PANDEMIC BABIES: INFANT COMMUNICATION DEVELOPMENT IN A GLOBAL DISASTER

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DEDICATION

This work is dedicated to my late grandmother, Bettina. As I learn more about the various factors relevant to and present in her life, I recognize how much strength it must have taken for her to overcome them. Bettina had a challenging life with many adversities, many of which I never knew of until my mid-20s. Despite these challenges, Bettina was an incredible role model to me and raised another incredible role model in my mother (Natalie).

I would also like to dedicate this work to the pandemic babies in my life: Riley, JJ, Savannah, AB, Bronson, Rhett, and Emilia. Your growth and development helped inspire this work and brought me joy along the way.

I would also like to thank my husband, Peter, for supporting me in this journey. Thank you. You made this experience so much easier to manage. I could not have made it without you.

ABSTRACT

Infant communication development is influenced by the home environment, particularly in low-income families where stressors and resource limitations are common. This thesis investigates the impact of two key factors (pandemic unemployment benefits and reading frequency) on infant communication development during the COVID-19 pandemic. Data were drawn from the Baby's First Years Study, a longitudinal study of approximately 600 mother-infant dyads living in low-income households across several U.S. cities.

Chapter two examined whether pandemic unemployment benefits were associated with communication development. The outcome variable was measured using the Ages and Stages Questionnaire at age one and the McArthur-Bates Communication Development Index at age two. Pandemic unemployment benefits were weakly but significantly associated with higher infant communication scores over a one-year period, even after adjusting for confounders. Infants in households receiving benefits scored, on average, 0.15 standardized units higher than those in non-recipient households (95% CI: 0.02 – 0.29).

Chapter three investigated whether maternal reading frequency was associated with changes in infant communication scores over a one-year period. Reading frequency was measured categorically, and results were stratified based on whether the age one data were collected before or during the pandemic. Infants whose mothers read to them daily scored 0.33 units higher in communication z-score (95% CI: 0.15 – 0.52). Stratified analyses showed significant associations prior to the pandemic but not during, suggesting that pandemic stress may have attenuated this association.

These findings highlight the potential of economic and educational supports to promote communication development in low-income families. This research underscores the importance of policies and interventions that buffer against crises and support equitable developmental outcomes for infants in vulnerable populations.

CONTRIBUTION OF AUTHORS

Mahala Swisterski, Master of Science student, was the primary author of this thesis. The work within chapters two and three will be condensed and submitted for publication after the defense date. Cheryl Currie, Richard Larouche, Robbin Gibb, and James Sanders will be listed as coauthors on these future publications. I conceptualized and designed the secondary analysis, determined the research questions, analyzed the data, drafted the original thesis, and critically reviewed and revised the thesis. Cheryl Currie assisted in the conceptualization and design of the research, supervised the data analysis, and critically reviewed thesis chapters. Cheryl Currie, Richard Larouche, and Robbin Gibb provided feedback and direction on the methodology, research questions, and variables. Richard Larouche, Robbin Gibb, and James Sanders critically reviewed and revised thesis chapters.

ETHICS STATEMENT

Work described in this thesis received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Pandemic Babies: The potential impact of pandemic-related parental job loss on infant communication in low-income families", Pro00129505, March 31st, 2023.

USES OF GENERATIVE AI IN THIS WORK

This thesis adheres to SGS Policies and Procedures for the use of generative AI. Grammarly was used to identify grammatical errors and provide suggestions. Suggestions were then extensively edited and revised to ensure that the final content remained original work.

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LIST OF ABBREVIATIONS

BFY	Baby's First Years (the dataset)
MBCDI	McArthur-Bates Communicative Development Inventory
ASQ	Ages and Stages Questionnaire
ACEs	Adverse Childhood Experiences
MSEL	Mullen Scales of Early Learning

1.0 CHAPTER 1

1.1 BACKGROUND

Studies suggest the impacts of the COVID-19 pandemic have been particularly felt by low-income families.[1, 2] Job loss and increased stress have amplified existing struggles for low-income families, such as financial hardship and mental health concerns.[3, 4] In this thesis, I examined the effects of parental job loss and reading frequency on infant communication trajectories longitudinally, using a repeated measures analysis. The Baby's First Years dataset was used, which collected data from approximately 924 low-income mother-infant dyads in the US between 2018 and 2021.[5, 6]

1.1.1 State of Infant Development Research in the Pandemic

It is well documented that an infant's environment impacts their biological and social development.[7, 8] Early developmental intervention, such as have been shown to moderate the risk of poor development.[9] A 2014 longitudinal study examined the progress of infants born with and without birth asphyxia taking part in a home-based early development intervention. All infants in the intervention developed normally, and there was no statistically significant difference in the development of those who experienced birth asphyxia and those who did not.[9] This highlights how swiftly delivered intervention can improve developmental trajectories, even for vulnerable infants.

Researchers are starting to investigate how changes to the infant's environment during the pandemic may have impacted their development. A 2022 nested cohort study compared the cognitive development of infants born before and after pandemic restrictions were enacted, in 2018 and 2020, respectively.[10] Infants born after pandemic restrictions began in spring 2020 showed a significant drop in their cognitive scores on the Mullen Scales of Early Learning (MSEL) compared to infants born in 2018 (27 to 37 point decrease). This trend only existed among those born during the pandemic, with no significant difference among those born a month or more before restrictions were implemented.[10] These findings are suggestive of a period effect among infants. A period effect is when a particular factor equally affects all age groups at a point in calendar time.[11, 12] This thesis research builds on these findings by examining how pandemic unemployment benefits may have impacted infant development in low-income homes.

Environmental changes can alter the course of an infant's development, which can continue across their lifespan.[13] Major events like war, natural disasters, and famine have impacted infant development.[14, 15] While it is essential to study the impact of disasters, there are significant limitations in how these studies are conducted. Studies on disasters are primarily limited to retrospective or cross-sectional designs, largely due to the inability to control the disaster itself.[14] Temporal sequence is the order that events occur relative to the exposure. Cross-sectional and retrospective designs often fail to establish clear temporal sequence because of the timing of the exposure and outcome in the design.[12] Maintaining temporal sequence was a key consideration in this thesis, as it addressed a current gap in research and could improve our understanding of child development. Retrospective and cross-sectional designs make it difficult to establish the order of these events, as the study is conducted after their occurrence.[12, 14] This thesis used data collected prospectively, with a dataset that followed infants over time. The pandemic occurred as data were being collected, meaning the outcome can be tracked relative to when the event occurred.[5, 6]

1.1.2 Pandemic Unemployment Benefits (X1)

In this thesis, I examined the impact of *pandemic unemployment benefits* on infant development by conducting a secondary analysis of an existing dataset. The effect of job loss was amplified in the pandemic due to several factors, including increased spending, parental stress, and a change in household dynamic.[1, 2, 16] Pandemic unemployment benefits were more quickly and widely dispersed, in order to offer a stability of income during a rapidly evolving crisis. Pandemic benefits were offered to workers who had been temporarily laid off or had their work impacted by the pandemic, where traditionally one had to be laid off or let go from work to receive these benefits. In addition to expanded criteria to receiving unemployment benefits, individuals also received an extra $300 a week on top of their regular unemployment benefits. Pandemic unemployment benefits were different than the standard, in that the criteria were relaxed and the waiting period was decreased.[17, 18] I sought to understand the role that pandemic unemployment benefits may have had on infant development in low-income homes.

Income and spending

The pandemic's impacts on families have disproportionately affected those of low-income status. Low-income families experienced greater material hardship during the pandemic, which triggered a 'chain reaction' of events.[16] Financial hardships brought about by the pandemic have negatively affected the well-being of caregivers and increased distress in these individuals. This impact on caregivers has been shown to have negative emotional health outcomes in young children.[16] A 2022 study on household chaos—defined as disorganization, instability, noise, and crowding—found that higher levels of chaos were associated with food insecurity and parental depressive symptoms prior to the pandemic.[2] Therefore, it is likely that low-income families experienced compounding effects of the pandemic with pre-existing financial instability.

Pandemic containment measures also influenced the ability to maintain work and the impact of job loss. Measures affecting remote schooling and daycare services placed low-income families under greater financial burden.[19] A US study found that the lowest income quintile pre-pandemic was more likely to report increased spending during the pandemic, with having children at home associated with a large number of extra costs.[1] Families in the lowest income quintile before the pandemic were twice as likely to report an increase in spending than a decrease over the pandemic.[1] Restrictions on social gatherings limited the ability of family, friends, and professionals to provide care or social support. Some low-income families had to keep a financial provider at home, which subsequently decreased household income.[20] These extra costs and adverse pandemic experiences may have been present in most families, but their burden was amplified in those with low income. This disproportionate financial burden was a key area of focus in this thesis since it likely amplified the impact of job loss during the pandemic for low-income households.

Remote work and job loss

People were at home for longer periods of time during the COVID-19 pandemic, whether due to job loss, pandemic restrictions, or a combination of both. A 2020 study developed for the Federal Reserve Bank of Dallas found that among a sample of 5,000 working-age adults, the percentage working from home increased from about 8% in February 2020 to 35% in May 2020.[21] In April 2020, about 40% of Canadian employees worked most of their hours from home, in contrast to 4% in 2016.[22] It is estimated that approximately three-quarters of workers in the United States shifted to remote work environments by May 2020. In addition, high-income, educated individuals were more likely to shift to remote work and maintain employment over the pandemic.[21] This shift to working from home likely changed the environment in the household, leading to strengthened infant development in some contexts and slowed development in others.

In addition to increased proportions of people working from home, the early stages of the pandemic resulted in widespread job loss. Of individuals in the US who commuted to on-site work daily in February 2020, more than a quarter were no longer employed by May 2020. This trend was consistent among those working off-site during the same period.[21] The impacts of this pandemic-related job loss are far-reaching. Parents not only spent more time at home, but there may have also been an increase in subsequent household stress.[2, 3, 19] These factors may have disproportionately affected low-income families, which was a focus of this thesis.

1.1.3 Reading frequency (X2)

Early language exposure is critical to infant communication development. A 2020 systematic review highlighted how reading to infants can improve their expressive and receptive language abilities with increased doses of reading improving the effect.[23] These improvements are further aided by parents being engaged in the reading process, such as asking questions and re-reading sections.[24] A 2022 longitudinal study of infants in the US found significant effects of reading as early as 9 months of age.[25] One group received no instructions, and the other group was provided books and were instructed to read at least one book per day to their infant from 2 weeks old. The group that read to their infants 7 times or more per week had infants with significantly higher expressive, receptive, and combined language scores at 9 months. The difference between the daily reading group and the no instruction group grew at age 12 months in these same areas. This early and consistent level of reading showed improvement in communication outcomes in these infants.[25]

The negative impacts of stress may override the association between reading and communication development. When exposed to chronic stress, infants can have maturational lags in brain development and exhibit alterations in brain function, the effects of which are long-lasting and can be noticed early.[26, 27] Stress may also impact whether parents are willing to read to their infants. A 2003 study on parents and infants found that mothers who had higher income with less parenting stress and fewer general hassles were more likely to read to their infants.[28] It is reasonable to infer that reading frequency may have slowed during the pandemic, or that its impact may be weaker in the context of higher environmental stress.

1.1.4 Research questions

In summary, this paper-based thesis examined the following research questions:

1. How do pandemic unemployment benefits impact communication development trajectories among infants in low-income households?
2. How does reading frequency impact communication development trajectories in low-income homes during the COVID-19 pandemic?

1.2 METHODS

1.2.1 Dataset

For this thesis I used data from the *Baby's First Years* (BFY) randomized controlled trial (RCT).[29] The Baby's First Years data is available for public use in North America through the Inter-University Consortium for Political and Social Research.[30] This study randomized families to receive cash gifts that supplemented their income. The experimental group received $333/month and the control group $20/month, in addition to ongoing federal or state support.[6] Data collection began in 2018 under Dr. Kimberley Noble and Dr. Katherine Magnuson. The BFY study is affiliated with many institutions in the United States, including Duke, New York University, Columbia University, UC Irvine, University of Maryland, and the University of Wisconsin. Data were collected yearly from birth and are still being collected.[5, 6] Baby's First Years was registered with Clinicaltrials.gov in 2018 (national clinical trial number NCT03593356).[31]

This thesis used data from the first three years of the BFY study, including the baseline, age one, and age two data collection time points. Mother-infant dyads were followed over a two-year period between 2018 and 2021. Data used included demographic and communication development data for ages one and two, data on reading frequency, and data on COVID-19 impacts. While the randomized variable (i.e., the monthly cash gift amount) was not of primary interest in this thesis, it was assessed as a potential confounder and added into statistical models accordingly. The BFY study recruited 1,000 mother-infant dyads at baseline, with 931 reporting at age one and 924 reporting at age two.[6, 32] Thus, the sample size for this thesis was N = 924 infants. Data was accessed through the Inter-University

Consortium for Political and Social Research data archive.[30] Access to this repository is available to any researcher affiliated with any institution in North America.[30]

The BFY study has been making ongoing monthly payments to participants and has published early results on infant development outcomes. Infants in the low cash gift group ($20/month), have lower activity in high-frequency bands on an EEG.[32] It has been affirmed in the literature that infants who demonstrate these EEG results are at an elevated risk of autism spectrum disorder.[33] This early work highlights differences in development related to income and its impacts on infants within this dataset.

1.2.2 Setting and Participants

The BFY study recruited mothers who gave birth in a hospital in one of five US metropolitan areas: New York City, Greater New Orleans, Minneapolis, St. Paul, and the Omaha metropolitan area.[6] The BFY study recruited at birth to minimize potential bias from differential access to care. These recruitment sites were chosen to obtain a diverse sample across regions that varied in cost of living and the overall amount of state safety net programs. Local officials in each state ensured that the cash gift from the trial did not disqualify the individuals from receiving benefits from the state.[6] Table 1 identifies the inclusion and exclusion criteria used by the study and this thesis.

Table 1: Inclusion and exclusion criteria used in this thesis

Criteria Group	***Sample***	***Inclusion Criteria***	***Exclusion Criteria***
Baby's First Years criteria	Low-income mother-infant dyads in the United States (*N*=1000)	• Infant born between 2018 and 2019 (May 2018 – June 2019) • Infant discharged into custody of mother in hospital after birth • Mother met US definition of "below the poverty line" at time of infant's birth • Mother lived in and gave birth in one of 5 US metropolitan areas: New York City, Greater New Orleans, Minneapolis, St. Paul, or Omaha • Mother was able to provide informed consent • Mother was legal age for informed consent at the time of infant's birth (≥18 years in New York, Minnesota, and Louisiana; ≥19 years in Nebraska) • Mother spoke English or Spanish	• Infant admitted to NICU at birth • Mother reported they were "highly likely" to move to a different state or country within the next 12 months
Additional Ages and Stages norming criteria	Normed baseline score for the ASQ. (*N*= 931) Infants included will be used to create a baseline normal curve for ASQ scores.	• Infant completed the ASQ at age one (July 2019 – June 2020)	• Developmental or cognitive delays diagnosed prior to the age one assessment
Additional thesis criteria	Low-income mother-infant dyads in the United States (*N*= 924)	• Infant completed both age one and age two assessments	• None

Procedures

All mothers in this study completed four interviews, two of which were in-person and the others via telephone. The first three interviews were used in this thesis. The *birth interview* was collected within a few days of the infant's birth and includes demographic information.[6] The *age one interview* was collected when the infant was one year of age and included questions on reading frequency, infant communication development using the Ages and Stages Questionnaire (ASQ) and updated demographics. The *age two interview* was collected when the infant turned two and included questions on infant communication development using the McArthur-Bates Communication Development Inventory, reading frequency, demographics, and questions about COVID-19. Figure 1 summarizes the data collected during the BFY study and when it was collected. Written informed consent was obtained at baseline and for some mothers at the age one interview, with verbal consent being obtained from halfway through the age one collection onward. Full data collection procedures are outlined elsewhere.[6, 31, 32] It is important to note that the age one interview was done in person for some dyads and by telephone for others, due to the pandemic.[34]

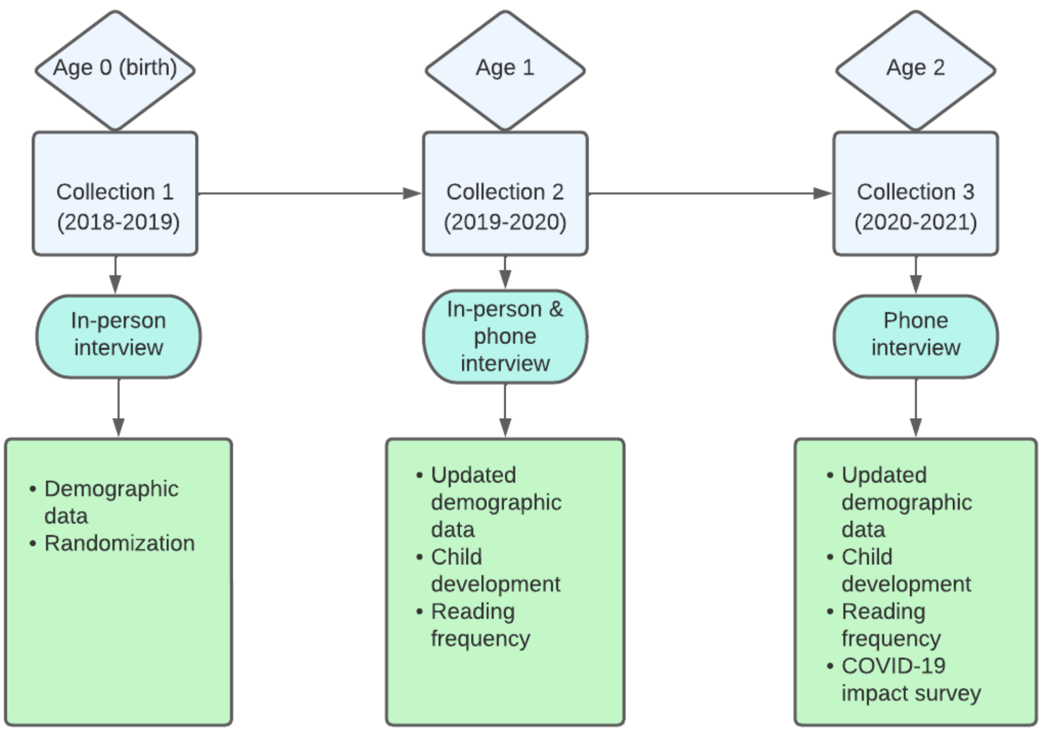

Figure 1: Thesis data and collection timeline

1.2.3 Methods of follow-up

Approximately 95% of the mothers approached for the study met inclusion criteria and completed the *at birth interview* (*N* = 1000).[35] Of these, 931 mother-infant dyads completed the *age one interview*, and 924 completed the *age two interview*. Overall, about 92% of recruited mother-infant dyads were retained over the three years of study that are relevant to this thesis (*N* = 924), which is generally considered an exceptionally low loss to follow-up rate.[34] The most common reason for loss to follow-up was loss of contact with the family, which accounted for 72% of the mother-infant dyads lost before the age one interview could take place. Other reasons included infant death, maternal incarceration, and refusal of the mother to be re-interviewed.[34, 35] To engage mothers, text message notifications were sent every month when their cash gift was loaded onto their study-affiliated debit card.[6] In this thesis, only those who completed each time point will be included. However, Little's test of Missing Completely At Random (MCAR) and other statistical tests were used to determine the nature of why data were missing.[11, 36]

1.2.4 Research question 1 – 2: Outcome variable - Infant communication development

The outcome variable for this thesis was communication development between one and two years of age. The variable was generated from two screening measures: the communication section of the Ages and Stages Questionnaire (ASQ) conducted at *age one* and the McArthur-Bates Communication Development Inventory or MBCDI) at *age two*. These measurements are well-suited for their respective ages and are well studied, however, they are not fully comparable.[37-41] The ASQ is a more subjective score that relies on parent observations, while the MBCDI is a more objective measure focused on identifying the words known by the infant.[39-43] While both measures are correlated, the MBCDI should be used when available as it is superior in its assessment of language development at age two.[39-41] Although there are differences in the measures, they are both well-suited for their respective ages and have a more flexible delivery than the Bayley III. The gold standard test for infant development, the Bayley III, is less flexible due to its length and the requirement of a trained professional to administer it.[37] The ASQ and MBCDI both yield standardized scores, which were examined in this thesis.

Ages and Stages Questionnaire

In this study, the ASQ was given to infants at age one. The ASQ is widely used for assessing infant development.[38, 40, 44] It has been developed in 16 languages and has a long list of validation studies.[42] The ASQ can be completed by the mothers, making it non-invasive and easy to administer.[44] The ability of the mother to complete the ASQ on behalf of the infant allowed the research team and mother flexibility during the pandemic.[6, 34]

A validation study in 2019 compared the findings of the ASQ with the 'gold-standard' Bayley III scale. The ASQ was significantly yet weakly correlated with the Bayley III scale for the category of communication.[40] The sensitivity of the ASQ relative to the Bayley III ranges from 47% to 75%.[37, 38, 45] The specificity of the ASQ to the Bayley III also ranged from 72% to 81%.[37, 38, 45] These ranges are likely due to the enhanced complexity and robust methodology of the Bayley III being compared with the less complex ASQ.[46] A 2017 retrospective cohort study compared the theoretical referral decisions and final integrated decisions of clinicians when the ASQ and the Bayley III were used. When the ASQ was used in combination with medical and socio-familial findings, it predicted 93% of the referral decisions made with the Bayley III.[37] This indicates positive predictive value, which is the percent of children correctly identified as a positive case.[47] Positive and negative predictive validity has been assessed for the ASQ in relation to the Bayley III, with values of 76% and 86% respectively.[37] These findings suggest that the ASQ was a good alternative to use in the BFY study, as it is easy to administer and minimized the risk of viral spread during a critical period of COVID-19 transmission.

McArthur Bates Child Development Inventory (MBCDI) Short form

In this study, the short form MBCDI was given to infants at age two. The MBCDI is a recognized screening tool for language and communication issues in children under five.[43, 48, 49] This tool is a parent report instrument, with the short form focusing on the number of words a toddler knows from a list of 100 common words.[43] The original MBCDI has been used in many languages and has predictive validity for long-term learning outcomes.[48, 50] A 2016 study used the MBCDI to assess the early expressive language skills of toddlers with cochlear implants. The results predicted long-term language, executive functioning, and academic skills up to 16 years later.[50]

An early validation study of the long form MBCDI computed Cronbach's alpha and found an internal consistency of 0.96 for both halves of the toddler scale.[51] They also found internal consistency within a test-retest study of toddlers. The average lag between tests was 1.35 months, and the Pearson correlation between the test and retest was 0.95 for the first half and 0.86 for the second half (both at $p<0.01$).[51] The long form was also validated with the Bayley Scales of Infant development, the original Bayley Scale and predecessor to the Bayley III.[52] This validation study found, among 4 subsamples of varying socioeconomic and term characteristics (pre-term and full term), that the MBCDI was consistently correlated to the early Bayley for 3 of the 4 groups ($p<0.01$). The correlation coefficients ranged with the different sections of the early Bayley, from 0.39 to 0.63. [52]

The short form of the MBCDI, which was used by Baby's First Years and assessed in my research, is highly correlated with the long form test. The internal consistency of the short-term version of the MBCDI was very high (Cronbach's alpha = 0.95 and 0.99 for the two sections).[43] A more recent validation study of the short form test in 2021 found a significant low to moderate correlation between the ASQ, MBCDI, and the Bayley III. The short form MBCDI had a Pearson correlation coefficient of 0.189, which was a significant correlation to the Bayley III ($p<0.001$).[41] This validation study had many limitations as it was conducted in rural China and compared the short form of the MBCDI with the complete versions of the Bayley III. However, a correlation was demonstrated between these two tests.[41] In addition to its validity, several sources have indicated that the MBCDI works best for children around two years of age. [41, 43, 51, 53]

Common communication trajectory

The ASQ and the MBCDI were compared to make a combined variable of communication trajectory. This placed the score obtained in the ASQ and MBCDI on a similar scale. The ASQ and MBCDI output numeric scores that were compared as standardized scores; however, it is important to highlight key differences in what these tools measure.

Scores for the ASQ are generated based on the responses in each section. Different responses yield various values: "Yes" equals 10 points, "Sometimes" equals 5 points, and "Not yet" equals 0 points. These are summed at the end of the questionnaire. Higher sums indicate normal development, while lower sums indicate the risk of a developmental delay.[44, 45] Standardized scores were generated for the ASQ by the BFY study. This score serves as a baseline score to compare against the results of the MBCDI at age two. The MBCDI is scored based on the number of words that the child knows. This numeric value has been normed through research for the long-form and has been validated for the short form.[43, 49] These numeric values, coupled with the age at which the tool was completed, yield a standardized score for that child. That score indicates the infant's performance in relation to their peers.[43, 49] Each of the two standardized scores (ASQ and MBCDI) for each child was treated as a repeated measure. The repeated measures analysis of this outcome variable was conducted with a linear regression inside of a Generalized Estimating Equation (GEE).

1.2.5 Research question 1: Exposure variable – Pandemic unemployment benefits

The exposure variable in chapter two was the receipt of pandemic unemployment benefits. Given that the burden of the pandemic on households was differential across families, the receipt of unemployment benefits was chosen to help distinguish the resulting negative impact.[1, 20, 54] "Have you or someone in your household received unemployment benefits to help replace earnings lost due to coronavirus?" Response options were 'you' (the mother), 'someone else in your household', and 'no one'. This variable was included as part of the age two interview in 2021.[55] This variable was later collapsed into two categories, 'member of household received unemployment benefits' and 'no one received unemployment benefits'.

1.2.6 Research question 2: Exposure variable – Reading frequency

The exposure variable in chapter three was reading frequency. The variable 'reading frequency' was assessed using the question: "*How often do you read books or look at pictures in a book with [child name]?".* Response options were 'every day', 'a few times a week', 'a few times a month', and 'rarely or not at all'. This variable was included as part of the age one and two interviews, in 2019-2020 and 2020-2021 respectively.[34, 55] This variable was later collapsed into three categories, 'A few times a month or less', 'A few times a week', and 'Everyday'.

1.2.7 Covariates

Several covariates were tested for the conditions of confounding, and are outlined below.

Infant assigned sex: This is stated as biological sex in the BFY study and was taken from the baseline questionnaire (birth). The question asked, “Is your baby a boy or a girl?” and only had two response options of “Boy” or “Girl”.

Maternal marital status**:** This was assessed using the question “How would you describe your marital status?” at birth. The response options include never married, single living together, married, separated, divorced, widowed, and other. This was later collapsed into categories of “Single, never married”, “Single, living with partner”, “Married”, and “Separated/Divorced/Other”.

Parity: Parity was measured at birth by asking mothers if this was their first child (yes or no).

Earned income: Earned income was measured as the earned income of the family, which was measured by the BFY RCT. This measure estimated the annual income from all sources and was calculated by the study.

Maternal education level**:** This data was collected from five separate questions asked in the baseline survey: “What is the highest grade in elementary school or high school that you finished and got credit for?”, “Do you have a high school diploma or GED certificate?”, “Do you have any college degrees?”, and “What was the highest degree that you earned while in college?”. Within each of these questions there were many possible response options. These questions were collapsed into categories of maternal education, including: some high school, completed high school, some college (no degree), and college or university degree.

Randomization term **($333 or $20/month):** The cash gift was assigned after the consent and baseline data collection. Participants were randomly assigned to receive either $20/month or $333/month. The study was double blinded, meaning participants and study staff were both unaware of what amount they received. The assigned amount can be found in all datasets but is not asked or discussed during the survey. Participants were chosen randomly, with about 40% of the sample receiving the higher cash gift.

Pandemic data collection: This variable indicated whether the first data collection time point took place before or during the pandemic. If the age one interview was completed after March 3, 2020, it was categorized as taking place during the pandemic. This variable was named “*pandemic data collection*”. Age two data collection took place during the pandemic for all participants, therefore, the timing of its delivery has not been included as a covariate.

1.3 ANALYSIS STRATEGY

1.3.1 Data management

Data from the BFY study was cleaned of any identifying information and prepared for public use by BFY study staff members. The dataset itself is publicly available, meaning no special permissions, qualifications, or privileges are required to access and use the data. Additionally, permission in writing was given by a principal investigator of the BFY study stating that the data could be used in this thesis.

1.3.2 Sample description

The study population was characterized using means, medians, and standard deviations for continuous variables and proportions for categorical variables. A sample size calculation was not carried out as there is not enough literature to support an accurate effect size, and the calculation of sample sizes post-data collection has been criticized in the literature.[56] In addition, it is likely that the BFY study has an adequately powered sample for this thesis.

This thesis used the resampling method of bootstrapping. This method randomly selected and resampled participants from the sample pool. In addition, bootstrapping conducts multiple iterations of statistical tests.[11] A number of responses were selected to help adjust for missing data or missed measurements between time points. Since there is likely a more than adequate sampling pool in the study, a smaller subsample could have helped alleviate the effect of missing data. The decision to bootstrap depends on the data itself and how much data are missing. While there was not much data missing, the decision to bootstrap was still made to help account for differences in how the data were distributed. In this case, the distribution of the residuals was non-normal. Bootstrapping itself is non-parametric, which means that data is no longer required to be normally distributed when it is used.[11]

1.3.3 Regression Modelling

This thesis focused on data collected from the BFY study at baseline, age one, and age two. Data was analyzed using Stata.[57] The exposure variable in paper one was pandemic-related job loss, with those who did not experience pandemic-related job loss forming the unexposed group. The exposure variable in paper two was reading frequency, with those read to the least often forming the unexposed group. The outcome variable was communication development changes between ages one and two, modelled using linear regression. Since this variable was continuous, a linear model was used. Each standardized score was assessed using a repeated measures analysis.

Since job loss was a categorical exposure variable and communication development trajectory was an assumed continuous outcome variable, simple linear regression was first applied to understand the basic association between these variables. Multiple linear regression was also used to control for the confounding variables. Simple and multiple linear regression was also used in research question two since the outcome of communication development is assumed continuous, and the exposure variable of reading frequency is categorical. Both the simple and multiple linear regression models utilized 95% confidence intervals.

One way to analyze repeated measures data is by using a derived variable, otherwise known as a change score. A change score would be generated for each infant to determine the difference in their percentile rank between time points. Often this is done by simply subtracting the score of one time point from another.[11] While this method is used frequently, it is unable to estimate causal effects. Part of this limitation is that the implied effect from a change score may be in the complete opposite direction compared to the direct causal effect. This means that there is a chance for inferential bias to occur and the ability to infer causality is limited.[58]

Another method commonly used to analyze repeated measures data is a Random Effects Model (REM).[11] REM are models that have some defining parameters that are random.[59] As an example, in the BFY study the random parameter would be the group that they were assigned to. However, this parameter is not being used to reflect randomization in this thesis.[6, 32] While the RCT used this variable, the random nature of this variable was not assessed in this secondary analysis. Another reason REM was not chosen concerns the intention behind this study. The hypothesis was that the group whose household received pandemic unemployment benefits would have stronger communication development on average, compared to those in the other group who did not receive these benefits. This hypothesis underlines the key difference between GEE and REM: individual effect versus group effect.[11] This project sought to understand the group effect pandemic unemployment benefits had rather than the effect on individuals. In this case, GEE was better suited to this data since it is focused on group effects.

GEE was chosen as a more sophisticated method that is less susceptible to inferential bias and better suited the hypothesis. GEE was applied to a linear regression model, with the outcome assumed to be continuous in nature. A GEE model simultaneously analyzes associations between variables collected at different time points.[11] Multivariate GEE was used in order to adjust for confounders.

Testing model assumptions

To use linear regression four key assumptions must be met. The first is linearity, which implies that the association between the predictor variable and the mean of the outcome variable is linear. The degree to which this was true was assessed with locally weighted scatterplot smoothing (LOWESS) for the simple linear model, and a component plus residual (CPR) plot for the multiple linear model. The shape of these plots determined whether the data met the assumption of linearity. If this test determined the relationship as non-linear, it would be addressed with methods such as variable centering, creating a quadratic term, cubic splines, or log and square root transformation. The method used to address this would depend on what non-linear shape best fit the association between the exposure and outcome variables.[11]

Another assumption of linear models is normality. Since the outcome variable was standardized and based on a normal curve itself, it was assumed the data were normally distributed. However, a test for the normality assumption was carried out to confirm this. The test used involved a combination of a Shapiro-Wilk test and a Kernel Density plot. If normality had not been met, the methods to address this may include bootstrapping, addressing outliers, and a transformation of Y.[11] Again, the choice of method is dependent on the scale of the deviation from the assumption itself.

The third linear model assumption assessed was homoscedasticity, or constant variance. Homoscedasticity was met, due to the nature of the outcome data being in the form of percentiles. The variance remained the same. This was tested using a residual versus fitted plot and a set Y-intercept at zero.[11]

The final assumption assessed was outliers. The purpose of this was to determine if there were influential points that would have a large impact on the regression. These were identified using DFBETA statistics by predicting coefficient changes with the removal of observations. Outliers were detected by the boxplots created from DFBETA statistics. [11]

The use of GEE depends on the distribution of data being within the exponential family.[11] For this thesis, the data was normally distributed through the z-score outcome which suits this condition. In addition to data distribution, the covariance structure of the repeated measures must be known.[11] Correlational structures help account for how far or close different measurement points are together, as this distance can make measures more or less correlated. An autoregressive covariance structure accounts for the fact that measures closer together are more correlated than those further apart. For example, if we had four measures the first and second would be more closely correlated than the first and fourth. In this case an autoregressive correlational structure may be used to account for these differences in correlation between measurements. In my thesis there were only two measurements, which meant that a exchangeable correlational structure was applied. An exchangeable correlational structure is used when all pairs of responses (time points for each individual) are equally correlated. When there are only two measures, these responses are equally correlated and an exchangeable correlational structure is the best fit[11] All assumptions of GEE and linear regression were met.

1.3.4 Confounding

Given this thesis was an observational design, all regression models were adjusted for relevant confounders. Potential confounders for each research question were determined using a direct acyclic graph (DAG), comparing the estimated measures before and after confounding to ensure it is greater than 10% to satisfy Greenland's rule, and checked to ensure they were not an effect modifier. A potential confounder must also be associated with the exposure and outcome variable. These steps ensure that confounders are identified and appropriately dealt with.[11, 60, 61]

A DAG is a visual tool to help identify potential confounders. Individual DAGs were created for both research questions. DAGs allow us to visualize causation and confounding in relation to the exposure and outcome variables.[62] DAGs can be informative for identifying potential confounders, however, Greenland's rule was used as well.[61, 62] Greenland's rule, which is when a 10% or more difference in estimates is seen when confounders are included in a model, was assessed in the analysis for each research question.[60] Multiple linear regression was used with 95% confidence intervals to test for this.

Some potential confounders were identified for the thesis generally. These potential confounders included income, maternal education, marital status, and the assigned sex of the infant. Income was selected as a potential confounder of the pandemic unemployment benefit-infant development association as it could have influenced the severity of the burden of job loss. Income is associated with job loss and pandemic unemployment benefits by proxy, as being low-income pre-disposes an individual to job loss and job loss decreases income.[4, 63] Low-income workers were much more likely to lose their job during the pandemic than higher-income workers.[63] Income was also seen to affect infant development as indicated by the early results of the BFY study.[32] Income was determined to meet the first three criteria of confounding (associated with exposure, associated with outcome, and is not on a causal pathway) based on findings in literature.[11, 60]

Another potential confounder was maternal education. Parental education level may affect the exposure of job loss, as certain sectors like the service industry and the gig economy experienced increased job loss during the pandemic.[54] Maternal education could also influence infant development, through subtle differences in the understanding of development and learning support for young children.[64] Maternal education was assessed for the conditions of confounding for both research questions, the details of which can be found in their corresponding chapters. While another potential confounder, assigned sex, did not meet the condition of being associated with the exposure, its impact was assessed based on *a priori* research.[65]

Marital status was also included in the analysis as a potential confounder. The experience of job loss, emotional health, and overall stress could have been differential across marital status categories.[66] For example, pandemic restrictions paused or ceased day care and on-site school operations which could have played a role in whether a single parent was able to return to work, whereas those in a partnership may have been able to continue some level of paid employment.[1, 66]

All variables in the models for both research questions were tested for collinearity using Variance Inflation Factors (VIFs).[11] VIFs determine how correlated each of the confounder and predictor variables are in a model, with a large Pearson's R value indicating a high degree of collinearity. Generally, a VIF is acceptable if its Pearson's R value is less than 10, but a value under 5 is ideal.[11] VIFs were assessed for each research question.

1.3.5 Missing data

When handling missing data, the first step is to determine how data are missing. Missing Completely at Random (MCAR) means that the missingness of the data is separate from the values of the data. Missing at Random (MAR) is when missingness is not completely random but can be accounted for with existing variables. Missing Not at Random (MNAR) is when the missingness depends on observed and unobserved variables. MCAR is the strictest condition to obtain. [11, 67-69] While there are statistical tests to determine whether data meets the condition of MCAR, there is no test to distinguish between MNAR and MAR.[69] Little's MCAR test can be used to determine whether or not MCAR is met. This determines what process should be used to handle the missing data.[36]

If the data meets the condition of MCAR, listwise deletion of these missing values can be used. If MCAR is not met, then we have to assume MAR. MAR is the condition required to use multiple imputation.[67] Multiple imputation is the most popular method for handling missing data. Multiple imputation creates several copies of a dataset that each have their own estimates for the values that are missing. These estimates are generated from responses to other variables within the data. The final step of imputation is to pool or compile these estimates together from these various copies.[67, 68] In the case of this thesis, the amount of missing data was far less than the 5% threshold to use multiple imputation (1.5%) and listwise deletion was used.

1.3.6 Avoiding Harm and Bias

Avoiding bias

There is a responsibility to ensure that research minimizes harm and limits bias. Bias is the presence of systematic error, or error that is not random. There are several types of bias, the first of which is selection bias. Selection bias is when the chances of someone being in the study are not random and are in fact due to characteristics they possess. One way selection bias may have been present is through who is retained in the study.[70] In the case of the cash gifts, those receiving the gift may be more likely to be retained in the study. The BFY study used three different methods to minimize this potential bias. The first of these methods was to ensure that enrollment and cash gift receipt were not linked. Only after consent was obtained and the baseline interview was complete were participants randomized to the cash gift amount. The other method involved the amounts themselves. The control group still received a cash gift, and both groups could still obtain state-level supports. The third method used concerned how individuals got their funds. The cash gifts were loaded onto a pre-paid debit card every month for both groups.[6] This was to minimize any selection bias regarding connection to financial institutions. These methods highlight the attention paid by the BFY study to the details of the protocol. One of the main ways to prevent selection bias is to ensure the design, methods, and procedures themselves limit bias.[70]

Another type of bias is information bias. Information bias occurs when a flaw in the measurement of the variables leads to a weakness in their accuracy.[70] One way this could have been present within this sample is the collection method used. When the BFY study began, interviews were completed in person at baseline. The pandemic occurred part-way through the collection of the age one data. To minimize risk to study staff and participants, the study shifted to conducting the interviews by telephone and paused the in-person measurements. This resulted in some participants following the protocol as written and some participants conducting interviews remotely and missing a measurement.[6, 34, 35] While the study did everything possible to limit risk, there is likely some information bias and missing data as a result. However, considering the level of risk and the information at the time, this move was necessary.

The final bias to consider is generalizability. Generalizability is the degree to which the sample is representative of the population and how the research can be *generalized* to a broader population.[70] The BFY RCT only included parents aged 18 or older, which is important in obtaining informed consent.[6] This may not represent the experiences of the low-income population of the US. A cross-national comparison of the US and Canada highlighted that the risk of teen pregnancy was higher in adolescents from economically insecure families.[71] Teen pregnancy may pose a barrier to certain social programs. A 2002 report highlighted that welfare and social programs were restrictive based on education attainment and other requirements.[72] This suggests teen mothers were not only more likely to be in poverty, but that supports were inaccessible to them. Data from the US Department of Health & Human services highlighted that in 2019 more than three-quarters of all teen births occurred in 18 to 19 year olds.[73] While teen pregnancy may be of particular interest to low-income studies, there is likely adequate representation in this age-restricted sample.

Avoiding harm

It is important to discuss the distribution of cash gifts under the lens of potential harm. Individuals in the BFY RCT were randomized to receive one of two levels of cash gifts. Mothers in the treatment group or 'high cash gift group' received $333 per month, increasing the annual income of a family of three by about 20% in a year. Mothers in the control group or the 'low cash gift group' received $20 monthly. Both groups got their gift loaded onto a debit card to control for confounders, such as connections to financial institutions.[6] This study could have caused harm if the value of the cash gifts disqualified them from supports they relied on. This discussion of cash gifts and welfare is highly relevant as the high cash group would see an increase in their annual income by about $4000 per year. This could put families in a higher tax bracket or disqualify them for social supports. The RCT protected for this by ensuring legislators in the states the project was in understood the project and that participant's eligibility for public benefits would not change.[6]

1.3.6.3 Research ethics approval

This thesis research was conducted in accordance with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans. This study uses secondary data and does not deal with participants directly; however, an ethics approval was obtained from the University of Alberta's Human Research Ethics Board (Pro00129505). The BFY study received approval from the Institutional Review Board of University of California, Irvine (85 2016-3336) and the Review Board for the Protection of Human Subjects at Teachers College, Columbia University (Protocol 18–210)[5, 31].

1.4 THESIS OVERVIEW

This thesis was written in a paper format. Both papers include their own introduction, methods, results, and discussion so that each may be submitted for publication. The same dataset was used for both papers.

Chapter 2: Whether pandemic unemployment benefits affected infant communication development

The purpose of paper 1 was to understand the effects that pandemic unemployment benefits had on infant communication development. While Piaget's development theory and the literature surrounding stressful environments supports the hypothesis that income supports could improve development, this research has yet to be conducted in the context of a pandemic.[74] The purpose of this research was to assess whether this effect existed and differed by whether the household experienced job loss in the pandemic. Data for this paper was derived from the Baby's First Years dataset, using data collected between 2018 and 2021. Access to the BFY dataset was obtained by direct download through the Inter-university Consortium for Political and Social Research (ICPSR). Regression techniques were used to examine the association between pandemic unemployment benefits and the development of infant communication.

Chapter 3: Post-hoc analysis of whether reading frequency affected infant communication development

The purpose of paper 2 was to assess post-hoc whether reading frequency between ages one and two impacted infant communication development. This was further stratified by whether the age one data collection took place prior to or during the pandemic. Data for this paper was also taken from the BFY dataset, using data from 2018-2021. Access to the BFY dataset was obtained by direct download through the Inter-university Consortium for Political and Social Research (ICPSR).

Chapter 4: Summary

Chapter four is a general discussion and summary of the findings.

<u>2.0 CHAPTER 2</u>

CONTRIBUTION OF AUTHORS

Mahala Swisterski, Master of Science student, was the primary author of this chapter. The work within chapter two will be condensed and submitted for publication after the defense date. Cheryl Currie, Robbin Gibb, Richard Larouche, and James Sanders will be listed as co-authors on the intended publication. I conceptualized and designed the secondary analysis, determined the research questions, analyzed the data, drafted the original thesis chapter, drafted the original manuscript, and critically reviewed and revised the thesis chapter and manuscript. Cheryl Currie assisted in the conceptualization and design of the research, supervised the data analysis, critically reviewed and revised the chapter, and provided revisions to a manuscript draft. Richard Larouche, Robbin Gibb, and James Sanders critically reviewed and revised the chapter.

ABSTRACT

Introduction: The home environment has significant impacts on how infants grow and develop. Sudden unemployment was common during the COVID-19 pandemic, creating stress in families, particularly within low-income homes. From a health promotion perspective, unemployment benefits during the pandemic may have helped ease tensions in low-income homes and improved developmental outcomes for infants. The objective of this study was to test this hypothesis by examining whether infant communication development differed between low-income homes that did and did not receive unemployment benefits during the COVID-19 pandemic.

Material and methods: This study used data from the Baby's First Years Study, which collected longitudinal data from approximately 600 mother-infant dyads living in low-income homes between 2018-2021. Families were recruited from hospitals in low-income neighbourhoods across several US cites. Women with self-reported incomes that fell below the US poverty line were invited to participate. Data were collected in-person between 2018-2020 and transitioned to telephone in March 2020 due to the pandemic. The outcome variable, infant communication, was measured with the Ages and Stages Questionnaire at age one and the McArthur-Bates Communication Development Index at age two and analyzed on a continuous scale. The exposure variable, pandemic unemployment benefits, was a categorical variable that measured whether any member of the household received unemployment benefits during the pandemic. Data were analyzed in Stata using linear regression and generalized estimating equations adjusting for infant sex, pandemic data collection, randomization term, and earned income.

Results: Overall, approximately 40% of families in this study received unemployment benefits during the pandemic. Receiving pandemic unemployment benefits was weakly and significantly associated with infant communication development scores in a model adjusted for confounders. When averaged across all dyads, infants living in homes that received pandemic unemployment benefits increased their standardized communication score by 0.15-units more over a one-year period than infants living in homes that did not receive benefits (95% CI: 0.02 – 0.29).

Conclusion: The findings of this study suggest infant communication development was stronger in low-income homes that received unemployment benefits during the COVID-19 pandemic.

2.1 BACKGROUND

Parents know all too well that infants are like sponges, absorbing everything around them in their early years of life. This characteristic of infants is crucial to their development. Piaget's cognitive development theory highlights this, stating that the environment of the infant determines how they understand the world. Small alterations in the infant's experience of the world impacts their understanding and development.[74] Thus, exposure to stress in early childhood can have lasting implications on development.[75] A 2017 study found an inverse association between cortisol levels and infant cognitive development.[75] Higher baseline cortisol among mothers is also associated with higher baseline cortisol in their infants.[75] Numerous studies have shown how dysregulated stress hormones in infants can lead to behavioural, developmental, and sleep problems.[76] This research underscores the fundamental principle highlighted in Piaget's theory: that the environment the infant is in has a direct impact on their development. These effects are particularly detrimental when those changes are stressful.[74]

Stressful environments have been shown to exacerbate problem behaviour and language development in toddlers.[77] Job loss is an enormous source of stress for families, resulting in sudden changes in routine and income. Pandemic job loss was especially stressful, as it had unique hurdles. Parents without work faced daycare closures, infection risk, and changes in spending. These changes were more impactful for low-income families.[1, 4, 78-80] Income loss during the pandemic also impacted the mental health of parents and caregivers, which studies show impacts infant development.[81, 82] These stressful environments, propelled by job loss, have noted effects on infants and children.[1, 4, 77, 79-82] Monetary support has been shown to minimize the impact of parental job loss on infants and children in terms of test scores, school performance and attendance, and brain development.[32, 83, 84] The purpose of this chapter was to examine if infant communication development was stronger in low-income homes that received unemployment benefits during the COVID-19 pandemic.

2.1.1 Infant communication development

The primary outcome in this chapter was infant communication, which is the bedrock of learning. Achievements in early language learning have consistently indicated later developmental success.[85, 86] A 2020 systematic review found a longitudinal association between eye gaze following (an early communication skill in infants between 0 and 24 months old) and later receptive and expressive vocabulary.[87] Early and simple communication skills build the mechanistic foundations for later learning, making this early period especially important for development.[87] Communication shifts from largely non-verbal to verbal shortly after age one.[88, 89] The communication skills built between age one and two contribute to later reading and language abilities.[89] Between the ages of one and two, a shift occurs in the number of words a child knows and is able to say. Toddlers at 24 months of age who know less than 50 words and cannot say two-word sentences are said to be 'late talkers'.[89, 90] Late talkers are at risk for reading, behavioural, and language problems, all of which can affect their later life.[89, 90] There is evidence to suggest that infants in poverty are disadvantaged, based on differences in early language learning opportunities.[91]

2.1.2 Poverty

This chapter examines the impact of poverty on infant development in low-income families in the United States (US). Poverty is defined in the US by two factors: household income and the number of people living in the household. The US threshold for poverty changes yearly and increases with household size. In 2021, the threshold for a four-person household was $26,500. If a family made that amount or lower, they would be considered 'under the poverty line'.[92] This is in contrast to the median household income, which in 2021 was $70,784. It is estimated that 11.6% of the total US population was living under the poverty line in 2021.[93] To qualify for programs like the Supplemental Nutrition and Assistance Program (SNAP or 'food stamps'), families must meet a percentage multiplier of the poverty threshold to be eligible (such as 125 percent).[94] Experiencing poverty in the US involves navigating the balance between having access to essential benefits and generating income to overcome financial challenges.

Notably, poverty puts infants at risk of delays in development and creates gaps in access to vital supports and services.[95] A key part of communication development is how much the baby hears and is exposed to language, and this differs significantly by income level. The relational effect between income and language exposure has been dubbed the '30-million gap', as infants in more advantaged families had 30 million more words directed at them before age four than infants in poverty.[91] This difference has predicted long-term outcomes such as late talking, difficulty reading, and challenges in school.[96, 97] Studies estimating the prevalence of language delay among low-income countries have found that even when the disparities in income were not large, the prevalence in language delays remained high at about a quarter of the total population aged 36-59 months.[98] It is apparent that infant communication suffers in poverty, independent of additional stressors like job loss.

2.1.3 Pandemic unemployment

Job loss was widespread during the early stages of the pandemic. Among individuals in the US who commuted to on-site work daily in February 2020, more than a quarter were no longer employed by May 2020.[21] The US unemployment rate in May 2020 was 19%, up from a record low of 3.5% in 2019.[99, 100] Unemployment and subsequent increases in stress amplified existing struggles for low-income families, such as financial hardship and poor mental health.[4, 79] Pandemic containment measures also influenced the ability to maintain work. Remote work opportunities were less likely for low-income individuals, and job loss in this income group was more common.[1, 21] A 2021 longitudinal study found job loss in low-income families was 24% compared to 13% in middle- and high-income families.[101] Only 44% of low-income families could work from home in this study, compared to the 73% of middle-high income families.[101] Increased spending during the pandemic was also more common among families in the lowest income quintile.[1] Job loss can be catastrophic outside of a pandemic, yet it is clear in the literature that job loss had greater impacts on low income families during the pandemic.

Research shows unemployment benefits can improve infant and parental health. A 2017 analysis of 25 years of longitudinal data found that those receiving unemployment benefits were significantly less likely to report poor health.[102] The probability of reporting poor health was five percentage points lower among those receiving unemployment benefits.[102] Other studies have found that maintaining income for those who are unemployed also maintains their health status.[103, 104] These improvements also extend to their family members and are vital for infants and children. A 2022 study analyzed data from Switzerland following a referendum that decreased unemployment benefits by more than 56%. Mothers with this lower unemployment benefit birthed infants with lower birthweights (80g decrease on average) and body lengths (6mm decrease on average).[105] Unemployment also impacts the number of Adverse Childhood Experiences (ACEs), with children in unemployed families being at a 29% increased risk of sexual abuse, 54% increased risk of neglect, 60% increased risk of physical abuse, and about a 90% increased risk of maltreatment and parental mental illness.[106] Increased ACE scores have been shown to be associated with poor engagement in school, learning difficulties, and behavioral and social problems.[106] Exposure to ACEs also affects development, particularly social and behavioral development, that varies based on the age of exposure.[107]

While unemployment can negatively affect infants and parents, cash assistance programs have proven to be effective. The Baby's First Years Study found that infants from low-income families that received high stipends ($333 per month), simulating additional government assistance, had improved brain activity compared to the control.[32] For low-income families already susceptible to poor birth and infant outcomes, these findings on unemployment benefit receipt and amount add to a constellation of factors that can impact their infant's well-being. There is a significant gap in our understanding of how unemployment benefits may impact infant communication development in infants, especially during the COVID-19 pandemic.

2.1.4 Research Objective

This chapter seeks to address a gap in our understanding on the role that pandemic unemployment benefits may have played in reducing the impact of unemployment on infant communication development among low-income families. The objective of this chapter was to examine if infant communication development was stronger in low-income homes that received unemployment benefits during the COVID-19 pandemic.

2.2 METHODS

2.2.1 Design and setting

In this this thesis I completed a secondary repeated measures analysis of the Baby's First Years (BFY) randomized control trial (RCT). The BFY study is affiliated with many institutions in the United States including Duke, New York University, Columbia University, UC Irvine, University of Maryland, and the University of Wisconsin. This study is ongoing, with data collected yearly from birth.[6, 108] The analysis in this thesis prospectively followed the cohort between the years of 2018 and 2021. BFY was registered with Clinicaltrials.gov in 2018 (national clinical trial number NCT03593356).[6] This secondary analysis of the data was approved by the Health Research Ethics Board at the University of Alberta (Ethics ID Pro00129505).

BFY recruited participants from low-income metropolitan areas in the US including New York City, Greater New Orleans, the Twin Cities (Minneapolis and St. Paul), and the Omaha metropolitan area. These recruitment sites were chosen to obtain a diverse sample across regions that varied in the cost of living and the overall amount of state safety net programs.[6] Participants in BFY were randomized to receive a monthly stipend for 52 months. The high stipend group received $333 per month and the low stipend group received $20 per month from birth until the infant was 52 months of age (a little over 4 years). This period occurred between May 2018 and late 2023.[6, 108] Local officials in each state ensured that the stipend from the BFY trial did not disqualify the individuals from receiving state benefits.[6] BFY began recruiting dyads in 2018, and has since collected data every year on these same dyads. Dyads were recruited at the hospital within 1-2 days of the child being born.[6] This thesis used data collected from birth, age one, and age two.

2.2.2 Sample

Mothers in the BFY study had to self-identify as being ‘under the poverty line’ the year prior to be included in the study.[6] Being ‘under the poverty line’ is determined by family income relative to the number of household members.[92] Mothers were provided the general definition and self-assessed based on this definition. Included mothers were over the age of 18, living in the recruitment state, and had the baby discharged to their care. Dyads were eligible if the baby was in the nursery, and were excluded if the baby had been admitted to the NICU.[6] Babies were excluded if they had a diagnosed neurological condition at birth.

BFY had an overall sample size of 1,000 at baseline, 931 at age one and 924 at age two. Follow-up for the BFY study was high, with a 92% retention rate over the three years included in this thesis.[34] The most common reason for loss to follow-up was a loss of contact (i.e., the research team could not reach participants for follow-up), representing 72% of lost dyads between birth and age one. Other less common reasons were infant death, maternal incarceration, and refusal of the mother to be re-interviewed.[34, 35] To engage mothers, text message notifications were sent every month when their stipend was loaded onto their study-affiliated debit card. High retention was likely aided by the monthly stipends provided to mothers, which represented the randomization term. Every dyad received a stipend loaded onto a study debit card, without any restrictions on how it could be used. The high stipend group (the experimental group) received $333 a month, while the low stipend group (the control) received $20 a month.[6]

For this analysis, dyads were removed if the baby had a diagnosed neurological condition at birth (*n* =7) or if they did not complete either of the communication development tools (*n* =311). The sample size for this thesis analysis was 606 dyads followed from 2018 to 2021.

2.2.3 Variables

Outcome variable: Communication development. The gold standard for measuring infant development is the Bayley III assessment. This tool has excellent inter-rater reliability and is the most-widely used tool to quantify infant developmental progress.[109] However, the Bayley III is a lengthy test and requires a trained professional to administer.[37] Thus, the BFY study opted for more accessible alternatives including the Ages and Stages Questionnaire (ASQ) and the McArthur-Bates Communication Development Inventory (MBCDI). These tools are valid, reliable, and can be compared to each other.[39-41] In addition, these tools could be completed remotely which ensured safety and continuous data collection during the pandemic.

The communication section of the ASQ was conducted at age one (2019-2020) and the MBCDI was completed at age two (2020-2021). These measurements are well-suited for their respective ages, and both provide a numeric score that can be standardized.[39-41] When measuring language, the MBCDI is much more complex than the relevant portion of the ASQ.[39] While they are correlated, the MBCDI should be used when available as it is superior in its assessment of language development.[39-41] In this case, the MBCDI was used at age two since it is a more comprehensive evaluation of language at this age.[110]

Z-scores, otherwise known as standardized scores, of the ASQ and the MBCDI were used in this thesis analysis.[111] Z-scores were generated for each measurement of communication development. The ASQ outputs a score which the BFY study converted into a standardized z-score.[34, 112] The MBCDI outputs a percentile rank based on literature and extensive research by the developers.[43, 49] These percentile ranks were converted to z-scores to compare with the ASQ.[111] Z-scores and percentile ranks are often converted between each other as a way to measure a score relative to the average. Z-scores measure the distance from the mean in units of standard deviation. Percentile ranks, on the other hand, represent the percentage of scores that are lower than it. Percentile ranks, however, are based on the normal curve which means that the percentiles are also based on units of standard deviation.[113] This highlights how these two measures can be converted from one to the other for analysis, but choosing which to use is often a difficult task. While percentile ranks are generally easier to interpret, generating cut points across two measurements can be challenging and may lead to a misinterpretation of the results.[113] For the ASQ, its cut-points represent whether the infant should receive targeted parental support or professional care.[42] These cut-points do not exist for the MBCDI, which measures how many words a child knows rather than whether a child has attempted certain verbal skills like the ASQ.[42, 49] In order to avoid this potential misinterpretation of varying cut-points, I compared z-scores as it was determined to be a more robust and accurate measurement.

Exposure variable: Pandemic unemployment benefits. Given that the burden of the pandemic on households was different across families, the receipt of pandemic unemployment benefits was chosen to help distinguish the resulting differential negative impact.[1, 20, 54] Pandemic unemployment benefits was measured as the receipt of unemployment benefits during the pandemic from a government body. This variable is specific to the pandemic and job loss. Individuals had to have worked consistently for the last 12-24 months to qualify for unemployment benefits in the US.[114] These benefits were more quickly and widely dispersed, in order to offer a stability of income during a rapidly evolving crisis. During the pandemic, unemployment benefits were offered with expanded criteria. They offered benefits to workers who had been temporarily laid off or had their work impacted by the pandemic, where traditionally one had to be laid off or let go from work to receive these benefits. In addition to expanded criteria to receiving unemployment benefits, individuals also received an extra $300 a week on top of their regular unemployment benefits. The pandemic unemployment assistance program allowed individuals who would otherwise not qualify for unemployment benefits to receive them. This program offered self-employed and freelance workers the opportunity to receive unemployment benefits for up to 79 weeks. Pandemic unemployment benefits were different than the standard, in that the criteria were relaxed and the waiting period was decreased.[17, 18]

The variable ‘pandemic unemployment benefits’ was assessed using the question: "*Have you or someone in your household received unemployment benefits to help replace earnings lost due to* *coronavirus?*" Response options were 'you' (the mother), 'someone else in your household', and 'no one'. This variable was included as part of the age two interview in 2021.[55] This variable was later collapsed into two categories, 'member of household received unemployment benefits' and 'no one received unemployment benefits'.

2.2.4 Covariates

Four maternal covariates were examined in this chapter: education, income, marital status, and parity. Maternal education was measured by asking mothers their highest level of education, and categorized as: less than high school, high school diploma or equivalent, some college, associate degree, and bachelor's degree or higher. Income was measured as the earned income of the family from all sources, which was measured by the BFY RCT. Marital status was assessed by asking mothers to state their marital status at the baby's birth: never married, single living with partner, married, separated, divorced, and widowed. Parity was measured at birth by asking mothers if this was their first child (yes or no). These variables are referred to as "*maternal education*", *"income*", "*marital status*" and "*parity*" throughout the rest of this chapter.

One infant covariate was examined in this chapter: assigned sex. Assigned sex was assessed at birth, with mothers reporting their infant as male or female. This variable will be referred to as "*infant sex*" for the remainder of the chapter. Infant age was not examined as a covariate given infant development was assessed at the same age for all participants in the study.

Two additional variables were in the analysis to help control for possible confounding. First, a variable to indicate whether the first data collection time point took place before or during the pandemic was included. If the age one interview was completed after March 3, 2020, it was categorized as taking place during the pandemic. This variable is called "*pandemic data collection*" for the remainder of the chapter. Age two data collection took place during the pandemic for all participants. Thus, the timing of its delivery has not been included as a covariate in this thesis. Second, given that the dataset used for this thesis was experimental and randomized families into groups, this randomization will be controlled for as a potential confounder. Mother-infant dyads were randomized to receive either a high monthly stipend of $333 for 52 months or low monthly stipend of $20 for 52 months. Thus, those in the high stipend group received more than 10 times the amount of those in the low stipend group.[6] Approximately, 44% of the sample that met inclusion criteria for my secondary analysis received the high-stipend. This variable is referred to as "*randomization group*" for the remainder of the chapter.

2.2.5 Bias

Selection bias may be present in the BFY study through differential loss to follow-up.[70] Those receiving the higher stipend may be more likely to be remain in the study. Although it is not the exposure of interest in this thesis, it may affect the results. This was assessed in this thesis using cross tabulations of subsamples. The tabulation of the treatment group at birth was compared to the same tabulation at age 2, to assess how many participants in each condition were missing. By age 2, 924 of the original 1,000 participants were retained in the study. Of those missing, about 5% of the total sample had been assigned to the high stipend group and 2% had been assigned to the low stipend group. The percentage missing from each of these groups does not differ greatly, however, this difference opposes what was expected. It is not clear in the study design whether participants continued receiving the stipend after contact was lost. If these gifts had continued despite a loss of contact, it may explain the slight differential loss to follow up. The high-stipend group may be less motivated to keep contact, as the amount of money may be significant enough that they may not feel the study is relevant for them after seeing a benefit.

The BFY study used three different methods to minimize differential loss to follow-up. The first of these methods was to ensure that enrollment and stipend receipt were not linked. Only after consent was obtained and the baseline interview was complete were participants randomized to the stipend amount. The other method involved the amounts themselves. Though the control group received a much more modest amount, $20 compared to a potential $333, all participants received stipends and were not disqualified from state-level supports. The third method used concerned how individuals got their funds. The stipends were loaded onto a pre-paid debit card every month for both groups. Having the gifts loaded onto a debit card ensured that the study did not solely include those with pre-existing connections to financial institutions. This ensured consistent, reliable compensation processes that remained standard between the groups.[6]

Information bias occurs when a flaw in the measurement of the variables leads to reduced internal validity.[70] When the BFY study began, interviews were completed in-person, but switched to data collection by phone during the pandemic. Thus, in person measures were missing for some participants at various time points (e.g. hair cortisol samples).[6, 34, 35] Given this change occurred, a variable was created to assess if shifting data collection to phone was a confounder of the exposure-outcome association examined in this chapter.

2.2.6 Analysis strategy

Descriptive analysis

Univariate analyses were used to describe the variables examined in this chapter including frequencies, crosstabulations, means, standard deviations, and ranges.

Hypothesis testing

The research question for this chapter was: How does receiving pandemic unemployment benefits impact communication development trajectories among infants in low-income households? The hypothesis was that infant communication development was stronger in low-income homes that received unemployment benefits during the COVID-19 pandemic. A linear regression model was used to examine if there was a difference in infant communication development for households that received unemployment benefits during the pandemic compared to households that did not. Infant communication development was operationalized as the difference in infant communication score between age one and two. This difference in infant communication score was examined as a continuous variable. A linear regression was used to understand how the average value of a continuous outcome varies over levels of an exposure variable.[11]

Assessing confounders

Seven covariates were examined as potential confounders of the association between pandemic unemployment benefits and infant communication development. These were chosen *a priori* based on existing literature: maternal education, earned income, marital status, parity, infant sex, pandemic data collection, and randomization group. Six criteria were used to determine if these variables confounded the association.[12]

First, *a priori* variables that are to be included in the model based on research were described. These variables were then presented in a directed acyclic graph (DAG) to visualize potential associations between these variables.[70] Next, the association of these potential confounders with the independent and dependent variables were assessed. Then, a DAG was used to help determine whether potential confounders sit on the causal pathway between unemployment benefits and infant communication. The associations were tested using Greenland's rule.[11] Finally, variance inflation factors (VIFs) were used to assess if the potential confounders included in the model are correlated with each other. Each of these steps is outlined below.

Four variables were included based on *a priori* research. These potential confounders had direct noted effects in prior research. These four potential confounders were included in the final model, notwithstanding other confounding criteria, to align with the findings of previous research.

Infant assigned sex was determined to be an *a priori* covariate. There is evidence that there are sex-based differences in communication development and neurodevelopment disorders.[65] Not including infant sex could potentially bias the results, especially considering potential differences in scores. Other studies have determined that essential diagnostic criteria, such as sex in this case, are included as potential confounders.[115, 116] The other *a priori* covariate was income. There is evidence to suggest that poverty has an effect on infant physical and neurocognitive development.[91, 97, 117-120] Even though every dyad identified as being in poverty, the estimated earned income could have differed between each dyad.[6] Thus, due to its potential impact, income was included in the final model. Another *a priori* covariate was pandemic data collection. Part of the sample completed the measurement before the pandemic, and part of the sample completed the interview during the pandemic. Research by Deoni et al. highlighted the pandemic as impacting child development. This study found a significant difference amongst infants born and assessed for cognitive development during the pandemic, compared to infants born and assessed before the pandemic.[10] The final *a priori* covariate was the randomization term used in the dataset. This variable is a randomization term of receiving a stipend of either $20 a month (low stipend) or $333 a month (high stipend). The increase in income in the high stipend group is about $4,000 per year. This amount is significant, as it would increase the average income for a family of three in poverty by about 20% per year.[6] When we consider the impact of being in poverty on child development, we must also consider how this stipend may play into the intricacies of income.[91, 97, 119] There is also evidence in research that unemployment benefits can improve the health of families.[102]

Figure 2 shows the DAG created using the software daggity.[121] This DAG offers a visualization of the potential associations between these variables.[70] The DAG suggests that the covariates do not lie on the causal pathway between pandemic unemployment benefits and infant communication. The bidirectional arrows in the DAG suggest that these covariates may be non-causal. In the case of infant sex, pandemic data collection, and randomization group, the single arrow also suggests that these covariates do not lie on the causal pathway. In a DAG, causal associations are represented by an arrow moving in one direction from exposure to covariate to outcome. This information from the DAG is used to inform the next step, which is determining whether any confounders lie on the causal pathway.[12]

Maternal education does not lie on the causal pathway, as the education attained by the mother occurred prior to the pandemic. Pandemic unemployment benefits would not have influenced the education of the mother; however, the mother's education may have indirectly impacted the amount of benefit received. Marital status also would not have been changed due to receiving pandemic unemployment benefits, and thus is not on the causal pathway. Maternal age and parity also do not lie on the causal pathway, as they were asked prior to the pandemic. The randomization term would not lie on the casual pathway, as it did not impact the mother's ability to qualify for unemployment or change their unemployment amount. This was confirmed by the RCT, who worked alongside state lawmakers to ensure that participants remained eligible for all state benefits.[6] Infant sex would also not lie on the causal pathway, as it would not impact pandemic unemployment benefits or be impacted by them. One may think that income may determine the receipt of unemployment benefits, however, in the pandemic this was not the case. Eligibility in the pandemic was determined by whether one's employment was impacted by COVID-19. This included temporary layoffs, being unable to work due to the conditions of COVID-19, or being unable to work due to yourself or a family member being ill with COVID-19.[18] Earned income does not lie on the causal pathway as the eligibility for pandemic unemployment benefits was only determined by employment status.[18] Finally, the date of the age one interview also does not lie on the casual pathway, as pandemic benefits would not have played a role in the timing of the interview. Interviews were based on the infant's age alone, with some interviews being pushed back due to being in the initial period of the pandemic. The delayed measurements used the relevant ASQ tool for the age of the infant (in months) at the time of the interview.[6, 34]

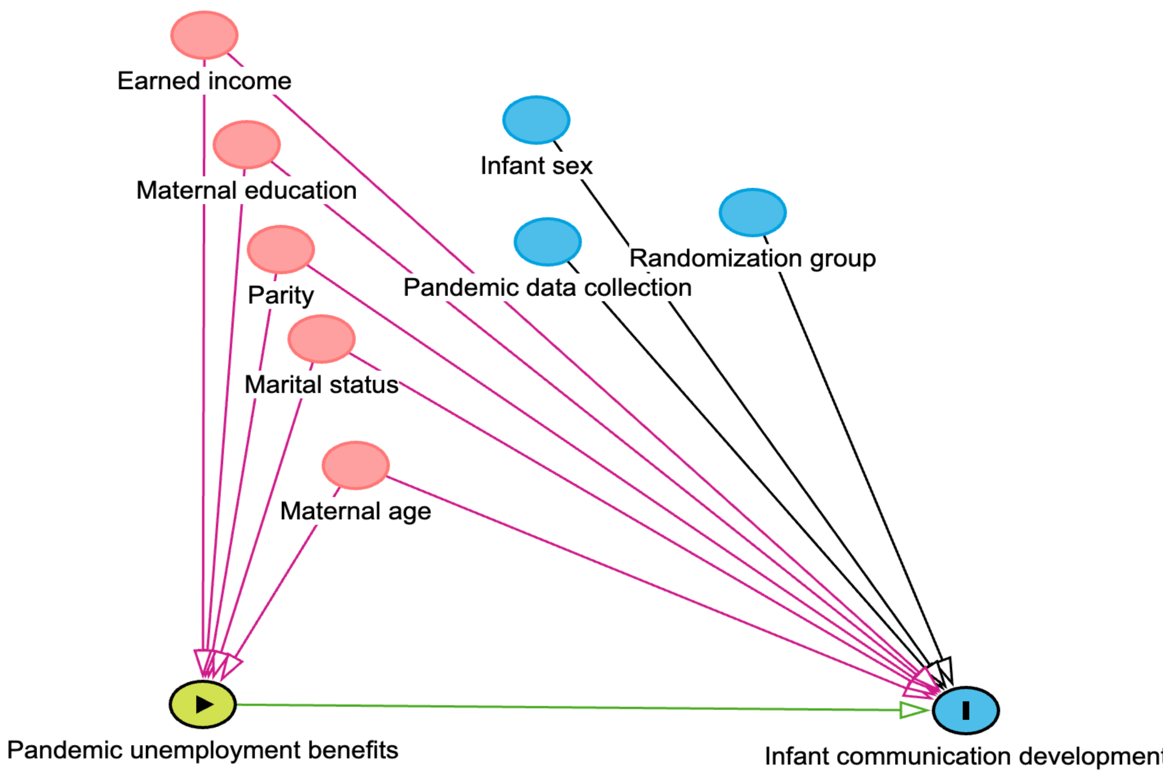

Figure 2: A DAG of the association and the potential confounders in chapter two. Blue covariates have a single directional arrow, whereas pink covariates show a bidirectional arrow not on the causal pathway.

Next each covariate identified in the DAG was examined for its association with the exposure and outcome.[11, 70] In Table 2 below, the associations were assessed and are presented. These associations were determined using simple linear regressions. Bolded cells indicate significant associations.

Table 2: Statistical tests for each potential confounder with the exposure and outcome variable in chapter two.

Potential confounder	Association with unemployment benefits (95% CI)	Association with child communication development (95% CI)
Maternal education	***0.16 (0.07 – 0.26)***	***0.06 (0.00 – 0.12)***

Infant assigned sex	0.01 (-0.02 – 0.04)	0.05 (-0.00 – 0.09)
BFY randomization term	**0.05 (0.00 – 0.10)**	0.02 (-0.01 – 0.05)
Maternal relationship status	-0.18 (-0.28 – 0.07)	-0.05 (-0.11 – 0.00)
Earned income	**0.04 (0.03 – 0.07)**	0.02 (-0.03 – 0.07)
Pandemic data collection	0.04 (-.0.00 – 0.09)	-0.03 (-0.05 – -0.00)
Parity	-0.14 (-0.03 – 0.02)	0.10 (-0.00 – 0.19)
Maternal age	0.05 (-0.05 – 0.14)	0.03 (-0.03 – 0.08)

Greenland's rule was tested next for the significant associations. It states that the regression coefficient of the association must change by 10% or more to be included in the model.[11, 60] When maternal education was adjusted for in the model, the coefficient changed by less than 10% (6.67%). This meant that maternal education was excluded from the model since it did not meet Greenland's rule. The *a priori* variables (infant sex, earned income, pandemic data collection, and randomization term) were not assessed for Greenland's rule. These variables were not significantly associated in Table 2 above, however, their noted effect in research supports their inclusion in the model. Since their association was not significant, Greenland's rule was not tested.

Variance inflation factors (VIFs) determine whether the variables being used (including the covariates) are correlated to each other. This effect of many variables being correlated to each other outside of the XY association is called multicollinearity. When testing for multicollinearity with Variance Inflation Factors (VIFs), we usually decide that a VIF over five indicates multicollinearity.[11] The following variables were included in the test for multicollinearity: pandemic unemployment benefits (the exposure variable), randomization term (covariate), infant sex (covariate), pandemic data collection (covariate), and earned income (covariate). The resulting VIFs were all around 1.0. Since these VIFs were under five, these variables are not correlated with each other and can be included in the model.[11]

Based on these steps, four confounders were included in the regression model: Infant sex, earned income, pandemic data collection, and randomization term.

Addressing repeated measures in the data

A generalized estimating equation (GEE) was used to account for the use of repeated measures across two time points. Having multiple time points presents unique problems. Time, as an additional factor, can show how things may adjust over intervals and provides a new layer of information with its own dependencies.[122] For example, data on child development is dependent on time. Time must be accounted for as children's abilities will continue to grow.[123] Controlling for time ensures that the temporality is upheld and is appropriately analyzed.[11] There are specific methods that are used to ensure that time is accounted for appropriately, however, some methods are better to suited to different analyses.[11]

One way to analyze repeated measures data is by using a derived variable, otherwise known as a change score. A change score would be generated for each infant to determine the difference in their percentile rank between time points. This is done by subtracting the score at one time point from the other.[11] A limitation of this method is that the implied effect from a change score may be in the opposite direction compared to the actual effect. This means that there is a chance for inferential bias to occur and the ability to infer causality is limited.[58]

Another method used to analyze repeated measures is a Random Effects Model (REM).[11] A REM is used when there is a random effect (also called *random factor)* present in the model. Fixed effects are when we collect data for all levels of a particular variable, whereas the random effects in REM may have a random sample and distribution of these different variable levels. To better account for these random effects or factors, a REM is used.[59] As an example, in the BFY study the random parameter would be the group that they were assigned to.[6, 32] However, this parameter is not being used to reflect randomization in this thesis, and is being assessed as a potential confounder. While the RCT used this variable, the way it will be handled in this secondary analysis (as a confounder) would not require the use of REM. This is because the random effect of this variable is not central to the research question of this thesis. Another reason REM was not chosen concerns the intention behind this study. The hypothesis is that the group who did not receive unemployment benefits will have weaker communication development than those who received this benefit. This hypothesis helps underline the key difference between GEE and REM: individual effect versus group effect.[11] This project will seek to understand the group effect pandemic unemployment benefits had rather than the effect on individuals. In this case, GEE is better suited to this data given it is focused on group effects.

GEE simultaneously analyzes associations between variables collected at different time points.[11, 124] GEE was the best method to address repeated measures in this thesis given that it is suited for measuring group effects.[11] GEE with linear regression highlighted the association between pandemic unemployment and infant communication development. Within GEE models, different correlational structures help to account for time in different ways.[11, 124] For example, one of these correlational structures (autoregressive) can specify that measurements taken closer together are more correlated.[124] In this thesis, the correlational structure chosen was ‘exchangeable’. An exchangeable correlational structure is used when all pairs of responses (time points for each individual) are equally correlated. Further, this study only had two repeated measures which is why exchangeable was chosen as the best fit. There were only two measures, which meant they were equally correlated to each other. If there were more measurements, the measurements may be unbalanced and a different correlational structure may fit better.[124]

Another decision to be made with GEE is to determine whether to use ‘robust’ standard errors. These robust standard errors incorporate non-constant variance into the calculation of standard error.[125] There is an assumption that needs to be met for linear regression that states that variance needs to be constant (homoscedasticity).[11] When robust standard errors are used, it incorporates non-constant variance and allows this assumption to be bypassed.[125] However, bootstrapping was used to account for the lack of normality within the residuals within linear regression. This is discussed in more detail in the next section. Bootstrapping is itself non-parametric, meaning that the normality assumption no longer applies.[11] In addition, when using a bootstrap there is no need to run robust standard errors as the conditions they account for do not apply.[11, 126]

Testing regression assumptions

There are four assumptions of linear regression that need to be met. The assumptions are linearity, normality, constant variance, and outliers. All these assumptions were met or did not apply, with each being outlined below.

Linearity

The assumption of linearity was met in this analysis. The linearity assumption states that the relationship between the exposure and outcome variables must be linear, usually tested using a LOWESS or a CPR plot.[11] However, one crucial exception to this assumption is the levels of the exposure variable. If the exposure variable is binary (meaning it has only 2 levels), then the linearity assumption is always true.[11] For this thesis, the exposure variable of pandemic unemployment benefits only had two levels (a household member received and no one received). Due to the variable being binary, this assumption is automatically met.

Normality

Normality of the distribution of the residuals is an assumption required by both GEE and linear regression. This assumption was not met by this data. When the residuals were plotted in a kernel density plot, the distribution of the residuals did not resemble the normal curve. In response to this, the regression model was bootstrapped (k = 5000) to account for any potential issues in sample size. Bootstrapping resamples a data set to create many simulated samples. It can resample from the data by creating a series of estimates for accuracy (such as variance, confidence intervals, or standard errors). These estimates allow a bootstrap to run many tests (with some participants being selected more than once) where it compiles their means to estimate the regression coefficient.[11, 127] Bootstrapping data makes the data itself non-parametric, which means that the normality assumption does not need to be met when it is used.[11]

Constant variance

Constant variance of the residuals is another assumption that is contested by bootstrapping. Bootstrapping resamples and reattaches residuals to fitted values.[127] This process begins to approximate and get closer to constant variance, however, is not perfect and constant variance may not be reached. In this case, constant variance should still be tested even if the assumption may be close to being exempted.[127]

This thesis tested constant variance using Levene's test on the non-bootstrapped regression. Levene's test is an alternate way of testing for homoscedasticity when the graphical approach of using a residual versus fitted plot is difficult to interpret.[128] Since the exposure variable of this thesis chapter was binary, the graphical approach would be difficult to interpret. Levene's test uses hypothesis testing to see if the difference in variance between groups is significantly different. The null hypothesis is that variance is homogenous between groups (homoscedasticity). When the values of the test are greater than 0.05 this null hypothesis cannot be rejected. In other words, the homoscedasticity assumption is met when the outputted values (labelled W0, W5, and W10) all exceed 0.05.[128] When this test was run for this thesis, without bootstrapping the regression, the values of these statistics were 0.4, 0.3, and 0.2, respectively. Since these all exceed 0.05, the null hypothesis cannot be rejected and homoscedasticity is met.

Outliers

Outliers are data points that go far outside of the average value and can affect the results. Typically, outliers at specified distances from the average are removed as they are said to be influential and skew the results of statistical tests.[11] A DFBETA statistic was used to assess for the presence of influential outliers. DFBETA statistics are in error units, much like a t-test. DFBETA quantify how much a coefficient would change if specific points were removed. In other words, these measures identify points that would skew the coefficient.[11] For this thesis analysis, a DFBETA statistic was run and its output, a box plot, is included as Figure 3. This boxplot identifies where outliers may exist that could potentially impact the results. Once the range of DFBETA statistics to test had been identified, usually those greater than 0.1 and less than -0.1, then the regression is tested with and without these points to determine their effect. These values indicate how much change would be observed in the coefficient if certain observations were removed. Values at a greater distance from zero, in the positive and negative direction, indicate a greater change in the coefficient.[11] For this thesis chapter, no DFBETA points were within the range considered to be influential on the coefficient (less than -0.1 and greater than 0.1).[11]

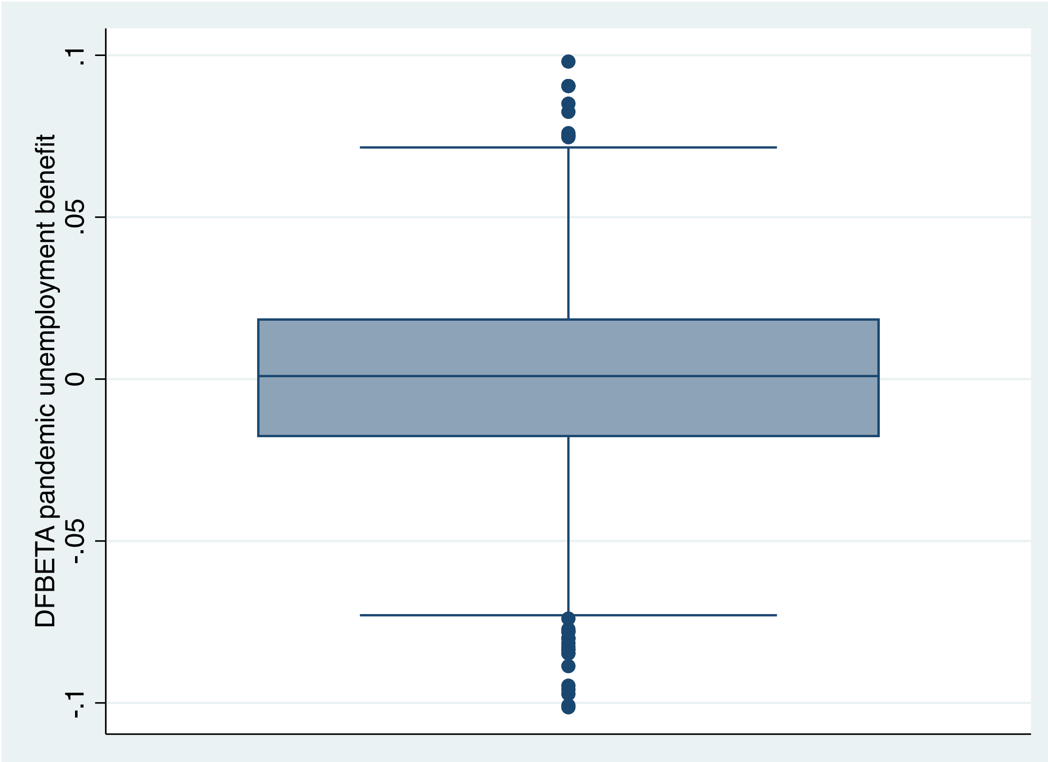

Figure 3: The resulting boxplot of the DFBETA statistic for pandemic unemployment benefits and communication development.

Final regression model

Linear regression was used with all assumptions being met, exempted, or addressed. The unstandardized coefficients were interpreted for both the unadjusted and adjusted regressions. Unstandardized regression coefficients are often interpreted in place of standardized coefficients, especially when the predictor variable is binary. Standardized coefficients, like Pearson's R, are expressed in standardized units and allow the effect to be interpreted with equal standard deviation when the variables may have different measurement units. Unstandardized coefficients estimate the difference in average values between two groups one at a time while holding the other group constant. Their interpretation is in the original units of the dependent variable, which means it is more directly interpretable. This advantage is useful in public health and clinical studies, as the results are in terms of direct units.[11] GEE was applied using an exchangeable correlational structure to address the balanced correlation of having only two repetitions. The GEE was bootstrapped (k = 5000) to improve the normality of the residuals. The confounders included in the model were infant sex, pandemic data collection, randomization group, and earned income. The statistical significance level used was α = 0.05, or 95% confidence intervals.

Missing data

This research planned to use multiple imputation (MI) to address missing data, however, only one variable contained missing data. Pandemic unemployment benefits had 9 individuals who either did not answer or did not know the answer to the question.[55] Since this amount of missing data (1.5%) falls below the 5% threshold where MI is minimally significant, MI was not necessary.[129] BFY had a very low loss to follow-up (8%), likely due to the monetary incentives offered by the study. BFY also prevented loss to follow-up over the pandemic by shifting to remote data collection methods.[6, 34, 55]

2.3 RESULTS

2.3.1 Sample description

Maternal age at infant birth ranged from 18-43 years (mean = 27 years, SD = 5.7 years). About 70% of mothers had a high school degree or less. About 10% had an associate degree or higher. About 45% of mothers reported that they were never married or single. As shown in Table 1, approximately 10% of mothers took maternity leave (paid or unpaid) after their infant was born. About 29% of mothers reported that this child was their first. About 16% of mothers reported that the father was incarcerated between the infant's birth and 1st birthday. About a third of mothers earned under $1,000/year. The average number of people in the household ranged from 2 to more than 9 (mean = 4.7 people, SD = 1.7 people). Half the infants were female. About 65% of the sample completed the age one interview before the pandemic began.

Unemployment benefits

Almost 40% of participants (n = 235) lived in a household that received an unemployment benefit during the pandemic. About 60% that received pandemic unemployment benefits reported the mother as the recipient. There was a higher proportion of single mothers who received pandemic unemployment benefits at 50% of this sub-sample, compared to 45% in the general sample. Further sociodemographic differences between the general sample and those who received pandemic unemployment benefits can be found in Table 3.

Infant communication development

The average infant communication z-score at age one was 0.24 (SD = 0.87), which translates to the 59th-percentile of the ASQ communication section. Compared to the median value the z-score is based on, infants in this sample demonstrated a slight improvement on average at 9-percentiles above the median. At age two, the average communication z-score for this sample was -0.33 (SD = 1.11), which is the 37th-percentile of the MBCDI. This represents a decline in language ability on average, when compared to the median. This sample had an average score 13-percentiles below the average reported by the MBCDI. Overall, there is a 22-percentile difference between the average reported at age one and two. A paired t-test was run and determined that the difference in means between age one and two was significant (p= 0.01). This decline in communication development is consistent with research on language deficits among infants in low-income families.[91] This is particularly relevant between ages one and two, as exposure to language and diversity of vocabulary is reduced in low-income families.[91]

The average age one z-score reported for those assessed before the pandemic was 0.25 (SD = 0.04). This is the 59th-percentile. Comparatively, one-year-olds assessed after the pandemic began had a z-score of 0.23 (SD = 0.06), or the 58th-percentile. When these means were compared in a t-test, it was determined that these two means were not significantly different at the 95% CI level (p= 0.80). At age two, however, there was a more pronounced difference in means. The average age two z-score for those assessed before the pandemic at age one was -0.25 (SD= 0.06). This is the 40th-percentile. The average age two z-score for those assessed during the pandemic at age one was -0.48 (SD= 0.08). This is the 31st-percentile. When the means were compared using a t-test at the 95% CI level, the difference was statistically significant (p= 0.01). This finding is consistent with the findings of Deoni et al., where infants had poorer cognitive development scores during the pandemic.[10]

2.3.2 Unemployment benefits and infant development

The hypothesis for this study was that infants in households who received pandemic unemployment benefits would have a stronger communication development trajectory than those in households who did not receive these benefits. When comparing the mean development scores between these groups, they both decreased. At age one, the mean communication score was the 62nd percentile among those who would be later exposed to pandemic benefits and the 58th percentile among those who would not be exposed to receiving these benefits. At age two the mean communication development score was the 42nd percentile for those who received the pandemic benefits, while the mean for those who did not receive these benefits was the 34th percentile. These means are shown in Figure 4 below. Mean scores decreased with age for both groups.

As shown in Table 4, in an unadjusted bootstrapped linear regression GEE model infants in homes that received pandemic unemployment benefits had, on average, a 0.15-unit increase in their communication z-score between ages one and two compared to those who did not receive this benefit (0.02 – 0.29).

As shown in Table 4, in a bootstrapped linear regression GEE model adjusted for infant sex, pandemic data collection, earned income, and randomization group, infants in dyads who received pandemic unemployment benefits had a 0.15-unit increase in their communication development z-score between age one and two (95% CI: 0.01 – 0.28) compared to infants in households who did not receive this benefit. The unit of this increase is that of a z-score, which ranges from -3 to +3.[130] The 0.15-unit increase in z-score (95% CI 0.01 – 0.28) represents a five-percentile increase from the mean between ages one and two for the group who received the pandemic unemployment benefit.[130].

Table 3: Sociodemographic characteristics of the full sample in chapter two (N = 606 mother-child dyads), and the subsample that received unemployment benefits (n = 235 mother-child dyads).

Sample characteristic	Full sample *N* (%)	Received unemployment benefit *n* (%)	*p* value
Total Sample	606 (100)	235 (100)	
COVID unemployment benefits			
Yes	235 (39.4)		
No	362(60.6)		
Randomization group			0.25
High stipend	265 (43.7)	110 (46.8)	
Low stipend	341 (56.3)	125 (53.2)	
Maternal age at infant birth			0.32
18-23	194 (32.0)	66 (28.1)	
24-29	232 (38.3)	101 (43.0)	
30-35	120 (19.8)	47 (20.0)	
36+	60 (9.9)	21 (8.9)	
Maternal education			0.37
Less than high school	120 (19.9)	40 (17.0)	
High school diploma or GED	311 (51.5)	120 (51.1)	
Some college, no degree	111 (18.4)	45 (19.2)	
College degree or higher	62 (10.2)	30 (12.8))	
Marital status			0.19
Never married	266 (44.6)	116 (50.2)	
Single, living with partner	145 (24.3)	48 (20.8)	
Married	140 (23.5)	53 (22.9)	
Separated/divorced/other	46 (7.2)	10 (4.3)	
Took maternity leave			0.49
Yes	63 (10.4)	27 (11.5)	
No	541 (89.6)	208 (88.5)	
Parity			0.33
Yes	173 (28.6)	73 (31.1)	
No	433 (71.5)	162 (69.0)	
Number of government supports*			0.02
1 or less	120 (19.8)	36 (15.3)	
2	170 (28.1)	82 (34.9)	
3	156 (25.7)	55 (23.4)	
4	79 (13.0)	35 (14.9)	
5+	81 (13.4)	27 (11.5)	
Biological father incarcerated between birth and age 1			0.17
Yes	88 (15.5)	28 (12.4)	
No	481 (84.5)	197 (87.6)	

Household earned income (annual)			0.03
$1,000 or less	210 (34.7)	66 (28.1)	
$1,100 - $9,500	105 (17.3)	39 (16.6)	
$10,000 - $19,500	128 (21.1)	58 (24.7)	
$20,000 or more	163 (26.9)	72 (30.6)	
Number of people in household			0.70
3 or less	153(25.2)	56 (23.8)	
4	159 (26.2)	66 (28.1)	
5	137 (22.6)	53 (22.6)	
6	79 (13.0)	27 (11.5)	
7+	78 (12.9)	33 (14.0)	
Pandemic data collection			0.28
Before pandemic	393 (64.9)	147 (62.6)	
During pandemic	213 (35.2)	88 (37.5)	
Child assigned sex			0.28
Female	303 (50.0)	125 (53.2)	
Male	303 (50.0)	110 (46.8)	

*Number of government supports represents the sum of 8 available support categories received by mother-infant dyads. Supports include unemployment, childcare subsidies, Supplemental Nutrition Assistance Program (SNAP or food stamps), Early Head Start, Medicaid, Women, Infants and Children (WIC), housing assistance, cash assistance, and other assistance by a public program.

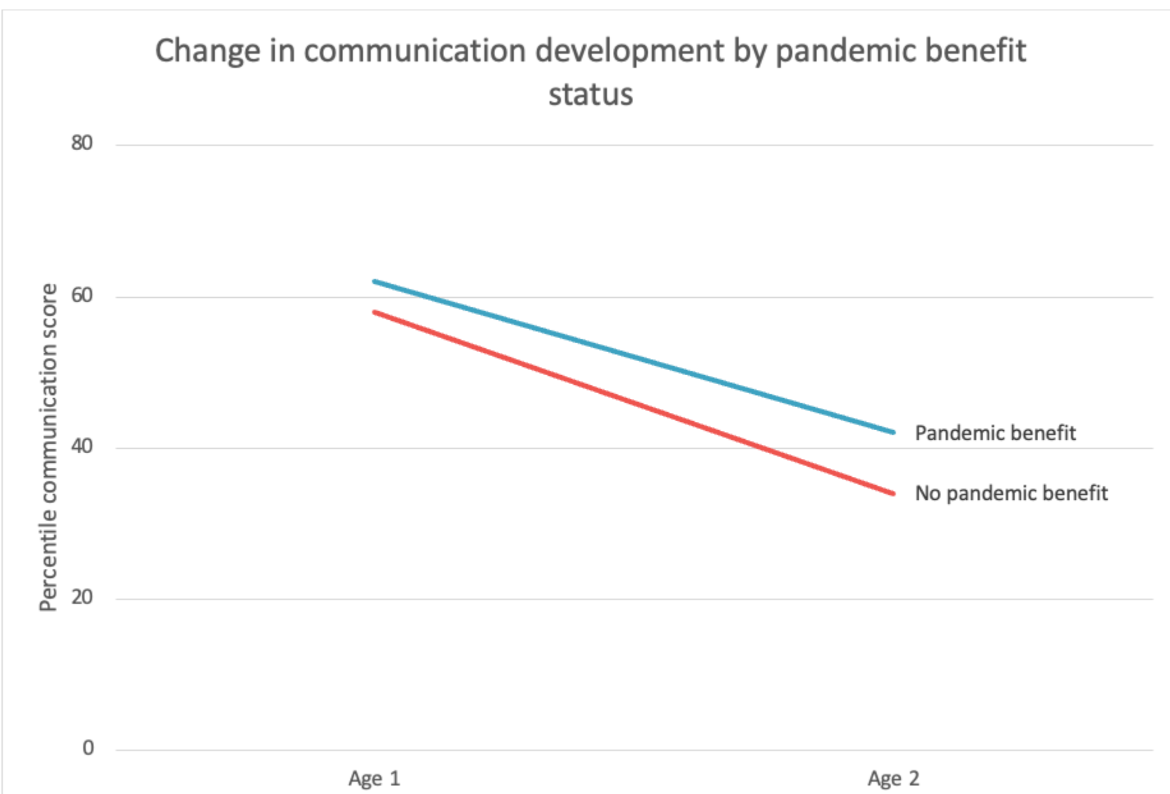

Figure 4: Changes in the mean communication percentile score over time for those that did or did not receive a pandemic unemployment benefit.

Table 4: Linear regression for pandemic unemployment benefits and infant communication development fit inside a GEE model (n = 597)

Variables	**%**	**Unadjusted β1 (95% CI)[1]**	**Adjusted β1 (95% CI)**
Unemployment benefit during pandemic			
No	60.6	Reference (0.0)	Reference (0.0)
Yes	**39.8**	**0.15 (0.02 – 0.29)**	**0.15 (0.01 – 0.28)**
Infant assigned sex			
Male	50.0	Reference (0.0)	Reference (0.0)
Female	50.0	0.05 (-0.00 – 0.09)	0.05 (-0.08 – 0.18)
BFY randomization term			
Low stipend	56.3	Reference (0.0)	Reference (0.0)
High stipend	43.7	0.02 (-0.01 – 0.05)	0.06 (-0.07 – 0.20)
Earned income			
$1,000 or less	34.7	Reference (0.0)	Reference (0.0)
$1,100 - $9,500	17.3	0.13 (-0.04 – 0.31)	0.14 (-0.04 – 0.32)
$10,000 - $19,500	21.1	-0.01 (-0.19 – 0.17)	-0.02 (-0.21 – 0.16)
$20,000 or more	26.9	0.09 (-0.08 – 0.26)	0.07 (-0.10 – 0.24)
Pandemic data collection			
Before pandemic	64.9	Reference (0.0)	Reference (0.0)
During pandemic	35.2	-0.12 (-0.24 – 0.01)	-0.12 (-0.26 – 0.01)

[1]This column represented the unadjusted regressions and the associations between the variable in each row with the dependent variable to determine whether this condition of confounding is met.

2.4 DISCUSSION

Results from this thesis chapter showed that communication development was stronger in infants whose low-income household received pandemic unemployment benefits, in a model fully adjusted for confounders. Consistent with the hypothesis, the effect was a weakly significant positive association between receiving pandemic unemployment benefits and infant communication z-score ($ß1 = 0.15$, 95% CI: 0.02 – 0.28). These findings translate to a five-percentile improvement in infant communication between ages one and two in families who received unemployment benefits, compared to those who did not receive the benefit.

This result, in context, does not necessarily mean that infants in households who received pandemic unemployment benefits had an overall increase in communication. When we compare the mean score for child development at ages one and two for this group, we see that the mean score went down for both infants whose families did and did not receive pandemic unemployment benefits. However, the decrease in the group who received benefits was less than the group who did not. This is highlighted by the group who did not receive these benefits having a 24-percentile decrease in infant communication score, compared to the 20-percentile decrease observed in those that received the benefit. In other words, the result is indicating an attenuated decline in one group compared to the other. When looking at the GEE results, the difference in the decline in development was five-percentiles less for those who had pandemic unemployment benefits in the fully adjusted model.

In the context of the MBCDI, a five-percentile difference can represent a large difference in the number of words a child can say. A two-year-old in the lower 10^{th} percentile may produce about 10 words. In comparison, a two-year-old in the top 10^{th} percentile can produce around 300 words.[131] While a mere five-percentile (or 0.15 units of standard deviation) difference may be viewed as small at the individual child level, it may present a substantial effect at the population level. Pandemic unemployment benefits were a population-level intervention. The population approach, while it may offer little benefit to the individual, gives insight into the systemic factors that improve, worsen, or moderate risk. Understanding how population factors, such as pandemic unemployment benefits, impact larger groups can help develop policies and programs.[132]

2.4.1 Building on previous findings

These findings support the developmental theory that informed them; that changes in the infant's environment impact their development.[74] What this research has shown is that the impact of negative environmental changes on infant development can be reduced through a population-wide intervention. By alleviating the family stress of income after job loss, pandemic unemployment benefits created a positive change in the infant's environment that reduced the negative impact of COVID-19. This is supported by research on supplemental income programs and the improvements they have had on infant development and wellbeing.[32, 84, 133] Providing stability in income has shown to have an effect on development, and this thesis chapter highlights how important this is during a crisis.[32, 84]

The findings of Deoni et al also support this thesis chapter, as the results indicated the negative effects of the pandemic on child development. Deoni et al. completed a study that looked at infants under one year of age and compared their scores on the Mullen Scales of Early Learning (MSEL) based on their birth year. This research compared birth cohorts from 2018 and earlier to those born after March 2020. Those born in mid 2020 to 2021 had a 27-to-37-point decrease in the MSEL. This difference is equivalent to almost 2 full standard deviations, indicative of a very strong effect.[10] This research was ground-breaking and was one of the first to support the observations of teachers, parents, and researchers with evidence of a potential cognitive difference in infants and children who experienced the pandemic.[134-136] The finding that the pandemic had a negative effect on infants is supported by the findings of this thesis, which found that infants performed poorer than the median after the pandemic. This effect was regardless of if their household received pandemic unemployment benefits or not.

This thesis and the research of Deoni et al. complement one another, since they measure different stages of learning.[10] While Deoni et al. focused on infants at one year of age, this thesis chapter looked at the year beyond this measurement.[10] Young children are able to adapt and overcome adversity in supportive environments.[14, 15, 137]. Providing children with adequate resources, or even improving the stability of their life, can allow them to adapt to the adverse circumstances around them.[15, 137-139] Providing families with a maintenance of income through pandemic unemployment benefits may have reduced developmental impairments in their babies, allowing them to adapt to pandemic adversity. This is especially interesting when we consider how Deoni et al. looked at the very early effects (under one year) and this thesis looked at later effects (between ages one and two).[10] At this stage, this is only a hypothesis. This theory of adaptation, however, should be explored in future research on infant development and global disasters in early life. However, the findings of this thesis are plausible. Deoni's study puts the findings of this thesis into perspective by highlighting the negative impact of the pandemic alongside the positive impacts of unemployment benefits in this critical period.

2.4.2 Strengths and limitations

This thesis chapter has two strengths: continuous data collection and study design. Maintaining data collection throughout the pandemic was no small feat. Where other studies may have had to make major modifications to their protocols or delay their collection timelines, the dataset for this thesis only had slight modifications to its delivery.[6, 34] While this presented a slight delay in measurement, the tools used could be easily adapted for the child's age. Not only did data collection continue, but it also upheld its validity when faced with the unique challenges of the pandemic. The robust, longitudinal design of this thesis is also a key strength supported by that data collection. The design focused on whether the effect persisted over time, rather than occurring at one point. However, only two time points were analyzed. More data points are needed to understand this potential effect beyond one year.

This thesis research has five weaknesses: non-random assignment to the exposure variable, potential measurement error, limited generalizability, residual confounding, and missing data. The first weakness was that the sample was not randomly assigned to the exposure variable. Receiving pandemic employment benefits, while the central question of this research, was not the primary focus of the BFY RCT. This variable was not randomized, which limits the internal validity. Having random assignment would help limit any residual confounding and would determine the effect of receiving unemployment benefits would have on any family.

The second weakness was that there was potential measurement error. The change in measurement tools used, from the ASQ at age one to the MBCDI at age two, may have introduced some measurement error. The ASQ looks at milestones that have been met or attempted, and the MBCDI looks at the number of words a child knows.[39-41] Comparing these different measurements of communication is a weakness, however, the measurement at age two better captures communication development at this stage.[39, 110] Another potential source of measurement error was identified as the date of the age one interview. Usually, infants completed this interview within a window of time. When the pandemic occurred, some infants had their interviews postponed but used updated tools for their age.[6, 34] About 65% of the sample completed the age one questionnaire before the pandemic. However, there was an 9-percentile difference in the mean at age two between those who completed the age one measurement before or during the pandemic. Those who completed during the pandemic performed poorer than those who completed the measurement prior to the pandemic. These results indicate a potential for measurement error, as the scores are different between these two groups. While this was handled as a confounder in this thesis chapter, future research should look deeper into this potential effect to determine its significance.

The third weakness was that this thesis research may have limited generalizability. An exclusion criterion for this thesis chapter was that infants must not have had a diagnosed neurological condition at birth. This thesis research is not generalizable to all infants as a result of this criteria. The results are only generalizable to children born without any identified delays at birth. Another factor limiting generalizability was that the sample was truncated to include only low-income families. Since all dyads identified as being in poverty, these findings are not generalizable to all income levels.

The fourth weakness of this thesis was that certain elements of the pandemic were not accounted for, meaning there was likely residual confounding. The literature when this thesis was proposed indicated that maternal education, child sex, and income were important factors to consider. However, as the pandemic evolved and literature expanded, other potential confounders emerged such as changes to childcare or the home environment.[140, 141] There were no variables in the RCT on how much time parents spent at home during the pandemic, or if there were changes to their home environment or childcare. These are likely important factors, as sudden changes in environment have been shown to impact child development.[142-144] Particularly, changes in child care arrangements have been documented as negatively impacting child development and behaviour.[142] This is relevant to this thesis as changes in childcare and home environment occurred for many families in the pandemic, particularly those of low-income.[2, 141] It is likely that these factors may be residual confounders and should be analyzed in future research.

The fifth weakness of this study is missing data. The exposure variable, pandemic unemployment benefits, had nine dyads who did not know or did not answer whether they received these benefits. This missing data could have impacted the results. However, the amount of missing data was relatively small (1.5% of the sample) and this likely limited its potential impact. In addition, the BFY study overall had a high rate of follow-up, at about 92%. This high degree of follow-up also alleviates some of the concerns around missing data, as most participants who began in the study remained in it.

2.4.3 Directions for future research

The findings of this thesis chapter suggest pandemic unemployment benefits may have strengthened infant communication development within low-income homes. There is a need to expand research in this area to develop our understanding of how these forms of assistance can impact child well-being. Future research should focus on exploring whether there is a difference in development based on the dollar amount of unemployment benefits received. The research that has begun on supplemental stipends is showing promising results in this area, however, this research should also develop protocols that have more robust definitions and measurements of job loss and benefit receipt.[32, 133, 145] Future research should investigate the effects of maintaining these programs and how a sudden loss of them may result in changes in child development.

2.5 CONCLUSION

The pandemic disproportionately burdened low-income families. This study found communication development may be stronger in infants from low-income households who received pandemic unemployment benefits, in a model fully adjusted for confounders. This research highlights the importance of unemployment benefits for low-income families impacted by a crisis. There is a need for quantitative and qualitative research on how receiving benefits may have impacted the development of infants in low-income homes. This research should be centered around how these benefits are used or important during crises such as floods, droughts, and recessions. This would help to understand the effect of these benefits and the stability they provide during unstable life events.

3.0 CHAPTER 3

CONTRIBUTION OF AUTHORS

Mahala Swisterski, Master of Science student, was the primary author of this thesis. The work within chapter three will be condensed and submitted for publication after the defense date. Cheryl Currie, Robbin Gibb, Richard Larouche, and James Sanders will be listed as co-authors on the intended publication. I conceptualized and designed the secondary analysis, determined the research question, analyzed the data, drafted the original chapter, and critically reviewed and revised the chapter. Cheryl Currie assisted in the conceptualization and design of the research, supervised the data analysis, and critically reviewed and revised the chapter. Richard Larouche, Robbin Gibb, and James Sanders critically reviewed and revised the chapter.

ABSTRACT

Introduction: The home environment has significant impacts on how infants grow and develop. Reading books to infants has been shown to improve their later language abilities. The objective of this post-hoc analysis was to test whether there was an association between reading books to infants and their subsequent communication development over a one-year period.

Material and methods: This study used data from the Baby's First Years Study, which collected longitudinal data from approximately 600 mother-infant dyads living in low-income homes between 2018-2021. Families were recruited from hospitals in low-income neighbourhoods across several US cites. Women with self-reported incomes that fell below the US poverty line were invited to participate. Data were collected in-person between 2018-2020 and transitioned to telephone in 2020 due to the COVID-19 pandemic. The outcome variable, infant communication, was measured with the Ages and Stages Questionnaire at age one and the McArthur-Bates Communication Development Index at age two and was analyzed on a continuous scale. The exposure variable, reading books, was a categorical variable that measured how often mothers read books to their infants. Data were analyzed in Stata using linear regression and generalized estimating equations. Adjusted results were stratified based on whether the age one data was collected before or during the pandemic. These were adjusted for infant sex, maternal education, randomization term, and earned income.

Results: Overall, approximately 33% of mothers in this study read books to their infants every day. Reading books every day was significantly associated with changes in infant communication development scores ($\beta 1 = 0.33$, 95% CI: 0.15 – 0.52). When stratified by pandemic data collection at age one, the adjusted association between reading frequency and communication development was significant for infants whose age one measure was recorded prior to the pandemic. This same adjusted association was not significant in infants whose age one measurement was recorded during the pandemic.

Conclusion: Reading frequency was associated with communication development, with pandemic measurements influencing its significance and highlighting its external impacts.

3.1 BACKGROUND

Early language exposure is critical to infant communication development. A 2020 systematic review highlighted how reading to infants can improve their expressive and receptive language abilities with increased doses of reading improving the effect.[23] These improvements are further aided by parents being engaged in the reading process, such as asking questions and re-reading sections.[24] Stress, such as having low-income, may impact the association between reading and communication development.[28, 146] When exposed to chronic stress, infants can have maturational lags in brain development and exhibit alterations in brain function. The effects of which are long-lasting and can be noticed early.[26, 27] What is not yet understood is whether the positive impacts of reading persist in low-income environments.

3.1.1 Infant communication development

The primary outcome in this chapter is infant communication, which is the bedrock of learning. Achievements in early language learning have consistently indicated later developmental success.[85, 86] A 2020 systematic review found a longitudinal association between eye gaze following (an early communication skill in infants between 0 and 24 months old) and later receptive and expressive vocabulary.[87] Early and simple communication skills build the mechanistic foundations for later learning, making this early period especially important for development.[87] Communication shifts from largely non-verbal to verbal shortly after age one.[88, 89] The communication skills built between ages one and two contribute to later reading and language abilities.[89] Between the ages of one and two, a shift occurs in the number of words a child knows and is able to say. Toddlers at 24 months of age who know less than 50 words and cannot say two-word sentences are said to be ‘late talkers’.[89, 90] Late talkers are at risk for reading, behavioural, and language problems, all of which can affect their later life.[89, 90] There is evidence to suggest that infants in poverty are disadvantaged, based on differences in early language learning opportunities.[91]

3.1.2 Population focus: Low-income households

This thesis focuses on low-income families in the United States (US). Poverty is defined in the US by two factors: household income and the number of people living in the household. The US threshold for poverty changes yearly and increases with household size. In 2021, the threshold for a four-person household was $26,500. If a family made that amount or lower, they would be considered ‘under the poverty line’.[92] This is in contrast to the median household income, which in 2021 was $70,784.[93] It is estimated that 11.6% of the total US population was living under the poverty line in 2021.[93] To qualify for programs like the Supplemental Nutrition and Assistance Program (SNAP or ‘food stamps’), families must meet a percentage multiplier of the poverty threshold to be eligible (such as 125 percent).[94] Experiencing poverty in the US involves navigating the balance between having access to essential benefits and generating income to overcome financial challenges.

Notably, poverty puts infants at risk of delays in development and creates gaps in access to vital supports and services.[95] A key part of communication development is how much the baby hears and is exposed to language, and this differs significantly by income level. The relational effect between income and language exposure has been dubbed the ’30-million gap’, as infants in more advantaged families had 30 million more words directed at them before age four than infants in poverty.[91] This difference has predicted long-term outcomes such as late talking, difficulty reading, and challenges in school.[96, 97] Studies estimating the prevalence of language delay among low-income countries have found that even when the disparities in income were not large, the prevalence in language delays remained high at about a quarter of the total population aged 36-59 months.[98]

While poverty can negatively affect infants and parents, cash assistance programs have proven to be effective. The Baby’s First Years Study found that low-income families that received high stipends ($333 per month), simulating additional government assistance, had babies with improved brain activity compared to the control.[32] For low-income families already susceptible to poor birth and infant outcomes, these findings add to a constellation of factors that can impact their infant’s well-being.

3.1.3 Research objective

This thesis chapter sought to address a gap in our understanding of reading and early communication development in infants in low-income families. The main objective of this research was to understand the association between reading frequency and early communication development in low-income families. A secondary objective was to assess if data collection during the pandemic at age one influenced this association. Pandemic data collection at age one was examined as a potential interaction term.

3.2 METHODS

3.2.1 Design and setting

This thesis chapter is an exploratory post-hoc analysis, meaning that the research question was formed after the initial proposal had been submitted and data analysis had begun.[70] This thesis chapter used a secondary repeated measures analysis of the Baby's First Years (BFY) randomized control trial (RCT).[29] The BFY study is affiliated with many institutions in the United States including Duke, New York University, Columbia University, UC Irvine, University of Maryland, and the University of Wisconsin. This study is ongoing, with data collected yearly from birth.[6, 108] The analysis in this thesis chapter prospectively followed the cohort between the years of 2018 and 2021. BFY was registered with Clinicaltrials.gov in 2018 (national clinical trial number NCT03593356).[6] This secondary analysis of the data was approved by the Health Research Ethics Board at the University of Alberta (Ethics ID Pro00129505).

BFY recruited participants from low-income metropolitan areas in the US including New York City, Greater New Orleans, the Twin Cities (Minneapolis and St. Paul), and the Omaha metropolitan area. These recruitment sites were chosen to obtain a diverse sample across regions that varied in the cost of living and the overall amount of state safety net programs.[6] Participants in BFY were randomized to receive a monthly stipend for 52 months. The high stipend group received $333 per month and the low stipend group received $20 per month from birth until the infant was 52 months of age (a little over 4 years). This period occurred between May 2018 and late 2023.[6, 108] Local officials in each state ensured that the stipend from the BFY trial did not disqualify the individuals from receiving state benefits.[6] BFY began recruiting dyads in 2018, and has since collected data every year on these same dyads. Dyads were recruited at the hospital within 1-2 days of the child being born.[6] This thesis used data collected from birth, age one, and age two.

3.2.2 Sample

Mothers in the BFY study had to self-identify as being 'under the poverty line' the year prior to be included in the study.[6] Being 'under the poverty line' is determined by family income relative to the number of household members.[92] Mothers were provided the general definition and self-assessed based on this definition. Included mothers were over the age of 18, living in the recruitment state, and had the baby discharged to their care. Dyads were eligible if the baby was in the nursery, and were excluded if the baby had been admitted to the NICU.[6] Babies were excluded if they had a diagnosed neurological condition at birth.

BFY had an overall sample size of 1,000 at baseline, 931 at age one, and 924 at age two. Follow-up for the BFY study was high, with a 92% retention rate over the three years included in this thesis.[34] The most common reason for loss to follow-up was a loss of contact (i.e. the research team could not reach participants for follow-up), representing 72% of lost dyads between birth and age one. Other less common reasons were infant death, maternal incarceration, and refusal of the mother to be re-interviewed.[34, 35] To engage mothers, text message notifications were sent every month when their stipend was loaded onto their study-affiliated debit card. High retention was likely aided by the monthly stipends provided to mothers, which represented the randomization term. Every dyad received a stipend loaded onto a study debit card, without any restrictions on how it could be used. The high stipend group (the experimental group) received $333 a month, while the low stipend group (the control) received $20 a month.[6]

For this analysis, dyads were removed if the baby had a diagnosed neurological condition at birth (n =7) or if they did not complete either of the communication development tools (n =311). The sample size for this thesis analysis was 606 dyads followed from 2018 to 2021.

3.2.3 Variables

Outcome variable: Communication development. The gold standard for measuring infant development is the Bayley III assessment. This tool has excellent inter-rater reliability and is the most-widely used tool to quantify infant developmental progress.[109] However, the Bayley III is a lengthy test and requires a trained professional to administer.[37] Thus, the BFY study opted for more accessible alternatives including the Ages and Stages Questionnaire (ASQ) and the McArthur-Bates Communication Development Inventory (MBCDI). These tools are valid, reliable, and can be compared to each other.[39-41] In addition, these tools could be completed remotely which ensured safety and continuous data collection during the pandemic.

The communication section of the ASQ was conducted at age one (2019-2020) and the MBCDI was completed at age two (2020-2021). These measurements are well-suited for their respective ages, and both provide a numeric score that can be standardized.[39-41] When measuring language, the MBCDI is much more complex than the relevant portion of the ASQ.[39] While they are correlated, the MBCDI should be used when available as it is superior in its assessment of language development.[39-41] In this case, the MBCDI was used at age two since it is a more comprehensive evaluation of language at this age.[110]

The z-scores, otherwise known as standardized scores, of the ASQ and the MBCDI were used in this thesis analysis.[111] Z-scores were generated for each measurement of communication development. The ASQ outputs a score which the BFY study converted into a standardized z-score.[34, 112] The MBCDI outputs a percentile rank based on literature and extensive research by the developers.[43, 49] These percentile ranks were converted to z-scores to compare with the ASQ.[111] Z-scores and percentile ranks are often converted between each other as a way to measure a score relative to the average. Z-scores measure the distance from the mean in units of standard deviation. Percentile ranks, on the other hand, represent the percentage of scores that are lower than it. Percentile ranks, however, are based on the normal curve which means that the percentiles are also based on units of standard deviation.[113] This highlights how these two measures can be converted from one to the other for analysis, but choosing which to use is often a difficult task. While percentile ranks are generally easier to interpret, generating cut points across two measurements can be challenging and may lead to a misinterpretation of the results.[113] For the ASQ, its cut-points represent whether the infant should receive targeted parental support or professional care.[42] These cut-points do not exist for the MBCDI, which measures how many words a child knows rather than whether a child has attempted certain verbal skills like the ASQ.[42, 49] In order to avoid this potential misinterpretation of varying cut-points, this thesis will compare z-scores as it was determined to be a more robust and accurate measurement.

Exposure variable: Reading frequency. The variable ‘reading frequency’ was assessed using the question: “*How often do you read books or look at pictures in a book with [child name]?”.* Response options were ‘every day’, ‘a few times a week’, ‘a few times a month’, and ‘rarely or not at all’. This variable was included as part of the age one and two interviews in 2019-2020 and 2020-2021, respectively.[34, 55] This variable was collapsed into three categories, ‘A few times a month or less’, ‘A few times a week’, and ‘Everyday’.

Interaction term: Pandemic data collection. The variable ‘pandemic data collection’ was assessed by assigning a category to the date that the age one measurement was taken. March 3, 2020 was chosen as the cut-off date as this had been used in other studies assessing the impact of the pandemic.[10] If the age one measurement had been completed before this date, dyads would be assigned to a category of ‘before pandemic’. If the age one measurement had been completed after this same date, dyads were assigned to a category of ‘during pandemic’. This was not done with the age two measurement as all infants were measured during the pandemic.

3.2.4 Covariates

Four maternal covariates were examined in this chapter: education, income, marital status, and parity. Maternal education was measured by asking mothers their highest level of education, and categorized as: less than high school, high school diploma or equivalent, some college, associate degree, and bachelor’s degree or higher. Income was measured as the earned income of the family, which was measured by the BFY RCT. This measure estimated the annual income that they earned and was later categorized. Marital status was assessed by asking mothers to state their marital status at the baby’s birth: never married, single living with a partner, married, separated, divorced, and widowed. Parity was measured at birth by asking mothers if this was their first child (yes or no). These variables will be referred to as “*maternal education*”, *“income*”, “*marital status*” and “*parity*” throughout the rest of this chapter.

One infant covariate was examined in this chapter: assigned sex. Assigned sex was assessed at birth, with mothers reporting their infant as male or female. This variable will be referred to as “*infant sex*” for the remainder of the chapter. Infant age was not examined as a covariate given infant development was assessed at the same age for all participants in the study.

Two additional covariates were also included as variables in the analysis. First, a variable was created to indicate whether the first data collection time point took place before or during the pandemic. If the age one interview was completed after March 3, 2020, it was categorized as taking place during the pandemic. This variable will be called “*pandemic data collection*” for the remainder of the chapter. Age two data collection took place during the pandemic for all participants. Thus, the timing of its delivery has not been included as a covariate in this thesis. Second, given the use of an experimental dataset for this thesis that randomized families into groups, the randomization group will be controlled for as a potential confounder. Mother-infant dyads were randomized to receive either a high monthly stipend of $333 for 52 months or a low monthly stipend of $20 for 52 months. Thus, those in the high stipend group received more than 10 times the amount of those in the low stipend group.[6] Approximately 44% of the sample that met inclusion criteria for this secondary analysis received the high stipend. This variable will be referred to as "*randomization group*" for the remainder of the chapter.

3.2.5 Bias

Selection bias may be present in the BFY study through differential loss to follow-up.[70] Those receiving the higher stipend may be more likely to remain in the study. Although it is not the exposure of interest in this thesis, it may affect the results. This was assessed in this thesis using cross-tabulations of subsamples. The tabulation of the treatment group at birth was compared to the same tabulation at age 2, to assess how many participants in each condition were missing. By age 2, 924 of the original 1,000 participants were retained in the study. Of those missing, about 5% of the total sample had been assigned to the high stipend group and 2% had been assigned to the low stipend group. The percentage missing from each of these groups does not differ greatly, however, this difference opposes what was expected. It is not clear in the study design whether participants continued receiving the stipend after contact was lost. If these gifts had continued despite a loss of contact, it may explain the slight differential loss to follow-up. The high-stipend group may be less motivated to keep contact, as the amount of money may be significant enough that they may not feel the study is relevant for them after seeing a benefit.

The BFY study used three different methods to minimize differential loss to follow-up. The first of these methods was to ensure that enrollment and stipend receipt were not linked. Only after consent was obtained and the baseline interview was complete were participants randomized to the stipend amount. The other method involved the amounts themselves. Though the control group received a much more modest amount, $20 compared to a potential $333, all participants received stipends and were not disqualified from state-level supports. The third method used concerned how individuals got their funds. The stipends were loaded onto a pre-paid debit card every month for both groups. Having the gifts loaded onto a debit card ensured that the study did not solely include those with pre-existing connections to financial institutions. This ensured consistent, reliable compensation processes that remained standard between the groups.[6]

Information bias occurs when a flaw in the measurement of the variables leads to reduced internal validity.[70] When the BFY study began, interviews were completed in-person, but switched to data collection by phone during the pandemic. Thus, in-person measures were missing for some participants at various time points (e.g. hair cortisol samples).[6, 34, 35] Given this change occurred, a variable was created to assess if shifting data collection to phone was a confounder of the exposure-outcome association being examined.

3.2.6 Analysis strategy

Descriptive analysis

Univariate analyses were used to describe the variables examined in this chapter including frequencies, crosstabulations, means, standard deviations, and ranges.

Hypothesis testing

The research question for this chapter was: How does reading frequency impact communication development trajectories among infants in low-income households? The hypothesis was that infant communication development was stronger in homes with increased frequency of reading. A linear regression model was used to examine if infant communication z-score was stronger in households that read to their infants more frequently. Infant communication development was operationalized as the difference in infant communication z-score between age one and two. This difference in infant communication scores was examined as a continuous variable. A linear regression is typically used to understand how the average value of a continuous outcome varies over levels of an exposure variable.[11] This fits the research question, as it examines changes in the average value of infant development by the frequency infants were exposed to reading.

Assessing confounders

Seven covariates were examined as potential confounders of the association between reading frequency and infant communication development. These were chosen *a priori* based on existing literature: maternal education, earned income, marital status, parity, infant sex, pandemic data collection, and randomization group. Six criteria were used to determine if these variables confounded the association.[12]

First, the *a priori* variables that are to be included in the model based on research are described. These variables are then presented in a directed acyclic graph (DAG) to visualize potential associations between these variables.[70] Next, the association of these potential confounders is assessed with the independent and dependent variables separately. Then, these potential confounders are assessed for whether they sit on the causal pathway between reading frequency and infant communication. When a variable sits on the causal pathway, it means this variable is a step linking the source to the cause. This typically determined using a DAG to understand the direction and placement of the potential confounder.[12] The associations were further tested using Greenland's rule. Finally, variance inflation factors (VIFs) were used to assess if the potential confounders included in the model are correlated with each other. Each of these steps is outlined below.

Four variables were included based on *a priori* research. These potential confounders had direct noted effects in prior research. These four potential confounders were included in the final model, notwithstanding other confounding criteria in order to align with the findings of previous research.

Infant assigned sex at birth was determined to be an *a priori* covariate. There is evidence that there are sex-based differences in communication development and neurodevelopment disorders.[65] Not including infant sex could potentially bias the results, especially considering potential differences in scores. Other studies have determined that essential diagnostic criteria, such as sex in this case, are included as potential confounders.[115, 116] The other *a priori* covariate was income. There is evidence to suggest that poverty has an effect on infant physical and neurocognitive development.[91, 97, 117-120] Even though every dyad identified as being in poverty, the estimated earned income could have differed between each dyad.[6] Thus, due to its potential impact, income was included in the final model. Another *a priori* covariate was pandemic data collection. Part of the sample completed the measurement before the pandemic, and part of the sample completed the interview during the pandemic. Research by Deoni et al. highlighted the pandemic as impacting child development. This study found a significant difference among infants born and assessed for cognitive development during the pandemic, compared to infants born and assessed before the pandemic.[10] The final *a priori* covariate was the randomization term. This variable is a randomization term of receiving a stipend of either $20 a month (low stipend) or $333 a month (high stipend). The increase in income in the high stipend group is about $4,000 per year. This amount is significant, as it would increase the average income for a family of three in poverty by about 20% per year.[6] When we consider the impact of being in poverty on child development, we must also consider how this stipend may play into the intricacies of income.[91, 97, 119]

Figure 5 shows the DAG created using the software daggity.[121] This DAG offers a visualization of the potential associations between these variables.[70] The DAG suggests that the covariates do not lie on the causal pathway between reading frequency and infant communication. The bidirectional arrows in the DAG suggest that these covariates may be non-causal. In the case of infant sex, pandemic data collection, marital status, maternal age and randomization group, the single arrow suggests that these covariates do not lie on the causal pathway. In a DAG, causal associations are represented by an arrow moving in one direction from exposure to covariate to outcome. This information from the DAG is used to inform the next step, which is determining whether any confounders lie on the causal pathway.[12]

Maternal education does not lie on the causal pathway, as education occurred and was measured prior to the infant's age one interview where reading was assessed. Reading to the infant would not have influenced the education of the mother, by this same logic of measurement order. Parity also does not lie on the causal pathway as it was measured at infant birth, however, having multiple children may impact the prioritization of reading.

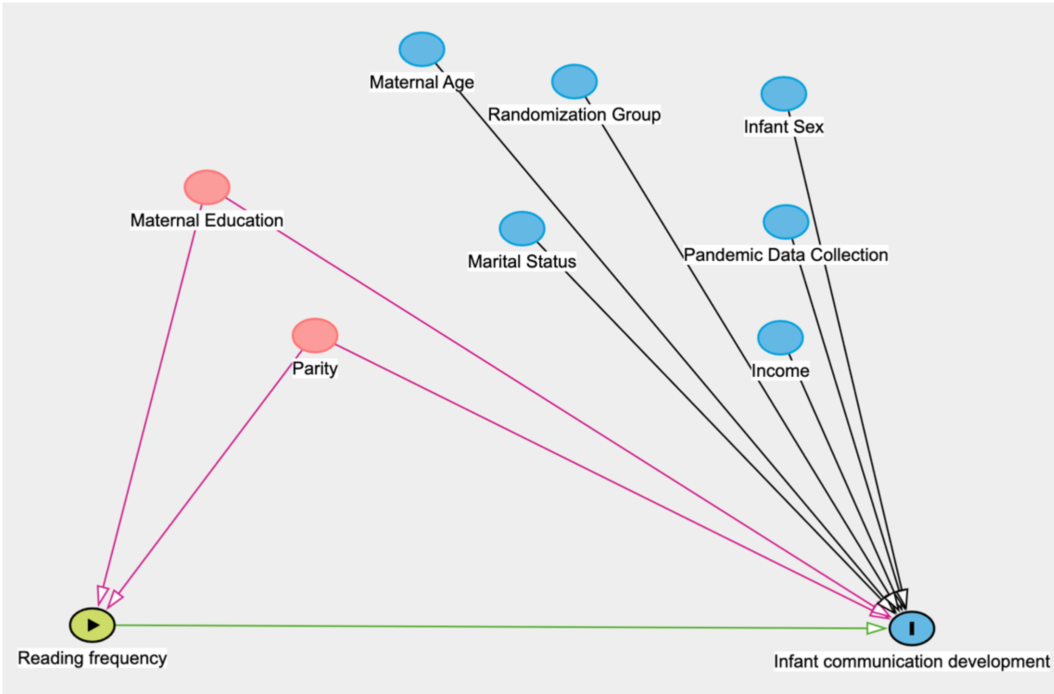

Figure 5: A DAG of the association and the potential confounders in chapter three. Blue covariates have a single directional arrow, whereas pink covariates show a bidirectional arrow not on the causal pathway.

Next, each covariate identified in the DAG was assessed for its association with the exposure and outcome.[11, 70] In Table 5 below, the associations were assessed and are presented. These associations were determined using simple linear regressions. Bolded cells indicate significant associations.

Table 5: Statistical tests for each potential confounder with the exposure and outcome variable in chapter three.

Potential confounder	**Association with reading frequency (95% CI)**	**Association with child communication development (95% CI)**
Maternal education	***0.12 (0.07 – 0.16)***	***0.06 (0.01 – 0.12)***
Infant assigned sex	0.06 (-0.03 – 0.16)	0.03 (-0.08 – 0.15)
BFY randomization term	**0.13 (0.04 – 0.23)**	0.05 (-0.06 – 0.17)
Maternal relationship status	-0.01(-0.06 – 0.3)	-0.06 (-0.11 – 0.00)
Annual estimated earned income	0.00 (-0.03 – 0.042)	0.02 (-0.02 – 0.07)
Pandemic data collection	0.09 (-0.2 – 0.19)	-0.14 (-0.26 – 0.02)
Parity	-0.03 (-0.07 – 0.00)	0.03 (-0.01 – 0.07)
Maternal age	0.01 (-0.00 – 0.02)	0.00 (-0.01 – 0.1)

Greenland's rule was tested next for the significant associations. It states that the regression coefficient of the association must change by 10% or more to be included in the model.[11, 60] When maternal education was adjusted for in the model, the coefficient changed by more than 10% (10.31%). This meant that maternal education was included in the model since it met Greenland's rule. The *a priori* variables (infant sex, earned income, pandemic data collection, and randomization term) were not assessed for Greenland's rule. These variables were not significantly associated in Table 5 above, however, their noted effect in research supports their inclusion in the model. Since their association was not significant, Greenland's rule was not tested.

Variance inflation factors (VIFs) determine whether the variables being used (including the covariates) are correlated to each other. This effect of many variables being correlated to each other outside of the XY association is called multicollinearity. When testing for multicollinearity with VIFs, we usually decide that a VIF over five indicates multicollinearity.[11] Said another way, if a VIF is greater than five the variables in the list are too correlated with each other to all be included in the model.[11] The following variables were included in the test for multicollinearity: reading frequency (the exposure variable), randomization term (covariate), infant sex (covariate), pandemic data collection (covariate), maternal education (covariate), and earned income (covariate). The resulting VIFs were all around 1.0.

Since these VIFs were under five, these variables are not correlated with each other and can be included in the model.[11] Based on these steps, five confounders were included in the regression model: Infant sex, earned income, pandemic data collection, maternal education and randomization term. Since pandemic data collection was the stratification term, it was omitted as a confounder in the stratified analysis.

Interaction: Pandemic data collection

The age one measurement occurred between mid-2019 and mid-2020. Since the measurement dates depended on the infant's birthday, some infants were assessed during the pandemic. This may have produced different effects on the outcome based on whether the infant was assessed prior to or during the pandemic. To test this, the sample was stratified for each of these groups (measured before pandemic and measured during pandemic). The results were compared between these two groups to assess for changes in effect size and significance.[11]

Addressing repeated measures in the data

A generalized estimating equation (GEE) was used to account for the use of repeated measures across two time points. Having multiple time points presents unique problems. Time, as an additional factor, can show how things may adjust over intervals and provides a new layer of information with its own dependencies.[122] For example, data on child development is dependent on time. Time must be accounted for as children's abilities will continue to grow alongside the child.[123] Controlling for time ensures that the temporality is upheld and is appropriately analyzed.[11] There are specific methods that are used to ensure that time is accounted for appropriately, however, some methods are better to suited to different analyses.[11]

One way to analyze repeated measures data is by using a derived variable, otherwise known as a change score. A change score would be generated for each infant to determine the difference in their percentile rank between time points. This is done by subtracting the score at one time point from the other.[11] A limitation of this method is that the implied effect from a change score may be in the opposite direction compared to the actual effect. This means that there is a chance for inferential bias to occur and the ability to infer causality is limited.[58]

Another method used to analyze repeated measures is a Random Effects Model (REM).[11] A REM is used when there is a random effect (also called *random factor)* present in the model. Fixed effects are when we collect data for all levels of a particular variable, whereas the random effects in REM may have a random sample and distribution of these different variable levels. To better account for these random effects or factors, a REM is used.[59] As an example, in the BFY study the random parameter would be the group that they were assigned to.[6, 32] However, this parameter is not being used to reflect randomization in this thesis, and is being assessed as a potential confounder. While the RCT used this variable, the way it will be handled in this secondary analysis (as a confounder) would not require the use of REM. This is because the random effect of this variable is not central to the research question of this thesis. Another reason REM was not chosen concerns the intention behind this study. The hypothesis is that infants read to more frequently had higher communication development scores than those infants read to less frequently. This hypothesis helps underline the key difference between GEE and REM: individual effect versus group effect.[11] This project will seek to understand the group effect reading frequency had rather than the effect on individuals. In this case, GEE is better suited to this data given it is focused on group effects.

GEE simultaneously analyzes associations between variables collected at different time points.[11, 124] GEE is the best method to address repeated measures for my thesis given that it is suited for measuring group effects.[11] GEE with linear regression highlighted the association between pandemic unemployment and infant communication development. Within GEE models, different correlational structures help to account for time in different ways.[11, 124] For example, one of these correlational structures (autoregressive) can specify that measurements taken closer together are more correlated.[124] In this thesis, the correlational structure chosen was ‘exchangeable’. An exchangeable correlational structure is used when all pairs of responses (time points for each individual) are equally correlated. Further, this study only had two repeated measures which is why exchangeable was chosen as the best fit. There were only two measures, which meant they were equally correlated to each other. If there were more measurements, the measurements may be unbalanced and a different correlational structure may fit better.[124]

Another decision to be made with GEE is to determine whether you use 'robust' standard errors. These robust standard errors incorporate non-constant variance into the calculation of standard error.[125] There is an assumption that needs to be met for linear regression that states that variance needs to be constant (homoscedasticity).[11] When robust standard errors are used, it incorporates non-constant variance and allows this assumption to be bypassed.[125] However, bootstrapping was used to account for the lack of normality within the residuals within linear regression. This is discussed in more detail in the next section. Bootstrapping is itself non-parametric, meaning that the normality assumption no longer applies.[11] In addition, when you are using a bootstrap there is no need to run robust standard errors as the conditions they account for do not apply.[11, 126]

Testing regression assumptions

There are four assumptions of linear regression that need to be met. The assumptions are linearity, normality, constant variance, and outliers. All these assumptions were met or did not apply, with each being outlined below.

Linearity

The assumption of linearity was met in this analysis. The linearity assumption states that the relationship between the exposure and outcome variables must be linear, usually tested using a LOWESS or a CPR plot.[11] However, one crucial exception to this assumption is the levels of the exposure variable. If the exposure variable is categorical, then the linearity assumption is met.[11] For this thesis chapter, the exposure variable of reading frequency is categorical with three levels. Due to the variable being categorical, this assumption is automatically met.

Normality

Normality of the distribution of the residuals is an assumption required by both GEE and linear regression. This assumption was not met by this data. When the residuals were plotted in a kernel density plot, the distribution of the residuals did not resemble the normal curve. In response to this, the regression model was bootstrapped (k = 5000) to account for any potential issues in sample size. Bootstrapping resamples a data set to create many simulated samples. It can resample from the data by creating a series of estimates for accuracy (such as variance, confidence intervals, or standard errors). These estimates allow a bootstrap to run many tests (with some participants being selected more than once) where it compiles their means to estimate the regression coefficient.[11, 127] Bootstrapping data makes the data itself non-parametric, which means that the normality assumption does not need to be met when it is used.[11]

Constant variance

Constant variance of the residuals is another assumption that is contested by bootstrapping. Bootstrapping resamples and reattaches residuals to fitted values.[127] This process begins to approximate and get closer to constant variance, however, is not perfect and constant variance may not be reached. In this case, constant variance should still be tested even if the assumption may be close to being exempted.[127]

This thesis chapter tested constant variance using Levene's test on the non-bootstrapped regression. Levene's test is an alternate way of testing for homoscedasticity when the graphical approach of using a residual versus fitted plot is difficult to interpret.[128] Since the exposure variable of this thesis chapter was binary, the graphical approach would be difficult to interpret. Levene's test uses hypothesis testing to see if the difference in variance between groups is significantly different. The null hypothesis is that variance is homogenous between groups (homoscedasticity). When the values of the test are greater than 0.05 this null hypothesis cannot be rejected. In other words, the homoscedasticity assumption is met when the outputted values (labelled W0, W5, and W10) all exceed 0.05.[128] When this test was run for this thesis, without bootstrapping the regression, the values of these statistics were 5.6, 5.5, and 5.3, respectively. Since these all exceed 0.05, the null hypothesis cannot be rejected and homoscedasticity is met.

Outliers

Outliers are data points that go far outside of the average value and can affect the results. Typically, outliers at specified distances from the average are removed as they are said to be influential and skew the results of statistical tests.[11] A DFBETA statistic was used to assess for the presence of influential outliers. DFBETA statistics are in error units, much like a t-test. DFBETA quantify how much a coefficient would change if specific points were removed. In other words, these measures identify points that would skew the coefficient.[11] For this thesis analysis, a DFBETA statistic was run and its output, a box plot, is included as Figure 6 This boxplot identifies where outliers may exist that could potentially impact the results. Once the range of DFBETA statistics to test had been identified, usually those greater than 0.1 and less than -0.1, then the regression is tested with and without these points to determine their effect. These values indicate how much change would be observed in the coefficient if certain observations were removed. Values at a greater distance from zero, in the positive and negative direction, indicate a greater change in the coefficient.[11] A cut-off value of 0.2 and -0.2 DFBETA was chosen for this thesis, as this is considered reasonable cut-off value. Higher DFBETA statistics result in fewer observations being removed.[147] Removing fewer outliers, especially in a sample sized below 1000, may help improve study power and reduce type II error. For this thesis chapter, two DFBETA points were within the range considered to be influential on the coefficient (less than -0.2 and greater than 0.2). When the regression (linear regression inside GEE) was tested, the coefficients changed by about 5% and the confidence intervals narrowed slightly. It was determined that these points were influential given these changes to the coefficients and confidence intervals. This resulted in the removal of two mother-infant dyads, making the final sample 604 dyads.[11]

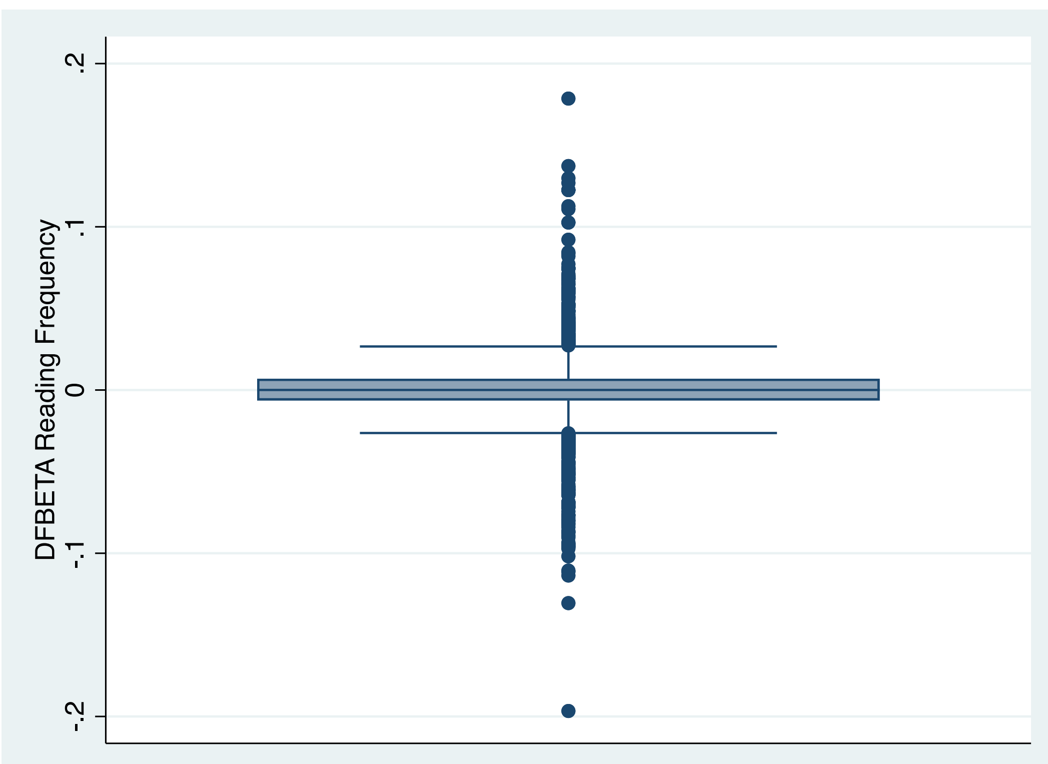

Figure 6: The resulting boxplot of the DFBETA statistic for reading frequency and communication development.

Final regression model

Linear regression was used with all assumptions being met, exempted, or addressed. The unstandardized coefficients were interpreted for both the unadjusted and adjusted regressions. Unstandardized regression coefficients are often interpreted in place of standardized coefficients, especially when the predictor variable is categorical. Standardized coefficients, like Pearson's R, are expressed in standardized units and allow the effect to be interpreted with equal standard deviation when the variables may have different measurement units. Unstandardized coefficients estimate the difference in average values between two groups one at a time while holding the other group constant. Their interpretation is in the original units of the dependent variable, which means it is more directly interpretable. This advantage is useful in public health and clinical studies, as the results are in terms of direct units.[11]

GEE was applied using an exchangeable correlational structure to address the balanced correlation of having only two repetitions. Bootstrapping (k = 5000) the GEE was used to improve the normality of the residuals. Two influential outliers were removed, leaving an updated sample size of n = 604. The final selection of confounders included in the model were infant sex, pandemic data collection, randomization group, maternal education, and earned income. The statistical significance level used was $\alpha = 0.05$, or 95% confidence intervals.

Missing data

This research planned to use multiple imputation (MI) to address missing data, however, only one variable contained missing data. Just three responses were missing for the reading frequency variable, and these only occurred at age two.[55] Since this amount of missing data (0.5%) falls below the 5% threshold where MI is minimally significant, MI was not necessary.[129] BFY had a very low loss to follow-up (8%), likely due to the monetary incentives offered by the study. BFY also prevented loss to follow-up over the pandemic by shifting to remote data collection methods.[6, 34, 55]

3.3 RESULTS

3.3.1 Sample description

Maternal age at infant birth ranged from 18-43 years (mean = 27 years, SD = 5.7 years). About 70% of mothers had a high school degree or less. About 10% had an associate degree or higher.

Approximately 45% of mothers reported that they were never married or single. As shown in Table 6, approximately 10% of mothers took maternity leave (paid or unpaid) after their infant was born. About 29% of mothers reported that this child was their first. A third of mothers earned under $1,000/year. The average number of people in the household ranged from 2 to more than 9 (mean = 4.7 people, SD = 1.7 people). Half the infants were female.

Reading frequency

Approximately 27% of mothers read to their infant every day at age one. By age two, this increased to 38% of mothers. In a simple linear regression, higher levels of maternal education were significantly associated with increases in reading frequency at age one ($\beta 1 = 0.11$, 95% CI: 0.05 - 0.18). At age two, the association remained with the coefficient unchanged ($\beta 1 = 0.11$, 95%CI: 0.05 – 0.17). The higher cash gift group was significantly associated with increasing reading frequency at age one ($\beta 1 = 0.12$, 95% CI: 0.01 – 0.23). At age two, this association was no longer significant ($\beta 1 = 0.09$, 95% CI: -0.02 – 0.20). Reading frequency was not significantly associated with whether there were other children in the household ($\beta 1 = -0.01$, 95% CI: -0.04 -0.02), and this persisted at age two ($\beta 1 = -0.05$, 95% CI: -0.18 – 0.07).

Infant communication development

The average infant communication z-score at age one was 0.24 (SD = 0.87), which translates to the 59th-percentile of the ASQ communication section. Compared to the median value the z-score is based on, infants in this sample demonstrated a slight improvement on average at 9-percentiles above the median. At age two, the average communication z-score for this sample was -0.33 (SD = 1.11), which is the 37th-percentile of the MBCDI. This represents a decline in language ability on average, when compared to the median. This sample had an average score 13-percentiles below the average reported by the MBCDI. Overall, there is a 22-percentile difference between the average reported at age one and two. A paired t-test was run and determined that the difference in means between age one and two was significant ($\alpha = 0.01$). This decline in communication development is consistent with research on language deficits among infants in low-income families.[91] This is particularly relevant between ages one and two, as exposure to language and diversity of vocabulary is reduced in low-income families.[91]

The average age one z-score reported for those assessed before the pandemic was 0.25 (SD = 0.04). This is the 59th-percentile. Comparatively, one-year-olds assessed after the pandemic began had a z-score of 0.23 (SD = 0.06), or the 58th-percentile. When these means were compared in a t-test, it was determined that these two means were not significantly different at the 95% CI level ($p = 0.80$). At age two, however, there was a more pronounced difference in means. The average age two z-score for those assessed before the pandemic at age one was -0.25 (SD= 0.06). This is the 40th-percentile. The average age two z-score for those assessed during the pandemic at age one was -0.48 (SD= 0.08). This is the 31st-percentile. When the means were compared using a t-test at the 95% CI level, the difference was statistically significant ($p = 0.01$). This finding is consistent with the findings of Deoni et al., where infants had poorer cognitive development scores during the pandemic.[10]

Communication z-scores at age one were not significantly associated with the education level of the mother ($\beta_1 = -0.05$, 95% CI: -0.03– 0.13); however, this association was significant at age two ($\beta_1 = 0.11$, 95% CI: 0.01 – 0.22). Whether this infant was the first child was also not significantly associated with communication z-score at age one ($\beta_1 = -0.01$, 95% CI: -0.05– 0.03); yet at age two this association was significant ($\beta_1 = 0.07$, 95% CI: 0.02 – 0.12).

Table 6: Sociodemographic characteristics of the full sample in chapter three (N = 606 mother-child dyads) before outliers were removed.

Sample characteristic	**Full sample** *N* **(%)**	**Age 1 measured before pandemic** *N* **(%)**	**Age 1 measured during pandemic** *N* **(%)**	**p-value between before and during pandemic groups (alpha =0.05)**
Total Sample	606 (100)	393 (64.9)	213 (35.2)	
Reading frequency at age one				0.43
A few times a month or less	136 (22.5)	92 (23.4)	44 (20.7)	
A few times a week	304 (50.2)	198 (50.4)	104 (48.8)	
Every day	166 (27.4)	101 (25.7)	65 (30.5)	
Reading frequency at age two				0.67
A few times a month or les	89 (14.8)	61 (15.5)	28 (13.1)	
A few times a week	285 (47.3)	185 (47.1)	98 (46.0)	
Every day	229 (38.0)	145 (36.9)	84 (39.4)	
Randomization group				0.12
High stipend	265 (43.7)	180 (45.8)	84 (39.4)	
Low stipend	341 (56.3)	211 (53.7)	129 (60.6)	
Maternal age at infant birth				0.22
18-23	194 (32.0)	127(32.3)	67 (31.5)	
24-29	232 (38.3)	146 (37.2)	85 (39.9)	
30-35	120 (19.8)	84 (21.4)	36 (16.9)	
36+	60 (9.9)	34 (8.7)	25 (11.7)	
Maternal education				0.21
Less than high school	120 (19.9)	73 (18.6)	47 (22.1)	
High school diploma or GED	311 (51.5)	196 (49.9)	115 (54.0)	
Some college, no degree	111 (18.4)	81 (20.6)	30 (14.1)	
College degree or higher	62 (10.3)	41 (10.4)	21 (9.9)	
Marital status				**0.002**
Never married	266 (44.6)	186 (47.3)	79 (37.1)	
Single, living with partner	145 (24.3)	95 (24.2)	49 (23.0)	
Married	140 (23.5)	83 (21.1)	57 (26.8)	
Separated/divorced/other	46 (7.2)	20 (5.1)	26 (12.2)	
Took maternity leave				0.29
Yes	63 (10.4)	44 (11.2)	18 (8.5)	
No	541 (89.6)	347 (88.3)	193 (90.6)	
Parity				0.71
Yes	173 (28.6)	110 (28.0)	63 (29.6)	
No	433 (71.5)	281 (71.5)	150 (70.4)	
Number of government supports*				0.54
1 or less	120 (19.8)	61 (15.5)	46 (21.6)	
2	170 (28.1)	99 (25.2)	52 (24.4)	

3	156 (25.7)	109 (27.7)	52 (24.4)	
4	79 (13.0)	67 (17.0)	41 (19.2)	
5+	81 (13.4)	55 (14.0)	70 (32.9)	
Dad incarcerated between birth - age 1				0.20
Yes	88 (15.5)	63 (16.0)	25 (11.7)	
No	481 (84.5)	310 (78.9)	170 (79.8)	
Household earned income (annual)				0.81
$1,000 or less	210 (34.7)	141 (35.9)	69 (32.4)	
$1,100 - $9,500	105 (17.3)	66 (16.8)	39 (18.3)	
$10,000 - $19,500	128 (21.1)	80 (20.4)	48 (22.5)	
$20,000 or more	163 (26.9)	104 (26.5)	57 (26.8)	
Number of people in household				0.47
3 or less	153(25.2)	91 (23.2)	62 (29.1)	
4	159 (26.2)	110 (28.0)	48 (22.5)	
5	137 (22.6)	81 (20.6)	56 (26.3)	
6	79 (13.0)	54 (13.7)	24 (11.2)	
7+	78 (12.8)	55 (14.0)	23 (10.8)	
Child assigned sex				0.67
Female	303 (50.0)	193 (49.1)	109 (51.2)	
Male	303 (50.0)	198 (50.4)	104 (48.8)	

*Number of government supports represents the sum of 8 available support categories received by mother-infant dyads. Supports include unemployment, childcare subsidies, Supplemental Nutrition Assistance Program (SNAP or food stamps), Early Head Start, Medicaid, Women, Infants and Children (WIC), housing assistance, cash assistance, and other assistance by a public program.

3.3.2 Reading frequency and infant development

The hypothesis for this study was that infants read to more often by mothers (exposure variable) would have a stronger communication development trajectory (outcome variable). As shown in Table 7, reading to infants (even just a few times a week) increased communication development by 0.27 z-score units compared to infants read to a few times a month or less (95% CI: 0.12 – 0.42). In terms of percentiles, weekly reading resulted in a 10-percentile increase in infant communication score on average. Reading to infants every day was significantly associated with infant communication development, compared to infants read to a few times a month or less (β_1= 0.33, 95% CI: 0.15 – 0.52). The z-score of 0.33 represents a 12-percentile difference between infants read to every day and those read to a few times a month or less. In a model adjusted for confounders (infant sex, maternal education, randomization group, and pandemic data collection), this effect and its significance persisted for both reading a few times a week (β_1= 0.26, 95% CI: 0.11 – 0.41) and every day (β_1= 0.32, 95% CI: 0.14 – 0.51). These results are shown in Table 7.

Table 7: Linear regression for reading frequency and infant communication development fit inside a GEE model (n = 604)

Variables	**%**	**Unadjusted β1 (95% CI)[1]**	**Adjusted β1 (95% CI)**
Reading frequency			
A few times a month or less	17.5	0.0 (Reference)	0.0 (Reference)
A few times a week	**49.2**	**0.27 (0.12 – 0.42)**	**0.26 (0.11 – 0.41)**
Every day	**33.3**	**0.33 (0.15 – 0.52)**	**0.32 (0.14 – 0.51)**
Maternal education			
Less than high school	19.9	0.0 (Reference)	0.0 (Reference)
High school diploma or GED	51.5	**0.17 (0.01 – 0.34)**	0.16 (-0.01 – 0.32)
Some college, no degree	18.4	0.20 (-0.00 – 0.41)	0.15 (-0.06 – 0.35)
College degree or higher	**10.3**	**0.27 (0.03 – 0.51)**	0.22 (-0.02 – 0.47)
Infant assigned sex			
Male	49.8	0.0 (Reference)	0.0 (Reference)
Female	50.2	0.04 (-0.09 – 0.17)	0.04 (-0.08 – 0.17)
BFY randomization term			
Low stipend	56.1	0.0 (Reference)	0.0 (Reference)
High stipend	43.9	0.08 (-0.05 – 0.22)	0.05 (-0.07 – 0.18)
Annual estimated earned income			
$1,000 or less	34.9	0.0 (Reference)	0.0 (Reference)
$1,100 - $9,500	17.4	0.14 (-0.04 – 0.31)	0.16 (-0.03 – 0.34)
$10,000 - $19,500	21.0	-0.01 (-0.19 – 0.17)	-0.003 (-0.18 – 0.18)
$20,000 or more	26.7	0.08 (-0.08 – 0.25)	0.07 (-0.10 – 0.24)
Age one data collection			
Before pandemic		0.0 (Reference)	0.0 (Reference)
During pandemic		-0.13 (-0.26 – 0.01)	-0.12 (-0.27 – 0.01)

[1]This column represented the unadjusted regressions and the associations between the variable in each row with the dependent variable to determine whether this condition of confounding is met.

3.3.3 Interaction term: Pandemic data collection

An additional post-hoc analysis was completed which measured whether the association between reading and communication differed by whether infants completed their age one measurement before or during the pandemic (i.e., before or after March 2020). About 65% of infants completed their age one communication assessment prior to the start of the pandemic. The interaction was explored with an adjusted GEE model only. The association between reading and communication was significant for infants with age one measures taken pre-pandemic, but not for those measured post-pandemic (Table 8). In the pre-pandemic group, infants read to a few times a week had significantly higher communication scores compared to those read to a few times a month or less (β= 0.28, 95% CI: 0.11 – 0.46). A stronger effect size was observed for this same group when read to every day (β= 0.35, 95% CI: 0.13 – 0.57). This same association was not significant amongst infants whose age one measurements were taken during the pandemic for reading a few times a week (β= 0.22, 95% CI: -0.07 – 0.50) and every day (β= 0.27, 95% CI: -0.07 – 0.60). This means that the effect of reading on communication depended on when the infant had their age one measurement taken in relation to the pandemic. The effect was only significant for one group, which is characteristic of a qualitative interaction term.[12]

Quantitative interaction terms describe when a third variable strengthens or weakens the magnitude of the association. Qualitative interaction terms describe when a third variable affects the direction and/or magnitude of the association.[12, 70, 148] In this case, the interaction is qualitative as the significance (direction) differed between the groups even when the difference in magnitude was negligible. For the group measured before the pandemic, reading frequency was significantly and positively associated with communication development. For those measured during the pandemic, this same association was not significant. In clinical applications, qualitative interaction is typically used to describe when an intervention works or does not work for different groups.[148] In the case of those measured during the pandemic, reading frequency did not significantly aid their communication development like it did for their pre-pandemic counterparts.

Table 8: Linear regression for reading frequency and infant communication development fit inside a GEE model stratified by pandemic data collection.

Variables	**Adjusted β1 (95% CI)** **Age 1 before pandemic (*n* = 393)**	**Adjusted β1 (95% CI)** **Age 1 during pandemic (*n* = 213)**
Reading frequency		
A few times a month or less	0.0 (Reference)	0.0 (Reference)
A few times a week	**0.28 (0.11 – 0.46)**	0.22 (-0.07 - 0.50)
Every day	**0.35 (0.13 – 0.57)**	0.27 (-0.07 – 0.60)
Maternal education		
Less than high school	0.0 (Reference)	0.0 (Reference)
High school diploma or GED	0.16 (-0.05 – 0.37)	0.14 (-0.14 – 0.42)
Some college, no degree	0.15 (-0.10 – 0.40)	0.09 (-0.30 – 0.47)
College degree or higher	**0.35 (0.04 – 0.66)**	0.23 (-0.37 – 0.42)
Infant assigned sex		
Male	0.0 (Reference)	0.0 (Reference)
Female	0.10 (-0.06 – 0.25)	-0.02 (-0.25 – 0.21)
BFY randomization term		
Low stipend	0.0 (Reference)	0.0 (Reference)
High stipend	0.14 (-0.02 – 0.29)	-0.13 (-0.35 – 0.10)
Annual estimated earned income		
$1,000 or less	0.0 (Reference)	0.0 (Reference)
$1,100 - $9,500	0.21 (-0.01 – 0.43)	0.07 (-0.24 – 0.39)
$10,000 - $19,500	-0.06 (-0.28 – 0.16)	0.05 (-0.26 – 0.37)
$20,000 or more	0.16 (-0.04 – 0.37)	0.10 (-0.41 – 0.20)

[1]This column represented the unadjusted regressions and the associations between the variable in each row with the dependent variable to determine whether this condition of confounding is met.

3.4 DISCUSSION

The purpose of this chapter was to address two post-hoc research questions: (1) How does reading frequency impact communication development trajectories among infants in low-income households? and (2) Does pandemic data collection moderate this association? Findings from this study indicate that mothers reading books to infants daily is positively associated with their communication development over a one-year period. However, this association was moderated by the timing of data collection. When all data was collected during the pandemic (age one and two time points) there was no association between reading frequency and infant communication development.

3.4.1 Association between reading and communication

The results indicate that increased reading frequency is associated with improved communication outcomes, aligning with existing literature on the importance of early literacy for language development. Prior studies have consistently demonstrated that exposure to reading and verbal interactions in infancy can enhance vocabulary acquisition, improve grammar skills, foster early communicative abilities, and improve cognitive development.[25, 85, 149] Specifically, this thesis found that mothers who read to their infants daily exhibited significantly higher communication scores in their children by age two, with an effect size (of about 12 percentiles) that suggests a small but meaningful impact on language development.[150] This finding is particularly relevant for low-income families, where access to enriching early childhood experiences can be limited due to socioeconomic constraints.[91, 151] By demonstrating that reading frequency plays a key role in early communication skills, these results reinforce the importance of early literacy interventions in these populations.[25, 85, 149]

While the association is significant, it is important to recognize that other factors (such as maternal education and family income) likely contribute to the variability in communication outcomes. The adjusted models controlled for maternal education, earned income, and other confounders, but it is acknowledged that unmeasured variables—such as parenting style or the home literacy environment—could also influence these results.

3.4.2 The role of the COVID-19 pandemic

The second part of this analysis explored whether the COVID-19 pandemic moderated the association between reading frequency and communication development. The findings revealed that the positive association between reading and communication outcomes was significant only for infants whose data were collected before the pandemic. For infants whose data were collected during the pandemic, the association between reading and communication was no longer significant. This is indicative of a qualitative interaction term, as it is a third variable that alters the magnitude or direction of the association.[148] This suggests that the pandemic may have disrupted the home environment in ways that attenuated the potential benefits of reading.

The pandemic has had widespread effects on family life, including increased stress, economic hardship, and shifts in caregiving and educational practices.[1, 4, 79, 101, 152, 153] These disruptions may have impacted both parents' ability to engage in regular reading activities and the quality of interactions between parents and children. As a result, the absence of a significant association for the pandemic group could be reflective of broader stressors that affected both parenting practices and child development during this time. These stressors could have included changes to income, job loss, or pandemic related concerns such as disease risk or anxiety around infection.[4, 79, 101, 154, 155] It is important to note that the effect of the interaction observed here highlights the need to account for contextual factors, such as societal disruptions, when assessing the impact of early literacy practices on child development. Future research could focus on the impact of a reading intervention among high stress low-income groups, or if this qualitative interaction persists for individuals who maintained connections to essential services or had access to counselling supports.

3.4.3 Unintended findings

An unintended, yet interesting finding, was that there was a statistically significant difference in reading frequency at age one for those in the high cash gift group (randomization group). Compared to those in the low cash group at age one, there was a 0.12 unit increase in reading frequency. This effect; however, did not persist at age two. What is interesting is that this term was randomized by BFY, which means that there should be less room for confounding. This unintended finding is not definitive and serves only as a starting point for future studies. A more formal and robust analysis method should be used, to explore this potential association. This effect, if present in these robust analyses, could add to the theory for the previous finding: that interventions that reduce stress could improve the consistency of reading. More research is needed to test this with more robust methodologies and explore what other factors may be involved in this effect.

3.4.4 Strengths

This thesis chapter has two strengths: continuous data collection and study design. Maintaining data collection throughout the pandemic was no small feat. Where other studies may have had to make major modifications to their protocols or delay their collection timelines, the dataset for this thesis only had slight modifications to its delivery.[6, 34] While this presented a slight delay in measurement, the tools used could be easily adapted for the child's age. Not only did data collection continue, but it also upheld its validity when faced with the unique challenges of the pandemic. The robust, longitudinal design of this thesis is also a key strength supported by that data collection. The design focused on whether the effect persisted over time, rather than occurring at one point. However, only two time points were analyzed. More data points are needed to understand this potential effect beyond one year.

3.4.5 Limitations

While the results of this study provide valuable insights, there are several limitations that must be acknowledged. First, as with any observational study, causality cannot be definitively established. While we observed a significant association between reading and communication outcomes over time, other unmeasured confounders may have influenced the results. For instance, we did not account for more granular measures of the home environment, such as the overall quantity and quality of parent-child interactions or parental engagement in other forms of early learning activities. These factors could further explain the variation in infant communication development.

Second, Hill's postulates for causal inference, which guide the assessment of causality in epidemiological studies, were not fully met in this analysis.[156] Specifically, temporality was not as clearly met as the measure of reading frequency was self-reported and may have been influenced by recall bias. Additionally, there was potential for selection bias given the recruitment of participants from low-income neighborhoods, which may not fully represent the broader population of low-income families.

Third, the pandemic introduced several confounding variables that could not be fully controlled for in this analysis. The shift from in-person to telephone data collection during the pandemic may have introduced biases in reporting or sample attrition, particularly among families with limited access to technology. Moreover, the broader socio-economic effects of the pandemic, such as job loss and mental health challenges, were not directly measured, yet they likely played a role in shaping both reading habits and child development outcomes during this period.

3.5 CONCLUSION

This study contributes to the growing body of research highlighting the importance of early reading for child communication development. These findings suggest that daily reading can positively influence communication outcomes, particularly for low-income families. However, this association was no longer significant when data was collected during the COVID-19 pandemic. This effect underscores the need for further investigation into the broader social and environmental factors that influence child development. Future research should explore these factors in greater depth, particularly the long-term effects of the pandemic on early childhood development and consider alternative interventions that can support families in the face of social and economic challenges.

4.0 CHAPTER 4: DISCUSSION

4.1 PURPOSE

The aim of this thesis was to investigate the impact of the pandemic on infant communication in low-income homes through pandemic unemployment benefits and reading frequency. In this thesis I found that factors that alleviated stress (such as unemployment benefits) supported infant communication development. Communication development was stronger in infants whose parents received pandemic unemployment benefits. It also found that the association between reading frequency and infant communication differed by whether it was measured during the pandemic, indicating parental or environmental stress as impactful to early learning. Although a similar pattern emerged between the groups (increased reading frequency resulted in increased in communication development), the association was only significant for infants measured before the pandemic and not significant for those measured during.

The transition in language between ages one and two, from non-verbal to verbal, is an important milestone in development that predicts later communicative abilities.[85, 86, 89, 90] Home environments are important predictors of this development, often shaped by parents. The opportunities parents provide for their infants to learn can predict success.[23-25, 28, 146, 149] Often, stress in the home can determine whether these opportunities are available. Low-income families may experience stress to a degree where early language activities may not be prioritized, leading to subsequent lags in infant communication development.[91, 157]

This thesis highlights the interconnectedness of socio-economic factors and developmental milestones in shaping infant communication outcomes. The role of parental stress, as influenced by job loss or financial instability, serves as a reminder that early childhood development is not solely a product of innate capabilities or isolated activities like reading, but rather emerges within a complex ecosystem of environmental, economic, and emotional factors. The implications extend beyond individual families, suggesting that broader systemic changes (such as enhanced parental leave policies or community-based supports) could have lasting impacts on mitigating disparities in developmental trajectories. Furthermore, this research underscores the need for interdisciplinary approaches, bringing together fields such as developmental psychology, public policy, and social work to address these multifaceted challenges holistically.

4.2 PANDEMIC UNEMPLOYMENT BENEFITS

Parental job loss is a factor that has been shown to cause high levels of stress throughout the family.[158] In the COVID-19 pandemic, job loss was a collective experience that occurred quickly and across demographic groups.[1, 18, 63, 159] Qualitative studies have shown that job loss during the pandemic impacted the parent-child relationship by increasing parent-child conflict and negative child affect.[101] Adding a layer of stress to the home environment (on top of income related stressors) may impact child development; however, there is limited findings on how this exists in the context of a global pandemic.

Individuals must have worked consistently for 12-24 months prior to qualify for unemployment benefits in the US.[114] Pandemic unemployment benefits were more quickly and widely dispersed, in order to offer a stability of income during a rapidly evolving crisis. Pandemic benefits were available to workers who had been temporarily laid off or had their work impacted by the pandemic, where traditionally one had to be laid off or let go from work to receive these benefits. In addition to expanded criteria to receiving unemployment benefits, individuals also received an extra $300 a week on top of their regular unemployment benefits. The pandemic unemployment assistance program allowed individuals who would otherwise not qualify for unemployment benefits to receive them. This program offered self-employed and freelance workers the opportunity to receive unemployment benefits for up to 79 weeks. Pandemic unemployment benefits were different than the standard, in that the criteria were relaxed and the waiting period was decreased.[17, 18]

In this study, I measured pandemic unemployment benefits as a key variable, recognizing its potential role in mitigating the adverse effects of financial instability on infant communication development. However, it is important to acknowledge that job loss was not measured, yet it is connected to the receipt of unemployment benefits. A diagram of the measured and assumed variables in this thesis is included as Figure 7. While unemployment benefits provide crucial support, they do not capture the broader and often multifaceted impact of job loss itself (such as changes in household routines, parental stress, or emotional strain) that could influence communication development. In addition, not everyone who experienced job loss may have qualified for unemployment benefits. By focusing on unemployment benefits, the study evaluates one component of the broader economic disruption caused by the pandemic and does not account for the full scope of challenges associated with job loss. This distinction is critical when interpreting the findings of this thesis, as it underscores both the targeted nature of the variable and the potential for unmeasured variables to shape outcomes in ways not directly captured by the analysis.

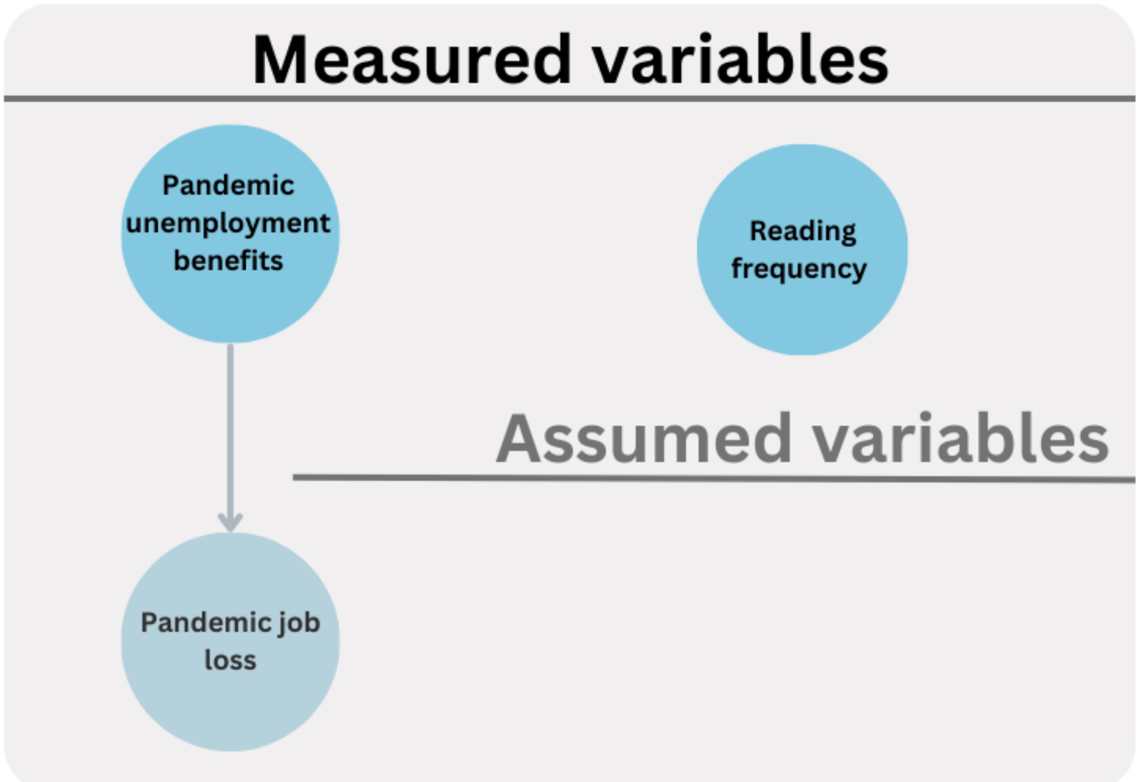

Figure 7: A diagram of measured and assumed variables

My work for this thesis found that pandemic unemployment benefits were associated with improved infant communication outcomes. However, it is important to note that unemployment itself was not directly measured. The receipt of pandemic unemployment benefits served as a proxy for financial stress mitigation. This variable does not provide a clear picture of the impact of job loss, and instead indicates the impact of the benefits provided. The findings of this thesis are consistent with other studies on the maintenance of income during job loss. In studies that have modelled cash assistance or unemployment, groups that receive benefits demonstrate improved cognitive development in children that extends into later life.[32, 160-162] The reduction of these benefits has been shown to have the opposite effect, notably reducing birth weight and height.[105] Given the lack of longitudinal research on the effect of unemployment benefits on child development, there is a clear need for research in this area. Parental job loss during the pandemic introduced unique stressors into the home environment, exacerbating existing financial pressures and altering family dynamics.[1] Research indicates that job loss is often associated with parental depression, anxiety, and reduced emotional availability, which can negatively affect the parent-child relationship.[4, 81] Expanding on this, future research could explore how these stressors interact with other pandemic-related changes (such as social isolation and limited access to childcare) to influence early development.

The use of pandemic unemployment benefits as a variable has limitations. It does not capture the full scope of job-related stress, including the duration of unemployment or the quality of re-employment opportunities. None of these variables were measured or available in the BFY dataset. To address this, future studies could adopt a mixed-methods approach, combining quantitative measures of economic stability with qualitative data on parental experiences during job loss. Researchers could also study what targeted interventions work to buffer its impact on child development. For example, mental health services tailored for unemployed parents or job retraining programs with childcare support could address the dual challenges of financial stress and parental availability. Additionally, future research could examine how extended periods of unemployment affect developmental outcomes differently than shorter bouts of job loss, offering insights into the cumulative effects of prolonged economic hardship. Comparative studies between families who experienced job loss with and without access to robust unemployment benefits could also shed light on the specific mechanisms by which financial stability supports early development. Expanding this research to include different cultural or regional contexts would provide a more comprehensive understanding of how social safety nets may mediate the relationship between parental job loss and infant outcomes.

4.3 READING FREQUENCY

Early and consistent reading is key for language development.[23-25] In chapter three of this thesis, the association between reading frequency and later communication development was shown to be statistically significant among those assessed prior to and was not significant for those measured during the pandemic. These findings are consistent with the results of other literature, indicating a period effect among infants.[10, 163] In Deoni et al. infants born after March 2020 demonstrated significant gaps on the Mullen Scales of Early Learning, with a 27 to 37 point decrease at age one compared to those born in 2018.[10] A cohort study of 50,000 children aged 0-5 years old found modest decreases in development when compared across pre-pandemic and intra-pandemic cohorts.[163] Results were age specific, with modest increases reported in communication, problem solving, and personal-social domains in the ASQ among older children.[163] In infants aged 0 to 12 months, only decreases in the communication domain were significant.[163] Early and consistent reading is a strong protective factor for development that has been extensively studied.[23-25] Chapter three showed that the pandemic may have limited this effect, which adds to the theory of a period effect.

Reading is not isolated from broader environmental factors. For instance, the quality of interactions during reading sessions—such as parental responsiveness and emotional tone—can amplify the benefits of this activity.[23-25, 85, 146, 149] Future research could investigate how these aspects of reading contribute to communication outcomes, particularly in low-income families experiencing pandemic-related stress. Moreover, interventions to enhance reading practices could be designed with these insights in mind, such as programs that provide parents with tools and strategies to make reading more engaging and interactive. The differential association between reading frequency and communication outcomes before and during the pandemic underscores how external stressors can attenuate the protective effects of early learning activities. These findings suggest that environmental instability, such as pandemic-related stress, may compromise the quality or frequency of parent-child interactions that facilitate language acquisition. Expanding on this finding, it would be valuable to examine whether structural inequities, such as unequal access to books and digital resources, limited the ability of some families to maintain consistent reading habits during the pandemic.

4.4 CONNECTING FINDINGS TO PIAGET'S THEORY OF DEVELOPMENT

Jean Piaget's cognitive development theory provides a useful framework for understanding the findings of this thesis, particularly the impact of pandemic stressors on infant communication.[74] Piaget proposed that infants actively construct knowledge through interactions with their environment, progressing through a series of developmental stages. For infants in the sensorimotor stage (birth to approximately two years), communication emerges as they develop schemas—mental frameworks for understanding their world—through exploration and interaction.[74]

The findings of this thesis align with Piaget's view that environmental factors shape developmental outcomes.[74] Pandemic-related stressors, such as parental job loss and limited opportunities for structured interaction, could have disrupted the environments in which infants typically develop their communication skills. Conversely, stabilizing factors like unemployment benefits may have helped mitigate these disruptions by reducing stress and enabling parents to engage more effectively with their children.

4.4.1 The role of parental stress in schema formation

Piaget emphasized the importance of consistent and supportive interactions for schema formation.[74] In low-income households, parental stress may interfere with these interactions. For instance, stress may reduce the frequency or quality of activities like reading, which are critical for building early communication.[28] The finding that reading frequency was less impactful during the pandemic further support this idea. High stress likely limited the emotional and cognitive availability of parents, affecting their ability to scaffold their infant's communication development effectively.

4.4.2 Adaptation and accommodation during the pandemic

According to Piaget, cognitive development occurs through adaptation, involving assimilation (incorporating new experiences into existing schemas) and accommodation (adjusting schemas to fit new experiences).[74] The pandemic likely created an environment requiring significant accommodation for families. Parents had to adapt to rapidly changing circumstances, such as job loss, remote work, and social isolation.[1, 79] Unemployment benefits may have provided the stability needed for parents to navigate these changes, enabling them to maintain consistent interactions with their infants. However, for families without such supports, the increased stress likely hindered these adaptive processes. Infants may have experienced fewer opportunities to assimilate and accommodate new communication-related experiences, potentially delaying their progression through key milestones in the sensorimotor stage.[74]

4.4.3 Impact on symbolic representation

The transition from non-verbal to verbal communication, a key milestone during the later sensorimotor stage, is closely tied to the development of symbolic thought.[74] Activities like reading and interactive play typically support this transition by exposing infants to language and reinforcing their ability to associate words with objects and actions. In this thesis I found that reading may be less effective during the pandemic, likely due to environmental instability. Piaget's theory helps explain this finding:

without stable and enriched environments, the development of symbolic representation may be compromised, delaying verbal communication.[74]

4.4.4 Broader implications for development

Piaget's theory underscores the interconnectedness of cognitive and environmental factors in early development.[74] The findings of this thesis highlight how systemic supports, such as unemployment benefits, can create conditions that support healthy cognitive and communication development by reducing parental stress. Conversely, the disruptions caused by the pandemic illustrate how adverse environmental conditions can hinder progress through Piaget's developmental stages.

By framing these findings within Piaget's theory, we see the importance of addressing both individual and systemic factors to support early development. Future research could explore interventions that enhance parent-child interactions during times of stress, aligning with Piaget's emphasis on the active role of environmental engagement in cognitive growth.[74] This approach could help mitigate the long-term developmental impacts of crises like the COVID-19 pandemic.

4.5 CONNECTION TO PANDEMIC LEARNING LOSS

Many countries around the world have noted changes in the academic abilities of children post-pandemic.[164, 165] It is clear that the development of infants was not only affected by the pandemic, but that this effect extended to young children and adolescents. This is described as COVID or pandemic learning loss among school-aged children. Many research papers highlight the temporary closure of schools as a key factor impacting the learning of children.[164, 165] A natural experiment of approximately 350,000 students in the Netherlands found that learning from home resulted in three-percentile points in learning loss.[165] In comparison to other countries, the Netherlands had a much shorter period of home learning of about 8 weeks.[165] In Alberta, it is estimated that children lost a year or more of expected learning progress.[166] In addition to this overall effect, pandemic learning loss seemed to be highest in low-income environments.[167] Many of these studies focus on the impact to students in school, and many of these effects may not be fully realized for many more years.[164-166] This thesis has shown developmental lags in infants, and with many of these early deficiencies being predictive of later delay, some of these impacts may not be seen until these individuals enter school.

4.6 AREAS OF FUTURE RESEARCH AND POLICY

Future research should continue examining the impacts of the pandemic on the development and learning loss of children. While this thesis adds to a growing body of evidence on the impact of the pandemic, there is still a gap in understanding what factors may be protective and what populations may have seen the greatest impact. This thesis was limited, as the sample was restricted to low-income families. Future research could investigate whether this effect exists across income levels and could compare across income groups. While there is literature indicating that low-income infants are at a greater risk of communication delays, it is unclear whether the effect of the pandemic on development was universal across income levels.[91]

What this thesis does emphasize, however, is that the full effect of pandemic related learning loss may not be realized until those born during the pandemic enter school. Many factors may have impacted this, such as abrupt changes in the learning environment and routine.[166, 168] Supporting kids with this need may be more challenging than previous years, unless a systematic approach is utilized. Traditionally, interventions to support children at school are individualized in nature. They tend to focus on providing direct support to children who require it most. This is helpful and does support the intended population; however, it leaves many children behind who may not immediately meet the threshold to access the support. Providing multi-tiered systems of support ensures that the greatest number of individuals receive support, and may be a solution to address this impending issue.[169]

Multi-tiered systems of support are not new concepts, with many studies over the past 50 years noting positive effects.[169] These systems of support typically include three levels with increasing complexity. Typically, the first level of support is available to all individuals, the second level provides interventions and lessons to small groups, and the third level of support provides more intensive individualized services.[169] In Alberta's education system, the multi-tiered system of support is called the "Continuum of Supports and Services".[170] All school authorities in the province are required to provide a continuum of supports and services that ranges from universal to targeted to individualized. Universal supports and services include providing learning sessions or activities in the classroom. Targeted supports can include system navigators to connect children to resources or expanded learning in small group settings. Finally, individualized supports are more specialized and involve working one-on-one with the individual.[170] Research and policy should focus on delivering interventions within a multi-tiered approach to assess the effect it may have on improving pandemic learning loss. Research is needed to support the development of learning interventions and assessment strategies that can be applied universally to identify individuals who may require support.

The long-term consequences of pandemic learning loss may extend well beyond academic delays, potentially influencing broader socio-emotional and cognitive domains. Expanding on the concept of learning loss, future studies could examine how disruptions in routines, peer interactions, and structured learning environments affected developmental trajectories in different age groups. Early interventions tailored to children born during the pandemic could help mitigate these effects, particularly in the transition to formal schooling. Programs that integrate developmental screenings with targeted supports, such as speech therapy or early literacy initiatives, may provide critical bridges for children showing early signs of delay. Moreover, cross-national research on countries with varying levels of pandemic restrictions and educational supports could yield valuable insights into best practices for addressing learning loss globally.

Future research should also investigate the role of technology in mitigating developmental delays during the pandemic. While digital tools like video conferencing and educational apps became more prominent, their effectiveness in supporting communication development in infants remains unclear. Exploring how families leveraged technology—or faced barriers to its use—could inform future strategies for integrating digital resources into early childhood interventions. Additionally, longitudinal studies tracking the cohort of children born during the pandemic into later childhood and adolescence could uncover critical insights into the lasting effects of early developmental delays. On the policy side, expanding universal childcare programs and offering targeted supports for at-risk families could provide a more equitable foundation for learning. Strengthening partnerships between healthcare, education, and social services could further enhance the effectiveness of these interventions.

4.6 STRENGTHS AND LIMITATIONS

This thesis underscores key findings regarding the impact of the COVID-19 pandemic on infant communication development through the lenses of parental job loss and reading frequency. While both chapters provide valuable contributions, they also present unique strengths and limitations that must be critically examined and compared.

4.6.1 Strengths

A strength across both chapters is the robustness of the data collection and study design. The longitudinal design allowed for the examination of developmental changes over time, establishing temporal sequence. Specifically, this thesis benefited from BFY continuing data collection during the pandemic. This maintained validity despite the challenges posed by the global crisis. Unlike many studies that experienced significant disruptions, slight protocol modifications allowed for seamless adaptation, preserving data quality and relevance.

Another strength lies in the practical implications of the findings. Chapter two highlighted the potential protective role of pandemic unemployment benefits, suggesting policy avenues for mitigating adverse developmental outcomes in low-income families during crises. Similarly, chapter three's emphasis on reading frequency underscored its critical role as a protective factor for early communication development, even in the face of broader societal disruptions. Together, these findings contribute actionable insights that may guide future interventions and policies.

4.6.2 Limitations

Despite these strengths, several limitations were identified in both chapters, reflecting challenges inherent in pandemic-related research. Chapter two faced limitations in its reliance on a non-randomized exposure variable (pandemic unemployment benefits), which reduces internal validity and raises the possibility of residual confounding. Similarly, chapter three's design impedes definitive causal inferences, as unmeasured confounders (such as the overall quality of parent-child interactions) may have influenced the observed associations.

Measurement challenges were also a shared limitation. Both chapters faced potential error due to changes in data collection tools, such as the shift from the ASQ to the MBCDI, which measure communication development differently. This limitation was compounded by the timing of assessments, with pandemic-era postponements potentially introducing bias. In chapter three, recall bias in self-reported reading frequency and the transition to telephone data collection during the pandemic may have introduced inaccuracies, especially among families with limited access to technology.

Another limitation common to both chapters was the restricted generalizability of findings. Both studies focused exclusively on low-income populations and excluded infants with diagnosed neurological conditions, narrowing the scope of applicability. While this focus provides valuable insights into vulnerable populations, it limits the ability to draw conclusions about broader or more diverse groups.

Another limitation amongst both chapters is that there is the potential for social desirability bias to have impacted the results collected. The MBCDI and ASQ are both parent reported measures, and there is a possibility that mothers may have overestimated their child's abilities to be perceived positively by the study. Although there is the potential for this to affect the results, there were several ways this may have been mitigated. The first being the unconditional stipend offered in the BFY study. By having each group receive some amount and having the receipt of the stipend be unlinked from the reports, this minimized any potential pressure to report certain outcomes. In addition, the measures used are also significantly correlated with their more objective counterpart the Bayley III.[40, 41] Regardless, future research should include objective assessment and qualitative evidence to validate the findings from parent reports.

Lastly, both chapters were constrained by the inability to fully account for pandemic-specific confounders. Chapter two lacked data on critical factors such as changes in childcare or the home environment, which are known to affect child development. Similarly, chapter three did not directly measure socio-economic disruptions, such as job loss or mental health challenges, which likely influenced both reading habits and developmental outcomes.

4.6.3 Comparative analysis

While both chapters highlight the impact of pandemic-related stressors on infant communication, their respective strengths and limitations underscore complementary perspectives. Chapter two's focus on pandemic unemployment benefits provides a macro-level view of economic stressors and their mitigation, whereas chapter three's examination of reading frequency offers a micro-level analysis of specific early learning activities. Together, these chapters demonstrate the multifaceted nature of pandemic effects on development, emphasizing the importance of addressing both structural and behavioral factors in future research and policy.

Both chapters contribute to a growing understanding of how low-income families navigated the challenges of the pandemic. Yet, they also highlight the need for more granular, diverse, and longitudinal research to capture the full scope of developmental outcomes and to disentangle the complex interplay of pandemic-related variables. Future studies should strive to overcome these limitations by incorporating randomized designs, expanding population diversity, and measuring broader environmental and behavioral factors.

4.7 CONCLUSION

In this thesis I investigated how the pandemic may have impacted the development of infants, highlighting that infants in this sample were experiencing developmental lags but that maintaining income improved these outcomes. This thesis adds to a growing body of evidence that indicates that there may be a pandemic period effect among developing infants. Future research and policy should focus on developing universal, targeted, and individualized interventions to support young children as they enter school.

Adding to the broader discussion on pandemic recovery, these findings highlight the urgency of designing adaptive systems that can respond to future crises with greater equity and efficacy. Future pandemics are more likely to occur and may occur more frequently due to increased world travel and climate change.[171] Supporting children born during the pandemic requires a multifaceted approach that not only addresses immediate developmental delays but also builds resilience within families and communities. By prioritizing early screening, accessible interventions, and robust social safety nets, policymakers can ensure that the long-term effects of the pandemic do not disproportionately burden the most vulnerable populations. Continued collaboration between researchers, practitioners, and policymakers will be essential in creating sustainable solutions that safeguard the developmental well-being of future generations.

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