Externalized Behavior, University Attainment, and Wages:
Evidence from a Randomized Controlled Trial of Kangaroo Mother Care (KMC)

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Externalized Behavior, University Attainment, and Wages: Evidence from a Randomized Controlled Trial of Kangaroo Mother Care (KMC)

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Abstract

This thesis examines the long-term effects of the Kangaroo Mother Care (KMC) program. It is based on data from a Randomized Controlled Trial (RCT) conducted in Bogota, Colombia, from 1993 to 1994. The study aims to demonstrate that early childhood interventions such as KMC can result in higher wages in adulthood by reducing aggressive behavior. Participants who received KMC are more likely to attain a university education. This research emphasizes the importance of supporting early childhood interventions for long-term educational and economic benefits.

1 Introduction

The impact of early childhood interventions has been receiving more attention in the fields of public health, economics, and social sciences due to their significant effects on

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both short- and medium-term outcomes. There is a consensus regarding their developmental benefits (Vegas & Santibañez, 2008; Karoly, 1998; Barnett, 2000; Almond, Currie, & Duque, 2018). Some have been linked to improvements in elementary education (Heckman et al., 2009), health outcomes (Conti et al., 2016), and social welfare (Nores & Barnett, 2010; Zigler, 2000). Although evidence of the long-term effects of early interventions is limited, the experiences and programs children are exposed to in their first years can profoundly impact adulthood outcomes (Tanner et al., 2015)

Kangaroo Mother Care (KMC) is a highly promising early childhood intervention known for being cost-effective (Castillo et al., 2013; Lowson et al., 2015). Approximately 1 in 10 babies are born prematurely worldwide, requiring specialized care.(WHO, 2024). KMC provides a scalable and affordable alternative with immediate benefits for babies, such as improved newborn survival and enhanced parent-infant bonding (Charpak, 1997; Tessier, 1998). Research shows that early childhood interventions like KMC not only yield short-term developmental benefits but also have a significant impact on long-term educational outcomes (Cortés et al., 2022).

This thesis aims to investigate the long-term impact of KMC on labor market outcomes. We hypothesize that KMC can influence wages by identifying key mediating factors, such as educational attainment and externalized behavior. Gross & Duke (1980) demonstrated that early exposure to physical touch and nurturing has long-term benefits on child behavior. Subsequent research supports the idea that behavior problems increase the likelihood of disengagement from school and academic underperformance (Breslau, 2009). Additionally, the established economic literature indicates a generally positive and significant return on education in terms of income. Hence, it is proposed that treatment (KMC) decreases the level of externalized behavior (aggressiveness) at 20 years old, which subsequently increases the probability of university attainment and, in turn, has a positive effect on wages in adulthood.

To test our hypothesis, we will analyze the long-term effects of KMC through a structural equation model (SEM) and mediation analysis with data from an RCT conducted in a developing country, Colombia. The methodology allows us to explore the causal pathways from early intervention to long-term outcomes. The RCT data includes detailed information on participants' socio-emotional development and educational achievements, which was collected over two decades, and labor market outcomes from January 2011 to August 2020 of "Planilla Integrada de Liquidación de Aportes" (PILA). The SEM will be used to estimate the direct and indirect effects of KMC on adult wages, taking into account mediating variables such as externalized behavior and educational attainment. This approach, similar to what Heckman et al.(2013) and others proposed, involves conducting a mediation analysis for the outcome of interest, which in this case is wages.

The present thesis contributes to a wider literature that helps to understand how early childhood interventions can improve human capital and economic well-being over a person's lifetime, as demonstrated by previous studies. For instance, the effect of the Jamaica early childhood stimulation intervention on labor market outcomes at age 31 revealed a 37% increase in earnings compared to the control group (Gertler, 2014). Our study specifically focuses on the effects of KMC, indicating a significant 9% reduction in externalized behavior for the KMC group, as well as a 2% increase in the likelihood of university attainment. This information is vital for shaping policies that seek to enhance long-term outcomes through targeted early childhood interventions, particularly for newborns, such as KMC.

The initial section will establish the background of the KMC program. Following this, the section on data will describe the data sources of the RCT, socio-emotional, and university variables, as well as wages from PILA and descriptive statistics. The fourth section will present the empirical strategy. Then, the fifth section will present the results. Finally, the conclusion section will summarize the key findings.

2 KMC, Randomized Control Trial and theory framework

The Kangaroo Mother Care (KMC) program is a groundbreaking early intervention developed in the 1970s by a team of pediatricians at the Instituto Materno Infantil: Dr. Rey (creator), Dr. Martínez, and Dr. Navarrete, in response to a shortage of incubators and infant infections in Bogota, Colombia. This program involves extended skin-to-skin contact and encourages exclusive breastfeeding for newborns.(Charpark, 1996)

A longitudinal study was conducted between September 1993 and September 1994 to evaluate the effect of the KMC protocol compared to Traditional Care (TC) i.e., newborn intensive care unit (NICU), on key health outcomes (Charpak et al., 1997). The randomized control trial (RCT) targeted preterm and low birth weight newborns born at the San Pedro Claver clinic, the main public hospital in Bogota at that time.

It included mother-child dyads who met specific criteria, mothers capable of understanding and following instructions, and infants who had overcome major adaptation issues, were gaining weight, and could suck and swallow properly. Participants meeting the criteria were randomly allocated to either Traditional Care (TC) or Kangaroo Mother Care (KMC) using four strata based on birth weights. Twins or triplets were assigned to the same treatment group.

The KMC program included two key elements: permanent skin-to-skin contact (Kangaroo position) until 37–38 weeks of gestational age and close clinical monitoring for early discharge. In contrast, the TC protocol used NICUs until infants could self-regulate their temperature, and there was no early discharge policy. Both protocols shared common elements, such as exclusive breastfeeding and pediatric controls. (Charpak et al., 1997)

Evaluations were carried out at birth, when eligibility criteria were met, at 41 weeks post-conceptional age, and at 3, 6, 9, and 12 months. The safety and health outcomes of KMC compared to those of TC have been established by several studies using data from this RCT and other research. Boundy et al. (2016) presented a meta-analysis demonstrating the associations between KMC and improved neonatal outcomes. Charpak et al. (2005) provided details on the implementation and historical development of the KMC protocol. As a result of the aforementioned studies, Kangaroo Mother Care (KMC) is now included in the list of approved protocols for managing health issues in premature infants (WHO, 2023).

The researchers conducted a follow-up of the RCT between 2012 and 2014 when the participants were 20 years old. During this comprehensive follow-up, the researchers used questionnaires from the Adult Behavior Checklist (ABCL) and Adult Self-Report (ASR) and also gathered feedback from the participants' parents and best friends. Additionally, the follow-up included visits and questions about other important cognitive measures, as well as inquiries about education and social factors for further study.

3 Data

3.1 KMC RCT

As mentioned before, the Kangaroo Mother Care (KMC) program has been the subject of extensive studies, particularly through the Randomized Controlled Trial (RCT) conducted at the San Pedro Claver clinic. The original sample comprised 746 premature infants, with 364 assigned to the control group (Traditional Care, TC) and 382 to the treatment group (Kangaroo Mother Care, KMC). By one year of corrected age, 19 infants in the control group and 11 in the treatment group had died. Randomization was stratified based on birth weight into four categories: less than 1200 grams, 1200-1499 grams, 1500-1800 grams, and 1801-2000 grams, ensuring balanced treatment and control groups regarding birth weight.

Follow-up studies were conducted between 2012 and 2014 when the participants were approximately 20 years old. During this period, researchers re-contacted 496 participants and successfully re-enrolled 441 individuals, comprising 213 from the control group and 228 from the treatment group. Two phenomena may explain attrition: traditional non-response because participants cannot be found or do not want to participate and, participant mortality.

It is important to mention that the sample was further refined to a fixed sample of **404 participants** for detailed analysis according to the availability of information on university enrollment and social-emotional questionnaire variables for this thesis. Figure 1 shows the progression starting from program enrollment until the 20 years of follow-up and the observations presented in the bottom boxes represent the fixed sample for this research.

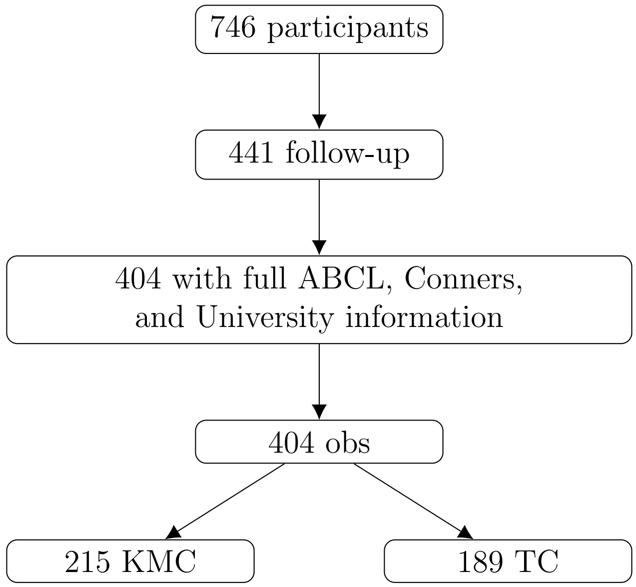

Figure 1

Table 1 presents descriptive statistics for baseline characteristics for the KMC and TC groups, comparing the follow-up fixed sample to the attrition group. In most variables, there is a balance among the fixed 20-year follow-up. Some of the significant differences are in the mother's age - in the follow-up group, the age is around 28 years old - and the Mother and father's education above secondary, in addition to income per capita, the attrition group on average had 77.060COP. In contrast, the follow-up group reported an average of 88.100COP. For the whole sample, the original group had a greater weight at eligibility on average than their follow-up peers.

Table 1: Descriptive statistics - Follow-up Vs. Attrition

Variable	Follow-up		Attrition		Difference
	N	Mean	N	Mean	
Girl	404	0.56	342	0.53	0.04
Mother age	404	27.82	341	26.64	1.18 ***
Mother Education: Primary or less	404	0.20	342	0.24	−0.04
Mother Education: Secondary	404	0.54	342	0.58	−0.05
Mother Education: Above Secondary	404	0.26	342	0.17	0.10 ***
Father Education: Primary or less	404	0.20	342	0.21	−0.01
Father Education: Secondary	404	0.55	342	0.60	−0.05
Father Education: Above Secondary	404	0.23	342	0.15	0.08 ***
HH income per capita in 1000, 1993	402	88.10	341	77.06	11.05 ***
Multiple pregnancy	402	0.17	338	0.20	−0.04
Gestational age	404	33.82	342	33.72	0.10
Birth weight	404	1,713.48	342	1,727.76	−14.29
Age at eligibility	404	35.03	342	34.95	0.08
Weight at eligibility	404	1,692.61	342	1,704.01	−11.39
Hospitalized in neonatal period	404	0.60	342	0.62	−0.02

Note: Significance for the t-test on the means difference: * 90%, ** 95%, *** 99%. Descriptive statistics for baseline characteristics of the Kangaroo Mother Care (KMC) and Traditional Care (TC) groups, comparing the fixed 20-year follow-up sample to the attrition group.

Table 2 reports pre-treatment characteristics for the final follow-up sample used for this thesis. Except for weight at eligibility, multiple pregnancies, and the fraction of fathers with secondary education, both groups are balanced. Furthermore, the probability of multiple pregnancies was larger for KMC than TC children. On average, gestational age is approximately 33 weeks in both groups. The table also shows that around 56% of the participants were girls.

Approximately 75% of the infants' mothers and fathers had secondary or lower education as the maximum attainment level. The baby's average gestational age was 33.8 weeks, and the average birth weight was around 1714 g. On average, the participants were stabilized to the extra-uterine life and then entered the RCT at 35 weeks (age at eligibility). Moreover, around 60% of newborns were hospitalized during the neonatal period.

Table 2: Fixed sample - KMC Vs TC

Variable	KMC		TC		Difference
	N	Mean	N	mean	
Girl	215	0.54	189	0.59	−0.04
Mother age	215	27.54	189	28.13	−0.58
Mother Education: Primary or less	215	0.21	189	0.19	0.02
Mother Education: Secondary	215	0.54	189	0.53	0.02
Mother Education: Above Secondary	215	0.25	189	0.28	−0.03
Father Education: Primary or less	215	0.21	189	0.19	0.02
Father Education: Secondary	215	0.51	189	0.59	−0.09 *
Father Education: Above Secondary	215	0.25	189	0.21	0.04
HH income per capita in 1000, 1993	215	88.55	187	87.59	0.96
Multiple pregnancy	214	0.20	188	0.13	0.06 *
Gestational age	215	33.79	189	33.86	−0.07
Birth weight	215	1,695.23	189	1,734.23	−39.00
Age at eligibility	215	35.03	189	35.02	0.01
Weight at eligibility	215	1,670.51	189	1,717.75	−47.24 **
Hospitalized in neonatal period	215	0.62	189	0.57	0.05

Note: Significance for the t-test on the means difference: * 90% ** 95% *** 99% Descriptive statistics for baseline characteristics of the fixed 20-year follow-up sample by Kangaroo Mother Care (KMC) and Traditional Care (TC) groups

3.2 Externalized Behavior

The assessment of individual socio-emotional variables was an integral part of understanding the long-term impact of the KMC intervention. These variables were measured in the 20-year follow-up using the Adult Behavioral Checklist (ABCL), part of the Achenbach System of Empirically Based Assessment (ASEBA), which is designed for adults (ASEBA, 2017). The ABCL captures a wide range of emotional and behavioral functioning, like hyperactivity and antisocial behavior.

Moreover, information was gathered from those close to the participants, such as parents and best friends, to provide a more comprehensive view of their socio-emotional status. The Adult Self-Report (ASR) is also part of the ABCL but is a self-administered questionnaire that provides additional insights into the participants' self-perceived emotional and behavioral issues. This approach ensures that the socio-emotional variables are assessed from multiple perspectives, enhancing the reliability and validity of the data.

The follow-up also included the Comprehensive Behavior Rating Scale-Self-Report (Conners), an assessment tool that encourages young people to provide important information about themselves. Conners' Adult ADHD Rating Scales (CAARS) is part of the broader Conners suite of assessment tools designed for adults (Conners, 2008). The CAARS offers a comprehensive evaluation of ADHD symptoms, including inattention, hyperactivity, impulsivity, and related behavioral issues, providing valuable insights into the participants' emotional and behavioral functioning.

Due to the strong association between Attention-deficit/ hyperactivity disorder (ADHD) and externalized behavior (Angold et al., 1999; Wit et al., 2023), we used hyperactivity and antisocial behavior scores reported by the best friend from ABCL, the hyperactivity and antisocial scores from ASR, and the score from the Conners self-reported instrument, all standardized to create an externalized behavior latent variable (Cronbach's $\alpha > 0.7$). [1] Table A1 in the annex shows the confirmatory factor analysis for it. Table A2 shows the relation between our variables of interest and externalized behavior.

The externalized behavior is important to our study because KMC has been shown to positively influence various aspects of child development, including emotional and behavioral regulation. Studies suggest that the close physical and emotional contact inherent in KMC promotes secure attachment, which can reduce externalized behaviors such as aggression and hyperactivity (Feldman et al., 2002; Charpak et al., 2005). A reduction in externalized behavior can have significant implications for educational outcomes. Specifically, lower levels of externalized behavior are associated with higher academic achievement and a greater likelihood of university attainment (Moffitt et al., 2011). This is because students with fewer behavioral problems tend to have better school engagement and performance, which are critical for pursuing higher education. Moreover, employment and work experience can be influenced by these behaviors. (Heckman et al., 2006).

3.3 University Attainment and Real Wages.

This thesis relies on university attainment information based on data collected at the 20-year follow-up. During the interview, participants were asked whether they had

[1] All scores used for the factor analysis were standardized

started their university education. This measurement includes individuals who have completed their university studies as well as those who had started but not yet finished at the time of the interview. From our sample of 404, 148 (36.63%) participants were registered with university attainment. Table 3 provides additional information on this topic.

The data from wages comes from the Integrated Contribution Settlement Form (PILA) - a virtual platform that allows for the unified payment of contributions to the Social Security System in Colombia. This platform enables contributors to report information for each subsystem, including the pension plan and health insurance. The data from PILA provides insight into various aspects of the labor market dynamics in Colombia, such as the type of worker (independent or dependent), the field of work identified by CIIU code, and *the contribution base income* (IBC).

We requested information from the Ministry of Labor in Colombia and got monthly information on the RCT follow-up participants from **January 2011 to August 2020**. The 30.060 observations came from 'planillas', which are the individual register of social security payments from the PILA. Some of the observations were duplicated because the employee or employer made corrections. However, after cleaning observations into one collapsed planilla per individual by month, we ended up with 26.767 observations.

After another collapse to get the average information per participant, we found that of the 404 individuals fixed to this study's sample, only 379 were registered as workers at least once in the PILA. Table 3 shows the descriptive statistics for these variables. 22 participants simply did not register any information in the PILA.

Of the 382 participants with information in PILA, 3 participants were missing IBC information because they were listed as beneficiaries of another adult's health insurance coverage under the figure of "additional UPC." This means that these individuals do not work but still have health insurance because a parent or another family member pays for them. This coverage is available until the age of 23. However, some of them are still registered as beneficiaries because they have reported a disability or got married.

Even though the planilla does not reflect the wages, we utilized the IBC as an approximate of it, which varies depending on the type of worker; for independent workers, the IBC is equal to 40% of the net income received in the month. The IBC cannot be less than the current legal monthly minimum wage, nor greater than 25 minimum wages. For the dependent workers, the IBC is the full salary payment that the worker receives during a month.

After cleaning the database, for the participants who registered as independents and with an IBC less than 2,5 times the minimum wage of the period, the wage was calculated as 2,5 times the IBC, and all of those participants who were registered as dependent or with IBC less than 2,5 times of the minimum wage of the period, the IBC represented the full monthly wage, this was also fixed to real values with information of the Consumer price index (CPI) based on December of 2018 from Banco de la República de Colombia.

We also used the natural logarithm transformation of the wages (1), this represents a basic principle of perception known as Weber's Law, which states that the effective stimulus for the detection and evaluation of changes or differences in quantitative dimensions is the percentage change, not the absolute amount [2](Portugal & Svaiter, 2011)

$$real\_wage = log(real\_wage + 1) \tag{1}$$

However, we encountered an issue with 25 participants in the sample who did not have the IBC information for the reason we mentioned before (22 were never registered in PILA and 3 were registered as additional UPC), which resulted in the logarithm being missing for them. The literature mentions adding one to each value as a way to address the missing information, so that is how we proceeded. (Ruppert, 2001)

[2] There has been an extensive discussion about why using logarithms for transformation is better than using arcsin. We chose to use logarithms because Lifeng and Chang Xu (2020) argued that the arcsin transformation lacks intuitive practical interpretations, especially when compared to the traditional log transformation.

Table 3: Descriptive statistics University attainment and Wages

Variable	Obs.	Mean	Stan. dev.	Min.	Max.
	(1)	(2)	(3)	(4)	(5)
University Attaintment	404	0.366	0.482	0	1
Real Wage (Log)	404	12.8	3.36	0	15.4
Additional UPC	382	0.036	0.188	0	1
Independant worker	382	0.296	0.457	0	1

Note: The sample consisted of 404 participants. Among them, 379 individuals were registered as workers for at least one period in the PILA. From the 382 participants that were included in the dummy of additional UPC, for 3 participants, the variable took the value of log(1) because they were reported as additional UPC with no IBC information, and their wage was fixed to 0. Additionally, 22 participants did not have any register in PILA, which was also indicated by a value of 0 in real wage.

4 Empirical Strategy

In this section, we describe the statistical techniques used to identify differences between KMC and TC in their causal effect on externalized behavior, university attainment, and wage outcomes. In Figure 2, we explore the paths from which Kangaroo Mother Care (KMC) as an intervention during early childhood leads to increased wages in adulthood. We aim to confirm this relationship through a mediation analysis. Specifically, we intend to establish the link between the KMC treatment and the level of externalized behavior (aggressiveness) at 20 years old. This behavior, in turn, may impact university attainment and ultimately affect wages in adulthood.

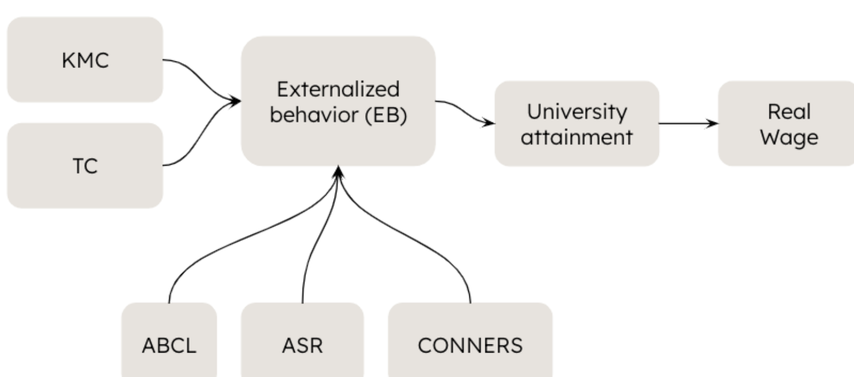

Figure 2: Path Analysis diagram

To address the mediation analysis, we will employ a structural equation model (SEM). First of all, SEM enables the simultaneous testing of relationships among multiple variables; that is, rather than examining them in isolation, as is typical in regression, we are going to do it simultaneously (MacKinnon et al., 2016). This allows for a more comprehensive understanding of the interplay between different factors, as we have described in our path analysis diagram: treatment, externalized behavior, university attainment, and how they collectively influence wages.

We proposed the following equations that will be tested simultaneously through the SEM command. Where KMC_i takes the value of 1 for treatment KMC and 0 for TC, D_j is a set of dummies that identify weight blocks used in the RCT design. Coefficients β_i, δ_i, and λ_i are the coefficients of interest. X_i is the vector of unbalanced covariates of individual i. These variables might explain outcomes, enhancing the precision of β_i δ_i and λ_i estimates.

- Outcome: Externalized Behavior (EB)

  Independent variable: Treatment (KMC_i) and unbalanced covariates (X)

  EB_i is the externalized behavior latent variable.

$$EB_i = \alpha_1 + \beta_1 \cdot KMC_i + \sum_{j=2}^{4} \gamma_{1j} \cdot D_j + \theta_1 \cdot X_i + \epsilon_{1i} \quad (2)$$

- Outcome: University Attainment (U)

  Independent variable: EB_i and unbalanced covariates (X)

  U_i represents the university attainment. It includes participants with complete and incomplete university education.

$$U_i = \alpha_2 + \beta_2 \cdot KMC_i + \delta_2 \cdot EB_i + \sum_{j=2}^{4} \gamma_{2j} \cdot D_j + \theta_2 \cdot X_i + \epsilon_{2i} \quad (3)$$

- Wages on University Attainment (U) and unbalanced covariates (X):

  W_i represents the real wages.

$$W_i = \alpha_3 + \beta_3 \cdot KMC_i + \delta_3 \cdot EB_i + \lambda \cdot U_i + \sum_{j=2}^{4} \gamma_{3j} \cdot D_j + \theta_3 \cdot X_i + \epsilon_{3i} \quad (4)$$

The randomized control trial (RCT) design enables us to establish causal effects through the Rubin Causal Model (Rubin, 1974). As the assignment to each treatment (TC or KMC) is random, we can calculate the average treatment effect of KMC using standard OLS regression. However, it's important to note that the entire system of equations from (2) to (4) can be done with the Structural Equation Modeling (SEM), which allows us to isolate causal effects and simultaneously run regressions. In summary, the SEM approach facilitates the development of our hypothesis by allowing us to test the goodness-of-fit between our model and the observed data. (Gunzler et al., 2013; Danner, 2015; MacKinnon et al., 2009)

4.1 Attrition

To address attrition, we checked the Lee bounds method (Lee, 2009), which provides an interval for the true value of the treatment effect without making parametric assumptions on attrition. This method relies on two assumptions: random assignment of treatment and monotonicity in the assignment selection, meaning that the treatment makes selection more or less likely.

Since KMC participants are more likely to be observed, we calculate the bounds on the average treatment effect by trimmed sample so that the share of observed individuals is equal for both groups, including the attrition group. This trimming provides both lower and upper bounds for the treatment effect, as established by the stata command `leebounds`. We also adjust our outcome variables for covariates (unbalanced variables) to improve the precision of our estimates, i.e., The residuals from these regressions are used in the Lee bounds analysis.

Table 4: Leebounds

	(1) Externalized Behavior	(2) University Attaintment	(3) Wage Real
Treatment			
Lower	-0.0121	-0.0199	-0.840***
	(-0.29)	(-0.36)	(-3.01)
Upper	0.0177	0.0331	0.208
	(0.34)	(0.51)	(0.56)
N	746	746	746
Selected obs.	440	434	403
RCT blocks	Yes	Yes	Yes
Unbalances controls	Yes	Yes	Yes

Note: t statistics in parentheses. Significance for the p-value: * 90% ** 95% *** 99%. The table reports the estimated treatment effects using the lee bound command in Stata. The lower and upper bounds on the average treatment effect account for potential non-random attrition and non-compliance. Standard errors are in parentheses. The sample includes observations near the cutoff point of the running variable. Ordinary Least Squares regression is employed, and all specifications include dummies for RCT weight blocks. Unbalanced controls include multiple pregnancies, weight at eligibility, and father's secondary education. The significance does not affect the results, but the change in sign indicates that attrition might play a role in this study.

The Lee Bounds method, as shown in Table 4, indicates that attrition has a significant impact on the results because the lower bound has a different effect on the dependent variable than the upper bound. However, this issue can be mitigated by using a specific trimming approach. Cortés et al. (2022) suggested a method where the group with less attrition (KMC) is trimmed at the quantile determined by the proportion of additional observations. Trimming the upper tail provides the lower bound, while trimming the lower tail gives the upper bound. Since the number of observations varies across outcomes, the quantile also varies. In their study, attrition did not play a significant role, so this method could be applied in future studies.

4.2 Multiple Hypothesis

Since we are testing three outcomes, the likelihood of a Type I error (false positives) increases. Studies of RCTs have been criticized for overestimating treatment effects due to this "multiplicity" effect (Doyle et al., 2013). To address the issue of multiple hypothesis testing, we employ the Romano-Wolf correction in OLS, which adjusts p-values to control the familywise error rate. (FWER) The methodology of Romano and Wolf (2005) ensures that the largest unadjusted p-value corresponds to the largest adjusted p-value (Heckman et al., 2010).

4.3 Non-normality assumption

We will apply the Satorra-Bentler correction in the SEM to account for the non-normal distribution of these data. This correction method adjusts the chi-square test statistic and standard errors of model parameters, ensuring robustness against violations of multivariate normality assumptions (Satorra & Bentler, 1994). By using robust standard errors and scaled chi-square statistics, the Satorra-Bentler correction provides more accurate estimates of model fit and parameter significance, which are essential for valid inference in SEM when data exhibit skewness or other forms of non-normality (Gao et al., 2008). This approach enhances the reliability and validity of our findings by mitigating biases that could arise from traditional maximum likelihood estimation under non-ideal distributional conditions.

5 Results

5.1 OLS results

The OLS regression estimates of the causal effects between the mediation of our hypothesis are presented in Table 5. The first line in the table reports the estimated coefficient. In parenthesis, in the second line, we present the robust standard error of the coefficient. The third line, in square brackets, corresponds to the p-value of the Romano and Wolf (2005) test. Column 1 reports the results of the dependent variable of externalized behavior controlling for weight blocks used at the randomization. The specification in Column 2 reflects Equation (3), which is specified in section 4. Results in Column 3 include Wages on university attainment, externalized behavior, treatment, and unbalanced covariates.

The findings of the OLS indicate that, on average, the KMC is associated with a 6.5% decrease in externalized behavior, reflecting a reduction in behavioral issues among participants who received KMC compared to those who did not. However, KMC does not exhibit significant direct effects on university attainment or real wages, as evidenced by their respective coefficients and p-values. On the other hand, an increase in one standard deviation on externalized behavior significantly reduces the likelihood of university attainment by 21.3% ($p < 0.01$). Given the logarithmic transformation of wages, there is an increase of 173.5% real wages for individuals with a university education compared to those without, showing the substantial wage premium associated with higher education, as it is well studied in extensive economic literature. (Conlon & Patrignani, 2011)(Relative earnings of workers by educational attainment (2019), 2021).

Table 5: OLS Results

Dependant variable		(1) Externalized Behavior	(2) University attainment	(3) Log wage real
KMC	Coef	-0.065*	-0.021	0.133
	Robust Std.error.	(0.033)	(0.049)	(0.330)
	Romano-Wolf	[0.063]		
	R-squared	0.022	0.027	0.045
	Observations	403	403	403
Externalized Behavior	Coef		-0.213***	-0.889
	Robust Std.error.		(0.069)	(0.619)
	Romano-Wolf		[0.008]	
	R-squared		0.027	0.045
	Observations		403	403
University Ed.	Coef			0.991***
	Robust Std.error.			(0.329)
	Romano-Wolf			[0.008]
	R-squared			0.045
	Observations			403
RCT weight blocks		Yes	Yes	Yes
Unbalanced controls		Yes	Yes	Yes

Note: Significance for the p-value: * 90% ** 95% *** 99%. Ordinary Least Squares regression is employed. Robust standard errors are presented in parenthesis and Romano-Wolf p-values in square brackets. All specifications include dummies for RCT weight blocks. Unbalanced controls include multiple pregnancies, weight at eligibility, and the father's secondary education

Nonetheless, we need to delve into the results of simultaneously running the regressions. The next section presents the results of the SEM.

5.2 SEM model results

Although OLS yields significant results, it is important to analyze the equations simultaneously. The estimates of the structural model, presented in Panel A of Table 5, highlight the direct effects of treatment on externalized behavior(EB), EB on university attainment (U), and U on real wages (W). Panel B presents the indirect effects of the treatment on university attainment and real wages.

The treatment (KMC) shows a statistically significant reduction in externalized behavior by approximately 9.9%, suggesting that participants who received KMC treatment exhibited significantly lower levels of externalized behavior compared to those who did not. Furthermore, a one-standard-deviation increase in externalized behavior is associated with a 20.1% decrease in the likelihood of going to university. University attainment, in turn, positively affects real wages. Given that wages are log-transformed, a one-unit increase in the probability of university attainment leads to an increase in real wages of approximately ($e^{5.314} - 1$), or about 201.2% ($\beta = 5.314, p \leq 0.10$).

Regarding panel B, KMC has a significant indirect effect on university enrollment through reduced externalized behavior, leading to a 2.0% increase in the probability of university attainment. This means that the treatment indirectly boosts the chances of attending university by lowering externalized behavior. Furthermore, the treatment's indirect effect on real wages through both externalized behavior and university attainment is estimated to be around 11.2%, but it is not statistically significant at the usual levels. However, if we consider a more lenient significance level, such as 80%, the results in Table 6 suggest that the treatment does impact wages. The strength and significance of this effect vary depending on the statistical threshold used in the analysis.

All specifications in Table 6 include dummies for RCT weight blocks. Unbalanced controls include multiple pregnancies, weight at eligibility, and the father's secondary education.

Table 6: Estimates of the structural model

Panel A: Direct effects	Estimate.
Externalized Behavior	
Treatment - KMC (a_1)	-0.099**
	(0.047)
University attaintment	
Externalized Behavior (a_2)	-0.201***
	(0.069)
Real wages (Log)	
University attaintment (a_3)	5.314*
	(3.315)
Panel B: Indirect effects	Estimate.
Treatment on University	
(a_1 x a_2)	0.020*
	(0.011)
Treatment on wages	
(a_1 x a_2 x a_3)	0.106
	(0.078)
Observations	403
SRMR	0.048
Prob > chi-square	0
CD	0.064

Note: The model was estimated using the SEM command in Stata. To correct normality in the errors, Satorra–Bentler Standard errors are in parentheses. Significance for the p-value: * 90% ** 95% *** 99%. The indirect effects were calculated using the `nlcom` command in Stata. The covariance between university attainment and real wages was included to control for potential correlation between these variables. All specifications include dummies for RCT weight blocks. Unbalanced controls include multiple pregnancies, weight at eligibility, and father's secondary education. SRMR stands for Standardized root mean squared residual. CD stands for Coefficient of determination. The chi-square is under Satorra–Bentler scaled test

In our SEM model, we also include the covariance between university attainment and real wages. This covariance accounts for the potential correlation between the errors of these two variables, recognizing that factors affecting university attainment might also influence real wages. Including this covariance helps to ensure that the estimated direct and indirect effects are not biased due to unaccounted shared variance between university attainment and wages. By controlling for this relationship, our model provides a more accurate representation of the pathways through which the treatment influences educational and economic outcomes.

6 Conclusions

This research clearly demonstrates the positive impact of Kangaroo Mother Care (KMC) on reducing externalized behavior and enhancing university enrollment. While the overall indirect effect of KMC on adult wages is not statistically significant, the program shows a noteworthy reduction in externalized behavior by approximately 9.9%. The decrease in externalized behavior by one standard deviation is associated with a substantial increase in the likelihood of university attainment by 20.1%. Furthermore, university enrollment correlates with a significant rise in real wages, estimated at 201.2%.

The economic theory of human capital formation provides a solid framework for interpreting these findings. According to Becker's (1964) theory, investments in health and education during childhood yield significant returns in adulthood. Although we did not find statistically significant results regarding wages, KMC enhances the emotional and cognitive development of participants, mitigating behaviors that could hinder academic success, as documented in the economics literature (Papageorge et al., 2019; Heckman, 2011). By reducing externalized behavior, KMC participants are better equipped to thrive in educational environments, ultimately leading to higher rates of university enrollment.

The lack of a significant indirect impact of KMC on wages should not be seen as a drawback. Instead, it highlights the complexity of wage dynamics in the job market. In this context, some of the benefits of KMC are evident behaviorally in the participant rather than solely as indicators of education level. Our analysis indicates that the long-term outcomes observed should be viewed as genuine improvements in human capital rather than just signaling effects. While Spence (1973) suggested that education can signal productivity to employers, in our case, these signals could mask the substantial productivity gains resulting from interventions such as KMC.

However, these results indicate the need for further research, including new mediation variables and considering other factors important to delve into our hypothesis, such as the type of worker, area of employment, university degrees obtained, socioeconomic status, and formal versus informal employment rates. Additionally, conducting robustness checks with attrition and multiple hypothesis testing is necessary. This thorough approach will contribute to a more comprehensive understanding of how early interventions like KMC can impact long-term economic success.

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7 Annex

Table A1: Confirmatory factor analysis - Externalized behavior

	(1)
Externalized behavior (Std)	Coeff.
ABCL std antisocial best-friend	
	1.00
	(.)
ABCL std hyperact best-friend	
	0.88***
	(0.18)
ABCL std antisocial self-reported	
	1.86***
	(0.30)
ABCL std hyperact self-reported	
	1.80***
	(0.31)
Conners std hyperact self-reported	
	1.33***
	(0.25)
Conners std antisocial self-reported	
	1.49***
	(0.25)
Observations	404

Note: Significance for the p-value are * 90% ** 95% *** 99%. Standard errors are shown in parentheses. The table displays the results of the Confirmatory Factor Analysis (CFA) performed to validate the factor structure of ABCL antisocial and hyperactivity scores from the best friend, the ASR (part of the ABCL) on self-reported antisocial and hyperactivity behaviors, and the self-reported hyperactive and antisocial scores measured at the 20-year follow-up. Each of the variables is standardized. The analysis assesses the fit of the hypothesized model to the data using standardized factor loadings.

Table A2: Externalized behavior relation to variables of interest

Variable	(1) Externalized behavior	(2) Univ. Ed	(3) Real Wage (Log)
KMC	-0.0695**	-0.0159	0.183
	(0.0339)	(0.0494)	(0.334)
University Ed.			0.978***
			(0.330)
Externalized Behavior		-0.209***	-0.854
		(0.0689)	(0.633)
Constant	0.0512	0.292	9.159***
	(0.192)	(0.257)	(2.234)
Observations	403	403	403
R-squared	0.027	0.029	0.048
Robust errors	Yes	Yes	Yes
RCT blocks (FE)	Yes	Yes	Yes
Unbalanced controls	Yes	Yes	Yes

Note: Ordinary Least Squares regression is employed. Robust standard errors are presented in parentheses. All specifications include dummies for RCT weight blocks. Unbalanced controls include multiple pregnancies, weight at eligibility, and father's secondary education. Externalized behavior variables that compound it are standardized.