The Chain of Accountability

Globally, there is increasing interest in understanding how air quality policy interventions are translating into improvements in air quality levels. Assessing their efficacy and ensuring accountability is a sequential process that requires multiple datasets. In this discussion, we explore how this can be approached using the chain of accountability framework. The accountability chain provides a framework for evaluating the effectiveness of air quality polices. This chain describes how regulations impact emissions, ambient air quality, personal exposure, and ultimately public health. For example, assessing changes in emissions requires emission data and also additional information, such as details on other regulations enacted within the same timeframe, efficiency gains, compliance levels, fuel prices, and more. Similarly, understanding shifts in air quality demands comprehensive air quality data, alongside information on meteorology, atmospheric transport mechanism, chemical processes, deposition, and other factors. Figure 1 provides an overview of the accountability chain. Without these datasets, evaluating the success of policy interventions become challenging.

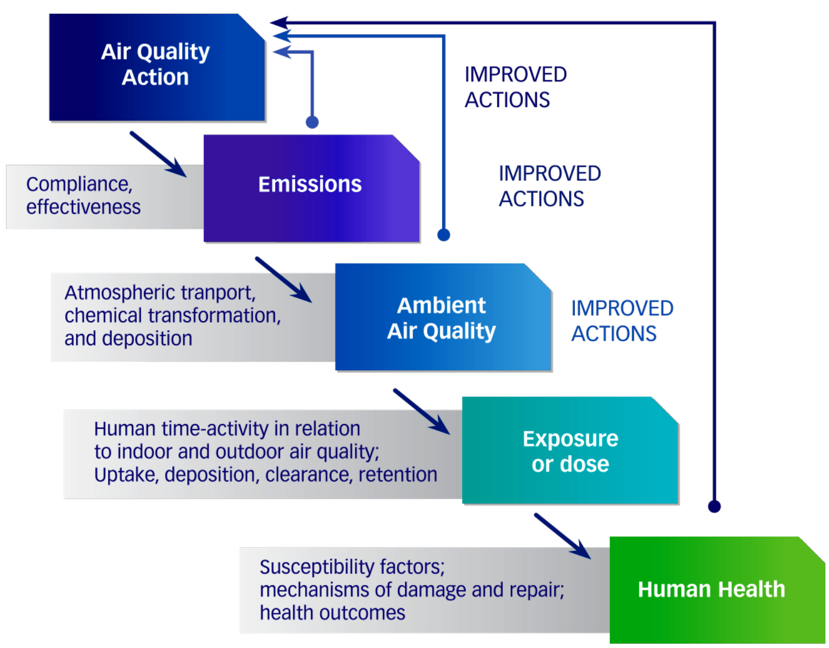

Figure 1: The chain of Accountability (Health Effects Institute, 2003)

Summary of studies on effectiveness of air quality policies globally

The field of accountability research is progressing where there is solid evidence from studies ranging from assessing the impact of short-term interventions to complex large-scale regulatory programs. However, it is challenging due to lack of statistical power, availability of air quality and health data, and attributing the effect to a single policy intervention among many regulatory policies (Boogaard et al., 2017). The data that goes into accountability research includes emissions, long-term air quality, meteorological, policy, exposure, health, and socioeconomic data (HEI Accountability Working Group, 2003). *It is important to note that there is no "one-size-fits-all" method/framework that can be adopted to conduct an accountability study that can assess the relationships between intervention and change in emissions, air quality, exposure, and health.*

For example, in China, the Air Pollution Prevention and Control Action (APPCA) was launched in the year 2013. Studies have shown that there were considerable reductions in emissions in the year 2017(Zheng et al., 2018). This was calculated by quantifying anthropogenic emission trends from 2010 to 2017 by using a combination of bottom-up emission inventory and index decomposition analysis approaches. During this time, there was also a significant improvement in the air quality. For example, a study that estimated $PM_{2.5}$ exposure by combining in-situ measurements, satellite observations, and simulations from a chemical transport model has found a decrease in $PM_{2.5}$ exposure from 67.4 μg/m^3 in 2013 to 45.5 μg/m^3 in 2017 (Xue et al., 2019). Studies have examined not only changes in emissions and air quality improvements but also their impact of APPCA on health. For example, in Beijing-Tianjin-Hebei (BTH) region, a reduction in $PM_{2.5}$ levels has reduced the total and cardiovascular mortality (Li et al., 2024).

In United States, several accountability studies have assessed the impact of air quality regulations on air quality and health, including several studies funded by the Health Effects Institute (HEI). For example, Zigler et al., (2016) studied whether the U.S. EPA's designation of PM_{10} nonattainment areas actually led to cleaner air and better health outcomes in western U.S. counties. They compared nonattainment counties with those that were not, analyzing PM_{10} levels, mortality, and hospitalizations. They found small declines in PM_{10}, all-cause mortality, and respiratory hospitalizations. Mortality also declined in areas without major pollution drops, suggesting other contributing factors and regional policy differences. Another study conducted in Atlanta has found that the pollution control policies have led to improvements in air quality and fewer cardiorespiratory emergency department visits between the periods 1999-2013 (Abrams et al., 2019). This study calculated the changes in emissions in the absence of policies and used those changes to calculate the counterfactual daily pollutant concentrations. One recent study used an accountability framework to test targeted air quality interventions, looking at the effects of funding new school buses on student health, academic performance, and community air quality. The results showed improvements in student performance, attendance, and air quality where old diesel buses were replaced, and showed that shifting to lower-emitting technologies brings benefits on both air quality and health (Adar et al., 2024).

Summary of studies on effectiveness of air quality policies in India

In India, there have been only a handful of studies that have estimated the changes in air quality as a result of a policy interventions like switching to compressed natural gas (CNG), odd-even scheme in Delhi and the National Clean Air Programme (NCAP). Most studies evaluated changes in air quality but did not account for confounding factors such as meteorology and data quality issues. Below we list a few examples of such studies.

Impact of compressed natural gas (CNG) conversion in Delhi

To address the issue of rising air pollution in Delhi, Honorable Supreme court of India in 1998 directed all the public transport vehicles should be converted to CNG. To assess the efficacy of this intervention, (Chelani & Devotta, 2005) analyzed PM_{10} data from 1999 to 2003 Delhi using the non-parametric Mann-Kendall test and reported no significant change in PM_{10} levels after the introduction of the policy, concluding that the CNG program did not improve air quality. However, one study reported a decreasing trend for PAHs, SO_2, and CO after the introduction of the policy, while NOx levels were reported to have increased between 1997-2003 (Ravindra et al., 2006). Neither of the studies account for any other confounding factors that may have contributed to the observed reduction.

Kathuria, (2002) controlled for confounding factors and reported a reduction in CO levels in Delhi as a result of the introduction of the CNG program but found no impact on Suspended Particulate Matter, PM_{10}, or NO_2 (Kathuria, 2002). Kumar & Foster, 2009) reported a reduction in $PM_{2.5}$ levels near high bus traffic areas, based on analysis of $PM_{2.5}$ data from 113 sites in Delhi, considering factors like proximity to roads and industrial clusters (Kumar & Foster, 2009).

At least one study reported a reduction in PM_{10}, CO, and SO_2 levels without an increase in NO_2 (Narain & Krupnick, 2007). This was attributed to the conversion of buses from diesel to CNG; limited impacts were reported for the conversion of three-wheelers to CNG. The study also analyzed the effects of meteorology, showing that higher wind speeds reduce concentrations of NO_2, CO, and SO_2 in the atmosphere and concentrations of all four pollutants increase with rising temperatures. The study also found that the policy for reducing sulfur in diesel and petrol helped lower SO_2 and PM_{10} levels, leading to improved air quality. However, these gains are being offset by the rise in diesel cars and the growing number of vehicles, which are increasing PM_{10} and NO_2 levels (Narain & Krupnick, 2007).

Impact of the odd-even scheme in Delhi

The government of Delhi implemented the Odd-Even vehicle rule from January 1-15, 2016 (Phase I) and April 15-30, 2016 (Phase II). The rule stipulated that private vehicles with registration numbers ending in an odd digit could operate on roads on odd dates and an even digit were permitted on even dates. Analyses conducted using research grade monitor data show that during Phase I, $PM_{2.5}$ and PM_{10} concentrations decreased by 13% and 5-6%, respectively, but in Phase II, the levels increased by 18 and 16% respectively (Sharma et al., 2017). An average reduction of 4.70% in $PM_{1.0}$ concentrations was also reported (Mishra et al., 2019). A third study found a reduction of up to 74% for hourly $PM_{2.5}$ and PM_{10} concentrations, compared to data from the previous year. A meaningful reduction in daily averages was not observed, likely due to emissions from heavy goods vehicles operating during the nighttime (Kumar et al., 2017). Notably, all three analyses utilized data from air quality monitoring campaigns and calculated the rate of change before and after the implementation of scheme; the effect of other confounding variables was not considered.

Impact of National Clean Air Programme in Indian cities

A recent study assessing the effectiveness of the NCAP used data from the national air quality monitoring network combined with regional model simulations. The results show an annual $PM_{2.5}$ reduction of 8.8% per year in six non-attainment cities with continuous monitoring since 2017. Four of these cities achieved over a 20% reduction in $PM_{2.5}$ levels by 2022 compared to 2017, meeting the NCAP targets. However, around 30% of the annual $PM_{2.5}$ improvements and nearly half of the reductions during the polluted winter months, were attributed to favorable meteorological conditions that may not continue as the climate warms (Xie et al., 2024). Another study, conducted within the same timeframe as NCAP but not focused on understanding its efficacy, analyzed data from the winter months (October 1 to January 31) over the past four years (2017 to 2023). It found that fluctuations in India's pollution patterns were part of a larger meteorological phenomenon linked to the final phase of the triple dip La Niña. This phase influenced large-scale synoptic systems, helping prevent stagnation in North India and improving air quality (Beig et al., 2024). Another study found that following the launch of the NCAP, $PM_{2.5}$ concentrations declined in most regions (−0.78 $\mu g/m^3/yr$) between 2018 and 2022. This study utilized datasets from multiple sources, including the CPCB air quality monitoring network, the ERA5-Land dataset from the fifth-generation ECMWF atmospheric reanalysis, and the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) (Wang et al., 2024). Gopikrishnan & Kuttippurath, (2025) assessed the impact of NCAP by looking at the changes in air quality with respect to PM_{10}. They found that 20 out of 28 cities show about 15-60% reduction of PM_{10} and have attributed the reduction to the implementation of NCAP. It is important to note that the study have not considered the influence of meteorological factors on reduction.

Air quality trend assessment is complicated because the behavior of the trend is a function of meteorology, changes in emissions, or chemical reactions in the atmosphere. For policymakers, it is important to understand if the emissions have been reduced to evaluate the efficacy of any policy intervention. In India’s case, there is no national emission inventory. Under NCAP, cities are required to develop emission inventories; however, only 37% of cities have done so, and this data remains publicly unavailable. Moreover, numerous sector-specific interventions introduced over the past decade make it difficult to attribute reductions in air pollution to any single intervention.

Regarding air quality data availability, many stations were established only recently, so long-term datasets for trend analysis may not yet be available in all non-attainment cities. The process of evaluating air quality changes by the regulatory organization does not account for meteorology. In such cases, the calculated trend is less likely to reflect the changes in pollutant levels caused by quality management efforts, which can lead to incorrect conclusions.

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