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Working Paper Estimating the Effect of China's 2013 Air Pollution Prevention and Control Action Plan

CESifo Working Paper, No. 11826

Provided in Cooperation with: Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Sager, Lutz (2025) : Estimating the Effect of China's 2013 Air Pollution Prevention and Control Action Plan, CESifo Working Paper, No. 11826, CESifo GmbH, Munich

This Version is available at: https://hdl.handle.net/10419/316940

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Impressum:

CESifo Working Papers ISSN 2364-1428 (electronic version) Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute Poschingerstr. 5, 81679 Munich, Germany Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de **Editor: Clemens Fuest** https://www.cesifo.org/en/wp An electronic version of the paper may be downloaded · from the SSRN website: www.SSRN.com www.RePEc.org • from the RePEc website: https://www.cesifo.org/en/wp · from the CESifo website:

Estimating the effect of China's 2013 Air Pollution Prevention and Control Action Plan

By Lutz Sager*

April 14, 2025

Abstract

In 2013, China introduced the ambitious Air Pollution Prevention and Control Action Plan (APPCAP) targeting ambient fine particle ($PM_{2.5}$) pollution. Using panel data covering 239 countries and territories worldwide, from 2000 to 2019, I provide quasiexperimental estimates of nationwide reductions in $PM_{2.5}$ exposure achieved since 2013. I find that the APPCAP lowered $PM_{2.5}$ exposure of the average Chinese resident in 2019 by over 20%, reducing $PM_{2.5}$ -related deaths by between 220 and 280 thousand depending on estimation strategy. Monetizing the mortality reductions with recent values of statistical life suggests total benefits of up to 1 trillion Renminbi or 1% of Gross Domestic Output.

JEL codes: I18, Q52, Q53, Q58 Keywords: Air pollution, health, mortality, regulation

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1 Introduction

Air pollution is one of the leading environmental risk factors in the world (Landrigan et al., 2018). In 2019, exposure to ambient fine particles smaller than 2.5 micrometers (PM_{2.5}), one of the most harmful pollutants, led to over 4 million preventable deaths worldwide according to the 2019 Global Burden of Disease (GBD) study (Murray et al., 2020). The last two decades have seen a divergence in pollution exposure, with PM_{2.5} levels falling in North America and Europe but rising in Asia and much of the developing world (Southerland et al., 2022; Sager, 2025). A notable exception to the trend has been China, where particle pollution appears to have peaked around in the early 2010s and fallen substantially since.

A landmark year in setting the course for China's air quality improvements was 2013. In January that year, Beijing and many other cities experienced several days of extreme pollution that were widely publicized. Later in 2013, the State Council of China enacted the "Air Pollution Prevention and Control Action Plan" (APPCAP).¹ The APPCAP aimed to reduce PM_{2.5} emissions from industry, non-point sources and vehicles, targeting in particular core regions such as Beijing, Jingjinji, the Yangtze River Delta, and the Pearl River Delta. The ambition was to reduce PM_{2.5} levels by up to 25% between 2013 and 2017. Previous work has documented substantial reductions in PM_{2.5} levels, in particular in the core regions, that come close to this ambitious target (Ma et al., 2019; Lu et al., 2020). These improvements in air quality appear to have gone hand-in-hand with sizable reductions in health burdens (Huang et al., 2018; Zhang et al., 2019; Yue et al., 2020).

This paper contributes to the literature evaluating China's efforts to reduce air pollution starting with the 2013 APPCAP in two ways. First, I use a quasi-experimental approach to estimate the air quality improvements relative to a counterfactual without the policy shift starting in 2013. Specifically, I adopt a Synthetic Control method, using global satellite-derived data on PM_{2.5} levels to construct a synthetic counterfactual based on pollution trends outside of China. This complements the existing literature that mostly compares pollution levels in China over time or across provinces within China. The results confirm large reductions in mean PM_{2.5} exposure across the Chinese population between 2013 and 2019, before the COVID-19 pandemic shock. Relative to a synthetic counterfactual, mean PM_{2.5} exposure was $12.9\mu g^{-3}$ (24%) lower in 2019 than without the trend break starting with the APPCAP in 2013. Alternative estimation strategies, including a panel fixed effect implementation of Difference-in-Differences (DID) and the Synthetic DID recently proposed by Arkhangelsky et al. (2021) produce similar estimates. Robustness checks show that estimates are likely not the result of bias from trends in economic output, population, or transboundary spillovers of pollution.

Second, to quantify the resulting health benefits, I build on the methodology from the Global Burden of Disease (GBD 2019) study (Murray et al., 2020; Vos et al., 2020) to estimate the number of avoided deaths resulting from these air quality improvements. I find that, in a counterfactual China without the APPCAP, there would have been between 220,000-280,000 more premature deaths due to $PM_{2.5}$ exposure in 2019 alone. Monetizing those health benefits using recent estimates of the Value of Statistical Life (Hammitt et al., 2019) produces savings of up to 1 trillion Renminbi or 1% of China's Gross Domestic Output.

¹Since 2013, the APPCAP has been complemented by further regulation at the national and regional level as part of a broader "war on pollution" (Greenstone et al., 2021, 2022).

Taken together, this paper provides quasi-experimental evidence that corroborates and confirms the substantial air pollution reduction effects achieved by the 2013 APPCAP in China, as well as the large associated reductions in mortality and monetized damages.

2 Background & Literature

In the years leading up to 2013, elevated levels of air pollution in many Chinese cities were receiving increasing attention. Then, in early 2013, several episodes of extreme pollution and smog were widely publicized, including the "airpocalypse" event in Beijing from 11-13 January during which $PM_{2.5}$ levels exceeded 350 μgm^{-3} (Ferreri et al., 2018). Against this backdrop the State Council of China launched the the Air Pollution Prevention and Control Action Plan (APPCAP) in late 2013.

The APPCAP targeted $PM_{2.5}$ specifically, aiming for 10% or more reductions in $PM_{2.5}$ levels by 2017 across prefecture-level and above cities, of which there are over 300. More stringent targets of up to 25% reductions were set in three target regions.² With a commitment of around 270 billion USD the APPCAP is one of the largest pieces of air quality regulation ever. It included a wide range of measures targeting emissions from coal-fired power plants, energy-intensive production (iron and steel, cement, flat glass), residential heating, and road vehicles (as disussed in e.g. Lu et al., 2020; Yue et al., 2020; Greenstone et al., 2022).³

A recent literature spanning multiple fields has linked the 2013 introduction of the APPCAP and related initiatives to air quality improvements in China over the following years. Substantial reductions in Chinese PM_{2.5} concentrations between 2013 and 2017 have been confirmed using data from ground-level monitors (e.g Huang et al., 2018), emission-based model predictions (e.g Zheng et al., 2017; Zhang et al., 2019), and satellite-based reanalysis products (e.g Ma et al., 2019; Yue et al., 2020).

Using monitor data from 74 select cities, Huang et al. (2018) observe a -25.2 μg^{-3} (33%) fall in PM_{2.5} concentrations between 2013 and 2017. For all of China, Zhang et al. (2019) simulate a 19.8 μg^{-3} (32%) reduction in population-weighted PM_{2.5} exposure over the same period, of which they attribute over 90% to emission control measures implemented under the APPCAP.⁴ Using satellite-derived estimates of PM_{2.5}, Ma et al. (2019) document reductions in the target regions that exceed ambitions (e.g. a 35.5% reduction in population-weighted PM_{2.5} in the Yangtze River Delta over 2013-2017 vs. a 20% APPCAP target). Looking again at the country as a whole, Yue et al. (2020) find a -10.3 $\mu g m^{-3}$ reduction (-20%) in population-weighted PM_{2.5} concentrations over 2013-2017.

Much of this work looks at changes in pollution levels over time. It thus relies on the assumption that changes in PM_{2.5} concentrations (or emissions) between 2013 and 2017 can entirely be attributed

²Specific targets included a 15% reduction in the Pearl River Delta, a 20% reduction in the Yangtze River Delta, and a 25% reduction in the Beijing-Tianjin-Hebei region, as well as a threshold target of 60 μgm^{-3} in Beijing.

³Specific measures included (1) equipping power plants and industrial plants with desulfurization and denitrification devices, (2) phasing-out older coal-fired power plants, (3), tightening standards for industrial boilers, (4) incentivizing the uptake of clean residential stoves, (5) upgraded vehicle emission standards, and more (see e.g Zhang et al., 2019). In addition to measures to reduce PM_{2.5} concentrations, the APPCAP also included provisions for more systematic air pollution monitoring and disclosure, allowing residents to avoid and safeguard against pollution exposure, which resulted in large additional benefits (Barwick et al., 2024a).

⁴An earlier study by Zheng et al. (2017) looks at changes from 2013 to 2015, finding a reduction in population-weighted PM_{2.5} concentration of -13 μgm^{-3} (21.5%).

to the 2013 policy shock, and that no unrelated changes occurred.⁵ In other words, much of the literature relies on quite restrictive assumptions regarding the counterfactual evolution of $PM_{2.5}$ levels in absence of the APPCAP. More recently, quasi-experimental methods have been used to create more credible comparisons. However, such efforts have largely focused on constructing adequate control groups within China to estimate APPCAP's effects on the target regions. For example, Yu et al. (2022) employ matching and Difference-in-Differences (DID) estimation in a panel of 271 cities to estimate APPCAP's effect on $PM_{2.5}$ levels in 47 target cities. They estimate $PM_{2.5}$ reductions between 18-26% in $PM_{2.5}$ levels on average, slightly smaller than the before-and-after comparison in Ma et al. (2019). Synthetic Control methods produce similar estimates of the effects in targeted regions compared to other regions in China (Peng et al., 2020; Zhang et al., 2022).

Building on this recent work, this paper sets out to generate quasi-experimental estimates of APPCAP's nationwide effects. Using global data from a apanel of 239 countries and territories allows me to construct counterfactuals from air quality trends outside of China. Doing so, I provide quasi-experimental estimates of the APPCAP's effect on nationwide PM_{2.5} exposure and health benefits. This contribution is relevant because the APPCAP was, after all, a nationwide policy. While some cities and regions were especially targeted, particle pollution can be transported for hundreds of kilometers. Some of the pollution reduction benefits may be missed when merely comparing targeted regions to other regions within China. Of course, my approach relies on other assumptions, which I discuss further below, and thus should be seen as complementary to the prior literature.

3 Data & Descriptive Evidence

3.1 Data

To measure air quality, I rely on satellite-derived estimates provided by the Atmospheric Composition Analysis Group at the Washington University of St. Louis. The data, further described in Shen et al. (2024), combine satellite readings of Aerosol Optical Depth (AOD) with the GEOS-chem chemical transport model to estimate concentrations of fine particles smaller than 2.5 micrometers (PM_{2.5}) with global coverage. Specifically, I use data from the V6.GL.02.02 version of Shen et al. (2024), which provides population-weighted annual mean PM_{2.5} exposure estimates for 239 countries or territories between 1998 and 2022.⁶ I truncate my sample to a 2019 endpoint because my health analysis uses that year as a reference point, and to avoid confounding by the Covid-19 pandemic which began in 2020. For later robustness checks, I complement those data with annual estimates of GDP and population from the World Bank (2025). To link PM_{2.5} exposure levels to health damages, I rely on damage functions and baseline mortality statistics from the GBD 2019 study (as provided by McDuffie et al., 2021).

⁵An exception to this claim is that Zhang et al. (2019) use model-based simulations to factor out the role of annual meteorological fluctuations.

⁶The data distinguishes 243 regions, most of which are countries, but some of which are islands or territories listed separately from the mainland. In some cases, the status of these regions may be disputed. I maintain the 243 regions as defined in the original data by Shen et al. (2024). However, my analysis is based on only 239 regions since 4 regions have 0 or missing population counts and are thus ignored in population-weighted analyses (Cocos Islands, Paracel Islands, Pitcairn Islands, and Tokelau).

3.2 Descriptive evidence on pollution trends

Figure 1 plots population-weighted mean $PM_{2.5}$ exposure in China compared to the rest of the world (RoW, right axis) from 2000 to 2019. It provides three insights. Firstly, air pollution exposure levels in China are high relative to the world. In 2010, mean $PM_{2.5}$ exposure in China was around $50 \ \mu gm^{-3}$ compared to an average of $32 \ \mu gm^{-3}$ in the rest of the world. Secondly, from 2000 to 2010, $PM_{2.5}$ levels rose in a similar fashion in both China and the RoW, by 33% and 21% respectively. Thirdly, the trends differ markedly over the following decade, with $PM_{2.5}$ exposure in China fell by 25% between 2010 and 2019, while it rose by 1% in the RoW. Chinese mean $PM_{2.5}$ exposure even fell below its' 2000 levels in 2019 (37.9 and 37.5 μgm^{-3} respectively).

The trend break in Figure 1 appears right around the implementation of APPCAP in late 2013, after which $PM_{2.5}$ levels in China began to fall rapidly. A crude estimate of the benefits of air pollution control efforts in China starting with the APPCAP in 2013 would be to credit it with the entire reduction in $PM_{2.5}$ that followed.

From 2013 and 2019, $PM_{2.5}$ exposure in China fell by -15.6 μgm^{-3} or 29% (relative to a starting point of 53.1 μgm^{-3} in 2013). Attributing all of this to the APPCAP and related efforts would be assuming that $PM_{2.5}$ would have remained constant in their absence. For various reasons, we may not consider this a realistic counterfactual, as another look at Figure 1 suggests that pollution levels were not stagnant in either China or the rest of the world.



Figure 1: Population-weighted mean $PM_{2.5}$ concentrations in China versus rest of the world. Author calculations based on original data from Shen et al. (2024).



Figure 2: Event Study Estimates. Difference in population-weighted mean $PM_{2.5}$ concentrations in China versus rest of the world, normalized to 0 in 2013. Author calculations based on original data from Shen et al. (2024).

4 Quasi-experimental estimates

The -15.6 μgm^{-3} reduction in PM_{2.5} between 2013 and 2019 constitutes a comparison of China with itself over time. My quasi-experimental approach instead uses data from other countries to construct a counterfactual that models Chinese pollution trends had it not adopted the 2013 APPCAP.

4.1 Event study approach

The simplest approach, again based on Figure 1, is to assume that $PM_{2.5}$ levels in China would have followed the same trend as those in the rest of the world, on average. This approach is shown in Figure 2, which shows annual differences in mean $PM_{2.5}$ exposure between China and the RoW, relative to that same difference in 2013. Such an event study approach can offer helpful suggestive evidence of trend breaks. It confirms that $PM_{2.5}$ levels fell much more rapidly in China between 2013 and 2020 than in the rest of the world. Meanwhile, $PM_{2.5}$ trends were broadly comparable over the recent pre-treatment period between 2005 and 2013. The effect estimate of -15.9 μgm^{-3} or 30% relative to 2013 levels is quite similar to the change within China over time, which can be explained by the fact that $PM_{2.5}$ in the RoW were similar in 2013 and 2019.

To interpret the -15.9 μgm^{-3} reduction in Figure 2 causally, we would have to assume that the difference in population-weighted PM_{2.5} exposure levels between China and the RoW would have remained at 2013 levels. In other words, absent China's policy shift, PM_{2.5} levels would have followed the same trend as in the RoW. No other factor influencing air pollution, other than policy, drove different trends in PM_{2.5} levels. Of course, it is easy to imagine a number such changes. Between 2010 and 2020, China's economy grew faster than that of most other countries, and its' population grew more slowly. Over the same time period, some countries adopted more aggressive air pollution control, while many others DID not. Recent work has documented regional divergence in air pollution levels (Southerland et al., 2022; Sager, 2025), suggesting that the global average (excluding China) may not be a good counterfactual for particle pollution in China. In principle those factors could mean that Figures 1 and 2 might over- or understate the benefits of China's push for clean air starting in 2013. In order to safeguard against this possibility I construct alternative counterfactuals below.

4.2 Synthetic Control Method

The first approach to constructing a counterfactual that might better describe China's $PM_{2.5}$ exposure trajectory than the world average, I rely on the Synthetic Control Method (SCM).

Following early implementations (Abadie and Gardeazabal, 2003; Abadie et al., 2010), SCM has become a common quasi-experimental approach to identifying treatment effects in panel settings with single treated units (as surveyed in Abadie, 2021). Among 239 regions in my sample, China is the single one treated by the APPCAP implemented in 2013. The other 238 regions constitute the potential 'donor pool', out of which SCM selects a subset and weights to construct a synthetic counterfactual that closely matches outcomes in China during the pre-treatment period (until 2013). Formally, let us denote China as unit j = 1 among J = 239 countries/territories and the PM_{2.5} concentration in year t as Y_{jt} . The SCM as applied here selects a vector of weights $\mathbf{W} = (w_2, w_3, ..., w_J)$ to construct the synthetic counterfactual $\hat{Y}_{1t} = \sum_{i\neq 1} w_i Y_{it}$ from the donor pool. The estimated treatment effect in year *t* is then $\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}$. In order for $\hat{\tau}_{1t}$ to yield an unbiased estimate of the treatment effect in every year, we have to assume that pollution levels would have been the same in China and the synthetic counterfactual in absence of the policy, i.e. $Y_{it} = \hat{Y}_{it}$ without APPCAP.

As the APPCAP was introduced later in the year 2013 and set out pollution reduction targets relative to 2013. Because of that, I treat 2013 as baseline year and the first year to be considered as 'treated' by the new air pollution control policies is 2014. This also ensures comparability with the prior literature, which has focused on reductions relative to 2013, and the above event study approach. Consequently, I select weights to minimize the Euclidian distance between $PM_{2.5}$ levels in China and the synthetic counterfactual in all years between 2000 and 2013.

The Synthetic Counterfactual is shown in Figure 3. The level and trend of PM_{2.5} exposure in the counterfactual track actual levels in China rather well up to 2013, and certainly much more closely than the unweighted world average shown in Figure 1. However, after the APPCAP is introduced in late 2013, there is a marked difference in trend with observed PM_{2.5} levels falling much more rapidly than in the counterfactual.⁷ The difference between actual and synthetic China estimates the treatment effect and is shown in Figure 4. The difference suggests a treatment effect of -11.9 $\mu g/m^3$ in 2019, which is a 22% reduction relative to 2013 levels. After correcting for a bias from imperfectly matched pre-treatment outcomes (Abadie and L'hour, 2021; Ben-Michael et al., 2021), the estimate is -12.9 $\mu g/m^3$ or 24% of 2013 levels. This is similar although somewhat smaller than the effect estimates produced by the event study approach in Figure 2. It is also highly significant with a bias-corrected p-value below 0.01. This is further confirmed by the placebo test shown in Appendix Figure A2. Out of all 239 countries/territories tested, China produces the largest PM_{2.5} reduction relative to a Synthetic Counterfactual in 2019.

⁷The Synthetic Control Method, bias-corection, placebo tests and calculation of p-values are all performed with the 'allsynth' Stata package developed by Justin C. Wiltshire.



Figure 3: Population-weighted mean $PM_{2.5}$ concentrations in China versus Synthetic Counterfactual constructed with SCM. Author calculations based on original data from Shen et al. (2024).



Figure 4: Synthetic Control Estimates. Difference in population-weighted mean $PM_{2.5}$ concentrations in China versus Synthetic Counterfactual. Author calculations based on original data from Shen et al. (2024).

4.3 (Synthetic) Difference-in-Differences Method

In addition to the SCM approach discussed above, I also implement regression-based approaches to estimating the effect of the APPCAP that exploit the panel format of the data. Perhaps the simplest panel regression approach to estimating the effect of the APPCAP introduction in China is Difference-in-Differences (DID) estimation. Here, I implement DID with a two-way fixed effect (TWFE) regression expressed as follows:

$$PM_{it} = \beta * APPCAP_{it} + \gamma_i + \delta_t + \epsilon_{it}$$
(1)

The population-weighted PM_{2.5} concentration in country *i* and year *t* is a function of a countryspecific time-invariant component (γ_i), a cross-country year-specific component (δ_t), and an unexplained residual (ϵ_{it}). In addition, China experiences a treatment effect β after 2013 (when APPCAP_{*it*} = 1). In order for $\hat{\beta}$ to yield an unbiased estimate of the treatment effect, we have to assume parallel trends: In absence of the APPCAP, PM_{*it*} would have evolved similarly in China and the other countries, on average, after 2013.

Another panel regression approach applicable in this setting is Synthetic Difference-in-Differences (SDID) estimation proposed by Arkhangelsky et al. (2021). Merging the logic of SCM and DID, SDID uses a weighting scheme of units (countries) and time periods (years) in order to generate a control group that is arguable more likely to fulfill the parallel trends assumption. Since SDID is designed for settings with multiple treated units, we can also use it to estimate the average treatment effect (ATT) across Chinese provinces, in addition to the country-level treatment effect where China is the single treated unit (akin to the SCM approach above). For both DID and SDID, the regression panel includes the entire pre-treatment period (2000-2013), but a single post-treatment year (2019) in order to estimate the effect on PM_{2.5} levels in the year 2019 in a comparable fashion.

Estimates are shown in Table 1. Columns (1) and (2) restate the event study and bias-corrected SCM estimates, showing respectively a -15.9 and $-12.9 \ \mu gm^{-3}$ reduction in population-weighted PM_{2.5} in 2019. The simple TWFE implementation of DID instead arrives at an estimate of -12.4 when China is a single unit (3), and -12.1 when Chinese provinces are included as separate units (5). The SDID estimator arrives at similar numbers, estimating a -13.9 reduction when China is a single unit (4), and a -11.9 reduction when provinces are included separately (5). The larger difference between SDID estimates in columns is likely explained by the fact that SDID does not use population weights in estimating the ATT across provinces. Since less populous provinces experienced smaller effects, as shown in Figure 5, the unweighted average is slightly closer to zero. Nevertheless, all estimates are significantly different from 0 at the 0.01 level.

In sum, the different quasi-experimental approaches confirm that the APPCAP resulted in significant reductions in PM_{2.5} concentrations, with estimates for the effect in 2019 ranging between -11.9 and $-13.9 \ \mu g m^{-3}$.

		China-level Effect			Province-level (avg.)	
	(1)	(2)	(3)	(4)	(5)	(6)
	ES	SCM	DID	SDID	pDID	pSDID
Effect	-15.9	-12.9***	-12.4***	-13.9***	-12.1***	-11.9***
			(0.51)	(1.29)	(0.53)	(0.46)
Ν		3585	3585	3585	4080	4080

Table 1: Estimates APPCAP effect on PM_{2.5} in 2019

Notes: Estimates of the effect on the APPCAP on population-weighted PM_{2.5} exposure in 2019. Columns (1)-(4) are from a panel where China is a single unit. Columns (5)-(6) are from a panel where Chinese provinces are separate units. 'ES' is the event study estimate described in 4.1. 'SCM' is the standard Synthetic Control Method (bias-corrected) described in Section 4.2. 'DID' is the TWFE implementation of Difference-in-Differences. 'SDID' is the Synthetic DID estimator proposed by Arkhangelsky et al. (2021) and discussed in Section 4.3. Author calculations based on original data from Shen et al. (2024).

4.4 Region-specific Effects

In addition to the treatment effect for China as a whole, I also estimate subnational heterogeneity in effects using data at the Chinese province level by Shen et al. (2024). To do so, I run separate SCM iterations for each province. The results are shown in Figure A4a. While virtually all provinces are estimated to have experienced reductions in PM_{2.5} levels, relative to their region-specific Synthetic Counterfactual, there is quite substantial variation. Notably, the larger regions of Central and Eastern China, and not only the regions most strongly targeted under the APPCAP, see the the largest air quality improvements.



Figure 5: Region-specific Synthetic Control Estimates. Improvement (reduction) in population-weighted mean PM_{2.5} concentrations ($\mu g m^{-3}$) in each Chinese province versus Synthetic Counterfactual from donor pool of 238 countries/territories outside of China. Author calculations based on original data from Shen et al. (2024).

5 Robustness

My quasi-experimental estimates of the air quality improvements caused by the 2013 APPCAP in China each rely on the validity of the chosen counterfactual. The specific assumptions are variations on a theme: Nothing else has changed in China after 2013 that influenced $PM_{2.5}$ levels in ways different from the respective counterfactual constructed from regions outside of China. I now explore some ways in which this may be violated.

Economic conditions: One important way in which China differed from many other countries over the sample period (2000-2019) is it's faster-than-average pace of economic development. At the same time, there has been somewhat of a slowdown in GDP growth in the later half of this period. Since a large share of air emissions is linked to economic activity, there is reason to worry that some of the observed divergence in PM_{2.5} levels between China and other regions may be related to changes in economic trajectories. An advantage of the panel regression approaches (DID and SDID) is that they allow for the inclusion of time-varying covariates. To test for potential confounding from economic trends, I add controls for annual (log) GDP (constant 2015 \$) and annual (log) population, both from World Bank (2025). The estimates shown in columns (1) and (2) of Table 2 are very similar to those in Table 1 albeit showing slightly larger PM_{2.5} reductions. This clearly contradicts the concern that any PM_{2.5} observed in China since 2013 may be driven by slowdowns in economic or population trends.

Transboundary spillovers: Another way in which results could be biased is if some of the countries used to construct the counterfactual also experienced changes in PM_{2.5} levels because of China's APPCAP introduced in 2013. Since fine particle pollution can be transported over hundreds of kilometers, this may be a realistic threat for countries close to China (as documented by, e.g., Cheung et al., 2020). To limit the possible bias that may occur from transboundary spillovers, I repeat the SCM analysis from Figure 3 but exclude the 14 countries that share a land border with China from the donor pool. The resulting Synthetic Counterfactual, shown in A5, again looks like a good fit until 2013. The (bias-corrected) effect estimate of $-13.6 \ \mu g m^{-3}$ in 2019 is slightly larger than in the baseline SCM (-12.9). Meanwhile, the corresponding DID/SDID estimates in Columns (3) and (4) of Table 2 are slightly smaller. Overall, transboundary pollution spillovers do not seem to be driving the results either.

	GDP/Population		Transboundary	
	(1)	(2)	(3)	4)
	DID	SDID	DID	SDID
treatpost	-16.5***	-14.4***	-10.4***	-13.5***
	(0.47)	(2.34)	(0.45)	(1.87)
Ν	2595	2595	3375	3375

Table 2: Robustness checks: economic conditions & transboundary spillovers

Notes: Replication of estimates in Table 1, Columns (3) and (4). Columns (1) and (2) add time-varying covariates for log GDP (2015 constant \$) and log population. Columns (3) and (4) exclude 14 countries with Chinese land borders. 'DID' is the TWFE implementation of Difference-in-Differences. 'SDID' is the Synthetic DID estimator proposed by Arkhangelsky et al. (2021) and discussed in Section 4.3. Author calculations based on original data from Shen et al. (2024) and World Bank (2025).

6 Quantifying the benefits of cleaner air

The above analysis has produced, using a variety of estimation approaches, large quasi-experimental estimates of the reduction in fine particle concentrations achieved by China's APPCAP introduced in 2013. I now turn to quantifying the resulting benefits.

To calculate the benefits associated with pollution reductions, I calculate avoided deaths due to the estimated change in PM_{2.5} exposure. I follow the methodology developed for Global Burden of Disease (GBD) 2019 assessment, which systematically calculates the country-level mortality that can be attributed to each of 87 risk factors including ambient PM_{2.5} (Murray et al., 2020; Vos et al., 2020).⁸ GBD2019 attributes around 4 million preventable deaths to PM_{2.5} exposure, quantifying effects for six causes separately by age group: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer (LC), lower respiratory infections (LRI) and type II diabetes (DM).

Using my 2019 data on population-weighted $PM_{2.5}$ exposure levels by Shen et al. (2024), I find a global total $PM_{2.5}$ -attributable mortality of 3.4 million. Of these, 1.3 million (1,269 thousand) deaths occur in China, as shown in Table 3. The benefits of the APPCAP become apparent in columns (1)-(6), which show counterfactual scenarios that subtract the pollution reduction benefits of the APPCAP. Each column corresponds to an estimated effect size from Table 1. Depending on estimation approach, total $PM_{2.5}$ -attributable mortality would have been between 223 and 284 thousand higher in 2019 without the APPCAP.

Focusing on SCM estimates, the air quality improvements from the APPCAP saved 239,000 lives in 2019 alone. Much of those avoided deaths would have been from Stroke (95,000) as well as COPD and heart disease (54,000 each). This number is within the range of prior estimates based on model simulations (Huang et al., 2018; Zhang et al., 2019; Yue et al., 2020).⁹

⁸I use GBD2019 baseline mortality and relative risk curves provided by McDuffie et al. (2021).

⁹Model simulations for all of China by Zhang et al. (2019) suggest a reduction in PM_{2.5}-attributable mortality of nearly 400,000 between 2013 and 2017. In their sample of 74 cities, Huang et al. (2018) estimate a reduction of -55 thousand (-13%) in PM_{2.5}-attributable deaths between 2013 and 2017. Factoring out tends in population growth, age structure and disease mortality, Yue et al. (2020) estimate the PM_{2.5} reductions relative to 2013 resulted in 64 thousand fewer deaths in 2017.

These are substantial health benefits even for a large country such as China. To see this, multiply avoided deaths by a recent estimate of the "value per statistical life" (VSL) in China. Hammitt et al. (2019) estimate a VSL in 2016 of 550,000 USD or 3,850,000 RMB.¹⁰ Using that VSL, the 239,000 saved lives could have been valued up to 920 billion RMB (or 131 billion USD). That is almost 1% of Chinese annual Gross Domestic Product.¹¹. An age adjusted VSL that takes into account that PM_{2.5}-related deaths are especially prevalent among older residents would likely reduce this value by about 50-70%. However, it should not be forgotten that pollution damages exceed mere deaths. Factoring in non-lethal morbidity benefits as well as productivity effects could very well bring the total cost estimate back up to similar numbers as with non-age-adjusted VSL¹²

While the VSL approach is subject to much uncertainty, the cost estimate of almost 1 trillion RMB showcases the enormous magnitude of the air quality benefits achieved through China's APPCAP and the associated push for clean air since 2013.

(6) pSDID -11 9
-11.9
49.4
1492
+223
570
395
273
179
36
39
-

Table 3: Counterfactual mortality from PM_{2.5} exposure in China

Notes: Estimates of annual PM_{2.5}-attributable mortality in China following the GBD2019 methodology from McDuffie et al. (2021). Author calculations using PM_{2.5} concentration data from Shen et al. (2024).

¹⁰The 2019 USD/RMB exchange rate was 6.96 according to the U.S. Treasury Department. https://fiscaldata.treasury.gov/datasets/treasury-reporting-rates-exchange/ treasury-reporting-rates-of-exchange

¹¹China's GDP in 2019 stood at 99 trillion RMB in 2019 according to China's National Bureau of Statistics. https://www.stats.gov.cn/sj/ndsj/2020/indexeh.htm

¹²For example, Barwick et al. (2024b) estimate that healthcare costs from PM_{2.5} exposure in China amount to 69% of mortality costs.

7 Conclusion

This manuscript provides quasi-experimental evidence on the air quality benefits from China's APPCAP enacted in 2013. Synthetic Control Method estimates—which compare fine particle (PM_{2.5}) exposure levels in China to a synthetic counterfactual constructed from other countries—suggest that PM_{2.5} levels would have been 12.9 μgm^{-3} (34%) higher in 2019 had the APPCAP not occurred. Alternative estimation techniques, including (Synthetic) Difference-in-Differences, arrive at similar results.

Health damage estimates relying on the Global Burden of Disease 2019 methodology thus suggest that China's push for clean air starting in 2013 reduced PM_{2.5}-attributable mortality by around 239,000 per year, avoiding monetized damages of 920 billion RMB or almost 1% of Chinese GDP. These enormous benefits of the APPCAP, achieved in less than a decade, provide hope for the on-going battle to achieve cleaner air in both China and around the world.

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Appendix



Figure A1: Regions targeted by 2013 APPCAP.



Figure A2: SCM Placebo estimates. Each line shows the difference in population-weighted mean PM_{2.5} concentrations in one of 239 countries/territories versus a Synthetic Counter-factual constructed from the other regions. Solid black line is for China. Author calculations based on original data from Shen et al. (2024).



Figure A3: Regional PM_{2.5} exposure levels

Notes: Author calculations based on original data from Shen et al. (2024).

Figure A4: Region-specific Synthetic Control Estimates

(a) Improvement 2013 to 2019 (in PM_{2.5} points)



Notes: Improvement (reduction) in population-weighted mean $PM_{2.5}$ concentrations in each province versus Synthetic Counterfactual construction for each province from donor pool of 238 countries/territories outside of China. Author calculations based on original data from Shen et al. (2024).



Figure A5: SCM excluding neighbor countries. Population-weighted mean PM_{2.5} concentrations in China versus Synthetic Counterfactual constructed with SCM. Author calculations based on original data from Shen et al. (2024). Countries excluded from original panel due to shared border with China: Afghanistan, Bhutan, India, Kazakhstan, Kyrgyzstan, Laos, Mongolia, Myanmar, Nepal, North Korea, Pakistan, Russia, Tajikistan, and Vietnam