Long-Term Effects of Early-Life Exposure to Severe Air Pollution on Cognitive Development and Mental Health

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Abstract

This study replicates and extends Shrestha's (2019) analysis of the long-term impacts of early-life exposure to severe air pollution from the 1997 Indonesian forest fires on cognitive development. Using the Indonesian Family Life Survey (IFLS) and a difference-in-differences approach, I confirm Shrestha's findings that early-life exposure to air pollution significantly reduced cognitive test scores by approximately 1 point 10 years after exposure, with more substantial effects among poorer households and those outside Java Island. However, these effects were not persistent after 17 years. I extend the analysis in two directions: First, I examine potential mechanisms of the lower cognitive development 10 years after the exposure by exploring household spending patterns, finding no significant impacts in education, health, or other spending channels, suggesting that the cognitive effects likely stem from biological factors rather than lower human capital investments. Second, I investigate mental health outcomes, finding no significant impact of early-life pollution exposure on mental health after 17 years. It could be that the impact on mental health diminishes over time or that the impact on mental health for those exposed to pollution in early life is not as significant compared to those exposed at an older age as complemented by additional analyses on a sample of older cohorts.

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1. Introduction

Severe air pollution from a particular episode of the Indonesian forest fires in 1997 has impacted the development of individuals, including children. Existing studies have explored the impact of the severe air pollution from the 1997 Indonesian forest fires on various outcomes, including health outcomes (Frankenberg et al. 2005; Kim, Knowles, et al. 2017; Rosales-Rueda and Triyana 2019), child mortality (Jayachandran 2009), mental health (Kim et al. 2020), and labour supply (Kim, Manley, et al. 2017).

In a recent study, Shrestha (2019) explored the impact of exposure to air pollution on cognitive development 10 and 17 years after exposure to the forest fires for those exposed in utero or born around the incidence of the forest fires, taking advantage of the natural experiment, and using a panel dataset to estimate the impact. Shrestha (2019) found a negative and significant impact of early-life exposure to pollution on cognitive development 10 years after the exposure; however, the impact is not significantly present 17 years after the exposure.

In this report, I replicate the findings of Shrestha (2019) in estimating the impact of pollution on cognitive development 10 and 17 years after exposure. I further extend Shrestha's (2019) study to include additional outcomes, including spending channels 10 years after the exposure and mental health 17 years after the exposure using the same empirical strategy. Regarding spending channels, I explore whether exposure to air pollution from the fires impacts households' spending channels, consisting of total spending, education spending, health spending, durable goods spending, and household supplies spending. The primary motivation for exploring the impact towards spending channels is that household spending channels can be a possible mechanism in driving the lower cognitive development of exposed children after the exposure, as households can potentially invest in lower human capital investments due to the damage caused by the forest fires.

Considering mental health, environmental exposures like air pollution can affect both cognitive development and mental health through shared biological pathways, and that early cognitive difficulties can also lead to mental health challenges through a decline in academic achievement and self-efficacy (Ren et al. 2019). Existing studies exploring the effects of pollution from the forest fires on mental health have not focused on exposure in early life. I explore the impact of early-life pollution exposure on mental health 17 years after the exposure as the IFLS asks questions related to mental health only for individuals aged 15 and above.

The result of my replication differs slightly in magnitude compared to Shrestha's (2019), although the conclusion of the replication results does not differ. On the other hand, the results of the extensions in this study suggest that early-life pollution exposure has no significant impact on spending channels and mental health.

A possible explanation for the results on spending channels is that the potential mechanism of lower cognitive development 10 years after exposure is biological rather than through households' lower investments in human capital. In contrast, mental health is not significantly impacted by early-life exposure to air pollution, as the impact of pollution towards mental health may diminish over time. I complement my findings with estimates of the impact of pollution on mental health using a sample of older cohorts as opposed to younger cohorts to observe the diminishing impact of pollution towards mental health. Alternatively, it could also be that the mental health of those exposed to pollution early in life is less impacted by severe air pollution.

The remainder of this report is organised as follows. Section 2 discusses existing literature that has explored the effects of pollution from the fires on various outcomes. Section 3 discusses the data and empirical strategy. Section 4 discusses the results of the replication and extension. Section 5 concludes.

2. Literature Review

Apart from Shrestha's (2019) study, Rosales-Rueda and Triyana (2019) also explored the impact of early-life exposure to severe air pollution on cognitive development using a distinct empirical strategy and utilising pollution data from NASA's Earth Probe Total Ozone Mapping Spectrometer (TOMS). Rosales-Rueda and Triyana (2019) also employ a difference-in-differences method and capture individuals' exposure to forest fires using the intensity of the aerosol index. The study found that early-life exposure to air pollution does not have a significant impact on cognitive score 17 years after the exposure, which is in line with Shrestha's (2019) findings; however, the study also did not find a significant impact 10 years after exposure which is different from the findings of Shrestha (2019). The reason for the difference in their findings is the use of various samples in the two studies for analysis. Rosales-Rueda and Triyana (2019) employ a variety of samples of individuals exposed at the early-life stages, with separate estimates for those exposed in utero, exposed from 0 to 12 months after birth, and exposed from 13 to 24 months after birth, whereas Shrestha (2019) uses a sample of individuals exposed in utero and born around the forest fires when it was most severe between September and November 1997.

Regarding the impact of air pollution on mental health, a notable study by Kim et al. (2020) explored the impact of the severe air pollution from the 1997 forest fires towards mental health. The study examined the impact on mental health 10 years after the exposure, though it did not focus on a sample of individuals exposed to the pollution in early life. The study found significant adverse effects of air pollution on mental health, where air pollution increases the incidence of depressive symptoms for men and women, as well as the incidence of clinical depression among women. Their estimates also revealed that men are less depressed than women.

On the other hand, studies have mainly explored the impact of the air pollution from the 1997 Indonesian forest fires on health outcomes (Frankenberg et al. 2005; Kim, Knowles, et al. 2017; Rosales-Rueda and Triyana 2019). The studies that explored the impact on health outcomes collectively reveal that exposure to severe air pollution has lasting adverse effects on health, especially in children and vulnerable adults. In particular, children exposed in utero showed stunted growth and reduced lung capacity (Rosales-Rueda and Triyana 2019). Poor respiratory health of mothers during pregnancy contributed to the long-term health issues of these children. Furthermore, adults experienced declining health conditions, with men and the elderly being particularly vulnerable (Kim, Knowles, et al. 2017; Frankenberg et al. 2005).

Other studies have also explored the impact of severe air pollution on child mortality (Jayachandran 2009) and labour supply (Kim, Manley, et al. 2017). Jayachandran (2009) found that the pollution led to 15,600 lost children (a 1.2% decrease in affected birth cohorts). The effects were most significant during prenatal exposure, in poorer areas, and areas with more use of wood-burning stoves. On the other hand, Kim, Manley, et al. (2017) found that exposure to pollution reduced labour supply even after 10 years of exposure.

3. Data and Empirical Strategy

3.1 Data

The data source used in this study is the Indonesian Family Life Survey (IFLS). The IFLS is a longitudinal dataset representative of 83% of the Indonesian population. The first wave of IFLS started in 1993, with follow-up waves in 1997, 2000, 2007, and 2014.[1]

In this study, the sample of individuals is obtained from IFLS 2000. This allows us to identify whether the individuals are exposed to air pollution, utilising information on region and year of birth. Using the IFLS 2000 also allows the inclusion of those born after the occurrence of the 1997 forest fires in the dataset. Furthermore, the IFLS 2007 and IFLS 2014 are also used to obtain the outcome variables post-exposure. The outcome variables used are cognitive score 10 and 17 years after the exposure for the replication and household spending channels and mental health for the extension (10 and 17 years after the exposure, respectively).

3.2 Empirical Strategy

This study uses a difference-in-differences strategy by taking advantage of the variations of affected cohorts and regions of the pollution from forest fires. In 1997, the pollution was most apparent from September to November. Assuming a nine-month gestation period, people born in the affected regions between November 1997 and July 1998 are most exposed to air pollution during a crucial period in utero. On the other hand, three provinces on Sumatra Island and three in Borneo had the worst pollution. All people born in unaffected and affected provinces between 1996 and 1999—but not from September 1997 to July 1998—comprise the control group. This approach ensures that any age- and province-specific factors influencing test results (measure of cognitive development) can be considered.

The difference-in-differences specification involves the interaction of the region of birth and birth cohorts as the explanatory variable of interest. The outcome variables are cognitive score (for

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[1] The IFLS dataset is publicly accessible through https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html.

replication), and household spending channels and mental health (for extension). The cognitive score is analysed 10 and 17 years after the exposure, and mental health is analysed 17 years after the exposure, as mental health data is only observed for individuals above 15 years old in the IFLS. Furthermore, household spending channels are analysed 10 years after the exposure. The econometric specification can be represented as follows:

$$Y_i = \beta_0 + \beta_1 cohort_i + \beta_2 region_i + \beta_3 region \times cohort_i + \beta_4 X_i + u_i$$

where Y_i represents the various outcome variables consisting of cognitive score, spending channels, and mental health, and X_i represents the set of control variables (female dummy, per capita household consumption in 2000, mother's education, province dummies, and year-of-birth dummies). Shrestha (2019) also uses education level as a control in estimating cognitive score 17 years after the exposure instead of per capita household consumption and mother's education. We are mainly interested in looking at β_3, which highlights the main effect.

4. Results

4.1 Replication

4.1.1 Results of 10 years after the exposure

I estimate the impact of exposure to air pollution on cognitive development about 10 years after the exposure using IFLS 2007 when those exposed to the air pollution are about 9 to 10 years old. Although the coefficients from my replication slightly differ from Shrestha's (2019) study, the conclusion remains unchanged: early-life exposure to air pollution reduces total cognitive test scores 10 years after exposure. The results are highly significant at the 1 per cent level. In Table 1, the baseline model and the model with controls imply that exposure to air pollution lowers cognitive test scores by about 1 point. This is comparable to an impact of 8.7 per cent at the mean total score of 11.5.

On the other hand, in Shrestha's (2019) study, exposure to air pollution impacted lower cognitive test scores by 0.7 points, implying that my findings result in a higher magnitude in the impact of

Table 1 Impact of pollution exposure on total cognitive test score 10 years after the exposure

	(1) Baseline	(2) Controls	(3) Poorer sample	(4) No Java
Exposed cohort	-0.0518	-1.967	6.350	-6.396*
	(0.161)	(2.569)	(5.800)	(3.481)
Exposed region	1.121***	1.324***	1.544***	1.333***
	(0.324)	(0.331)	(0.459)	(0.335)
Exposed cohort X region	-0.966***	-1.007***	-1.389***	-1.237***
	(0.373)	(0.369)	(0.451)	(0.420)
Female	0.0135	0.0684	0.0341	-0.172
	(0.112)	(0.110)	(0.164)	(0.163)
Log per cap consumption 00		0.329***	0.624**	0.380**
		(0.104)	(0.261)	(0.155)
Mother low sec educ		1.002***	1.049***	0.949***
		(0.162)	(0.233)	(0.278)
Mother sec educ		1.287***	1.315***	1.236***
		(0.154)	(0.237)	(0.235)
Mother ter educ		1.878***	1.829***	1.697***
		(0.255)	(0.677)	(0.477)
_cons	11.32***	6.627***	3.089	6.131***
	(0.229)	(1.216)	(2.964)	(1.800)
Observations	2813	2717	1449	1190
R^2	0.108	0.170	0.127	0.174

Source: Author’s calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies, year-of-birth dummies, interactions between exposed cohort and log per capita consumption, and interactions between exposed cohort and mother's education dummies are not reported. The base group for mother's education is primary or below; low sec stands for lower secondary. * p<0.1, ** p<0.05, *** p<0.01.

exposure to air pollution on cognitive development. At the mean total score of 11.5, Shrestha's (2019) findings on the impact are comparable to 6 per cent.

In line with Shrestha's (2019) findings, I found that the coefficient in the interaction term among the poorer sample increases in magnitude to -1.38 (see column 3 of Table 1), suggesting that the impact of air pollution exposure is greater among the poor. Given the higher magnitude of the impact on poorer households, poverty likely contributes to the effects of air pollution. In contrast, in column 4 of Table 1, I also found that the impact among the sample of individuals outside of Java Island is greater, as Shrestha (2019) implied that individuals in Java may have distinct trends in cognitive development compared to the rest of Indonesia due to more significant public service facilities.

Moreover, the estimation in Table 2 uses a placebo sample. The placebo sample consists of individuals born between 1993 and 1996, and the placebo exposure is assigned to individuals born between September 1995 and July 1996, referring to exposure to air pollution but not in early life. The results across all the columns are statistically insignificant for the placebo sample, which provides confidence that the main result in Table 1 is not due to statistical anomalies and random chance. Therefore, this shows that there are no underlying patterns in the outcome variable that could be influencing the key findings.

4.1.2 Results of 17 years after the exposure

I replicate Shrestha's (2019) estimation of the impact of air pollution on cognitive test scores using the 2014 wave of the IFLS in Table 3. The estimation refers to the impact 17 years after the exposure when the exposed individuals are about 16 to 17 years old. In line with the findings of Shrestha (2019) and Rosales-Rueda and Triyana (2019), I found that the results are not statistically significant and have opposite signs in some cases, making them counterintuitive. According to Shrestha (2019), the findings suggest that exposure to air pollution is more sensitive to cognitive development in younger than older individuals. Furthermore, the cognitive questions for the older group (15 years and above) in the IFLS questionnaire are less than the cognitive questions for the younger group (7 to 14 years)—8 as opposed to 12 questions—which can potentially reduce the power of the tests. Another possible explanation is that the impact 17 years after the exposure wea-

Table 2 Impact of pollution exposure on total cognitive test score on placebo sample

	(1)	(2)	(3)	(4)
	Baseline	Controls	Poorer sample	No Java
Exposed cohort	-0.171	-0.173	-0.235	-0.250
	(0.160)	(0.159)	(0.229)	(0.284)
Exposed region	0.900***	1.090***	1.285***	1.006***
	(0.310)	(0.311)	(0.465)	(0.315)
Exposed cohort X region	0.414	0.116	-0.134	0.238
	(0.360)	(0.350)	(0.586)	(0.412)
Female	0.100	0.107	0.225	0.155
	(0.105)	(0.104)	(0.151)	(0.165)
Log per cap consumption 00		0.363***	0.368*	0.477***
		(0.0854)	(0.212)	(0.122)
Mother low sec educ		0.825***	0.751***	0.484**
		(0.139)	(0.201)	(0.229)
Mother sec educ		1.067***	0.893***	0.987***
		(0.142)	(0.237)	(0.210)
Mother ter educ		1.517***	2.333***	1.086***
		(0.199)	(0.520)	(0.353)
_cons	12.18***	7.344***	7.209***	6.187***
	(0.227)	(1.039)	(2.438)	(1.487)
Observations	2687	2547	1336	1130
R^2	0.092	0.148	0.141	0.163

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies, year-of-birth dummies, interactions between exposed cohort and log per capita consumption, and interactions between exposed cohort and mother's education dummies are not reported. The base group for mother's education is primary or below; low sec stands for lower secondary. * p<0.1, ** p<0.05, *** p<0.01.

Table 3 Impact of pollution exposure on total cognitive test score 17 years after the exposure

	(1) Baseline	(2) Controls	(3) Poorer sample	(4) No Java
Exposed cohort	0.0415	-0.0702	-0.171	-0.134
	(0.202)	(0.182)	(0.236)	(0.233)
Exposed region	0.795*	1.146***	1.464***	1.093***
	(0.410)	(0.329)	(0.497)	(0.327)
Exposed cohort X region	0.0185	-0.122	-0.0531	0.00596
	(0.459)	(0.407)	(0.664)	(0.426)
Female	0.609***	0.284**	0.218	0.296*
	(0.134)	(0.120)	(0.155)	(0.171)
Educ junior		2.451***	2.158***	2.357***
		(0.249)	(0.311)	(0.395)
Educ senior		3.530***	3.118***	3.054***
		(0.256)	(0.320)	(0.400)
Educ college		4.025***	4.141***	3.814***
		(0.565)	(0.985)	(0.665)
_cons	7.048***	4.193***	4.680***	4.684***
	(0.265)	(0.331)	(0.411)	(0.472)
Observations	2558	2457	1310	1088
R^2	0.046	0.139	0.158	0.137

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies and year-of-birth dummies are not reported. The base group for education is primary or below. * p<0.1, ** p<0.05, *** p<0.01.

-kens over time, as evidence shows that exposed children are not delayed in starting school (Rosales-Rueda and Triyana 2019).

While Rosales-Rueda and Triyana (2019) found significant health impacts 17 years post-exposure (including 0.2 standard deviations shorter height), these did not translate to cognitive effects.

4.2 Extensions

4.2.1 Extension: Possible Mechanism

As an extension to the study, I explore possible mechanisms that might affect the lower cognitive score 10 years after the exposure through spending channels of households, using a similar empirical strategy to the estimation of the impact of air pollution on cognitive development 10 years after the exposure using the 2007 wave of the IFLS. Bimardhika & Moorena (2024) found evidence that households shift their spending from education to essential household goods after exposure to volcanic eruptions in Indonesia. There could be similar evidence in the case of severe air pollution from the 1997 forest fires. Hypothetically, lower investments in human capital could lead to lower cognitive outcomes. Existing studies in the literature have mainly explored the health outcomes of children impacted by the forest fires and have yet to explore spending channels.

The results from Table 4 are rather interesting since there is a positive relationship between air pollution exposure and total, education, and health spending, while spending on household essentials has a negative relationship with pollution exposure. However, the results from Table 4 are not statistically significant across all spending channels. This strengthens our confidence that the possible channel of the negative impact of pollution exposure on cognitive test scores, as previously estimated, is biological and not through lower spending in human capital investments.

Shrestha (2019) explains that the possible mechanisms through which pollution can impact cognitive development are mother's health and nutrition throughout pregnancy. Rosales-Rueda and Triyana (2019) highlight the adverse impacts of pollution exposure on children's height and respiratory functions to which mothers' health could contribute. Specifically, 10 years after the exposure, children exposed to the pollution in utero were on average 0.1 standard deviations (around 1.6 centimetres) shorter than those not exposed. Furthermore, those exposed to pollution in utero and the first two years of life had reduced lung capacity by five to six percentage points relative to those not exposed. On the other hand, pregnant women exposed to the pollution suffered a decline in lung capacity by six percentage points and an increase in self-reported breathing problems by seven percentage points. Therefore, mother's health is a possible mechanism that can impact children's health, and in turn, cognitive development.

Table 4 Spending channels post-exposure

	(1) Total spending	(2) Education spending	(3) Health spending	(4) Durable goods spending	(5) Household supplies spending
Exposed cohort	-535900.8	180713.9	-21991.9	-117776.5	93077.2
	(1581788.9)	(224970.8)	(86259.8)	(256175.2)	(302348.3)
Exposed region	-368780.0**	-63374.5**	-31347.6*	55761.4	3404.9
	(152028.9)	(32095.0)	(17952.9)	(54180.2)	(22932.1)
Exposed cohort X region	187940.2	54468.2	18173.7	-10038.2	-19500.4
	(213535.7)	(47629.3)	(12147.9)	(51969.3)	(35077.6)
Female	-8576.3	-1984.0	7567.1	-8704.2	10100.4
	(62410.7)	(10887.3)	(5368.7)	(13233.7)	(13541.7)
Log per cap consumption 00	835186.6***	78055.7***	13505.8***	59455.4***	145474.3***
	(72149.9)	(9377.5)	(4861.8)	(16542.3)	(17615.1)
Mother low sec educ	74860.8	15741.7	-3895.4	9608.8	23376.9
	(79815.1)	(12634.1)	(5876.6)	(16252.0)	(16006.8)
Mother sec educ	590337.6***	64465.0***	19554.6**	23855.0	92823.3***
	(92427.8)	(16554.7)	(9480.4)	(21336.0)	(18777.2)
Mother ter educ	2439774.2***	215540.0***	64237.9***	233686.3***	467605.5***
	(326166.3)	(39333.3)	(21036.2)	(79135.8)	(84938.1)
_cons	-7775219.7***	-687109.2***	-112445.3*	-664295.9***	-1561644.4***
	(851347.2)	(111623.3)	(60065.9)	(192151.4)	(203691.8)
Observations	2751	2803	2794	2794	2772
R^2	0.310	0.130	0.045	0.064	0.217

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies, year-of-birth dummies, interactions between exposed cohort and log per capita consumption, and interactions between exposed cohort and mother's education dummies are not reported. The base group for mother's education is primary or below; low sec stands for lower secondary. * p<0.1, ** p<0.05, *** p<0.01.

4.2.2 Extension: Air Pollution and Mental Health

I also explore the impact of early-life exposure to air pollution on mental health 17 years after the exposure as an extension of the study, using a similar approach to the estimates of air pollution on cognitive score 17 years after the exposure. The IFLS only provides information on mental health for individuals aged 15 years and above. The measure of mental health used in the estimates is based on a 10-item Centre for Epidemiological Studies Depression Scale (CES-D) reported in the IFLS, which is then constructed as a CES-D score, ranging from 0 (no depression) to 30 (severe depression).[2]

Table 5 depicts the estimates of the impact of early-life exposure to pollution on mental health. As shown in Table 5, I found that the results are not statistically significant, and the signs are negative, meaning that exposure to air pollution is associated with a lower CES-D score, implying better mental health.

Some studies that explore the impact of early-life exposure to various shocks like war and the rise of cocoa prices on mental health found significant impacts of the shocks on mental health (Singhal 2018; Adhvaryu et al. 2019). The results of the studies differ from the findings of this study in the case of air pollution and mental health.

In addition, I explore the impact of air pollution on mental health using a sample of older cohorts, or in other words, those exposed to air pollution at an older age. I use a sample of those in their late 20s as it corresponds to a crucial life stage when people often experience significant transitions such as entering stable employment, establishing long-term relationships, and perhaps starting families. These life changes could trigger mental health more sensitively than earlier life experiences.

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[2] The 10-item CES-D is attached in the appendix.

Table 5 Impact of pollution exposure on mental health

	(1) Baseline	(2) Controls	(3) Poorer sample	(4) No Java
Exposed cohort	0.249	0.253	0.546	-0.139
	(0.268)	(0.269)	(0.355)	(0.410)
Exposed region	0.755	0.732	1.712**	0.664
	(0.551)	(0.549)	(0.835)	(0.559)
Exposed cohort X region	-0.247	-0.256	-1.585	-0.00817
	(0.737)	(0.738)	(0.970)	(0.800)
Female	0.886***	0.937***	0.753***	1.066***
	(0.184)	(0.186)	(0.261)	(0.260)
Educ junior		-0.565	-0.806	-0.446
		(0.403)	(0.531)	(0.686)
Educ senior		-0.842**	-1.022**	-0.864
		(0.389)	(0.516)	(0.663)
Educ college		-1.779**	-2.537*	-2.186
		(0.887)	(1.350)	(1.399)
_cons	6.753***	7.563***	7.351***	7.526***
	(0.320)	(0.470)	(0.642)	(0.716)
Observations	2358	2351	1229	1055
R^2	0.027	0.031	0.044	0.031

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies and year-of-birth dummies are not reported. The base group for education is primary or below. * p<0.1, ** p<0.05, *** p<0.01.

The estimation uses a similar difference-in-differences strategy to the previous estimation of the impact of pollution exposure in early life on mental health. I use a sample of individuals aged 25 to 30 during the exposure to the forest fires and assign those aged 27 to 28 as the exposed cohort and estimate the impact on mental health 10 and 17 years after the exposure.

At 10 years after the exposure, as shown in Table 6, I found that pollution exposure leads to better mental health. The impacts are statistically significant at the 10% level at baseline and using controls—specifically, exposure to pollution impacted in lower CES-D score by about 0.8 points. The impact is also statistically significant at the 10% level on a sample of females, in which pollution leads to a lower CES-D score by 1 point for the sample of females, indicating that the mental health of males is less impacted by pollution (Kim et al. 2020). A possible explanation for why the sample of older cohorts has better mental health is posttraumatic growth (Tedeschi and Calhoun 2004). Posttraumatic growth suggests that individuals experience positive changes because of the incidence of past shocks. In this context, the results suggest the mental health of older cohorts is resilient when impacted by pollution.

Furthermore, I conduct mental health impact estimations using the sample of older cohorts 17 years after the exposure, as shown in Table 7. I found that the impacts of pollution on mental health are not statistically significant across all estimates. This suggests that the impact on mental health diminishes over time for the older cohorts. In contrast, in Table 5, I observe that the impact of pollution on mental health for individuals exposed in early life is also not present 17 years after the exposure.

It might potentially be the case that the mental health impact of individuals who are exposed to pollution in early life diminishes over time. Or that the mental health of those exposed to pollution in early life is less impacted than those exposed at an older age. However, a drawback of this study is that I cannot explicitly estimate the impact of pollution on mental health for the younger sample 10 years after the exposure due to the unavailability of the data as they are still less than 15 years old and not asked questions related to mental health in the IFLS, preventing us from acquiring the impact on initial mental health conditions for those exposed to pollution in early life which could potentially provide evidence that mental health diminishes over time as a consequence of the pollution.

Table 6 Impact of pollution exposure on mental health for older cohorts 10 years after exposure

	(1)	(2)	(3)	(4)
	Baseline	Controls	Female	Male
Exposed cohort	0.0398	0.0664	-0.0947	0.283
	(0.243)	(0.237)	(0.318)	(0.316)
Exposed region	-2.114***	-2.209***	-1.045	-3.478***
	(0.474)	(0.459)	(0.706)	(0.517)
Exposed cohort X region	-0.810*	-0.807*	-1.185*	-0.397
	(0.452)	(0.445)	(0.689)	(0.598)
Female	0.0834	0.00234		
	(0.127)	(0.129)		
Educ junior		-0.385**	-0.174	-0.621**
		(0.186)	(0.244)	(0.257)
Educ senior		-0.555***	-0.594**	-0.508**
		(0.159)	(0.234)	(0.217)
Educ college		-1.332***	-1.241***	-1.436***
		(0.200)	(0.285)	(0.274)
_cons	5.107***	5.587***	5.118***	6.120***
	(0.380)	(0.395)	(0.502)	(0.503)
Observations	2991	2991	1613	1378
R^2	0.032	0.045	0.046	0.066

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies and year-of-birth dummies are not reported. The base group for education is primary or below. * p<0.1, ** p<0.05, *** p<0.01.

Table 7 Impact of pollution exposure on mental health for older cohorts 17 years after exposure

	(1)	(2)	(3)	(4)
	Baseline	Controls	Female	Male
Exposed cohort	-0.0187	0.0159	-0.439	0.646
	(0.308)	(0.307)	(0.433)	(0.435)
Exposed region	0.518	0.467	1.270*	-0.434
	(0.506)	(0.501)	(0.769)	(0.748)
Exposed cohort X region	-0.876	-0.858	-1.397	-0.277
	(0.608)	(0.610)	(0.887)	(0.853)
Female	0.637***	0.557***		
	(0.184)	(0.185)		
Educ junior		-0.458	-0.573	-0.278
		(0.279)	(0.375)	(0.401)
Educ senior		-0.468**	-0.594*	-0.323
		(0.227)	(0.319)	(0.318)
Educ college		-1.387***	-1.365***	-1.449***
		(0.303)	(0.414)	(0.453)
_cons	5.145***	5.625***	6.162***	5.562***
	(0.429)	(0.448)	(0.624)	(0.625)
Observations	2638	2635	1467	1168
R^2	0.036	0.043	0.040	0.061

Source: Author's calculations using IFLS.

Note: Robust standard errors in parentheses. Coefficients for province dummies and year-of-birth dummies are not reported. The base group for education is primary or below. * p<0.1, ** p<0.05, *** p<0.01.

5. Conclusion

This report replicates and extends the study of Shrestha (2019), which explored the impact of pollution exposure from the 1997 Indonesian forest fires on cognitive development. The replication results I obtained are like Shrestha's (2019), with slightly different coefficients. The conclusion that I found from the replication remains the same with the main study, in which exposure to the pollution in utero and around birth impacted in lower cognitive development 10 years after the exposure. However, the impact does not persist 17 years after the exposure.

I extend the study by estimating the impact of early-life exposure to air pollution on spending channels and mental health. I found that there is no statistically significant impact of pollution exposure on household spending 10 years after the exposure, which strengthens our confidence that the lower cognitive development 10 years after the exposure is due to biological factors, most likely through mother's health during pregnancy, as this is supported by various existing studies that found adverse health effects of severe air pollution from the 1997 Indonesian forest fires. Moreover, I found that the impact of pollution exposure on mental health is not significant for those who were exposed in utero and around birth. Possible explanations are that the mental health impact from pollution exposure lessens over time or that the mental health of those exposed to pollution in early life is less impacted than those exposed at an older age.

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Appendix

Table A1 10-item Centre for Epidemiological Studies Depression Scale (CES-D)

1. I was bothered by things that usually don’t bother me
2. I had trouble concentrating on what I was doing
3. I felt depressed
4. I felt everything I did was an effort
5. I felt hopeful about the future
6. I felt fearful
7. My sleep was restless
8. I was happy
9. I felt lonely
10. I could not get going

Note: Each question has four frequency-based response options: 0 point for "Rarely/Never (0-1 days)", 1 point for “Sometimes (1-2 days)”, 2 points for “Occasionally (3-4 days)” and 3 points for "Most/All of the time (5-7 days)," except for questions 5 and 8 where the scoring is reversed (3 to 0 points).