent reproduction*, being composed of 4 variables. It is remarkable that only two predictors were able to predict 72% and 70% of the variances of these outcomes. A further examination of these predictive pathways, however, may facilitate a more comprehensive interpretation. The path on the top of Figure 3 describes the percentage of *Female lone-parents* in 2021 predicting the percentage of *Female lone-parents* in 2006. This means that the variable is predicting itself, which means we’re merely observing a geographical association of the variable over time. Therefore, this path offers little to no relevant information.

The outcome *Female lone-parents* is also predicted by *Low-income children* with a very significant path (*p* ≤ .001) but a lower coefficient. This association was similar to the one found in the CD model in Study 4.1, in which the prevalence of low-income children predicted the family size of one-parent families. Surprisingly, and unlike the association in Study 4.1, the association in this study was negative, meaning that a higher percentage of *Low-income children* in 2021 is associated with a lower percentage of *Female lone-parents* in 2006. This finding contradicts predictions that are common in the LHT-P literature (Hartman et al., 2018; Volk, 2025). We must highlight, however, that this timeline is reversed. Even though there are some suggestions of a repetitive pattern in LHS across generations (Del Giudice et al., 2015), LHT-P literature offers little support that faster strategists will have children that will live in harsher environments.

*Low-income children* also predicts *Frequent reproduction* remarkably well. When we take into account that this is a temporally flipped model, this results in an argument that CDs with a higher family size and a higher percentage of children will experience a higher percentage of children living in low-income households 15 years later. Finally, several of the predictors were removed from the model because they were not relevant and or not significant. This potentially indicates that reversing the timeline does not result in an acceptable model (i.e., iterations of the model does not improve explanatory power and the model does not stabilize with such variables). The failure to reach an acceptable model with a reverse timeline supports our hypothesis that this is a developmental phenomenon and argue against the alternative hypothesis that the findings are merely statistical artifacts.

## Study 4.3: Is there a sensitive period

## to experience harsh and unpredictable environments?

Here we are interested in further testing the developmental hypothesis that children who experience harshness and unpredictability are likely to have reproduced 15 years later instead of alternative hypotheses that the significant associations are due to a geographical correlation or some other statistical artifact. LHT-P historically points to the first 5 or 7 years of life as the most sensitive period to harsh and unpredictable environments (Ellis et al., 2003; Simpson et al., 2012; Webster et al., 2014; Xu et al., 2018). We hypothesized that models using quantile subsamples of Canadian CDs with the highest percentage of children will have better performance than CDs with a lower percentage of children.

### Method

We divided the data into quantiles: 1. Highest percentage of children aged 0-4 years; 2. Lowest percentage of children aged 0-4 years; 3. Highest percentage of children aged 5-9 years; 2. Lowest percentage of children aged 5-9 years. The inclusion of such year gaps intended to cover the 0-7 year range in which children would be most sensitive to their environment to adjust their LHS and because fertility has been globally declining (Roser, 2014) and the average age of the parents at the birth of the child has been in increasing in Canada (Provencher & Galbraith, 2024). An older year range for children would, therefore, allow for an association to older adults 15 years later.

The CD sample was divided into tertiles, given that it is composed of only 240 cases, and the DA sample was divided into quartiles because it is a much bigger data frame. The final subsamples were composed of 80 cases for the CD tertiles and 9871 for the DA quartiles. We applied the models constructed in Study 4.1 to the CD and DA subsamples. For brevity and simplicity, only the results observed with the CD sample – the model with better performance in Study 1 – will be reported in this manuscript. The full report can be found in *SM\_Study3.* Because we aimed at having the most comparable model possible between the ones using subsamples in this study and the one in Study 1, we did not assess the measurement model’s quality and focused solely on the structural model reports in this comparison.

### Results

Table 4 reports the collinearity values, coefficients, effect sizes and explanatory power of CD tertiles with the highest and lowest percentage of children aged 0-4 years and Table 5 reports the same metrics with the highest and lowest percentage of children aged 5-9 years. Considering our stablished criteria of *β* ≥ .1 for determining path relevance and Adj. *R²* ≥ .1 for determining statistically significant explanatory power, the models using the subsample with the highest percentage of children in both age groups provided better accounts of the variance in S*ingle parenting*. Judging by this metric, the models’ performance at predicting *Frequent reproduction* were similar.

Interestingly, the percentage of indigenous people was a significant predictor and had a higher and positive coefficient in the tertile with a higher percentage of children in comparison to tertile with the lowest percentage. This result may indicate an interaction between these variables, but testing this hypothesis was beyond the scope of this study. Counterintuitively, *Young children* had a stronger influence on both *Single parenting* and *Frequent reproduction* in the tertiles with the lowest percentage of children. This is counterintuitive because *Young children* is the variable we used to subsample the data (i.e., highest and lowest percentage of children aged 0-4 years). The stronger association found with the subsample with lowest percentage of children might be due to greater variability across regions in that subsample. However, inspection of the means and standard deviations of the tertiles suggests that this explanation is unlikely (lowest tertile M = 4.07, SD = 0.32; highest tertile M = 6.05, SD = 0.61). This result could also be due to the marginal effects in the lowest tertile: since these regions have a reduced number of children, the comparative effect of adding a small proportion of children can have greater impact on this subsample variance in comparison to the sample with a high percentage of children. Future studies could further explore these associations.

### Discussion

Overall, our hypothesis was supported when the model was predicting *Single Parenting*, but not when it was predicting *Frequent reproduction.* Measures ofeconomic conditions, particularly *Unemployed* and *High rents* in 2006, were negatively associated with *Frequent reproduction* and *Single parenting* in 2021. This finding is consistent with the findings in Study 4.1, but they contradict common conceptions of LHT-P. Notably, the *Unemployed* negative effect was either greater or smaller in the subsamples with different percentage of children depending on whether it was predicting *Single Parenting* or *Frequent reproduction*. In the tertile with the highest percentage of children, the negative association was greater when predicting *Frequent reproduction* in the and smaller when predicting *Single Parenting*. Conversely, the presence of *Young children* had a larger positive association in areas with fewer children, suggesting some sensitivity in demographic patterns to even slight increases in child population.

*Single parenting* predictors varied distinctly between tertiles, with *Low-income children* and *Indigenous* people being strongly associated with higher single-parent households particularly in areas with a higher percentage of children. Census Divisions with *High rents* consistently observed smaller *Single parenting* and the association was more robustly observed in areas with fewer young children.

## Study 4.4: Do Indigenous people and visible minorities face different circumstances?

Next, we tested whether Indigenous people or visible minorities experience would be particularly relevant predictors of reproduction indicators. Indigenous peoples and visible minorities have a long history of facing harsher circumstances than the general population (*Key Health Inequalities in Canada*, 2018; Prather et al., 2016). These harsher circumstances may be due to the history of colonization, racism, cultural and other forms of oppression and discrimination (Isumonah, 2024; Phillips-Beck et al., 2020). These factors are indicative of harsher circumstances, but they may not fully be captured in the usual measures of harshness and unpredictability in LHT-P. Therefore, in addition to using the percentage of Indigenous people and visible minorities as predictors of reproduction indicators (Study 1), here we hypothesized that models using a quantile subsample of the highest percentage of Indigenous people and visible minorities in Canadian DAs and CDs would perform better at predicting early reproduction than models using the lowest quantiles.

### Method

The method in this study followed the same procedure as the methods in Study 4.3. However, in this study the tertiles subsample using CDs were selected with the highest and lowest percentage of visible minorities and the quartiles subsample using DAs were selected with the highest and lowest percentage of Indigenous people. This choice aimed at avoiding subsampling a dataset using a variable that was already a significant predictor in that model. In other words, since *Indigenous* people was already a significant predictor in the CD model and *visible minorities* was already a significant predictor in the DA model, we decided to only select subsamples using the non-significant variable. We focused our analyses in the CD model (the one performing better in Study 4.1), but we will briefly report some of the statistics in the DA model. The full report can be found in *SM\_Study4*.

### Results

Table 6 reports the structural model measurements of CD tertiles. The models performed similarly based on our criteria. The two exceptions were *High rents*, which had a smaller negative association with *Single parenting* in the tertile with the lowest percentage of *Visible minorities*, and the *Unemployed* prediction of *Single parenting*, which was no longer significant in the lowest tertile. The models using the DA quartiles did not show any relevant difference between the areas with the highest and lowest percentage of visible minorities. See *SM\_Table\_1* in *SM\_Study4*.

### Discussion

Contrary to our prediction, selecting geographies with highest and lowest percentages of Indigenous people and visible minorities did not affect the performance of the models. The percentage of *Visible minorities* people did not substantially affect the model performance in Canadian CDs, and the percentage of *Indigenous people* did not affect the model performance in Canadian DAs. This lack of an effect may be explained by the observation that these variables were not significant in the models that used the whole sample, and therefore they would not substantially alter its subsamples.

Nevertheless, it is interesting and counterintuitive that *Indigenous people* and *Visible minorities* were only significant or relevant predictors in the CD and DA samples, respectively. Since these samples are only different geographical organizations of the same population in the same year, one could expect the same variables to be significant predictors in both models. One potential explanation for the difference is that *Indigenous people* and *Visible minorities* are significant predictors of different variables in the two models. *Indigenous people* is only a significant and relevant predictor of *Single parenting* in the CD model whereas *Visible minorities* is only a significant predictor of *Frequent reproduction* in the DA model. However, this difference does not explain why *Visible minorities* was not a significant predictor of *Frequent reproduction* in the CD model.

Another possible explanation concerns migration. DAs are small geographical areas that may be susceptible to high migration. Even though CDs are the most stable geographic unit (*Dictionary, Census of Population, 2021*, 2023) it is still susceptible to migration in a time span of 15 years. Canada has also observed high immigration from other countries in recent years (Statistics Canada, 2022), so it is likely that a considerable proportion of people answering the census in 2021 weren’t even in the country in 2006.

A final possible explanation is related to the skewness of the data. As with many variables used in this manuscript, the percentage of *Indigenous people* and *Visible minorities* were considerably low (*Indigenous people* in CD sample: M = 10.9, SD = 16.0; and *Visible minorities* in CD sample: M = 3.09, SD = 6.05). If one of these variables exhibited greater variance in one of the geographic divisions, but not the other, it could disproportionately influence the model and become a significant or relevant predictor. Indeed, the percentage of Indigenous people and of Visible minorities often was more than 50% of the population in the DA data frame, sometimes being the entire population of that area. However, the same does not occur in the CD sample. In sum, the hypothesis that subsampling *Indigenous people* or *Visible minorities* would increase model performance was not supported. Future studies could further explore how marginalized or discriminated populations face harsher and more unpredictable circumstances and how that can relate to LHT-P assumptions.

## General discussion

The results point to the viability of using census data, a longitudinal and multivariate approach to test common LHT-P assumptions. The models built with data from both geographic divisions could explain remarkable variance of reproduction patters. Namely, the CD, which is the bigger and more stable geographic division (*Dictionary, Census of Population, 2021*, 2023) was able to explain 81% of the variance of indicators of larger family sizes (named here *Frequent reproduction)* and 64% of the variance of the family size of one-parent families in 2021 using predictors in 2006. The DA, which is a smaller and expected to be a less stable geographic division over time explained 49% of the variance of similar larger family sizes measures in the same time frame.

The current findings suggest that proxies of common LHT-P measures from both geographic divisions are predictive of reproductive patterns in the Canadian population. The DA geographic division allows for more granular, although noisier, prediction and the CD use larger populations for more precise prediction. For the aims in this paper, the CD model was the best performing one and is the focus of this study. In general, the findings support the claim that the use of such data and methodologies can effectively project future reproduction trends among Canadians, which can be a useful tool for policy development and various Governmental initiatives.

Regarding LHT-P claims to environmental influence on development, we are interested in two aspects: 1. the developmental aspect, and 2. the hypothesis of harsher and more unpredictable environments leading to earlier and more frequent reproduction. Our findings provide some support for the longitudinal and developmental hypothesis proposed by LHT-P (Ellis et al., 2003; Simpson et al., 2012; Webster et al., 2014; Xu et al., 2018). Specifically, the percentage of children 0-4 years old was a significant and the highest predictor of reproductive patterns 15 years later in both models in study 1, and the percentage of children under 6 years old in low income families was a significant predictor of the family size of one-parent families. When we reversed the timeline between predictor and outcomes, most variables were non-significant predictors, which is consistent with the idea that the associations found in the original analysis are measures of a developmental phenomenon. Several of the variables were not significant or not relevant in the reversed-timeline model, which could mean that their prediction of reproduction was noisier (i.e., resulting in greater error).

Applying the model to a subsample consisting of geographic areas with the highest percentage of children did not result in an overall increase of the explanatory power of the model. Specifically, the explanatory power was greater for predicting *Single parenting* but not in predicting *Frequent reproduction*. However, the lower predictive power for *Frequent reproduction* may not be surprising because this variable was predicted by the percentage of young children and by *Unemployed*. Therefore, selecting the tertiles of highest and lowest young children essentially reduces its variance in both tertiles and leaves *Unemployed* as the only predictor able to fully vary in the data (since the other predictor is already divided into tertiles). This effect did not happen when predicting *Single parenting* because there were more predictors.

This brings the discussion to another issue. The percentage of *Children aged 0-4 year* was a predictor and was used for the quantile division. In addition, the same variable – but collected 15 years later – is an observed variable in the factor *Frequent reproduction*. Using the same variable in different parts of the model and with different purposes allows for alternative interpretations and obscures the phenomenon we are aiming to measure. This issue, however, is not present in the prediction of *Single parenting.*

The prediction of LHT-P that environmental harshness and unpredictability (Ellis et al., 2009; Stearns, 1992) shape a faster LHS were not strongly supported. The significant indicators in the CD sample – *Unemployed* and *High rents –* were actually *negatively* associated with *Frequent reproduction* and *Single parenting* in the CD sample. A similar pattern of results happened in the DA sample, in which *Lack of resources* and *Divorced or Widowed* – expected to be a measure of parental transition – were negatively associated with *Frequent reproduction*, while median family income was positively associated with *Frequent reproduction.* These results support the argument that modern environments, particularly the ones in developed countries, may not be reflective of harshness and unpredictability encountered in our environment of evolutionary adaptedness and that would cue LHS change (Nolin & Ziker, 2016; Volk, 2023). This claim is supported in a study conducted with data from Brazil with a similar approach (Koehler & Rutherford, 2025), in which harshness indicators were predictive of early reproduction.

There are, of course, explanations alternative to LHT-P ones that may explain this phenomenon. Fertility has been dropping, and the time of first pregnancy is also being delayed worldwide, including Canada (Provencher & Galbraith, 2024; Roser, 2014). These trends are thought to be the result of women having more to access to education, health care, and employment (Behrman & Gonalons-Pons, 2020; Olowolafe et al., 2025) and by a reduction in child mortality (Roser, 2014). While these may be reflective of a more standardized, stable and less harsh environment, there are other explanations such as lack of institutional support to effective reproductive plan and control (South & Crowder, 2010; Wodtke, 2013), local cultures and values (Wilson, 1987; Wodtke, 2013) and local contagion (South & Crowder, 2010), that is, observing others having children or having children at a younger age simply create a local contagion.

Even within the LHT-P framework, there are alternative explanations that were not considered in these analyses. The influence of genes, for instance, was not tested. Gene environment interactions are fundamental in evolutionary research (Stearns, 1992) and genetics should play a role in the phenomenon examined in this study. Genes influence time of puberty (Del Giudice et al., 2015) and the same genes that shape behaviours that may be associated with certain environments (e.g., discounting future rewards leading to not investing in education) can also influence reproductive behaviour (Belsky et al., 1991; Volk, 2025). At any case, these alternative explanations seem to agree that fertility is higher in places with harsher, resource-lacking conditions. Therefore, the results showing that *Frequent reproduction* and *Single parenting* were reduced in geographies with harsher environments is surprising and future research could focus on understanding such dynamics.

The percentage of *Indigenous people* was significantly and positively associated with *Single parenting* in the CD model, and the percentage of *Visible minorities* was a significant and positively associated of *Frequent reproduction* in the DA model. These being significant predictors in addition to the indicators of a harsher or more unpredictable life included in model can be interpreted as evidence that there are particularities of these communities that are not being measured by the model.

The long history of colonisation, structural inequities (Goghari & Kassan, 2022) and of confinement of Indigenous people in *reservations* (Neu & Graham, 2006; Romaniuk, 2008) can create specific harsh and unpredictable environments that are not usually measured in LHT-P literature. Marginalization and discrimination (Prather et al., 2016), experiencing or living in communities with higher levels of violence and crime (Griskevicius et al., 2011; Williams et al., 2022; M. Wilson & Daly, 1997), cultural differences (Trovato & Burch, 1980), or differences in access to institutional support such as health care, education or child care (Roser, 2014; Wilson, 1987; Wodtke, 2013) are factors historically neglected by Western culture and society and that could be influencing reproductive behaviour of both Indigenous people and Visible minorities in Canada. Future studies could explore how LHT-P can interact with the particular environments of these populations.

### Caveats

There are many considerations and limitations to this study. The first is that it uses populational data, and therefore conclusions about individuals are remarkably limited. Using LHT-P and other theoretical frameworks, it may be possible to draw some conclusions about individual circumstances and behaviours; however, it is possible that associations in a populational level do not exist in the level of the individual. For example, Canada has experienced a considerable amount of immigration (Statistics Canada, 2022), and this immigration trend is commonly tied to employment and education. Demographic measures can also be affected because immigrants in Canada also have more children than Canadian-born counterparts (Bélanger et al., 2006). Therefore, it is possible that the geographical areas that accept more immigrants are geographies that tend to have lower unemployment rates and more children, but these would not be the same individual or the same households.

The conclusions drawn here rely on an assumption that most of the population of a given geographic will remain on the same geographic unit 15 years later. This is not a guarantee, especially in a country with high level of immigration (Statistics Canada, 2022) or particularly in smaller geographic units such as DAs. Research conducted with a cohort of more than 800,000 people from the Canadian Community Health Survey identified that 54% of them moved within the last 10 years. However, around 37% of those who moved are likely to have moved within the same CD (Mah et al., 2025), which implies that around 34% of the population moved to a different CD in a 10-year period. This assumption may introduce selection bias if the individuals who moved to a new geographic unit differ significantly from those who stayed, potentially affecting the accuracy of the study's conclusions.

Another limitation of this study is the choice of PLS-SEM, which is an exploratory version of SEM. The choice of variables in this study was based on a largely used theory and some of the tests and comparisons conducted were aimed at assessing the likelihood of statistical artifacts or alternative explanations. When building the model, however, choices for maintaining or removing variables are based solely on statistical reasons. In addition, all the analyses were conducted with the same data from two time points (2006 and 2021). These issues increase the likelihood that the associations found in this manuscript to be due to confounding variables or to chance. Future research should aim at confirming these findings to allow for more generalizable, reliable or even causal conclusions.

Finally, as mentioned previously, LHT-P has been the target of serious criticisms (Nettle & Frankenhuis, 2020; Sear, 2020; Volk, 2025). These criticisms argue for the need of reconsideration of chore aspects of the theory and towards a re-approximation of its origin in biology (Frankenhuis & Nettle, 2020, 2020; Stearns & Rodrigues, 2020; Volk, 2025). This significantly limits the inferences and conclusions that can be drawn from this study, but it also highlights its importance. More research using data descriptive of entire populations and aiming at specific outcomes can help LHT-P to refine its assumptions and generate more accurate and formal predictions.

### Conclusion

Using Canadian data, we showed that indicators of harshness and of the proportion of children and visible minorities predict frequent reproduction and family sizes 15 years later. We also showed that using data from census divisions rather than dissemination areas results in a more accurate model. The proportion of Indigenous people and visible minorities in Canada are significant and relevant predictors of reproductive outcomes, highlighting the importance of understanding the ecological and social factors shaping reproductive strategies and outcomes in these communities. These findings help inform future research that can use more confirmatory approaches to confirm these results (Hair et al., 2022) and to make use of more formal modeling (Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020). These results and future results can also inform an array of public policies, especially those aiming at dealing with early pregnancy and family planning of Indigenous peoples and visible minorities.

## References

Albaladejo‐Robles, G., Böhm, M., & Newbold, T. (2023). Species life‐history strategies affect population responses to temperature and land‐cover changes. Global Change Biology, 29(1), 97–109. https://doi.org/10.1111/gcb.16454

Behrman, J., & Gonalons-Pons, P. (2020). Women’s employment and fertility in a global perspective (1960–2015). Demographic Research, 43, 707–744. https://doi.org/10.4054/DemRes.2020.43.25

Bélanger, A., Martel, L., Gilbert, S., & Berthelot, J.-M. (2006). Report on the Demographic Situation in Canada, 2002. Statistics Canada. http://www.statcan.ca

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. Developmental Psychology, 48(3), 662–673. https://doi.org/10.1037/a0024454

Belsky, J., Steinberg, L., & Draper, P. (1991). Childhood Experience, Interpersonal Development, and Reproductive Strategy: An Evolutionary Theory of Socialization. Child Development, 62(4), 647–670. https://doi.org/10.1111/j.1467-8624.1991.tb01558.x

Buss, D. M. (2024). Evolutionary psychology: The new science of the mind (Seventh edition). Routledge.

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. Developmental Psychology, 55(4), 890–903. https://doi.org/10.1037/dev0000655

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), Encyclopedia of Evolutionary Psychological Science (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Copping, L. T., & Campbell, A. (2015). The environment and life history strategies: Neighborhood and individual-level models. Evolution and Human Behavior, 36(3), 182–190. https://doi.org/10.1016/j.evolhumbehav.2014.10.005

Del Giudice, M. (2009). Sex, attachment, and the development of reproductive strategies. Behavioral and Brain Sciences, 32(1), 1–21. https://doi.org/10.1017/S0140525X09000016

Del Giudice, M., & Belsky, J. (2010). The Development of Life History Strategies: Toward a Multi-Stage Theory. In D. M. Buss & P. H. Hawley (Eds.), The Evolution of Personality and Individual Differences (pp. 154–176). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195372090.003.0006

Del Giudice, M., Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), The Handbook of Evolutionary Psychology (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

Dictionary, Census of Population, 2021. (2023). Statistics Canada = Statistique Canada.

Dinh, T., Haselton, M. G., & Gangestad, S. W. (2022). “Fast” women? The effects of childhood environments on women’s developmental timing, mating strategies, and reproductive outcomes. Evolution and Human Behavior, 43(2), 133–146. https://doi.org/10.1016/j.evolhumbehav.2021.12.001

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? Child Development, 74(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. Human Nature, 20(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. Evolution and Human Behavior, 41(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Goghari, V. M., & Kassan, A. (2022). Building a socially and culturally responsive psychology / engendrer une psychologie plus réceptive sur le plan social et culturel. Canadian Psychology / Psychologie Canadienne, 63(4), 467–470. https://doi.org/10.1037/cap0000351

Griskevicius, V., Delton, A. W., Robertson, T. E., & Tybur, J. M. (2011). Environmental contingency in life history strategies: The influence of mortality and socioeconomic status on reproductive timing. Journal of Personality and Social Psychology, 100(2), 241–254. https://doi.org/10.1037/a0021082

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (Third edition). SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. Development and Psychopathology, 30(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Henry, F., Ginzberg, E., Toronto, S. P. C. of M., & Relations, U. A. on R. (1985). Who Gets the Work?: A Test of Racial Discrimination in Employment. Urban Alliance on Race Relations and Social Planning Council of Metropolitan Toronto. https://books.google.ca/books?id=72NWuQAACAAJ

Honouring the truth, reconciling for the future: Summary of the final report of the Truth and Reconcilliation Commission of Canada. (2015). Truth and Reconcilliation Commission of Canada.

Husbands, W., Lawson, D. O., Etowa, E. B., Mbuagbaw, L., Baidoobonso, S., Tharao, W., Yaya, S., Nelson, L. E., Aden, M., & Etowa, J. (2022). Black Canadians’ Exposure to Everyday Racism: Implications for Health System Access and Health Promotion among Urban Black Communities. Journal of Urban Health, 99(5), 829–841. https://doi.org/10.1007/s11524-022-00676-w

Internal migration: Overview, 2016/2017 to 2018/2019. (2021). https://www150.statcan.gc.ca/n1/pub/91-209-x/2021001/article/00001-eng.htm

Intungane, D., Long, J., Gateri, H., & Dhungel, R. (2024). Employment Barriers for Racialized Immigrants: A Review of Economic and Social Integration Support and Gaps in Edmonton, Alberta. Genealogy, 8(2), 40. https://doi.org/10.3390/genealogy8020040

Isumonah, K. G. (2024). An examination of food insecurity among Canadian Aboriginal people. Journal of Global Health Economics and Policy, 4. https://doi.org/10.52872/001c.126467

Johnston, M. (2017). Secondary Data Analysis: A Method of which the Time Has Come. Qualitative and Quantitative Methods in Libraries, 3(3), 619–626.

Key health inequalities in Canada: A national portrait : executive summary. (2018). Public Health Agency of Canada = Agence de la santé publique du Canada.

Koehler, V. B., & Rutherford, M. D. (2025). Harshness predicts reproduction in Brazilian municipalities and US counties: A life history theory approach [Manuscript in preparation]. Department of Psychology, Neuroscience & Behaviour, McMaster University.

Mah, S. M., Buajitti, E., Pagalan, L., Diemert, L. M., Tjepkema, M., Christidis, T., Chiodo, S., Siddiqi, A., Brook, J. R., Chen, H., & Rosella, L. C. (2025). Robust Indicators of Residential Mobility Derived From Longitudinal Canadian Data to Examine Population Health Across the Life Course. Social Indicators Research, 177(3), 937–957. https://doi.org/10.1007/s11205-025-03521-0

Nau, R. (2020). What’s a good value for R-squared? https://people.duke.edu/~rnau/rsquared.htm

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? Philosophical Transactions of the Royal Society B: Biological Sciences, 375(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Neu, D., & Graham, C. (2006). The birth of a nation: Accounting and Canada’s first nations, 1860–1900. Accounting, Organizations and Society, 31(1), 47–76. https://doi.org/10.1016/j.aos.2004.10.002

Nolin, D. A., & Ziker, J. P. (2016). Reproductive Responses to Economic Uncertainty: Fertility Decline in Post-Soviet Ust’-Avam, Siberia. Human Nature, 27(4), 351–371. https://doi.org/10.1007/s12110-016-9267-6

Olowolafe, T. A., Adebowale, A. S., Fagbamigbe, A. F., Onwusaka, O. C., Aderinto, N., Olawade, D. B., & Wada, O. Z. (2025). Decomposing the effect of women’s educational status on fertility across the six geo-political zones in Nigeria: 2003–2018. BMC Women’s Health, 25(1), 107. https://doi.org/10.1186/s12905-025-03636-z

Phillips-Beck, W., Eni, R., Lavoie, J. G., Avery Kinew, K., Kyoon Achan, G., & Katz, A. (2020). Confronting Racism within the Canadian Healthcare System: Systemic Exclusion of First Nations from Quality and Consistent Care. International Journal of Environmental Research and Public Health, 17(22), 8343. https://doi.org/10.3390/ijerph17228343

Prather, C., Fuller, T. R., Marshall, K. J., & Jeffries, W. L. (2016). The Impact of Racism on the Sexual and Reproductive Health of African American Women. Journal of Women’s Health, 25(7), 664–671. https://doi.org/10.1089/jwh.2015.5637

Provencher, C., & Galbraith, N. (2024). Fertility in Canada, 1921 to 2022 (Demographic Documents No. 91F0015M). Statistics Canada.

Reading, C. L., & Wien, F. (2009). Health Inequalities and Social Determinants of Aboriginal Peoples’ Health. National Collaborating Centre for Aboriginal Health.

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat emptor. Personality and Individual Differences, 87, 76–84. https://doi.org/10.1016/j.paid.2015.07.019

Romaniuk, A. (2008). History-based Explanatory Framework for Procreative Behaviour of Aboriginal People of Canada. Canadian Studies in Population, 35(1), 159. https://doi.org/10.25336/P61K7T

Roser, M. (2014). The global decline of the fertility rate. Our World in Data.

Sear, R. (2020). Do human ‘life history strategies’ exist? Evolution and Human Behavior, 41(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. Developmental Psychology, 48(3), 674–686. https://doi.org/10.1037/a0027293

South, S. J., & Crowder, K. (2010). Neighborhood Poverty and Nonmarital Fertility: Spatial and Temporal Dimensions. Journal of Marriage and Family, 72(1), 89–104. https://doi.org/10.1111/j.1741-3737.2009.00685.x

Statistics Canada. (2017). Aboriginal peoples in Canada: Key results from the 2016 Census. The Daily.

Statistics Canada. (2022). Immigrants make up the largest share of the population in over 150 years and continue to shape who we are as Canadians. The Daily. https://www150.statcan.gc.ca/n1/daily-quotidien/221026/dq221026a-eng.pdf

Statistics Canada. (2023). Canada’s Indigenous population. https://www.statcan.gc.ca/o1/en/plus/3920-canadas-indigenous-population

Statistics Canada. (2024). Canadian census analyser [Dataset]. Computing in the Humanities and Social Sciences at the University of Toronto (CHASS). https://datacentre.chass.utoronto.ca/census/

Stearns, S. C. (1992). The evolution of life histories. Oxford University Press.

Stearns, S. C., Allal, N., & Mace, R. (2008). Life history theory and human development. In Foundations of evolutionary psychology. (pp. 47–69). Taylor & Francis Group/Lawrence Erlbaum Associates.

Stearns, S. C., & Rodrigues, A. M. M. (2020). On the use of “life history theory” in evolutionary psychology. Evolution and Human Behavior, 41(6), 474–485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Stone, B. W. G., Dijkstra, P., Finley, B. K., Fitzpatrick, R., Foley, M. M., Hayer, M., Hofmockel, K. S., Koch, B. J., Li, J., Liu, X. J. A., Martinez, A., Mau, R. L., Marks, J., Monsaint-Queeney, V., Morrissey, E. M., Propster, J., Pett-Ridge, J., Purcell, A. M., Schwartz, E., & Hungate, B. A. (2023). Life history strategies among soil bacteria—Dichotomy for few, continuum for many. The ISME Journal, 17(4), 611–619. https://doi.org/10.1038/s41396-022-01354-0

Trovato, F., & Burch, T. K. (1980). Minority Group Status and Fertility in Canada. Canadian Ethnic Studies = Etudes Ethniques Au Canada, 12(3), 1. Periodicals Archive Online.

Trzesniewski, K. H., Donnellan, M. B., Lucas, R. E., & American Psychological Association (Eds.). (2011). Secondary data analysis: An introduction for psychologists (1st ed). American Psychological Association.

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. Evolution and Human Behavior, 44(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Volk, A. A. (2025). Pumping the Brakes on Psychosocial Acceleration Theory: Revisiting its Underlying Assumptions. Evolution and Human Behavior, 46(1), 106657. https://doi.org/10.1016/j.evolhumbehav.2025.106657

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. Evolutionary Psychology, 12(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Williams, M. T., Khanna Roy, A., MacIntyre, M.-P., & Faber, S. (2022). The Traumatizing Impact of Racism in Canadians of Colour. Current Trauma Reports, 8(2), 17–34. https://doi.org/10.1007/s40719-022-00225-5

Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. BMJ, 314(7089), 1271–1271. https://doi.org/10.1136/bmj.314.7089.1271

Wilson, W. J. (1987). The truly disadvantaged: The inner city, the underclass, and public policy. University of Chicago press.

Wodtke, G. T. (2013). Duration and timing of exposure to neighborhood poverty and the risk of adolescent parenthood. Demography, 50(5), 1765–1788. https://doi.org/10.1007/s13524-013-0219-z

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. Evolution and Human Behavior, 39(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005

Young, E. S., Frankenhuis, W. E., & Ellis, B. J. (2020). Theory and measurement of environmental unpredictability. Evolution and Human Behavior, 41(6), 550–556. https://doi.org/10.1016/j.evolhumbehav.2020.08.006

**Table 1**

*Variables fed into the first models in Study 1.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
| Harshness | SES measures | Income | Median family income | DA |
|  |  | Prevalence children 6 years of age or less living with low income before tax | CD |
|  |  | Lack of resources | Occupied private dwellings needing minor repairs | DA |
|  |  | Occupied private dwellings needing major repairs | DA |
|  |  |  | Tenant occupied households spending more than 30% on rent | CD; DA |
|  |  |  | Employed labour force 15 years of age and over using public transit |  |
|  |  | Low schooling | Population 25 – 64 with no certificate, diploma or degree |  |
| Unpredictability | Parental transitions | Female lone parent | Female lone parent |  |
|  | Median of female lone-parent income |  |
|  |  |  | Percentage of female lone-parent income coming from other sources (i.e., neither employment nor government transfers) |  |
|  |  | Male lone parent | Male lone parent |  |

**Table 1** (continued)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
|  |  |  | Median of male lone-parent income |  |
|  |  |  | Percentage of male lone-parent income coming from other sources (i.e., neither employment nor government transfers) |  |
|  |  | Separated | Divorced | DA |
|  |  | Widowed | DA |
|  |  |  | Separated, but still legally married |  |
|  | Parental occupation transitions | Precariously labour | Unemployment rate of population 25 years and over | CD |
|  | People 15 years and over who worked in different census subdivision |  |
|  | Unemployment rate of population 15 years and over with children at home |  |
|  | People 15 years and over self-employed (unincorporated) without paid help |  |
|  |  |  | People 15 years and over who worked part year or part time |  |
|  | Geographical transitions | Migrants and speaking foreign languages | Movers 1 year ago |  |
|  | Movers 5 years ago |  |
|  |  | Neither English nor French as first official language spoken |  |
|  |  |  | Non-official language spoken in single responses |  |
|  |  |  | English and non-official language in multiple responses |  |
|  |  |  | French and non-official language in multiple responses |  |

**Table 1** (continued)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LHT Concept** | **Usual measure in LHT** | **Factor loaded in 1st iteration** | **Variables** | **Final Model** |
| - | - | Indigenous | Total aboriginal ancestry population | CD |
|  |  | Visible minority | Total visible minority population | DA |
|  |  | Non-official language spoken in single responses | DA |
| - | - | Young children | Age group 0 – 4 years of age | CD; DA |
|  |  | Age group 5 – 9 years of age | DA |
| Reproduction | Age of menarche, number of partners, number of children, and interbirth interval | Frequent reproduction | Average size of families | CD; DA |
|  | Average number of children in families with children | CD; DA |
|  |  | Families with 4 persons | CD; DA |
|  |  | Families with 5 or more persons | CD; DA |
|  | Single parenting | Average family size of one-parent families | CD |
|  | Big families | Private households with 4 persons |  |
|  |  | Private households with 5 or more persons |  |
|  |  | Recent reproduction | Age group 0 – 4 years of age | CD |

*Note*. Harshness and Unpredictability variables collected from Census 2006 and Reproduction variables collected from 2021. Final model indicates whether the variable was a relevant and significant in the models using Census division (CD) or Dissemination area (DA) sample.

**Table 2**

*Formative Latent Variables Assessment of Dissemination Areas Model in Study 1.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Latent variables** | | **VIF** | **Weights** | **Loadings** |
| Lack of resources | |  |  |  |
|  | Dwellings needing minor repairs | 1.14 | 0.30 | 0.58 |
|  | Dwellings needing major repairs | 1.19 | 0.29 | 0.62 |
|  | Households spending 30%+ of income on rent | 1.17 | 0.72 | 0.90 |
| Divorced or Widowed | |  |  |  |
|  | Divorced | 1.08 | 0.68 | 0.84 |
|  | Widowed | 1.08 | 0.57 | 0.75 |
| Visible minority | |  |  |  |
|  | Visible minority | 2.68 | 0.64 | 0.97 |
|  | Mother tongue is non official languages | 2.68 | 0.42 | 0.92 |
| Young children | |  |  |  |
|  | Children aged 0-4 years | 1.27 | 0.31 | 0.69 |
|  | Children aged 5-9 years | 1.27 | 0.82 | 0.96 |

*Note*. VIF: collinearity assessment. Bootstrapped weights and loadings were all significant (p. < .01) and confidence intervals did not cross zero. Income variable was a single-item variable; therefore no assessment was made.

**Table 3**

*Structural Model Assessment in Study 1.*

|  |  |  |  |
| --- | --- | --- | --- |
| Dissemination areas model | | | |
| **Predictors** | **Frequent reproduction** | | |
|  | VIF | Paths | f² |
| Income | 1.68 | 0.16 | 0.04 |
| Lack of resources | 1.87 | - 0.18 | 0.03 |
| Divorced or Widowed | 1.91 | - 0.17 | 0.03 |
| Visible minority | 1.07 | 0.17 | 0.06 |
| Young children | 1.27 | 0.39 | 0.21 |
| Adj. R² | .49 | | |
| Census divisions model | | | |
| **Predictors** | **Frequent reproduction** | | |
| Unemployed | 1.24 | - 0.38 | 0.62 |
| Young children | 1.24 | 0.66 | 1.82 |
| Adj. R² | .81 | | |
| **Predictors** | **Single parenting** | | |
| Low-income children | 1.60 | 0.34 | 0.20 |
| High rents | 1.49 | - 0.26 | 0.13 |
| Unemployed | 1.44 | - 0.17 | 0.06 |
| Indigenous | 1.62 | 0.30 | 0.15 |
| Young children | 1.73 | 0.42 | 0.28 |
| Adj. R² | .64 | | |

*Note*. VIF: collinearity assessment. Bootstrapped paths were all significant (p. < .01) and confidence intervals did not cross zero.

**Table 4**

*Structural Model Assessment of the Tertiles of Children Aged 0-4 years in Study 3.*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Highest percent of children aged 0-4 years | | | |  | Lowest percent of children aged 0-4 years | | | |
| **Predictors** | **Frequent reproduction** | | | |  | **Frequent reproduction** | | | |
|  | VIF |  | Paths | f² |  | VIF |  | Paths | f² |
| Unemployed | 1.00 |  | - 0.51\*\*\* | 0.52 |  | 1.03 |  | - 0.45\*\*\* | 0.47 |
| Young children | 1.00 |  | 0.48\*\*\* | 0.36 |  | 1.03 |  | 0.56\*\*\* | 0.75 |
| Adj. R² | .51 | | | |  | .59 | | | |
| **Predictors** | **Single parenting** | | | |  | **Single parenting** | | | |
| Low-income children | 2.06 |  | 0.48\*\*\* | 0.28 |  | 1.64 |  | 0.35\*\*\* | 0.13 |
| High rents | 1.83 |  | - 0.27\*\* | 0.09 |  | 1.59 |  | - 0.49\*\*\* | 0.26 |
| Unemployed | 1.87 |  | - 0.21\* | 0.06 |  | 1.23 |  | - 0.39\*\*\* | 0.21 |
| Indigenous | 2.99 |  | 0.48\*\*\* | 0.19 |  | 1.25 |  | 0.13 | 0.03 |
| Young children | 1.57 |  | 0.13 | 0.03 |  | 1.12 |  | 0.40\*\*\* | 0.25 |
| Adj. R² | .58 | | | |  | .39 | | | |

*Note*.VIF: collinearity assessment; Bootstrapped paths reported. \*: *p ≤ .05, \*\*: p ≤ .01, \*\*\*: p ≤ .001*.

**Table 5**

*Structural Model Assessment of the Tertiles of Children Aged 5-9 years in Study 3.*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Highest percent of children aged 5-9 years | | | |  | Lowest percent of children aged 5-9 years | | | |
| **Predictors** | **Frequent reproduction** | | | |  | **Frequent reproduction** | | | |
|  | VIF |  | Paths | f² |  | VIF |  | Paths | f² |
| Unemployed | 1.03 |  | - 0.54\*\*\* | 0.68 |  | 1.07 |  | - 0.37\*\*\* | 0.38 |
| Young children | 1.03 |  | 0.46\*\*\* | 0.41 |  | 1.07 |  | 0.64\*\*\* | 1.12 |
| Adj. R² | .59 | | | |  | .65 | | | |
| **Predictors** | **Single parenting** | | | |  | **Single parenting** | | | |
| Low-income children | 1.62 |  | 0.50\*\*\* | 0.37 |  | 1.72 |  | 0.35\*\* | 0.11 |
| High rents | 1.47 |  | - 0.20\* | 0.06 |  | 1.68 |  | - 0.47\*\*\* | 0.22 |
| Unemployed | 1.57 |  | - 0.25\* | 0.10 |  | 1.23 |  | - 0.37\*\*\* | 0.19 |
| Indigenous | 1.99 |  | 0.47\*\*\* | 0.27 |  | 1.15 |  | 0.12 | 0.02 |
| Young children | 1.21 |  | 0.18\* | 0.07 |  | 1.16 |  | 0.48\*\*\* | 0.33 |
| Adj. R² | .56 | | | |  | .37 | | | |

*Note*. VIF: collinearity assessment; Bootstrapped paths reported. \*: *p ≤ .05, \*\*: p ≤ .01, \*\*\*: p ≤ .001*.

**Table 6**

*Structural Model Assessment of the Tertiles of Visible Minorities in Study 4.*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Highest percent of Visible minorities | | | |  | Lowest percent of Visible minorities | | | |
| **Predictors** | **Frequent reproduction** | | | |  | **Frequent reproduction** | | | |
|  | VIF |  | Paths | f² |  | VIF |  | Paths | f² |
| Unemployed | 1.08 |  | - 0.41\*\*\* | 0.69 |  | 1.2 |  | - 0.42\*\*\* | 0.93 |
| Young children | 1.08 |  | 0.69\*\*\* | 2.07 |  | 1.2 |  | 0.66\*\*\* | 2.27 |
| Adj. R² | .79 | | | |  | .84 | | | |
| **Predictors** | **Single parenting** | | | |  | **Single parenting** | | | |
| Low-income children | 1.87 |  | 0.42\*\*\* | 0.25 |  | 1.41 |  | 0.31\*\*\* | 0.23 |
| High rents | 1.98 |  | - 0.35\*\*\* | 0.16 |  | 1.24 |  | - 0.11 | 0.03 |
| Unemployed | 1.70 |  | - 0.18\* | 0.05 |  | 1.44 |  | - 0.13 | 0.03 |
| Indigenous | 1.79 |  | 0.20\* | 0.06 |  | 1.97 |  | 0.22\*\* | 0.07 |
| Young children | 1.57 |  | 0.60\*\*\* | 0.63 |  | 1.97 |  | 0.52\*\*\* | 0.45 |
| Adj. R² | .62 | | | |  | .66 | | | |

*Note.* VIF: collinearity assessment; Bootstrapped paths reported. \*: *p ≤ .05, \*\*: p ≤ .01, \*\*\*: p ≤ .001.*

**Figure 1**

*Proportion of young children, rates of visible minorities in the population, and socioeconomic factors predict**early reproduction in Canadian Dissemination Areas.*

A diagram of a company

AI-generated content may be incorrect.

*Note*. Figure created in R using seminr package. Hexagons represent latent variables and rectangles represent items from Census. Predictors are formative latent variables using Census data in 2006 and outcomes are reflective latent variables using Census data in 2021. W: variable’s weights, λ: variable’s loadings, β; path’s beta coefficients; \*\*: *p* ≤ .01, \*\*\*: *p* ≤ .001.

**Figure 2**

*Proportion of young children, rates of indigeneity in the population, and socioeconomic factors predict**early reproduction in Canadian Census Divisions.*

A diagram of a product

AI-generated content may be incorrect.

*Note*. Figure created in R using seminr package. Hexagons represent latent variables and rectangles represent items from Census. Predictors are formative latent variables using Census data in 2006 and outcomes are reflective latent variables using Census data in 2021. λ: variable’s loadings, β; path’s beta coefficients; \*\*: *p* ≤ .01, \*\*\*: *p* ≤ .001.

**Figure 3**

*Later harshness an unpredictability are poor predictors of previous measures of early reproduction.*

A diagram of a computer program

AI-generated content may be incorrect.

*Note*. Figure created in R using seminr package. Hexagons represent latent variables and rectangles represent items from Census. Predictors are formative latent variables using Census data in 2006 and outcomes are reflective latent variables using Census data in 2021. λ: variable’s loadings, β; path’s beta coefficients; \*\*: *p* ≤ .01, \*\*\*: *p* ≤ .001.

# Chapter 5: Proportion of Indigenous Populations Predicts Teen Pregnancy and Birth Rates Only When the Cost of Living is High

## Preface

We found that the proportion of Indigenous people in Canadian census divisions was a significant and positive predictor of the proportion of single-parent households 15 years later in the previous study. Life history theory in psychology (LHT-P) literature usually assess harshness and unpredictability with socioeconomic and family or household configuration change (Belsky et al., 2012; Ellis et al., 2009; Webster et al., 2014; Xu et al., 2018). The history of colonialism, the assignment of Indigenous people to “reservations” and the replacement of their culture and way of living and governance by European and culture and political systems are examples of these particular circumstances (*Honouring the Truth, Reconciling for the Future*, 2015; Neu & Graham, 2006; Romaniuk, 2008).

Research on LHT-P has also assessed the impact of exposure to violence as a source of environmental unpredictability (e.g., Dinh et al., 2022; McLaughlin et al., 2021; Wilson & Daly, 1997) and there are some who argue about a cyclical component to life history strategies which could include genetics (Del Giudice et al., 2015; Stearns, 1992) or be due to experience and expectation. For example, children growing up in an environment in which one of the parents is not consistently present or available may grow up with the expectation that partners do not last or do not consistently invest in raising children, therefore they will shift their preferences to short-term relationships to a greater extent than those who consistently had their parents present (Volk, 2023). Lastly, one of the most propositions of LHT-P is how harsher and more unpredictable shift one’s metabolic clock towards earlier puberty and start of sex life (Dinh et al., 2022; Ellis et al., 2003; Webster et al., 2014; Xu et al., 2018), but this measure was not assessed in the previous study because it was not available in the census (Statistics Canada, 2024a). This study aimed to address these questions.

We collected data of the ratios of Indigenous people, cost of living to income, single-parent households, violence crime indices of Canadian provinces and territories between 2000 and 2022 and used forward stepwise linear regressions to predict the birth and teenage pregnancy ratios between 2015 and 2022 (Statistics Canada, n.d., 2017b, 2018, 2021, 2023a, 2023b, 2024b). We also tested the developmental hypothesis that early childhood environment – instead of current environment - cues individuals into different life history strategies. Hence, we tested whether the longitudinal model (i.e., using predictors between 2000 and 2005 and outcomes between 2015 and 2022) would perform better than a cross-sectional model (i.e., using both predictors and outcomes between 2015 and 2022).

The interaction between Indigenous and cost of living to income was significant a predictor of and explained more than 90% of the variance in birth and teenage pregnancy rates. When considering the main effect of Indigeneity, it was a significant and negative predictor of both outcomes. Single parent households and violent crime were highly correlated and collinear with Indigenous population, therefore they were not included in the model.

This data suggests that Indigenous children in Canada are more exposed to higher costs of living, single parent households and violent crimes than non-Indigenous children. The higher costs of living – and potentially single parent households and violent crimes – may all be part of the harsher and more unpredictable environments that Indigenous children encounter and that may help explain the higher fertility and younger age among Indigenous people (Government of Canada, 2022; Statistics Canada, 2017a).

We argue that this is a non-exhaustive list. There are many other forms of harshness and unpredictability that Indigenous people encounter and future research could focus in assessing their environments and ways of living (*Honouring the Truth, Reconciling for the Future*, 2015; Romaniuk, 2008). Moreover, future research should partner with Indigenous communities to explore alternative explanations that ensures deeper interpretations of the reasons and consequences of reproduction (Archibald, 2007; Finestone & Stirbys, 2017; Provencher & Galbraith, 2024).

### References

Archibald, J. (2007). An Indigenous Storywork Methodology. In J. G. Knowles & A. L. Cole (Eds.), Handbook of the Arts in Qualitative Research: Perspectives, Methodologies, Examples, and Issues. Sage Publications, Inc.

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. Developmental Psychology, 48(3), 662–673. https://doi.org/10.1037/a0024454

Del Giudice, M., Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), The Handbook of Evolutionary Psychology (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

Dinh, T., Haselton, M. G., & Gangestad, S. W. (2022). “Fast” women? The effects of childhood environments on women’s developmental timing, mating strategies, and reproductive outcomes. Evolution and Human Behavior, 43(2), 133–146. https://doi.org/10.1016/j.evolhumbehav.2021.12.001

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? Child Development, 74(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. Human Nature, 20(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Finestone, E., & Stirbys, C. (2017). Indigenous Birth in Canada: Reconciliation and Reproductive Justice in the Settler State. In Indigenous Experiences of Pregnancy and Birth (pp. 176–202). Demeter Press. http://www.jstor.org/stable/j.ctt1vw0sbs.15

Government of Canada. (2022). The Daily—Indigenous population continues to grow and is much younger than the non-Indigenous population, although the pace of growth has slowed. https://www150.statcan.gc.ca/n1/daily-quotidien/220921/dq220921a-eng.htm

Honouring the truth, reconciling for the future: Summary of the final report of the Truth and Reconcilliation Commission of Canada. (2015). Truth and Reconcilliation Commission of Canada.

McLaughlin, K. A., Sheridan, M. A., Humphreys, K. L., Belsky, J., & Ellis, B. J. (2021). The Value of Dimensional Models of Early Experience: Thinking Clearly About Concepts and Categories. Perspectives on Psychological Science, 16(6), 1463–1472. https://doi.org/10.1177/1745691621992346

Neu, D., & Graham, C. (2006). The birth of a nation: Accounting and Canada’s first nations, 1860–1900. Accounting, Organizations and Society, 31(1), 47–76. https://doi.org/10.1016/j.aos.2004.10.002

Provencher, C., & Galbraith, N. (2024). Fertility in Canada, 1921 to 2022 (Demographic Documents No. 91F0015M). Statistics Canada.

Romaniuk, A. (2008). History-based Explanatory Framework for Procreative Behaviour of Aboriginal People of Canada. Canadian Studies in Population, 35(1), 159. https://doi.org/10.25336/P61K7T

Statistics Canada. (n.d.). Labour income profile of tax filers by sex [Dataset]. [object Object]. https://doi.org/10.25318/1110003101-ENG

Statistics Canada. (2017a). Aboriginal peoples in Canada: Key results from the 2016 Census. The Daily.

Statistics Canada. (2017b). Crime severity index and weighted clearance rates, Canada, provinces, territories and Census Metropolitan Areas [Dataset]. [object Object]. https://doi.org/10.25318/3510002601-ENG

Statistics Canada. (2018). Detailed household final consumption expenditure, provincial and territorial, annual [Dataset]. [object Object]. https://doi.org/10.25318/3610022501-ENG

Statistics Canada. (2021). Population and dwelling counts, for Canada, provinces and territories, 2011 and 2006 censuses. https://www12.statcan.gc.ca/census-recensement/2011/dp-pd/hlt-fst/pd-pl/Table-Tableau.cfm

Statistics Canada. (2023a). Live births, by month [Dataset]. [object Object]. https://doi.org/10.25318/1310041501-ENG

Statistics Canada. (2023b). Selected income characteristics of census families by family type [Dataset]. [object Object]. https://doi.org/10.25318/1110000901-ENG

Statistics Canada. (2024a). Canadian census analyser [Dataset]. Computing in the Humanities and Social Sciences at the University of Toronto (CHASS). https://datacentre.chass.utoronto.ca/census/

Statistics Canada. (2024b). Income of individuals by age group, sex and income source, Canada, provinces and selected census metropolitan areas [Dataset]. [object Object]. https://doi.org/10.25318/1110023901-ENG

Stearns, S. C. (1992). The evolution of life histories. Oxford University Press.

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. Evolution and Human Behavior, 44(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. Evolutionary Psychology, 12(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. BMJ, 314(7089), 1271–1271. https://doi.org/10.1136/bmj.314.7089.1271

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. Evolution and Human Behavior, 39(1), 40–51. <https://doi.org/10.1016/j.evolhumbehav.2017.08.005>

## Abstract

This study investigates whether an elevated cost of living, single parent households and exposure to violence are better predictors of future fertility and teen pregnancy rates compared with the representation of Indigenous populations (First Nations, Métis, and Inuit communities) by province across Canada. Drawing on life history theory in psychology (LHT-P), we examine whether reproductive timing reflects adaptive responses to environmental harshness (cost of living-to-income ratio) and unpredictability (single-parent households, violent crime). Using Statistics Canada data (2000–2022) and stepwise linear regressions, we found that the proportion of Indigenous people predicts higher birth rates and rates of teenage pregnancy when the cost of living is high. Across economic circumstances, however, the proportion of indigeneity predicts lower birth rates and rates of teenage pregnancy. The proportion of single parent households and exposure to violence were highly correlated and colinear with the proportion of Indigenous people. These findings suggest that standard LHT-P models may be insufficient to explain reproductive outcomes among Indigenous communities. We propose that Indigenous cultural meaning systems, collective childrearing, and resistance to colonial reproductive governance may influence fertility and teen pregnancy rates. This study underscores the importance of integrating structural and cultural dimensions into evolutionary developmental models and calls for strengths-based, culturally responsive approaches to Indigenous reproductive health.

***Keywords:*** *Life History Theory, Indigenous, Teen Pregnancy, Birth Rates, Harshness,*

*Unpredictability, Reproduction.*

## Introduction

### Indigenous Populations in Canada

The terms “Indigenous” or “Aboriginal”, “Peoples, “Communities,” or “Populations,” does not sufficiently acknowledge or reference the heterogeneity of the cultural groups embodied by this term (Statistics Canada, 2017a). In the Canadian context, Indigenous Peoples include First Nations, Métis, and Inuit communities—each with distinct cultural identities, governance systems (e.g., Anishinaabe, Cree, Inuk, Mi’kmaq, etc.) and historical and contemporary relationships with colonialism (*Honouring the Truth, Reconciling for the Future*, 2015; Statistics Canada, 2017a). However, we use the term “Indigenous people” in this paper to refer to an aggregate of long-established, non-settler populations in Canada who share important commonalities—most notably, the experience of colonial imposition and its enduring, often harmful consequences.

The choice for the term “Indigenous people” also aims to more similarly refer to terms used in Statistics Canada reports (*Dictionary, Census of Population, 2021*, 2023; Statistics Canada, 2024a), which is data source for this study. As framed by Statistics Canada, the usage of the term ‘Indigenous’ is in alignment with the Government of Canada’s official terminology, especially since the adoption of international standards like the United Nations Declaration on the Rights of Indigenous Peoples. The Dictionary, Census of population, 2021 (2023) defines Indigenous group as:

[…] refers to whether the person is First Nations (North American Indian), Métis and/or Inuk (Inuit). A person may be included in more than one of these three specific groups. Aboriginal peoples of Canada (referred to here as Indigenous peoples) are defined in the Constitution Act, 1982, Section 35 (2) as including Indian, Inuit and Métis peoples (p. 259).

According to Statistics Canada, Indigenous Populations are growing faster than non-indigenous populations. Between 2006 and 2016 the Indigenous population grew more than 4 times faster than non-indigenous populations in Canada (Statistics Canada, 2017a). Moreover, the indigenous population is young. Nearly two-thirds of the First Nations population is of working age and one-quarter of the population are aged 14 years and younger (Statistics Canada, 2023a).

Teen pregnancy and elevated birth rates remain disproportionately high among Indigenous populations in Canada in comparison to non-Indigenous mothers, particularly in circumpolar and marginalized (Reading & Wien, 2009; Sheppard et al., 2017). While this phenomenon has often been interpreted through individual or cultural deficit models, recent research has rightfully called for a deeper analysis that centers structural inequities, colonial histories, and community-specific knowledge systems (Goghari & Kassan, 2022). The continued overrepresentation of Indigenous youth – especially First Nations, Métis, and Inuit young women – in early childbirth statistics points to enduring systemic factors that shape reproductive health outcomes across generations.

Research framed within Western perspectives on teenage pregnancy in the 21st century, for instance, highlights a range of challenges associated with teen parenthood. These include impaired mental health, often stemming from the competing demands of early parenting and the developmental pressures of adolescence (Tebb & Brindis, 2022; Wong et al., 2020). Conventional knowledge generated by research assuming a more Western lens also finds that teen parents are also more likely to have experienced adverse childhood experiences, been raised in single-parent households (Hartman et al., 2018; Reichman et al., 2001; Simpson et al., 2012), and to have mothers who gave birth at a young age (Vikat, 2002). Additionally, they are often part of larger families with multiple siblings and face poor socio-economic conditions (Koehler & Rutherford, 2025; Richter, 2004).

However, we might also consider broader cultural impacts on reproductive trends among Indigenous populations in Canada. The formation of Canada as a nation-state introduced a bureaucratic governance that disrupted Indigenous subsistence lifestyles. Nomadic cultures were replaced by European settler political structures, which resulted in Indigenous populations being confined to “reservations” where self-governance was highly limited (Neu & Graham, 2006; Romaniuk, 2008). This ‘in-between-cultures’ state of existence forced Indigenous peoples to partially accommodate the colonial system to access the resources necessary to survive while resisting full assimilation in an effort to preserve their cultural identity and traditions (Romaniuk, 2008). Culturally speaking, these imposed conditions inherently cultivated harshness and unpredictability within Indigenous communities across Canada (*Honouring the Truth, Reconciling for the Future*, 2015).

While all populations in Canada have experienced periods of baby boom, the underlying factors driving increased rates of reproduction are different. For non-Indigenous populations in Canada, historical events like the Great depression and the World Wars along with increased levels of prosperity and stability following the war have been attributed to the baby boom of the 1950s (Bélanger et al., 2006; Romaniuc, 1991; Romaniuk, 1984). Historical booms in fertility among Canada’s First Nations communities can be attributed to the eventual relaxation of harsh and unjust large-scale birth limitations enforced by colonial law (Romaniuk 2008).

### Life history theory

All species on Earth need to make trade-offs of where to allocate time and energy. Resources invested in one domain (e.g., acquiring food) are necessarily not invested in many other domains (e.g., finding mates, parenting, or maintaining one’s immune system; (Del Giudice et al., 2015; Stearns, 1992). Evolution favours the allocation of resources to maximize fitness given an individual’s environmental circumstances and LHT-P offers an explanation for the strategic allocation of finite resources (Ellis et al., 2009; Lack, 1954).

When collapsing all different investments that species can make, we end up with two categories: somatic effort (body maintenance and growth) and reproduction effort (Ellis et al., 2009; Griskevicius et al., 2011). During a species lifetime, different investment rates of energy and time towards these two major categories would maximize fitness and these different investment patterns have been named life history strategies (LHS; Del Giudice et al., 2015; Sear, 2020; Stone et al., 2023) Species then, could be aligned along a continuum that has been named as *fast-slow continuum*. Species closer to the fast pole would invest earlier and more frequently in reproduction. This means reaching puberty faster, having offspring faster and more often, resulting in reduced investment per offspring. Some of the trade-offs of this strategy is a reduced body size and the generation of lower quality offspring. Species closer to the slower pole, on the other hand, would invest longer in growing their bodies, acquiring resources (e.g., body fat, shelter, status) and reproduce at later period and slower rate and investing more in each offspring, resulting in higher offspring quality. One of the trade-off of this strategy is the generation of fewer offspring (Ellis et al., 2009; Stearns, 1992). Classic examples of such strategies would be the mouse (fast) and the elephant (slow). Although the theory majorly explains between-species variation, researchers have also found some within-species variation (Richardson et al., 2020; Sear, 2020; Stearns et al., 2008).

Environmental harshness and unpredictability – understood here respectively as the rates of death and disease outside of the organisms control and random variation of these rates – are two aspects that would cue species into shifting towards one of the poles (Del Giudice et al., 2015; Ellis et al., 2009). Harsher and more unpredictable environments would cue individuals into a faster life history strategy because one would be less sure of their future reproduction opportunities. They would also be less sure of their offspring survival and chances of reproduction, therefore making it more advantageous to have more offspring and spread them to maximize chances of passing on one’s genes. On the other pole, more gentle and predictable environments would favour slower life history strategists. Because one can be somewhat sure of their offspring survival, it is interesting to have fewer children, invest more resources in them to increase the children’s chances of outcompeting other in resources and mate acquisitions (Del Giudice et al., 2015; Ellis et al., 2009; Stearns, 1992).

In human studies, harshness is usually assessed using socio-economic factors,

whereas unpredictability has been assessed as the amount of parental transitions (changes in household configuration through divorce and remarriage for example), job transitions, and geographical moves (Belsky et al., 2012; Ellis et al., 2009; Hartman et al., 2018). Exposure to violence has also been found to influences the development of LHS (Dinh et al., 2022; McLaughlin et al., 2021; Wilson & Daly, 1997). There is a longitudinal aspect to this phenomenon. Early childhood environment, especially in the first 5 or 7 years of life, is a critical period and strongly predicts LHS, more so than the current environment (Chang et al., 2019; Nolin & Ziker, 2016; Simpson et al., 2012; Webster et al., 2014; Xu et al., 2018).

This theory was originated in evolutionary biology and has been used in evolutionary psychology, which ended up creating two different fields of research: life history theory in biology (e.g., Albaladejo‐Robles et al., 2023; Malone et al., 2022; Stone et al., 2023) and life history theory in psychology (LHT-P; Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Sear, 2020). Recently, the actual existence of this *fast-slow continuum* has been heavily criticized, especially among humans (Frankenhuis & Nettle, 2020; Sear, 2020; Stearns & Rodrigues, 2020). The critics point that human investments rarely vary or correlate along this continuum (Sear, 2020) and that it has been abandoned in evolutionary biology (Nettle & Frankenhuis, 2020). They also argue that modern environments lack harshness and unpredictability levels that would present in the environment of evolutionary adaptedness and there is evidence that humans have actually reacted in the opposite direction of what would be expected by LHT-P (Nolin & Ziker, 2016; Richardson et al., 2020; Volk, 2023, 2025; Wells et al., 2019).

### The current study

Critics of LHT-P have suggested narrowing its set of predictions and testing more formal models, similar to the field of biology (Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Volk, 2025). In addition, populational and cross-cultural findings are valuable to evolutionary psychologists because they can test the universality and developmental flexibility of adaptations (Buss, 2024). Governmental surveys are useful in testing the predictions of LHT-P (Copping, 2017). The reports are periodic (i.e., useful to test the developmental phenomenon of the first years of life shaping future behaviour), and they usually include socioeconomic indicators (i.e., harshness) and family characteristics like marital status, employment and migration change (i.e., unpredictability).

We have previously found that the percentage of Indigenous people in Canadian census divisions were predictive of the percentage of single-parent households 15 years later (Koehler, & Rutherford, 2025). Indigenous people are more likely than the population as a whole to experience harsh and unpredictable environments of (*Honouring the Truth, Reconciling for the Future*, 2015) and circumstances that are associated with early and frequent reproduction (Romaniuk, 2008). Parental absence (usually the father) is one of the strongest predictors of early sexual activity and early pregnancy (Belsky et al., 2012; Ellis et al., 2003). This phenomenon may be self-perpetuating: A child growing up without stable parental figures may grow up with the expectation that one of the parents will not invest equally invest in children, which reduces the advantages of seeking long-term relationships and stable partners (Volk, 2023).

Against this backdrop, our study asks whether the proportion of Indigenous people in the population in a province or territory serves as a stronger long-term predictor of birth and teen pregnancy rates than more conventional indicators of environmental adversity used in LHT-P. We also test whether the interaction between Indigeneity and structural hardship (e.g., high cost of living to income) better explains elevated reproductive rates than either factor alone.

Increased birth and teenage pregnancy rates are outcomes that are expected to occur under harsher and more unpredictable circumstances, but birth and teenage pregnancy variables were not available in the Canadian census (Statistics Canada, 2024a). Exposure to crime is another variable that is not present in the Census. The interaction between proportions of Indigenous peoples and indicators of harshness and unpredictability was also not tested in our previous study.

## Methods

### Data selection and transformation

The data assessed for this study was collected from publicly available data for all 13 provinces and territories in Canada reported by Statistics Canada between 2000 and 2022 (Statistics Canada, n.d., 2017b, 2018, 2021, 2023b, 2023c, 2024b). Considering our research question, the first variable selected was the proportion of Indigenous residents to the overall population by province and territory. The choice for this level of analysis was intended to add variables that are not available at smaller geographies (e.g., census divisions). We also selected the rate of single parent household and violent crime indices – understood here as indicators of unpredictability – and calculated the average cost of living to income ratio – understood here as an indicator of harshness. These predictors were used to predict birth rates and teen pregnancy by province and territory. Wherever available, data was collected for all years between 2000 and 2022. The data frame used for the main analysis used mean values between 2000 and 2005 as predictors and the mean values between 2015 and 2022 as outcomes. The intention for this longitudinal difference between predictors and outcomes is to test the developmental assumption of LHT-P that children exposed to to certain environments in their first years of life will have different reproductive trajectories.

Since the data was extracted from Statistics Canada and are representative of the mean or proportions values in Canadian provinces and territories, there were no missing data or data imputation from the data we collected. There may have been some data transformation conducted by Statistics Canada, variation in how data is collected or differences the quality of such data between provinces and territories, but it is still an interpretable data source. The raw and wrangled data, all materials and a full report of the analyses in this study are openly available on OSF at https://osf.io/akqxn/?view\_only=65fb56165b9b48e18d170213493b934d.

### Analytical approach

All data analysis was conducted in R with default, car (Fox et al., 2023), and corr (Kuhn et al., 2022) packages. Cases with a z-score > 3 were considered outliers. Given the descriptive nature of the data covering all 13 provinces and territories, analyses were conducted both with and without outliers. Since excluding outliers from any region does not improve the model’s ability to generalize findings to the entire population, the estimated model in this study incorporated data from all provinces and territories.

Forward stepwise linear regressions were employed to predict teenage pregnancy and birth rates between 2015 and 2022. There are criticisms regarding adopting this analysis (Field et al., 2014; Harrell, 2015). These criticisms involve making decisions about variables for statistical instead of theoretical reasons, which can produce results that are biased and more likely to be significant; model fit, which can include a suboptimal number of variables and an increase in Type II errors.

We have taken a series of measures to deal with such issues. First, our selection of variables was solidly guided by LHT-P and based on previous findings (Koehler & Rutherford, 2025). Secondly, we predetermined the order in which variables would be tested. The order was based on the research questions for this study – assess whether the proportion of Indigenous people would significantly predict birth rates and teenage pregnancy – and also based on LHT-P. Therefore, the primary predictor tested was the proportion of Indigenous Peoples to the general population by province or territory and subsequently, predictors including the cost of living to income ratio (indicating harshness), single-parent households (one of the strongest indicators of unpredictability in the literature), and violent crime (a less frequently used indicator of unpredictability that may be more directly linked to morbidity and mortality) were added sequentially in that order. Interactions among significant variables would also be tested and significant variables and interactions would be retained in the model. These measures make our approach far from having results purely based on statistics.

Thirdly, we also planned to test combinations of non-significant variables to compare them with the first model. Finally, to address collinearity among predictors, the variance inflation factor (VIF) was calculated, with VIF values > 5 indicating collinearity, which informs that the selection of a single variable should be sought. Simpler and nested models were compared for significance using ANOVAs. Non-significant results favoured the more parsimonious model.

We also planned a comparison to test whether this is likely a developmental phenomenon or merely geographical stability or some statistical association. The selected model, which used predictors from 2000-2005 and outcomes from 2015-2022, was tested using data encompassing both predictors and outcomes from the same temporal period (i.e., both predictors and outcomes from 2015-2022).

## Results

We observed high correlations between the proportion of Indigenous Peoples by province and both the single-parent household rate and violent crime index (r > .86). Due to high multicollinearity (VIF > 8.9), these variables could not be included in the same model. Therefore, only the proportion of Indigenous Peoples and the cost of living-to-income ratio were retained as primary predictors. Table 1 presents descriptive statistics and correlations among variables.

Measures for Indigeneity and their interaction with the cost of living were significant predictors of both teenage pregnancy (R² = 0.97, F(3, 9) = 89.29, p < .001, adj. R² = 0.96) and birth rate (R² = 0.94, F(3, 9) = 47.25, p < .001, adj. R² = 0.92). Table 2 reports the regressions of these two models and of the cross-sectional models. The interaction between Indigeneity and cost of living was statistically significant in both models. This interaction reveals that regions with both higher Indigenous populations and higher cost-of-living-to-income ratios experience disproportionately higher teen pregnancy and birth rates. Figure 1 shows a fitted linear regression with subsamples of the highest and lowest cost of living to income provinces and territories. It shows that increasing cost of living strengthens the positive association between Indigenous population proportion and birth rates. Teenage pregnancy plot depicts a considerable overlap in the confidence interval between the high and low cost of living to income subsamples. This is likely due to the smaller interaction coefficient in this model and to the smaller sample size (N=6). These are probably also the reason for the inverted association in the plot (i.e., the steeper line between Indigenous people and Teenage pregnancy in the low cost of living condition).

Analysis of variance demonstrated that the models including and not including the main effect of the cost of living to income were not different for either teenage pregnancy (F(9, 10) = 0.15, p = .704) or birth rate (F(9, 10) = 3.61, p = .090). However, we maintained cost of living to income in the model and reported its main effect on Table 2. Omitting the main effect of cost of living to income would hinder model interpretation and violate standard recommendations for modeling interaction effects (Aiken et al., 1991; Field et al., 2014). The main effect of the proportion of Indigenous Peoples per province and territory was significant, but negative, which indicates that the association between a larger proportion of Indigeneity and higher teenage pregnancies or birth rates is only present when a high cost of living and low income is also present.

The proportion of teenage pregnancy among Nunavut was the only data point with a z score > 3. In addition, Nunavut and Northwest territories appeared as visual outliers in most of the variables (see Boxplot A in Supplementary Figure 1). The model remained significant after removing outlier cases but had less explanatory power (teen pregnancies, R² = 0.84, F(3, 7) = 12.49 p < .003, adj. R² = 0.78; birth rate R² = 0.73, F(3, 7) = 6.17, p < .022, adj. R² = 0.61).

The correlations between predictors in the longitudinal and cross-sectional comparisons were comparable. All the correlations were high, with the cost of living-to-income ratio having the lowest correlation with the other variables. The cross-sectional model produced significant results for teenage pregnancy, but both performed worse than did the longitudinal model. Prediction of teen pregnancies (R² = 0.93, F(3, 9) = 42.26, p < .001, adj. R² = 0.91) and birth rate (R² = 0.87, F(3, 9) = 19.38, p < .001, adj. R² = 0.82) had comparable R² values but lower F values and higher residuals and residual standard errors, which indicated that the longitudinal model produced a better fit. Finally, we used collinear variables, namely, single-parent households and violent crime status, separately to predict teen pregnancy and birth rate, and the results were significant.

## Discussion

The proportion of Indigenous Peoples in the population and the cost of living to income ratio between 2000-2005 can predict both teenage pregnancy and birthrates between 2015-2022. This means that economic hardship does play a key role in the statistical association, as predicated by LHT-P. The study also found that models using longitudinal data performed better predictions than those using data from only one point in time. These findings support the developmental prediction that individuals who experience harsher environments early in life are more likely to start sex and have children earlier and more frequently (Dinh et al., 2022; Ellis et al., 2009; Simpson et al., 2012; Xu et al., 2018).

The proportion of Indigenous population by province – especially in economically harsh environments in northern provinces and territories – is a strong predictor of birth and teen pregnancy around 15 years later. This finding supports the conclusion that higher birth rates and teen pregnancy among Indigenous people (Reading & Wien, 2009; Sheppard et al., 2017) are likely influenced by a broader range of factors than those typically associated with harshness and unpredictability in LHT-P literature, which often emphasizes on socio-economic, parental transitions and geographical moves (Belsky et al., 2012; Hartman et al., 2018). The finding that the main effect of Indigenous people on birth and teenage pregnancy was negative further support this hypothesis that there are specific indicators of harshness and unpredictability not accounted for in the model.

Some of the variables collected in this study that could offer help in understanding this phenomenon (i.e., single parent households and violent crime index) could not be properly evaluated due to strong correlation and collinearity with higher proportions of Indigenous communities. The variables were removed from the linear regressions to avoid redundancy and problems in interpretation. However, this strong correlation and collinearity helps demonstrating the harsher life that Indigenous people experience in Canada (*Honouring the Truth, Reconciling for the Future*, 2015). We tested how single parent households and violent crime would isolated predict teenage pregnancy and birth rates. These variables were significant predictors of birth rates and teenage pregnancies but they were considerably weaker than the models using Indigenous people interaction with cost of living to income ratios. These further supports the hypothesis that different variables could help understanding the birth practices of Indigenous people in Canada.

The model remained significant even when the outliers, Nunavut and Northwestern Territories, were excluded, which suggests that the main finding is robust. The effect may be more pronounced in provinces and territories where the proportion of Indigenous population are the largest. Indeed, roughly 80% of the population in Nunavut and 45% of the population in the Northwest Territories is Indigenous and including them in the model increased the model’s explanatory power.

### Limitations

The use of provinces and territories reduced our data frame to only 13 data points per variable. Using these large geographic areas reduces the likelihood of attrition by populational mobility but also reduces contrasts that could reveal local differences. This approach also limits conclusions at the individual level. We predicted, based on LHT-P, that it is likely that a good proportion of Indigenous children living in a higher cost of living to income ratio – and potentially with a higher rate of being raised in single-parent households or more exposed to crime - are likely to become young parents and have more children 15 years later. However, the populational level of data allows for the possibility for the association among these variables to be true only in the populational level or to both being due to confounding variables.

This study also aggregates Indigenous people. This approach does not capture social, historical, and cultural differences among First Nations, Métis, and Inuit communities (*Honouring the Truth, Reconciling for the Future*, 2015). For example, regarding birth practices, several Indigenous cultures in Canada have also been reclaiming more traditional practices, which are not conceived as a part of medical practice invoking a ‘treatment’ approach to removing a fetus from the mother’s womb. It is also not as an individualistic process as it is in Western lens. Rather, the birth process is culturally framed as a process of ‘gift giving’ This ‘gift giving’ dynamic emphasizes the significance of a ‘receiver,’ which is generally characterized as the community into which the infant will become a member of and is understood as a sacred process (Finestone & Stirbys, 2017).

The ‘gifting’ pronatalist subculture of these traditions also posits that childbearing and birth are important to the norms, values, and practices of Indigenous cultures, offering important insight into potential historical and socio-cultural explanations for increased rates of childbirth and teen pregnancy among Indigenous people across Canada (Provencher & Galbraith, 2024; Statistics Canada, 2017a). This perspective could help explain fertility trends among Indigenous Populations, even when socio-economic considerations are held constant and these explanations are highly compatible with the tenets of LHT-P. This study have found, however, that when the cost of living and its interaction with the proportion of Indigenous people are held constant, proportion of Indigenous people actually predicts lower birth and teenage pregnancy rates. Future research in this area of inquiry could incorporate the ‘cultural natalist residual,’ the ‘gift giving’ childbirth ethos, and the ‘pronatalism’ hypothesis as potential predictors of higher birth rates and teen pregnancy among First Nations communities across Canada.

Although we used publicly available aggregated data, we acknowledge Indigenous data sovereignty principles including OCAP® (Ownership, Control, Access, and Possession; Schnarch, 2004) and CARE (Collective benefit, Authority to control, Responsibility, and Ethics; Carroll et al., 2020). Future research could partner with Indigenous communities to explore other interpretations (e.g., Indigenous methodologies) and ensure meaningful collaboration, benefit-sharing, and community-led interpretations (Archibald, 2007).

Using large but few geographic areas also converge values to mean values, which reduces local variance and limits statistical power. The finding that our models still yield significant values, even after removing outliers, highlights the strength of this association. Additionally, **s**patial dependencies among provinces and territories (e.g., shared historical, economic, or policy contexts) may violate the assumption of independent observations, which standard MLR does not account for.

### Conclusion

When the cost of living is high, the proportion of indigeneity predicts higher birth rates and rates of teenage pregnancy, but across economic circumstances, the proportion of indigeneity predicts lower birth rates and rates of teenage pregnancy. This study shows that early-life structural disadvantage of Indigenous people predicts reproductive outcomes 15 years later, supporting key predictions of LHT-P. The results also suggest that both teen pregnancy and birth rates are shaped not only by socio-economic adversity commonly used by LHT-P, but also by specific indicators not accounted in this study. Future research could work in partnership with Indigenous communities, incorporate indicators such as cultural continuity and pronatalism, and combine diverse methodologies to deepen our understanding of reproductive strategies in diverse contexts of Indigenous communities in Canada.

## References

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage Publications.

Albaladejo‐Robles, G., Böhm, M., & Newbold, T. (2023). Species life‐history strategies affect population responses to temperature and land‐cover changes. *Global Change Biology*, *29*(1), 97–109. https://doi.org/10.1111/gcb.16454

Archibald, J. (2007). An Indigenous Storywork Methodology. In J. G. Knowles & A. L. Cole (Eds.), *Handbook of the Arts in Qualitative Research: Perspectives, Methodologies, Examples, and Issues*. Sage Publications, Inc.

Bélanger, A., Martel, L., Gilbert, S., & Berthelot, J.-M. (2006). *Report on the Demographic Situation in Canada, 2002*. Statistics Canada. http://www.statcan.ca

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Buss, D. M. (2024). *Evolutionary psychology: The new science of the mind* (Seventh edition). Routledge.

Carroll, S. R., Garba, I., Figueroa-Rodríguez, O. L., Holbrook, J., Lovett, R., Materechera, S., Parsons, M., Raseroka, K., Rodriguez-Lonebear, D., Rowe, R., Sara, R., Walker, J. D., Anderson, J., & Hudson, M. (2020). The CARE Principles for Indigenous Data Governance. *Data Science Journal*, *19*. https://doi.org/10.5334/dsj-2020-043

Chang, L., Lu, H. J., Lansford, J. E., Skinner, A. T., Bornstein, M. H., Steinberg, L., Dodge, K. A., Chen, B. B., Tian, Q., Bacchini, D., Deater-Deckard, K., Pastorelli, C., Alampay, L. P., Sorbring, E., Al-Hassan, S. M., Oburu, P., Malone, P. S., Di Giunta, L., Tirado, L. M. U., & Tapanya, S. (2019). Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. *Developmental Psychology*, *55*(4), 890–903. https://doi.org/10.1037/dev0000655

Copping, L. (2017). Census Data. In T. K. Shackelford & V. A. Weekes-Shackelford (Eds.), *Encyclopedia of Evolutionary Psychological Science* (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-319-16999-6\_1852-1

Del Giudice, M., Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), *The Handbook of Evolutionary Psychology* (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

*Dictionary, Census of Population, 2021*. (2023). Statistics Canada = Statistique Canada.

Dinh, T., Haselton, M. G., & Gangestad, S. W. (2022). “Fast” women? The effects of childhood environments on women’s developmental timing, mating strategies, and reproductive outcomes. *Evolution and Human Behavior*, *43*(2), 133–146. https://doi.org/10.1016/j.evolhumbehav.2021.12.001

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? *Child Development*, *74*(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Field, A., Miles, J., & Field, Z. (2014). *Discovering statistics using R* (Repr). Sage.

Finestone, E., & Stirbys, C. (2017). Indigenous Birth in Canada: Reconciliation and Reproductive Justice in the Settler State. In *Indigenous Experiences of Pregnancy and Birth* (pp. 176–202). Demeter Press. http://www.jstor.org/stable/j.ctt1vw0sbs.15

Fox, J., Weisberg, S., & Price, B. (2023). *Companion to Applied Regression*. Sage. https://CRAN.R-project.org/package=car

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. *Evolution and Human Behavior*, *41*(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Goghari, V. M., & Kassan, A. (2022). Building a socially and culturally responsive psychology / engendrer une psychologie plus réceptive sur le plan social et culturel. *Canadian Psychology / Psychologie Canadienne*, *63*(4), 467–470. https://doi.org/10.1037/cap0000351

Griskevicius, V., Delton, A. W., Robertson, T. E., & Tybur, J. M. (2011). Environmental contingency in life history strategies: The influence of mortality and socioeconomic status on reproductive timing. *Journal of Personality and Social Psychology*, *100*(2), 241–254. https://doi.org/10.1037/a0021082

Harrell, F. E. (2015). *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*. Springer International Publishing. https://doi.org/10.1007/978-3-319-19425-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

*Honouring the truth, reconciling for the future: Summary of the final report of the Truth and Reconcilliation Commission of Canada*. (2015). Truth and Reconcilliation Commission of Canada.

Koehler, V. B., & Rutherford, M. D. (2025). *Harshness predicts reproduction in Brazilian municipalities and US counties: A life history theory approach* [Manuscript in preparation]. Department of Psychology, Neuroscience & Behaviour, McMaster University.

Koehler, V. B., & Rutherford, M. D. (2025). *Proportion of young children, rates of indigeneity in the population, and socioeconomic factors predict reproduction frequency and single parenting 15 years later in Canadian census divisions* [Manuscript in preparation]. Department of Psychology, Neuroscience & Behaviour, McMaster University.

Kuhn, M., Jackson, S., & Cimentada, J. (2022). *corrr: Correlations in R*.

Lack, D. (1954). The Natural Regulation of Animal Numbers. *AIBS Bulletin*, *5*(1), 12–12. https://doi.org/10.1093/aibsbulletin/5.1.12-b

Malone, E. W., Perkin, J. S., Keith Gibbs, W., Padgett, M., Kulp, M., & Moore, S. E. (2022). High and dry in days gone by: Life‐history theory predicts Appalachian mountain stream fish assemblage transformation during historical drought. *Ecology of Freshwater Fish*, *31*(1), 29–44. https://doi.org/10.1111/eff.12606

McLaughlin, K. A., Sheridan, M. A., Humphreys, K. L., Belsky, J., & Ellis, B. J. (2021). The Value of Dimensional Models of Early Experience: Thinking Clearly About Concepts and Categories. *Perspectives on Psychological Science*, *16*(6), 1463–1472. https://doi.org/10.1177/1745691621992346

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Neu, D., & Graham, C. (2006). The birth of a nation: Accounting and Canada’s first nations, 1860–1900. *Accounting, Organizations and Society*, *31*(1), 47–76. https://doi.org/10.1016/j.aos.2004.10.002

Nolin, D. A., & Ziker, J. P. (2016). Reproductive Responses to Economic Uncertainty: Fertility Decline in Post-Soviet Ust’-Avam, Siberia. *Human Nature*, *27*(4), 351–371. https://doi.org/10.1007/s12110-016-9267-6

Provencher, C., & Galbraith, N. (2024). *Fertility in Canada, 1921 to 2022* (Demographic Documents No. 91F0015M). Statistics Canada.

Reading, C. L., & Wien, F. (2009). *Health Inequalities and Social Determinants of Aboriginal Peoples’ Health*. National Collaborating Centre for Aboriginal Health.

Reichman, N. E., Teitler, J. O., Garfinkel, I., & McLanahan, S. S. (2001). Fragile Families: Sample and design. *Children and Youth Services Review*, *23*(4–5), 303–326. https://doi.org/10.1016/s0190-7409(01)00141-4

Richardson, G. B., Placek, C., Srinivas, V., Jayakrishna, P., Quinlan, R., & Madhivanan, P. (2020). Environmental stress and human life history strategy development in rural and peri-urban South India. *Evolution and Human Behavior*, *41*(3), 244–252. https://doi.org/10.1016/j.evolhumbehav.2020.03.003

Richter, L. (2004). *The importance of caregiver-child interactions for the survival and healthy development of young children: A review*. Dept. of Child and Adolescent Health and Development, World Health Organization. https://www.who.int/publications/i/item/924159134X

Romaniuc, A. (1991). Fertility in Canada: Retrospective and Prospective. *Canadian Studies in Population*, *18*(2), 56–77.

Romaniuk, A. (1984). *Fertility in Canada: From baby-boom to baby-bust*. Minister of Supply and Services Canada.

Romaniuk, A. (2008). History-based Explanatory Framework for Procreative Behaviour of Aboriginal People of Canada. *Canadian Studies in Population*, *35*(1), 159. https://doi.org/10.25336/P61K7T

Schnarch, B. (2004). Ownership, Control, Access, and Possession (OCAP) or Self-Determination Applied to Research: A Critical Analysis of Contemporary First Nations Research and Some Options for First Nations Communities. *Journal of Aboriginal Health*, *1*(1), 80–95.

Sear, R. (2020). Do human ‘life history strategies’ exist? *Evolution and Human Behavior*, *41*(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Sheppard, A. J., Shapiro, G. D., Bushnik, T., Wilkins, R., Perry, S., Kaufman, J. S., Kramer, M. S., & Yang, S. (2017). Birth outcomes among First Nations, Inuit and Métis populations. *Health Reports*, *28*(11), 11–16.

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. *Developmental Psychology*, *48*(3), 674–686. https://doi.org/10.1037/a0027293

Statistics Canada. (n.d.). *Labour income profile of tax filers by sex* [Dataset]. [object Object]. https://doi.org/10.25318/1110003101-ENG

Statistics Canada. (2017a). Aboriginal peoples in Canada: Key results from the 2016 Census. *The Daily*.

Statistics Canada. (2017b). *Crime severity index and weighted clearance rates, Canada, provinces, territories and Census Metropolitan Areas* [Dataset]. [object Object]. https://doi.org/10.25318/3510002601-ENG

Statistics Canada. (2018). *Detailed household final consumption expenditure, provincial and territorial, annual* [Dataset]. [object Object]. https://doi.org/10.25318/3610022501-ENG

Statistics Canada. (2021). *Population and dwelling counts, for Canada, provinces and territories, 2011 and 2006 censuses*. https://www12.statcan.gc.ca/census-recensement/2011/dp-pd/hlt-fst/pd-pl/Table-Tableau.cfm

Statistics Canada. (2023a). *Canada’s Indigenous population*. https://www.statcan.gc.ca/o1/en/plus/3920-canadas-indigenous-population

Statistics Canada. (2023b). *Live births, by month* [Dataset]. [object Object]. https://doi.org/10.25318/1310041501-ENG

Statistics Canada. (2023c). *Selected income characteristics of census families by family type* [Dataset]. [object Object]. https://doi.org/10.25318/1110000901-ENG

Statistics Canada. (2024a). *Canadian census analyser* [Dataset]. Computing in the Humanities and Social Sciences at the University of Toronto (CHASS). https://datacentre.chass.utoronto.ca/census/

Statistics Canada. (2024b). *Income of individuals by age group, sex and income source, Canada, provinces and selected census metropolitan areas* [Dataset]. [object Object]. https://doi.org/10.25318/1110023901-ENG

Stearns, S. C. (1992). *The evolution of life histories*. Oxford University Press.

Stearns, S. C., Allal, N., & Mace, R. (2008). Life history theory and human development. In *Foundations of evolutionary psychology.* (pp. 47–69). Taylor & Francis Group/Lawrence Erlbaum Associates.

Stearns, S. C., & Rodrigues, A. M. M. (2020). On the use of “life history theory” in evolutionary psychology. *Evolution and Human Behavior*, *41*(6), 474–485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Stone, B. W. G., Dijkstra, P., Finley, B. K., Fitzpatrick, R., Foley, M. M., Hayer, M., Hofmockel, K. S., Koch, B. J., Li, J., Liu, X. J. A., Martinez, A., Mau, R. L., Marks, J., Monsaint-Queeney, V., Morrissey, E. M., Propster, J., Pett-Ridge, J., Purcell, A. M., Schwartz, E., & Hungate, B. A. (2023). Life history strategies among soil bacteria—Dichotomy for few, continuum for many. *The ISME Journal*, *17*(4), 611–619. https://doi.org/10.1038/s41396-022-01354-0

Tebb, K. P., & Brindis, C. D. (2022). Understanding the Psychological Impacts of Teenage Pregnancy through a Socio-ecological Framework and Life Course Approach. *Seminars in Reproductive Medicine*, *40*(01/02), 107–115. https://doi.org/10.1055/s-0041-1741518

Vikat, A. (2002). Sociodemographic differences in the occurrence of teenage pregnancies in Finland in 1987-1998: A follow up study. *Journal of Epidemiology & Community Health*, *56*(9), 659–668. https://doi.org/10.1136/jech.56.9.659

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. *Evolution and Human Behavior*, *44*(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Volk, A. A. (2025). Pumping the Brakes on Psychosocial Acceleration Theory: Revisiting its Underlying Assumptions. *Evolution and Human Behavior*, *46*(1), 106657. https://doi.org/10.1016/j.evolhumbehav.2025.106657

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. *Evolutionary Psychology*, *12*(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Wells, J. C. K., Cole, T. J., Cortina-Borja, M., Sear, R., Leon, D. A., Marphatia, A. A., Murray, J., Wehrmeister, F. C., Oliveira, P. D., Gonçalves, H., Oliveira, I. O., & Menezes, A. M. B. (2019). Low Maternal Capital Predicts Life History Trade-Offs in Daughters: Why Adverse Outcomes Cluster in Individuals. *Frontiers in Public Health*, *7*, 206. https://doi.org/10.3389/fpubh.2019.00206

Wilson, M., & Daly, M. (1997). Life expectancy, economic inequality, homicide, and reproductive timing in Chicago neighbourhoods. *BMJ*, *314*(7089), 1271–1271. https://doi.org/10.1136/bmj.314.7089.1271

Wong, S. P. W., Twynstra, J., Gilliland, J. A., Cook, J. L., & Seabrook, J. A. (2020). Risk Factors and Birth Outcomes Associated with Teenage Pregnancy: A Canadian Sample. *Journal of Pediatric and Adolescent Gynecology*, *33*(2), 153–159. https://doi.org/10.1016/j.jpag.2019.10.006

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. *Evolution and Human Behavior*, *39*(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005

**Table 1**

*Proportion of Indigenous people is highly correlated with proportions of single-parent households and of violent crime, but not with cost of living.*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **2000-2005** | | | |  | | **2015-2022** | | |
|  | **1** | **2** | **3** | **4** | |  | | **5** | **6** |
| 1. Single-parent household |  |  |  |  | |  | |  |  |
| 2. Violent crime | 0.89\*\*\* |  |  |  | |  | |  |  |
| 3. Cost of living | -0.44 | -0.64\* |  |  | |  | |  |  |
| 4. Indigenous people | 0.94\*\*\* | 0.97\*\*\* | -0.53 |  | |  | |  |  |
| 5. Teenage pregnancy | 0.86\*\*\* | 0.79\*\* | -0.19 | 0.9\*\*\* | |  | |  |  |
| 6. Birth rates | 0.81\*\*\* | 0.88\*\*\* | -0.39 | 0.92\*\*\* | |  | | 0.92\*\*\* |  |
| Mean | 12.62 | 149.4 | 111.7 | 15.71 | |  | | 1.13 | 21.99 |
| SD | 3.14 | 107.7 | 14.41 | 23.42 | |  | | 2.08 | 8.10 |

*Note*. \**p* < .05. \*\**p* < .01. \*\*\**p* < .001.

**Table 2**

*Longitudinal interaction between proportion of Indigenous people and cost of living predicts teenage pregnancy and birth rates better than cross-sectional interaction.*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Effect** | |  | **β** | ***SE*** | ***t-value*** | ***p-value*** | **Std.β** |
| **Longitudinal** | |  |  |  |  |  |  |
| **Teenage pregnancies** | |  |  |  |  |  |  |
|  | Intercept |  | -0.997 | 1.993 | -0.500 | .629 |  |
|  | Indigenous people |  | -0.176 | 0.074 | -2.376 | .042\* | 1.29 |
|  | Cost of living |  | 0.007 | 0.017 | 0.392 | .704 | 0.33 |
|  | Indigenous people \* Cost of living |  | 0.003 | < 0.001 | 3.715 | .004 \*\* | 0.42 |
| **Birth rates** | |  |  |  |  |  |  |
|  | Intercept |  | 36.660 | 10.50 | 3.490 | 0.007\*\* |  |
|  | Indigenous people |  | -0.979 | 0.392 | -2.499 | 0.034\* | 1.22 |
|  | Cost of living |  | -0.172 | 0.091 | -1.901 | 0.090 | 0.04 |
|  | Indigenous people \* Cost of living |  | 0.013 | 0.004 | 3.387 | 0.008\*\* | 0.52 |

**Table 2** (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Cross-sectional** | |  |  |  |  |  |  |
| **Teenage pregnancies** | |  |  |  |  |  |  |
|  | Intercept |  | -9.544 | 3.833 | -2.490 | .034\* |  |
|  | Indigenous people |  | 0.736 | 0.184 | 3.993 | .003\*\* | 0.27 |
|  | Cost of living |  | 0.073 | 0.029 | 2.528 | .032\* | -0.08 |
|  | Indigenous people \* Cost of living |  | -0.005 | 0.002 | -3.518 | .007\*\* | -0.54 |
| **Birth rates** | |  |  |  |  |  |  |
|  | Intercept |  | 12.25 | 21.20 | 0.578 | .578 |  |
|  | Indigenous people |  | 0.922 | 1.019 | 0.905 | .389 | 0.75 |
|  | Cost of living |  | 0.035 | 0.160 | 0.219 | .831 | -0.05 |
|  | Indigenous people \* Cost of living |  | -0.005 | 0.009 | -0.584 | .574 | -0.13 |

*Note*. \**p* < .05. \*\**p* < .01. \*\*\**p* < .001.

**Figure 1**

When the cost of living is high, the proportion of indigeneity predicts birth rates

|  |  |
| --- | --- |
| A graph of a graph showing a number of people  AI-generated content may be incorrect. | A graph with lines and numbers  AI-generated content may be incorrect. |

*Note.* Figure created in R using ggplot2 package. Shades indicate confidence intervals.

# Chapter 6: General Discussion

Chapters 2 and 3 have helped answer my primary question: Is it possible to analyze publicly available government data with a longitudinal approach to assess life history theory in psychology (LHT-P)? It is. In *Chapter 2*, we showed that several considerations in the selection, processing and analysis of such data are required. In *Chapters 2, 3, 4,* and *5* we have seen that the ideal variable was not always available, and that asking the intended research question was not always possible. However, we also learned that different years or different editions of these governmental reports, from different countries, can be used to make developmental inferences about the population.

Multiple analytical approaches revealed significant findings. *In Chapter 3* and *4*, we used partial least squares structural equation modelling (PLS-SEM). PLS-SEM as a second-generation exploratory analytical approach (Hair et al., 2022). Like its related – and more confirmatory – analysis, covariance based structural equation modelling (CB-SEM), PLS-SEM can assess relationships between multiple observed and latent variables and describe them in a single model. However, PLS-SEM is more robust than CB-SEM in dealing with deviations from normality, and in dealing with formative factors (i.e., when variables are forming the factors instead of being commonly caused by the factor). The issues of non-normality and formative factors are common when dealing with secondary data (Hair et al., 2022) and also affected our hypothesized analyses. PLS-SEM yielded several variables that are predictive of reproductive indicators 10 to 15 years later. Still in *Chapter 3*, a multivariate linear regression using a robust standard error correction also yielded significant findings. In *Chapter 5*, forward stepwise multivariate linear regression using only 13 and 11 data points (i.e., underpowered) per variable also yielded significant findings. Even though stepwise linear regressions is frowned upon (Field et al., 2014; Harrell, 2015), our use of it was pre-determined and driven by theory, which considerably reduce the issues of using this analytical approach.

### Findings in Brazil and in the US

In *Chapter 3*, we examined indicators of harshness and unpredictability and the percentage of visible minorities population as reported in Brazil census (*Sistema IBGE de Recuperação Automática - SIDRA*, 2024) and the American Community Survey (U.S. Census Bureau., 2020) to predict indicators of reproduction 10 to 14 years later. We found that municipality-based measures of the lack of resources, the percentage of young mothers, and family size in 2000 explained 84% percent of the variance of early reproduction in 2010. All of the variables that composed these factors, except the percentages of people separated and divorced, were positively associated with their factor. The paths between factors also were positively associated. This result means that a harsher environment (i.e., one that lacks resources and has larger families living in smaller homes with younger mothers) in 2000 was associated with more children and more young mothers 10 years later. This association was stronger in municipalities with more children. These results mostly support the LHT-P developmental hypothesis that children exposed to harsher and more unpredictable environments are more likely to reproduce at an earlier age than children exposed to more bountiful and stable environments.

Similar findings with the previous study were observed using data from the US. Using variables that were similar to the significant predictors identified in Brazil data, we found that US counties with a higher percentage of households

i) that lacked complete kitchen facilities;

ii) that had an income below poverty level;

iii) with a greater number of rooms; and

iv) that had more than 1 occupant per room

had more children aged 0-4 around 14 years later. We also found significant predictors of young mothers and of women who had birth recently, but the explanatory power of these variables was negligible. These findings reduce the likelihood that the findings with Brazilian data were a statistical artifact or that they happened by chance. They also show the possibility for cross-country comparisons of LHT-P claims.

Although Brazil and the US obviously differ in a variety of ways, there are several similarities that may be important for our analyses. Considering the WEIRD (Western, Educated, Industrialized, Rich and Democratic) acronym (Henrich et al., 2010), Brazil and the US are western and democratic countries. Both countries have a large population counting in the hundreds of thousands and continental landmass. They both have considerable ethnic diversity and a long history of slavery and racism (Bleich et al., 2019; Couto & Brenck, 2024), although the US has experienced more discrimination against immigrants, specially in last decade or so (e.g., Canizales & Vallejo, 2021). All of these similarities could help understand why results of our two analyses were similar. Obviously, we argue that LHT-P is a possible explanation for the predictions found. It is possible that some indicators such as lacking complete housing facilities, living with income below poverty models with more occupants per room are indicative of a harsher and more unpredictable environments which can alter populational reproductive patterns. It is important here to remind the reader that the analysis used to build the model in two of our chapters were exploratory (PLS-SEM). It is possible that cofounding variables are necessary in the explanation of this prediction. This possibility is even greater because we are using a theory that is mainly used to explain individual behaviour and applying it to populational data. For example, municipalities and counties with higher levels of these predictors could also lack access to good quality education and health care. As seen in previous chapters, these factors have been proposed as explanations for fertility levels – especially to explain how access to these services can lower populational fertility (Roser, 2014). The risk of cofounding variables is also worth noting in the study utilizing US data because that analysis only used variables that were significant in the previous study and no analysis of correlation or collinearity among variables was conducted.

Brazil and the US differ in their levels of education, industrialization, and economic prosperity (Barro & Lee, 2015; Rohenkohl & Arriagada, 2025; United Nations Development Programme, 2025). Therefore, one can expect higher levels of harshness and unpredictability in Brazil, which would be closer to those encountered in our environment of evolutionary adaptedness, than those found in Western developed countries (Buss, 2024; Volk, 2023). More access to standardized education, higher relative income and lower economic inequality could help explain why some indicators of harshness were not associated with frequent or early reproduction and why the predictive power of variables indicative of earlier reproduction was negligible in the US.

In addition, a recent report about fertility on Southern Europe pointed out that lower marriage levels and marrying at an older age are partly responsible for lower fertility in the region (Stone & Wingerter, 2024). Considering the cultural and economic similarities between the US and Europe, a similar phenomenon may be present in the US data. This could also explain why both in US and in Brazil levels of divorce were *negative* predictors of the percentage of children. This association appears to be contrary to LHT-P claims that changes in parental and household configuration is a predictor of earlier and more frequent reproduction.

The percentage of Black people in Brazilian municipalities was not a significant predictor of reproduction and did not mediate the association between family size and young mothers with early reproduction. In the US, the percentage of Black and of Hispanic or Latino was a significant predictor of young children, but this association was negative. This is somewhat surprising as one would expect that visible and marginalized minorities would be likely encounter harsher and more unpredictable environments not captured by usual LHT-P measures (e.g., employment and career opportunities (Henry et al., 1985; Intungane et al., 2024). Although, these particularly harsh or unpredictable could correlate with the measures used in the study (e.g., income). These findings might point that, when the effect of harsher and unpredictable environments is removed, the effect of belonging to a visible minority itself is negative. In the case of Brazil, another explanation is the possible misrepresentation of the population, as most of the population likely self-identified as “Pardos” – miscegenation between Black, White and Indigenous ethnicities.

The finding that low education attainment (hypothesized to be indicative of harshness) and unemployment or precarious employment (hypothesized to be indicative of unpredictability was not a significant predictor of earlier reproduction in Brazil was surprising. Both of these variables are usually associated with socioeconomic status, which is a common measure of harshness in LHT-P (Belsky et al., 2012; Ellis et al., 2009). However, measures of harshness and unpredictability in LHT-P should also be associated with levels of extrinsic mortality and morbidity (Del Giudice et al., 2015; Ellis et al., 2009). Perhaps the variables in the Lack of resources factor (lack of electrical power and garbage collection service and people with 1 minimum wage or less) were more indicative of regions with higher extrinsic mortality and morbidity levels.

These studies partially support LHT-P claims. Future studies could investigate what variables best predict early and frequent reproduction in the US. Especially, the finding that that the percentage of Black and Hispanic or Latino are negative predictors of the percentage of children 14 years later deserves future exploration.

One of our hopes in this dissertation was to inform LHT-P proponents of populational associations based on LHT-P claims and help in the theory revision (Del Giudice, 2024; Volk, 2025) and approximation to LHT in evolutionary biology (Nettle & Frankenhuis, 2020; Stearns & Rodrigues, 2020). Therefore, we hope that these findings can help future research in generating confirmatory, more specific and more formal models.

### Findings in Canada

Results from Canadian data reinforced the developmental claim. Models using dissemination areas (around 10 blocks of houses and apartments with an average of 500 people) and census divisions (usually Canadian neighbouring municipalities; (*Dictionary, Census of Population, 2021*, 2023)) were predictive of frequent reproduction. However, the model that was built using census division data performed better, probably due to the greater stability of populations over time. To assess whether we would find support for LHT-P developmental claim that early environment predicts future reproduction, we reversed the timeline using census division data: we used harshness and unpredictability data in 2021 to predict reproduction data in 2006. According to the LHT-P developmental claim, the model using the correct timeline should reach a better solution than the reversed timeline. If both models were comparable or if the model with the reverse timeline performed better, the association found could be interpreted as mere spurious correlation or a statistical artifact. The model with the reverse timeline reached a solution in which one variable (i.e., the percentage of households with a lone, female parent) predicted itself and another variable (the percentage of children in low-income households) predicted frequent reproduction. The explanatory power of the reverse-timeline model also was generally lower than the model with the correct timeline. These results offer support to the idea that the associations found in our main analyses reflect a developmental phenomenon.

Interestingly, analyses of the Canada data revealed a different picture regarding the claim that harshness and unpredictability cue individuals towards earlier and more frequent reproduction (Belsky et al., 2012; Del Giudice et al., 2015; Ellis et al., 2009). Consistent with the predictions of LHT-P, a higher percentage of low-income children in 2006 was predictive of higher family sizes of one-parent families in 2021. However, higher unemployment rates and households spending more of their income on rent predicted *less* frequent reproduction, *smaller* family sizes, and *smaller* family size of one-parent families. These findings can be interpreted as contrary to LHT-P assumptions. They could, however, be due to the milder, more stable and more equitable environment in Canada in comparison to Brazil. In a sufficiently stable and bountiful environment, adverse circumstances may also cue individuals into postponing reproduction. A decline of populational fertility after economic adversity has been found before (Nolin & Ziker, 2016) and in LHT-P literature this is especially supported if such adversities are decoupled from levels or morbidity and mortality (Ellis et al., 2009). Finally the percentage of people who were divorced and separated were *negative* predictors of frequent reproduction. The same rationale applied for the similar finding in Chapeter 3 (US data) could be applied here: lower marriage rates and average marriage and divorce at a later age (Stone & Wingerter, 2024) could decouple *divorce* as a measure of parental availability early in life or it may extend the time frame in which the association between *divorce* and frequent reproduction would be observed. These results are nevertheless surprising considering the parental transition hypothesis (Ellis et al., 2003) and they could be due to lower marriage rates and marrying at a later age (Stone & Wingerter, 2024).

Unlike what was found in the analysis of the Brazil and US data, the percentage of Indigenous people in Canada’s census divisions was a significant and positive predictor of family size of one-parent families. In addition, the percentage of visible minorities in Canada’s dissemination areas was a significant and positive predictor of frequent reproduction. We interpreted that other variables that were not captured in these studies or that are commonly measured in LHT-P literature could explain this association. These other variables could also signal higher levels of harshness and unpredictability (e.g., employment and career opportunities discrimination, reduced institutional or social support, issues regarding cultural assimilation) or be associated with reproduction (e.g., a different perspective on reproduction and parenting), alternatively to LHT-P claims. Exploring some of these potential third variables motivated Chapter 5.

### Findings in Canada – Indigenous people

In Chapter 5 we aimed to use the proportion of Indigenous people and variables that were not available in the Canadian census (Statistics Canada, 2024) as both the predictors and outcomes of this LHT-P developmental claim. The predictors were cost of living to income ratio, the percentage of single-parent households, and the violent crime index. Single-parent households is a variable that is present in the census, but we included as there are some findings that this is one of the best predictors of a faster life history strategy (Belsky et al., 2012; Ellis et al., 2003; Hartman et al., 2018) and violent crime is a category of measure that has been associated with unpredictability in the literature (Dinh et al., 2022; McLaughlin et al., 2021; Wilson & Daly, 1997). The outcomes of teenage pregnancy rates and birth rates were not available in the Census. Statistics Canada reported these variables for Provinces and territories level, so this was the level of analysis here.

We have found that the interaction between the percentage of Indigenous people and cost of living to income in 2005 is a significant predictor of both teenage pregnancy and birth rates in 2022. The main effect of Indigeneity, however, was a negative predictor of these outcomes. These two variables explained a remarkable proportion of the variance of teenage pregnancy and birth rates. Single parent households and violent crime indices highly correlated with the proportion of Indigenous people in Canada’s provinces and territories.

Indigenous people in Canada may, in the same direction as Black people and visible minorities in the US and Canada, be subjected to harshness and unpredictability not comprised in the measures in these studies. Having higher costs of living and potentially living in single parent households and more exposure to violent crime may be part of these particularly harsh and unpredictable environments. Once these effects are held constant – as we hypothesise that could be the case in the model with the effect of cost of living to income ration and the interaction between percentage of Indigenous people – the percentage of Indigenous people is actually negatively associated with teenage pregnancy and birth rates. We argue that the findings in this study can be illustrative of the structural inequities and disadvantages suffered by Indigenous people in Canada (Goghari & Kassan, 2022). Future research should explore in more depth these environmental contexts and how that would be associated with fertility levels.

This chapter also supported LHT-P developmental claim. We tested the model with the interaction between proportion of Indigenous people and cost of living to income ratio, but using cross-sectional data (i.e., predictors and outcomes in 2022). The model performed worse with cross-sectional data than with longitudinal data.

### Limitation and future directions

All studies in this dissertation used secondary data from governmental sources to test LHT-P assumptions. They all were exploratory studies aiming at seeing which variables would be significant (*p* ≤ .05; *p* ≤ .01) and/or relevant (*β* ≥ 0.1 or Δ*R*² between models ≥ .1) predictors of frequent or early reproduction. Therefore, they all suffer from the same limitations.

First of all, they all used populational or geographical level data (i.e., provinces, counties, municipalities or a group of blocks) to test an individual level developmental phenomenon: people who lived in harsh and unpredictable environments during childhood are more likely to reproduce early and more often than those in bountiful and stable environments. The most we could observe in these studies was that this populational association was observed and that it was strongest in models using longitudinal data than models using cross-sectional data or data using a reversed timeline. However, this does not mean that this association existed in the individual level. It is possible that confound variables were the explanation for the observed associations.

Events such as reproduction, populational data and secondary data are all subject to high levels of noise (Del Giudice, 2024; Trzesniewski et al., 2011). Aside from the biological components that determine reproduction, humans may use contraceptives which can confound fertility measures (Richardson et al., 2024) or even cause an association in the opposite direction, that is, between those with more resources and more stable lives (such as older married couples) with higher fertility (Del Giudice, 2024; Stone & Wingerter, 2024). Large populational data sets are more susceptible to noise because they can vary in how data is collected (e.g., how questions are asked, the settings in which data is collected) and have more inconsistencies regarding missing data (Andersen et al., 2011; Trzesniewski et al., 2011). Because they are generally descriptive or correlational data, they are also obviously more susceptible to confounding variables.

This is a limitation of the studies in this dissertation; however, they may also serve as testament to the strength of these findings. We found remarkable explanatory power of fertility measures with a longitudinal data. These findings were observed using data from 3 countries with different human development, education and health access levels. Finally, we observed lower explanatory power with cross-sectional data and with reversed timeline data. All of these could reveal that the association between predictors and outcomes were strong enough to be detected even in consideration of all sources of noise.

We did not consider alternative theories or explanations that could be predictive of reproduction. Women access to education, health care and employment (Roser, 2014), institutional support for youth and parents (Wodtke, 2013), subcultures and different ways of living (Romaniuk, 2008; Wilson, 1987) and major global events (Romaniuk, 1984) have all have been identified as predictors for populational birth rates.

Among these alternative explanations, similarities due to geographic proximity weren’t considered. Economic activity, urbanization level and cultural aspects are possible variables that would make neighbouring geographies similar. Since we are considering countries with big populations and large landmasses, even weather, biomes, proximity to the coast or to big metropolitan regions (e.g., New York, São Paulo or Toronto) could influence the predictors and outcomes in these studies. Future studies could include population density, which LHT-P theorize to influence life history strategies (Copping & Campbell, 2015; Ellis et al., 2009). Future studies could density measures or assess geographic similarities through stratified cross validation (Diamantidis et al., 2000), for example.

Cultural differences being confounds are particularly true when considering Indigenous people in Canada. Their ways of living and governance system have been set/cast to reservations and a Westernized/European colonial culture and governances has been brought upon them (Neu & Graham, 2006; Romaniuk, 2008). Many Indigenous people consider the birth of a child as a gift to the community, for example (Finestone & Stirbys, 2017). This certainly can influence birth and parenting practices.

All studies in this dissertation are exploratory in nature. Therefore, they are not suitable for hypothesis testing and neither for more formal modeling that LHT-P should aim for (Frankenhuis & Nettle, 2020; Nettle & Frankenhuis, 2020; Sear, 2020). This is study is a contribution to showing that there are good developmental or longitudinal predictors of reproduction in populations that are compatible with LHT-P assumptions. Future studies could use more confirmatory approaches and propose more refined models and set of hypotheses.

### Final conclusions

In this dissertation, we made two novel applications to LHT-P literature. First, we utilized country-wide population data to test LHT-P assumptions. We have used Census data from countries that occupy large landmasses, with populations that reach the dozens or hundreds of million of people and that differ in their stages of development and social welfare. The findings show that variables mainly indicative of harshness, compatible with LHT-P assumptions, can explain a remarkable variance of indicators of reproduction.

Secondly, we have shown support for the developmental hypothesis. Models using data that separated predictors from outcomes by more than a decade could explain reproduction variables better than models that reversed the timeline or modes that used cross- sectional data. Again, this is also compatible with LHT-P claim that there is a critical period of development in which the environment cue individuals for different life history strategies (Ellis et al., 2003; Webster et al., 2014; Xu et al., 2018).

We have also found that the proportion of Black people, Hispanic of Latino people, Visible minorities and Indigenous people are significant predictors of reproduction outcomes in the US and Canada. The percentage of these populations are significant predictors even when considering other variables that are indicative of harshness and unpredictability that are also significant predictors of reproduction. This suggests that these populations are exposed to harsh and unpredictable environments in ways that are not being captured in traditional/common LHT-P literature. Colonialism (Romaniuk, 2008), racism (Canizales & Vallejo, 2021; Husbands et al., 2022), and discrimination in many settings (Bleich et al., 2019; Henry et al., 1985) are likely to help explain the reproduction practices/patterns in these populations (Pew Research Center, 2015; Statistics Canada, 2017).

## References

Andersen, J. P., Prause, J., & Silver, R. C. (2011). A Step-by-Step Guide to Using Secondary Data for Psychological Research: Using Secondary Data. *Social and Personality Psychology Compass*, *5*(1), 56–75. https://doi.org/10.1111/j.1751-9004.2010.00329.x

Barro, R. J., & Lee, J.-W. (2015). *Education Matters: Global Schooling Gains from the 19th to the 21st Century*. Oxford University Press. http://barrolee.com/

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662–673. https://doi.org/10.1037/a0024454

Bleich, S. N., Findling, M. G., Casey, L. S., Blendon, R. J., Benson, J. M., SteelFisher, G. K., Sayde, J. M., & Miller, C. (2019). Discrimination in the United States: Experiences of black Americans. *Health Services Research*, *54*(S2), 1399–1408. https://doi.org/10.1111/1475-6773.13220

Buss, D. M. (2024). *Evolutionary psychology: The new science of the mind* (Seventh edition). Routledge.

Canizales, S. L., & Vallejo, J. A. (2021). Latinos & Racism in the Trump Era. *Daedalus*, *150*(2), 150–164. https://doi.org/10.1162/daed\_a\_01852

Copping, L. T., & Campbell, A. (2015). The environment and life history strategies: Neighborhood and individual-level models. *Evolution and Human Behavior*, *36*(3), 182–190. https://doi.org/10.1016/j.evolhumbehav.2014.10.005

Couto, P., & Brenck, C. (2024). Monetary Policy and the Gender and Racial Employment Dynamics in Brazil. *Review of Political Economy*, 1–25. https://doi.org/10.1080/09538259.2023.2294306

Del Giudice, M. (2024). A turning point for the life history approach to individual differences. In S. Kanazawa (Ed.), *Genes, environments, and differential susceptibility: Current topics in evolutionary developmental psychology*. Cambridge University Press.

Del Giudice, M., Kaplan, H. S., & Gangestad, S. W. (2015). Life History Theory and Evolutionary Psychology. In D. M. Buss (Ed.), *The Handbook of Evolutionary Psychology* (pp. 68–95). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470939376.ch2

Diamantidis, N. A., Karlis, D., & Giakoumakis, E. A. (2000). Unsupervised stratification of cross-validation for accuracy estimation. *Artificial Intelligence*, *116*(1–2), 1–16. https://doi.org/10.1016/S0004-3702(99)00094-6

*Dictionary, Census of Population, 2021*. (2023). Statistics Canada = Statistique Canada.

Ellis, B. J., Bates, J. E., Dodge, K. A., Fergusson, D. M., John Horwood, L., Pettit, G. S., & Woodward, L. (2003). Does Father Absence Place Daughters at Special Risk for Early Sexual Activity and Teenage Pregnancy? *Child Development*, *74*(3), 801–821. https://doi.org/10.1111/1467-8624.00569

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental Dimensions of Environmental Risk: The Impact of Harsh versus Unpredictable Environments on the Evolution and Development of Life History Strategies. *Human Nature*, *20*(2), 204–268. https://doi.org/10.1007/s12110-009-9063-7

Field, A., Miles, J., & Field, Z. (2014). *Discovering statistics using R* (Repr). Sage.

Finestone, E., & Stirbys, C. (2017). Indigenous Birth in Canada: Reconciliation and Reproductive Justice in the Settler State. In *Indigenous Experiences of Pregnancy and Birth* (pp. 176–202). Demeter Press. http://www.jstor.org/stable/j.ctt1vw0sbs.15

Frankenhuis, W. E., & Nettle, D. (2020). Current debates in human life history research. *Evolution and Human Behavior*, *41*(6), 469–473. https://doi.org/10.1016/j.evolhumbehav.2020.09.005

Goghari, V. M., & Kassan, A. (2022). Building a socially and culturally responsive psychology / engendrer une psychologie plus réceptive sur le plan social et culturel. *Canadian Psychology / Psychologie Canadienne*, *63*(4), 467–470. https://doi.org/10.1037/cap0000351

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Third edition). SAGE.

Harrell, F. E. (2015). *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*. Springer International Publishing. https://doi.org/10.1007/978-3-319-19425-7

Hartman, S., Sung, S., Simpson, J. A., Schlomer, G. L., & Belsky, J. (2018). Decomposing environmental unpredictability in forecasting adolescent and young adult development: A two-sample study. *Development and Psychopathology*, *30*(4), 1321–1332. https://doi.org/10.1017/S0954579417001729

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature*, *466*(7302), 29–29. https://doi.org/10.1038/466029a

Henry, F., Ginzberg, E., Toronto, S. P. C. of M., & Relations, U. A. on R. (1985). *Who Gets the Work?: A Test of Racial Discrimination in Employment*. Urban Alliance on Race Relations and Social Planning Council of Metropolitan Toronto. https://books.google.ca/books?id=72NWuQAACAAJ

Husbands, W., Lawson, D. O., Etowa, E. B., Mbuagbaw, L., Baidoobonso, S., Tharao, W., Yaya, S., Nelson, L. E., Aden, M., & Etowa, J. (2022). Black Canadians’ Exposure to Everyday Racism: Implications for Health System Access and Health Promotion among Urban Black Communities. *Journal of Urban Health*, *99*(5), 829–841. https://doi.org/10.1007/s11524-022-00676-w

Intungane, D., Long, J., Gateri, H., & Dhungel, R. (2024). Employment Barriers for Racialized Immigrants: A Review of Economic and Social Integration Support and Gaps in Edmonton, Alberta. *Genealogy*, *8*(2), 40. https://doi.org/10.3390/genealogy8020040

Nettle, D., & Frankenhuis, W. E. (2020). Life-history theory in psychology and evolutionary biology: One research programme or two? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1803), 20190490. https://doi.org/10.1098/rstb.2019.0490

Neu, D., & Graham, C. (2006). The birth of a nation: Accounting and Canada’s first nations, 1860–1900. *Accounting, Organizations and Society*, *31*(1), 47–76. https://doi.org/10.1016/j.aos.2004.10.002

Nolin, D. A., & Ziker, J. P. (2016). Reproductive Responses to Economic Uncertainty: Fertility Decline in Post-Soviet Ust’-Avam, Siberia. *Human Nature*, *27*(4), 351–371. https://doi.org/10.1007/s12110-016-9267-6

Pew Research Center. (2015). *Childlessness Falls, Family Size Grows Among Highly Educated Women* [Report]. Pew Research Center. https://www.pewresearch.org/social-trends/2015/05/07/family-size-among-mothers/

Richardson, G. B., Bates, D., Ross, A., Liu, H., & Boutwell, B. B. (2024). Is reproductive development adaptively calibrated to early experience? Evidence from a national sample of females. *Developmental Psychology*, *60*(2), 306–321. https://doi.org/10.1037/dev0001681

Rohenkohl, B., & Arriagada, P. (2025). How does the World Bank classify countries by income? *Our World in Data*.

Romaniuk, A. (1984). *Fertility in Canada: From baby-boom to baby-bust*. Minister of Supply and Services Canada.

Romaniuk, A. (2008). History-based Explanatory Framework for Procreative Behaviour of Aboriginal People of Canada. *Canadian Studies in Population*, *35*(1), 159. https://doi.org/10.25336/P61K7T

Roser, M. (2014). The global decline of the fertility rate. *Our World in Data*.

Sear, R. (2020). Do human ‘life history strategies’ exist? *Evolution and Human Behavior*, *41*(6), 513–526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

*Sistema IBGE de Recuperação Automática—SIDRA*. (2024). https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2022/universo-populacao-por-cor-ou-raca

Statistics Canada. (2017). Aboriginal peoples in Canada: Key results from the 2016 Census. *The Daily*.

Statistics Canada. (2024). *Canadian census analyser* [Dataset]. Computing in the Humanities and Social Sciences at the University of Toronto (CHASS). https://datacentre.chass.utoronto.ca/census/

Stearns, S. C., & Rodrigues, A. M. M. (2020). On the use of “life history theory” in evolutionary psychology. *Evolution and Human Behavior*, *41*(6), 474–485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Stone, L., & Wingerter, E. (2024). *Is There Hope for Low Fertility? “Demographic Rearmament” in Southern Europe*.

Trzesniewski, K. H., Donnellan, M. B., Lucas, R. E., & American Psychological Association (Eds.). (2011). *Secondary data analysis: An introduction for psychologists* (1st ed). American Psychological Association.

United Nations Development Programme. (2025). *Human Development Report 2025: A matter of choice: People and possibilities in the age of AI*. United Nations Development Programme.

U.S. Census Bureau. (2020). *Understanding and Using American Community Survey Data: What All Data Users Need to Know*. U.S. Government Publishing Office. https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs\_general\_handbook\_2020.pdf

Volk, A. A. (2023). Historical and hunter-gatherer perspectives on fast-slow life history strategies. *Evolution and Human Behavior*, *44*(2), 99–109. https://doi.org/10.1016/j.evolhumbehav.2023.02.006

Volk, A. A. (2025). Pumping the Brakes on Psychosocial Acceleration Theory: Revisiting its Underlying Assumptions. *Evolution and Human Behavior*, *46*(1), 106657. https://doi.org/10.1016/j.evolhumbehav.2025.106657

Webster, G. D., Graber, J. A., Gesselman, A. N., Crosier, B. S., & Schember, T. O. (2014). A Life History Theory of Father Absence and Menarche: A Meta-Analysis. *Evolutionary Psychology*, *12*(2), 147470491401200. https://doi.org/10.1177/147470491401200202

Wilson, W. J. (1987). *The truly disadvantaged: The inner city, the underclass, and public policy*. University of Chicago press.

Wodtke, G. T. (2013). Duration and timing of exposure to neighborhood poverty and the risk of adolescent parenthood. *Demography*, *50*(5), 1765–1788. https://doi.org/10.1007/s13524-013-0219-z

Xu, Y., Norton, S., & Rahman, Q. (2018). Early life conditions, reproductive and sexuality-related life history outcomes among human males: A systematic review and meta-analysis. *Evolution and Human Behavior*, *39*(1), 40–51. https://doi.org/10.1016/j.evolhumbehav.2017.08.005