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Seeking natural capital projects: Forest fires, haze, and early-life exposure in Indonesia

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Natural capital will be depleted rapidly and excessively if the long-term, offsite impacts of depletion are ignored. By examining the case of tropical forest burning, we illustrate such myopia: Pursuit of short-term economic gains results in air pollution that causes long-term, irreversible health impacts. We integrate longitudinal data on prenatal exposure to the 1997 Indonesian forest fires with child nutritional outcomes and find that mean exposure to air pollution during the prenatal stage is associated with a half-SD decrease in height-for-age *z* score at age 17, which is robust to several statistical checks. Because adult height is associated with income, this implies a loss of 4% of average monthly wages for approximately one million Indonesian workers born during this period. To put these human capital losses in the context of policy making, we conduct social cost–benefit analyses of oil palm plantations under different scenarios for clearing land and controlling fires. We find that clearing for oil palm plantations using mechanical methods generates higher social net benefits compared with clearing using fires. Oil palm producers, however, would be unwilling to bear the higher private costs of mechanical clearing. Therefore, we need more effective fire bans, fire suppression, and moratoriums on oil palm in Indonesia to protect natural and human capital, and increase social welfare.

sustainable development | environmental health | oil palm | cost–benefit analysis | health irreversibility

Economists will argue that natural capital has been depleted rapidly and excessively because the offsite lagged impacts of depletion are either ignored or remain unmeasured (1–4). We use the case of Indonesia to illustrate the extent of such oversight. Despite its vast tropical forests, forest loss is rapid because forests are burned to clear land cheaply and plant lucrative job-friendly export crops such as oil palm (5, 6). Unfortunately, such economic development is unsustainable because we ignore externalities of forest fires—air pollution and biodiversity loss, chief among others (4, 7). For example, forest fires in Indonesia, started to establish estate crops, burned out of control due to the El Niño-induced abnormally dry weather in 1997. These fires destroyed habitat (around 11 million hectares of forests), compromised hydrological services, and generated health-damaging air pollution (around 25% of global carbon emissions from fossil fuels came from this single event) (8–11). Despite the severity of this event, we do not know the full extent of health damages, especially the irreversible, offsite lagged human capital impacts. In addition, we do not know whether the costs (in terms of jobs and profits) of policies to avoid the haze will outweigh the social benefits (12).

In the post-2015 sustainable development goals (SDGs) era, debates rage in the global community about how best to protect natural capital, promote health, mitigate climate change, and reduce poverty (13, 14). The main question posed in our paper—do the economic benefits of avoiding health damages of haze from forest fires outweigh the economic costs of alternative policies—is relevant to these debates. Specifically, our research illustrates why SDGs should focus on reducing negative externalities, promoting intergenerational equity, and improving capabilities (15). We focus on the 1997 forest fires in Indonesia and the associated haze. The 1997 fires were one of the largest in recent history, but unfortunately, such forest fires have become even more frequent lately, including a round of devastating forest fires in 2015. Despite their magnitude and frequency, we know surprisingly little about the full social costs of these fires. While there is evidence on short-run health damages of air pollution, little is known about the long-term and intergenerational costs of early-life exposure to air pollution.

Most studies of early-life exposure to air pollution are conducted in high- or middle-income countries and focus on immediate birth outcomes (16, 17). From past analyses, there is strong evidence showing that early-life exposure to air pollutants is associated with low birthweight and preterm birth (16, 17). The suspected pathways from air pollutants to birth outcomes are inflammation and direct toxic effects to the placenta and fetus, oxygen supply to the fetus, and DNA expression (17). With respect to longer-term outcomes, the literature on the "fetal origins" hypothesis suggests that intrauterine health insults can cause lasting and irreversible damage to cardiovascular and respiratory health and that low birthweight is associated with shorter height in adulthood (18–21). Still, there are very few studies that specifically make the connection between environmental exposure to air pollutants at early-life and long-term outcomes (22).

Demonstrating that a short-term episode of extremely high air pollution has long-term health impacts is salient to many low- and middle-income countries, especially as many parts of Asia face frequent "airpocalypses" in recent years. In our study setting, the 24-h total suspended particulate (TSP) concentration reached as high as 4,000 $\mu g/m^3$ during multiple days in October 1997 in parts of Sumatra—the World Health Organization (WHO) recommended 24-h maximum for TSPs is 120 $\mu g/m^3$ (23). More recently, New Delhi experienced 24-h $PM_{2.5}$ levels of 700–1,200 $\mu g/m^3$ in November 2016—the WHO daily guideline is 25 $\mu g/m^3$. Also in late 2016, multiple cities in northern China attained their highest level of air pollution warning. Because earlier studies were mainly conducted in rich countries that experience very different exposure profiles, economic development, and environmental institutions, there is little evidence to guide policy makers and practitioners in low- and middle-income contexts.

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It is not enough to stop at estimating environmental health damages, however, without considering how they stack up against the costs (and other benefits) of policies to control fires. The political economy of policies to control forest fires in Indonesia is complex and covers the entire gamut from government regulation to market incentives to voluntary control by firms and landowners (24–27). Currently, key policies include blanket bans on fires for clearing land and moratoriums on expanding oil palm (28, 29). Because oil palm is extremely lucrative in terms of foreign exchange revenue (e.g., it accounted for US$18.6 billion, or about 10% of Indonesia's total exports in 2015) and jobs (e.g., sector employs around 4.5 million workers), such moratoriums may be politically impractical and unsustainable. Moreover, firms will not comply with bans and moratoriums if enforcement is not strict (30, 31). Hence, we must consider costs and benefits of policies to detect and suppress forest fires before they spread, and to enforce bans and moratoriums (32). Such cost–benefit analyses (CBAs) can identify the parameters driving the maximizations of social welfare, given the health benefits of reduced fires and haze (7). All of these options are complicated by the fact that fire severity depends on the location, and the costs and benefits vary by stakeholders (33).

Study Rationale and Design

First, it is difficult to know the extent of irreversible and offsite lagged human capital impacts because high-quality longitudinal data that faithfully depict long-term impacts have been difficult to find in environmentally vulnerable and economically poor locations (7, 34). Thus, we carefully integrate longitudinal data on prenatal exposure to the pollution from the 1997 Indonesian forest fires with data on nutritional outcomes, genetic inheritance, climatic factors, household inputs, and various sociodemographic factors. Second, methodologically flexible approaches are needed because of the interdisciplinary nature of issues in sustainable development and planetary health (4). We show how rigorous statistical analyses and numerous robustness checks can be applied to a multisectoral panel dataset to control for potential sources of confounding the correlation of prenatal haze exposure with adult height. While previous research has drawn attention to the deaths caused by the forest fires, we show that survivors also suffer large and irreversible losses of human capital because of haze exposure (35, 36). Third, scientists are often unwilling (because of norms or incentives) to provide approximate, if imperfect, practical advice that policy makers seek, preferring to provide precise answers to questions, even if these questions are irrelevant or untimely for policy (37). To avoid such "type III" errors and to put such human capital losses in context, we conduct a CBA of various policies to avoid fires in oil palm plantations (38–40). Specifically, we combine our haze-height results with other costs and benefits, and also account for the heterogeneity and uncertainty inherent in the model parameters.

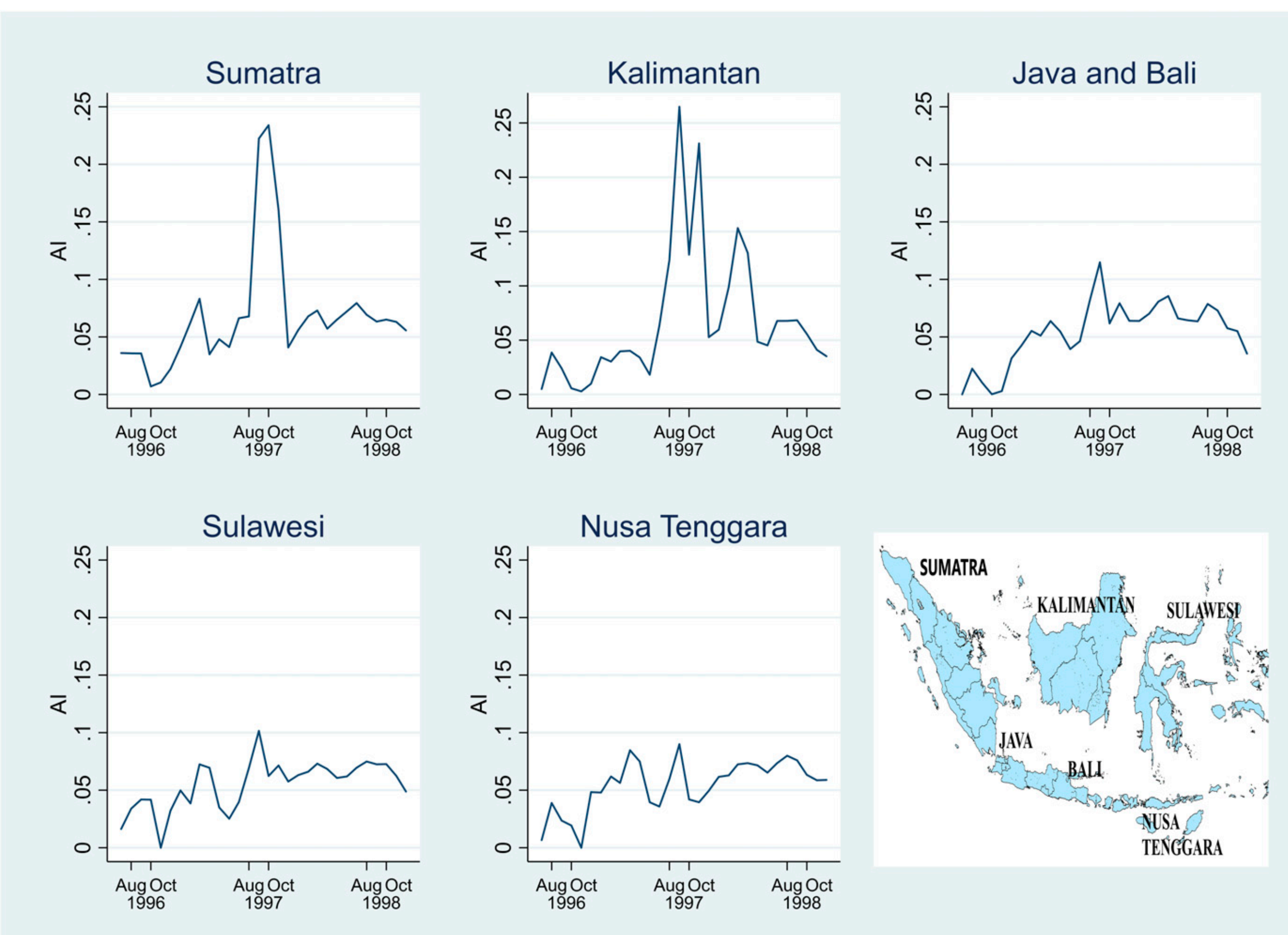

Fig. 1. Spatial and temporal distribution of air quality across Indonesia.

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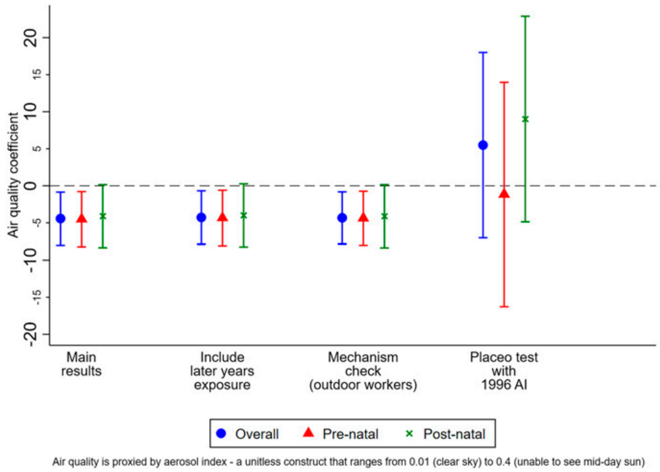

Fig. 2. Impact of early-life air pollution on HAZ for different regression specifications.

Results

Our data show that the average 1997 air pollution exposure [aerosol index (AI)] is 0.1 (where 0.01 represents crystal-clear sky with maximum visibility and 0.4 represents trouble seeing the midday sun). As shown in Fig. 1, however, AI varies significantly in space and time, with exposure ranging from 0 (18% of sample, from Sulawesi and Nusa Tenggara) to 0.3 (18% of sample, from Kalimantan and Sumatra). Average height-for-age *z* score (HAZ) is negative, suggesting that Indonesian children are shorter than the reference group from the United Kingdom. The other environmental, household, and parental variables are summarized in *SI Appendix*, Table S1.

Fig. 2 shows effects of AI, including the 95% confidence interval, on child's HAZ 17 y after exposure [i.e., fourth round of the Indonesian Family and Life Survey (IFLS)]. The first, second, and third coefficient in each set of results represent the overall, prenatal, and postnatal impact, respectively, of early-life exposure (*Materials and Methods*). Results from the main specification show that the mean level of exposure (i.e., AI = 0.1) translates to a 0.41 decrease in HAZ (or about 3.4 cm, equivalently) by 2014. The full results are also presented in *SI Appendix*, Table S2. These results show that the decrease in HAZ is statistically consistent across earlier waves of the IFLS. In other words, children in our analysis experienced a decrease in height from 3 y of age, and this impact persisted through the age of 17.

We further examined whether this early-life effect was attributable to prenatal or postnatal exposure. When exposed during the prenatal stage, the impact on HAZ is essentially unchanged—the average effect is 0.43. In contrast, while the coefficient for postnatal exposure is negative, it is statistically insignificant. Thus, the relationship we detect appears to be completely driven by prenatal exposure.

To ensure our results are not driven by confounders and spurious correlations, we undertake a series of robustness checks (*Materials and Methods*). We confirm that our findings are not driven by (*i*) high levels of pollution in later years, (*ii*) an indirect effect of severe air pollution on a family's ability to work and to earn income, (*iii*) something about the location, rather than the exposure per se, and (*iv*) overall reductions in food consumption during the forest fire months.

To put these estimates of irreversible health impacts in context, we conduct a CBA of oil palm plantations by including social externalities (*Materials and Methods*). Briefly, the analysis of haze-reducing policies considers benefits to health (both avoided losses in income and in mortality), tourism, and transportation, and costs to firms (land preparation) and to agencies for program implementation. To acknowledge and model the heterogeneity and uncertainty inherent in the parameters used in the CBA, we conduct Monte Carlo simulations by allowing each parameter to take on a range of values. This process yields 10,000 net present values (NPVs) for each scenario, summarized in a cumulative distribution function (CDF) for each scenario.

Starting with the baseline scenario of fire-based clearing, we see that 30% of the CDF is negative (Fig. 3). This finding is particularly sensitive to emissions attributed to oil palm fires, exposure to air pollution, income growth, and mortality and human capital losses (*SI Appendix*, Fig. S1). First, we consider the main alternative of clearing mechanically (and avoiding fires) to establish plantations and find that the CDF of social NPV is

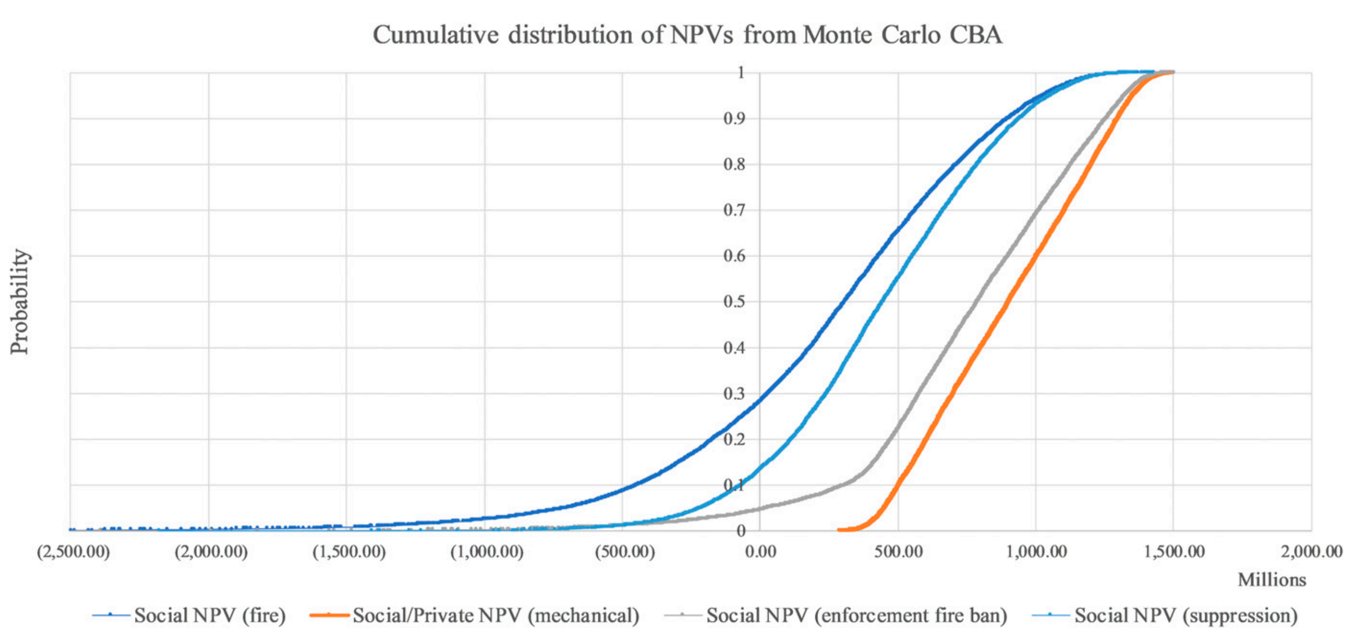

Fig. 3. Comparing social welfare of land clearing for oil palm using fire, mechanical options, and public policies (e.g., ban and suppression).

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wholly positive (Fig. 3). This is because the averted air pollution-related health losses are much larger than the increased mechanical clearing costs. Second, we consider stronger enforcement of the ban. The social NPV under this policy is now closer to the social welfare of mechanical clearing (Fig. 3) and is sensitive to the emissions attributed to oil palm, probability of being caught using fires, size of penalty, air pollution attributed to forest fires, and income growth (*SI Appendix*, Fig. S3). Finally, we also consider a fire detection and suppression policy. The distribution of social NPV is mostly positive and better than the baseline by 15 percentage points (Fig. 3). As expected, this finding is sensitive to program efficiency, program longevity, emissions attributed to oil palm, income growth, and program costs (*SI Appendix*, Fig. S4). Collectively, these analyses show that social net benefits from clearing for oil palm using fire is lower compared with net social benefits of (*i*) clearing using mechanical means, (*ii*) stronger enforcement of fire bans, and (*iii*) better fire suppression efforts.

Discussion

Recent studies have used simulations, derived from exposure-response models, to suggest that air pollution from fires is potentially causing deaths in Southeast Asia (36, 41). In our study, we use actual data on (*i*) smoke emissions from a major forest fire event, and (*ii*) children's demographics, to test hypotheses that complement such assumptions-based simulations. Also, unlike the earlier studies that focused on human lives potentially lost, we draw attention to the millions others who survive but with decreased functioning and capability (42, 43). We find a statistically significant negative effect of in utero exposure to air pollution on adults' height—a 0.41 decrease in HAZ at age 17 (or 3.4 cm) due to mean level of in utero exposure to air pollution during the 1997 Indonesian forest fires. Furthermore, these results are robust to a series of checks for confounding factors.

When we feed these health impacts into a broader CBA, and consider the various costs and benefits of policies and practices to control fires and avoid haze, we find that mechanical clearing delivers higher net social benefits compared with fire-based clearing. However, the additional costs of mechanical clearing will reduce firms' profits by 7% on average and as much as 25% (*SI Appendix*, Fig. S2), implying that most firms will not voluntarily comply with the ban. Indeed, previous studies documented the pervasive use of fires even though fire bans were implemented in the 1990s (30, 31).

This implies the need for complementary policies to detect and suppress fires or more rigorously enforce a fire ban. We find that such policies will increase social welfare, even without including the full list of ecological costs of fire-based land clearing such as carbon and habitat. More generally, our CBA illustrates a framework that could be used to evaluate other policies currently being considered by governments and nongovernmental consortiums (e.g., the roundtable for sustainable palm oil), such as green bonds to compensate oil palm firms for profit losses from mechanical clearing that would reduce emissions (26, 27, 44, 45).

Because Monte Carlo simulations reveal that the social NPV of these policies depend on factors that vary by location (e.g., policy effectiveness, emissions attributed to oil palm, local income growth), targeting will be efficient (45, 46). These findings provide strong justification for ongoing Indonesian government policies, including those that focus on restoring peatlands both inside and outside concessions so that forest fires will not spread to the peats (10, 47–49).

In sum, our study contributes to the literature on natural capital loss, forest fires, haze, health, and economic development in three ways. That is, following calls from implementation science research, we attempt to provide approximate, if imperfect, practical advice that policy makers seek, instead of stopping at precise (and sometimes irrelevant or untimely) estimates (7, 37, 50). First, we are one of the first studies of the lagged impacts of early-life exposures to air pollution, using data from Indonesia, a middle-income country critical to global conservation. Second, analyses of planetary health policies—which are multisectoral and interdisciplinary in nature—require methodologically flexible approaches (4). To this end, we first estimate the haze-height effect by applying rigorous quasi-experimental methods on a multisectoral dataset of health, socioeconomic, demographic, and environmental variables. Next, we use these impact estimates in a CBA of various policy solutions to the haze problem. Third, we use Monte Carlo simulations to account for the heterogeneity and uncertainty associated with the many costs and benefits (51, 52). More broadly, this combination of estimation and simulation illustrates an applied research framework (such as the Natural Capital Project) that can be used to mainstream conservation science into the decision making by communities, companies, governments, and donors (53, 54).

Materials and Methods

Data for Statistical Analysis. Data for our regression analysis of health outcomes on air pollution are drawn from three publicly available sources. First, health outcomes and household characteristics are from the 1997, 2000, 2007, and 2014 rounds of the IFLS (55). Early life is defined as prenatal or in utero to the first 6 mo following birth; this period represents the maximum growth velocity for humans (56). Using records of birth dates and mothers' location of residence (defined at the district level), we identify the air pollution exposure for each fetus from August to October 1997, when the fires and air pollution were most intense (23). The final panel used in analysis contains 560 children that were in their early life during August to October 1997 and appeared in each of four waves of the longitudinal survey. The birth months of these children ranged from March 1997 to August 1998 and are mostly uniformly distributed among all months (*SI Appendix*, Table S3). We consider HAZs for each child as our outcome because it is derived from well-established worldwide protocols for measurement and is strongly associated with adulthood socioeconomic outcomes (56, 57). The IFLS also provides data on child and parent demographics and other household variables.

Second, because ground monitoring of air quality is scarce in Indonesia (as in much of the developing world), we use satellite-derived data, that is, AI by the Total Ozone Mapping Spectrometer of the National Aeronautics and Space Administration (NASA) from August to October 1997, to proxy for air quality. AI is the monthly amount of atmospheric aerosols, such as dust and smoke, on a $1° \times 1.25°$ grid that has been shown to reliably represent ambient air quality (58). Third, we obtain data on rainfall and temperature from the National Center for Atmospheric Research Global Precipitation Climatology Centre and NASA's Goddard Institute for Space Studies surface temperature analysis, respectively. Climatic factors are included as controls as they may confound the association between health and AI (59).

We attribute AI exposure to each individual in the following manner. First, from the 1997 IFLS, we know birth dates and district locations of affected individuals ("affected" is defined as being in utero or first 6 mo of life from August to October 1997). While one might be concerned that households may have moved in anticipation of the impending haze, earlier studies using the IFLS data have shown that this is not the case (9). Second, using the satellite-derived data, we assign monthly AI to each district in Indonesia. Third, we assign an average AI exposure to each individual depending on how many months of their early-life stage fall within August to October 1997. For example, an individual born in March 1997 would be defined as being exposed to 1 mo of the haze in August 1997 for his early-life (postnatal) period. On the other hand, an individual born in December 1997 would be defined as being exposed to 3 mo of haze from August to October 1997 for his early-life period (prenatal) and his exposure would be defined as the average AI for the 3 mo. AI has also been used in earlier studies to analyze the health impacts from exposure to air pollutants caused by the 1997 Indonesia forest fires (9, 35, 60, 61). This is partly because AI has been ground truthed, as in, it tracks closely with ground-measured pollution from biomass fires (58). Any measurement error that stems from using AI to proxy for air quality would be classical in that it would result in attenuation bias (i.e., more conservative "smaller" estimates), not systematic bias (i.e., wrong inference).

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Statistical Approach. The impact of AI on height, β_1, is obtained by regressing child's health, y_{ijt}, on AI, AI_{ijt}, and a host of controls using least-squares regression method:

$$y_{ijkt} = \beta_0 + \beta_1 AI_{ijt} + \beta_2 AI_{ijt} \cdot I(y_{2000}) + \beta_3 AI_{ijt} \cdot I(y_{2007}) + I(y_{2000}) + I(y_{2007}) + X_i\gamma + \delta_j + \alpha_t + \varepsilon_{ijkt}, \quad [1]$$

where i, j, and t represent child i from location j and born in period t. The subscript k denotes the particular survey in which height was measured (i.e., IFLS 2000, IFLS 2007, or IFLS 2014). X is a vector of parent and household characteristics that could impact child's HAZ, for example, parents' education, parents' heights (a genetic contribution to the child outcomes), and household inputs at birth such as sanitation and clean cooking fuels. $I(y_{2000})$ is an indicator variable equal to 1 if the height was obtained from IFLS 2000. δ and α are district—the same scale at which AI is measured—and birth month fixed effects, respectively. The birth month-by-birth year fixed effects are included to control for unobserved factors that are constant across all individuals born in the same year and month, such as macroeconomic conditions (e.g., currency devaluation related to the Asian financial crisis) or seasonal weather patterns, which might otherwise confound the relationship between AI and HAZ. Similarly, district fixed effects are included to control for any unobserved factors constant across individuals born in the same location, such as access to local nutrition programs. Thus, following an established empirical method in applied statistics, the relationship between air quality and height is identified by removing any confounding differences attributable to location and season. Last, ε is an idiosyncratic error term. To guard against potential biases from the "Moulton" effect due to coarseness of the AI data, we cluster SEs at both the district and birth month-by-birth year levels (62). Three rounds of data from the same individuals are pooled. Therefore, when AI is interacted with the year in which the survey was administered, β_2 and β_3 represent changes in impact of early-life AI on height in the 2000 and 2007 surveys. In other words, the impact of early-life exposure of AI on height at 17 y is β_1, whereas the impact of early-life exposure of AI on height at 3 y is $\beta_1 + \beta_2$, and $\beta_1 + \beta_2 + \beta_3$ at 10 y. By way of summary, note that the AI coefficients are estimated using variation in air quality at the spatial-temporal level. This means that any potential confounders (e.g., the Asian financial crisis) would need to covary at the same temporal (by month) and spatial (by districts) scale with air pollution to bias the estimates of the AI coefficients.

Eq. **1** can be modified to separate the effects of prenatal versus postnatal exposure AI on height:

$$y_{ijkt} = \beta_0 + \beta_1 preAI_{ijt} + \beta_2 postAI_{ijt} + \beta_3 preAI_{ijt} \cdot I(y_{2000}) + \beta_4 preAI_{ijt} \cdot I(y_{2007}) + \beta_5 postAI_{ijt} \cdot I(y_{2000}) + \beta_6 postAI_{ijt} \cdot I(y_{2007}) + I(y_{2000}) + I(y_{2007}) + X_i\gamma + \delta_j + \alpha_t + \varepsilon_{ijkt}. \quad [2]$$

The main difference between Eqs. **1** and **2** is that β_1 and β_2 in Eq. **2** report the effects of prenatal and postnatal exposure to AI, respectively, when the respondents are at 17 y, whereas β_1 in Eq. **1** reports the overall effect of any exposure to AI. Similarly, the coefficients for the other interaction terms in Eq. **2** report any remaining effects of AI from prenatal and postnatal AI exposure. Statistical analyses are conducted using Stata 14.

Robustness Checks for Statistical Analysis. To confirm that our results are not driven by spurious correlations and confounding factors, we conduct four robustness checks.

First, it is possible that the height impacts are driven by high levels of pollution in later years. *SI Appendix*, Table S1 demonstrates that the 1997 pollution was unprecedented, and AI levels were much higher in 1997 compared with later years. Moreover, the district fixed effects control for later years' exposure for all individuals within the same district. The district fixed-effects strategy would not work, however, if those exposed at birth were systematically more likely to migrate to heavily polluted, dirtier locations. Thus, we gathered further information on households' migration history and computed the AI exposure for 1998 and 1999 for their updated locations. In regression analysis that includes 1998 and 1999 AI as additional explanatory variables, only the 1997 exposure is statistically significant (Fig. 2; full results in *SI Appendix*, Table S2). We are not claiming that exposure to air pollution later in life does not impact height, rather that the initial (1997) early-life exposure is the dominant channel.

Second, we consider other nonpollution mechanisms by which height could be affected by the fires. For example, all else being equal, severe air pollution may have reduced a family's ability to work, and, in turn, this would decrease household income and, consequently, caloric intake. This is especially true for those engaged in outdoor work. This loss-of-income mechanism can be tested by interacting the AI variable with proportion of adult household members engaged in outdoor work. Indeed, the impact on HAZ is stronger in this subsample of households with outdoor workers; that is, while the AI coefficient mostly retains similar magnitude and statistical significance from the main results, there seem to be additional impacts on HAZ for households with higher proportion of outdoor workers (Fig. 2 and *SI Appendix*, Table S2). This means that this channel of outdoor work partially explains HAZ differences. However, the key AI coefficients remain significant for all three waves, signaling that the loss-of-income mechanism still leaves room for a large, direct impact of exposure on growth.

Third, to test whether there is something about the location, rather than the exposure itself, that is driving the association, we used the true exposure group but assigned a placebo AI exposure (1996 AI, true exposed cohort). That is, we assigned the 1996 AI exposure to our existing sample of exposed children. These children could not have been exposed to the pollution in 1996, as this is the year before their conception. The placebo test demonstrates this effect: The total impact of 1996 AI on HAZ is insignificant for each of the three rounds (Fig. 2 and *SI Appendix*, Table S2).

Last, we consider another source of potential confounding: if the forest fires influenced reduced food consumption. We can test this channel because of the timing of the surveys, as some household were surveyed during and others after the forest fires. Regression analysis of food consumption shows no statistical difference in consumption during and after the forest fires (*SI Appendix*, Table S3).

CBA. CBAs essentially compare the discounted stream of costs and benefits arising from a project or policy. In this setting, the CBA puts our estimates of health irreversibilities in context but is also essential for understanding the implementation of conservation policies in general (12). First, we conduct a social CBA of oil palm plantations by including social externalities. Second, because the private optimum will diverge from what is best for society, we also conduct the CBA from firms' perspectives to learn, for example, if credible enforcement can incentivize firms to behave in a way so that higher social welfare is achieved. Briefly, the analysis of haze-reducing policies considers benefits to health (both reductions in mortality and morbidity), tourism, and transportation, and costs to firms (land preparation) and to agencies for program implementation. While we included the ecological costs of mechanical clearing, we are not able to include ecosystem-related costs of fire clearing related to carbon and habitat because we could not find conclusive quantitative data on these benefits. Including these other costs would make the net social benefits of oil palm cleared using fire even more negative.

Third, to acknowledge and model the heterogeneity and uncertainty inherent in the parameters used in the CBA, we conduct Monte Carlo simulations (63). That is, we allow each parameter to take on a range of values (obtained from the literature) and specify a statistical distribution for these values (either uniform or normal distribution). For example, the AI–HAZ relationship is estimated in this study with a SD. To fully utilize the range behind each parameter, we ran 10,000 trials in the Monte Carlo simulation whereby, in each trial, a value for each parameter is randomly from the specified statistical distribution. Eventually, this process yields 10,000 different NPVs, which constitute a CDF.

The 26 parameters that underlie these computations and the eight primary equations that combine these parameters to estimate benefits and costs are described in *SI Appendix*, Tables S3 and S4. Without describing each and every parameter and equation (*SI Appendix*), we briefly summarize some of the key computations here.

Haze attributed to oil palm. Neither are forest fires the only source of air pollution in Indonesia, nor are all forest fires caused by establishing oil palm plantations. While there is a large literature examining the role of the causes of the 1997 forest fires and its effects, there is no specific study that directly quantifies the pollution attributable to oil palm or any concessions (38, 39). However, we can draw on this literature and estimate the attributable fraction as follows. First, we compare the AI in the August to October 1997 period to both August to October 1996 and to January to June 1997 periods, when there were fewer forest fires. Thus, we estimate that 57–77% of air pollution is from forest fires during the August to October 1997 period. Second, we rely on a recent study to approximate the forest fire emissions attributable to oil palm plantations, which suggests the range 10–60% of all pollution emissions is because of oil palm plantations (48). Third, we multiply these two fractions to compute the proportion of air pollution attributed to oil palm-related forest fires. Critically, recognizing that this attributable fraction can vary (as with other causes) from the low to high range of this product, we build this variability into the 10,000 Monte Carlo simulations, introduced previously.

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Avoided mortality damages. Epidemiological models estimate the total mortality burden for the 1997 fires in Indonesia to be around 15,000 deaths (64). In monetary terms, we assign a value-of-statistical life (VSL) of US$108,900 (in 2008 US dollars) to these deaths. This VSL estimate is obtained by starting first with OECD baseline VSL of US$3.3 million (in 2008 US dollars) and then applying "benefits transfer" logic.

Avoided income loss. For loss of income, we start with a well-established literature that shows that relative height is correlated with adult mortality, morbidity, neurodevelopmental, and economic capability (56). Specifically, height has been shown to be correlated with earnings; for example, 1 SD in HAZ at adulthood is associated with 8% increase in adult income (57). Thus, our estimate of a 0.41 SD HAZ decrease (i.e., from the 2014 wave when the cohort is about 17 or 18 y old) translates into ∼3.3% decrease in income through human capital channels. Consider the fact that 1.13 million individuals were in their prenatal stage during August through October 1997 in the impacted provinces of Sumatra or Kalimantan, where the air pollution and fires were most intense (that is, what we report next is a conservative estimate because others in other provinces were partially exposed but we do not count them). Assuming, (*i*) their working age spans 21–58 (the official retirement age), (*ii*) the average annual wage for blue-collar work at US$860 (from Indonesian Statistical Department), (*iii*) a social discount rate of 8%, and (*iv*) an annual real wage increment of 2% for the first 15 working years (from Indonesian Statistical Department), we estimate that the lifetime productivity loss for this exposed population of 1.13 million is about US$392 for each individual.

Profits of oil palm plantations. The operating costs and revenue of oil palm plantations are obtained from Butler et al. (65). The plantations are evaluated on a 25-y basis and the range of operating costs and revenue is based off the high- and low-yield scenarios in the original analysis. The size of the oil palm planation is assumed to be 100,000 ha, based off new plantation area in 1998 (66). Clearing by fire costs between $82/ha to US$320/ha (47, 67). In contrast, clearing using mechanical means is much higher and ranges from low of $200/ha to $990/ha (47, 67).

Fire detection and suppression. Our analysis of the early detection and suppression policy rests primarily on the related parameters of program costs and effectiveness, and program life. The effectiveness of this policy ranges from 0 to 0.6. That is, emissions from oil palm plantations is reduced by 60% if fully effective. Additionally, to allow for spatial targeting of this policy, we model positive correlation between program effectiveness and both the levels of emissions from oil palm and the income growth. The Indonesian government approximates that the costs of early-detection and suppression program would range between US$450 million to US$2.3 billion. Last, we assume this program will last between 2 and 10 y.

Enforcing the fire ban. We model an enforcement policy for fire bans and the firm's reaction on three parameters—probability of detecting which plantations are using fires, the resulting penalties, and firms' risk aversion. We conservatively estimate the probability of identifying fires to range from 0 to 20%. The penalties are derived from recent court judgements on plantation owners that were found guilty of starting fires and are estimated to range from US$300/ha to US $40,000/ha. A risk-adverse firm would reduce fires more than proportional to the ratio of expected penalty vs. additional costs of mechanical clearing. We consider the risk aversion to range between 0.1 (risk averse) and 3 (risk taking).

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