Synergy between pollution and carbon emissions control: Comparing China and the United States*

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ABSTRACT

We estimate the potential synergy between pollution and climate control in the U.S. and China, summarizing the results as emissions cross-elasticities of control. In both countries, ancillary carbon reductions resulting from SO_2 and NO_x control tend to rise with the increased stringency of control targets, reflecting the eventual need for wholesale change toward non-fossil technologies when large reductions are required. Under stringent pollution targets, the non-target effects tend to be higher in China than in the U.S., due to China's heavy reliance on coal. This result suggests that China may have greater incentives to reduce SO_2 and NO_x with locally apparent pollution benefits, but related efforts would at the same time reduce CO_2 emissions significantly. We also find strong non-target effects of CO_2 abatement in both countries, but the cross effects in this direction depend less on the stringency of control and are stronger in the U.S. than in China.

1. Introduction

In this study, we explore synergistic effects of controlling emissions of nitrogen oxides (NO_x) and sulfur dioxide (SO_2) and of carbon dioxide (CO_2) in the U.S. and China—the world's largest carbon emitters. The primary motivation for this research comes from the fact that NO_x and SO_2, two conventional air pollutants, and CO_2, a primary greenhouse gas (GHG), are co-generated from combustion of fossil fuels, so their emissions are closely linked (Agee et al., 2012). The close link of emissions, in turn, suggests potential synergy between two different policies—pollution abatement and carbon mitigation policies (Nam et al., 2013). Carbon-mitigation policy may achieve substantial ancillary reductions in NO_x and SO_2 emissions, and control of the two air pollutants may lead to a substantial ancillary cutback in carbon emissions.

We are particularly interested in the following two questions: what potential synergy exists between pollution and carbon policies in the two countries; and whether the magnitude of the synergy changes over time or depends on the stringency of emissions control. While a variety of studies have looked at the effect of carbon targets on other pollutants, our interest is to directly compare the U.S. and China using comparable methods and metrics and to examine whether and how this relationship changes with the stringency of mitigation effort. In addition to the ancillary effects of carbon reduction, we also explore unintended carbon-mitigation potential from given pollution-abatement targets. Given the difficulties of reaching international

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Table 1
Studies of ancillary carbon-mitigation benefits from pollution control.

Study	City or country	Sectors	Pollutants	Policy considered	Ancillary CO_2 benefits (%ΔCO_2/%Δpollution)
Morgenstern et al. (2004)	Taiyuan (China)	Electric	SO_2	Shut down small boilers, switch to low sulfur fuels	0.76–0.97
Xu and Masui (2009)	China	All	SO_2	Emissions caps, energy efficiency, sulfur tax	0.90–0.97
Chae (2010)	Seoul (Korea)	Transportation (public buses)	NO_x, PM_{10}	Switch to low sulfur fuels	0.14–0.88
Agee et al. (2012)	U.S.	Electric	NO_x, SO_2	Cap and trade	n/a
Cao et al. (2012)	China	All	SO_2	Emissions caps	0.23
Nam et al. (2013)	China	All	NO_x, SO_2	Emissions caps	0.41–0.99

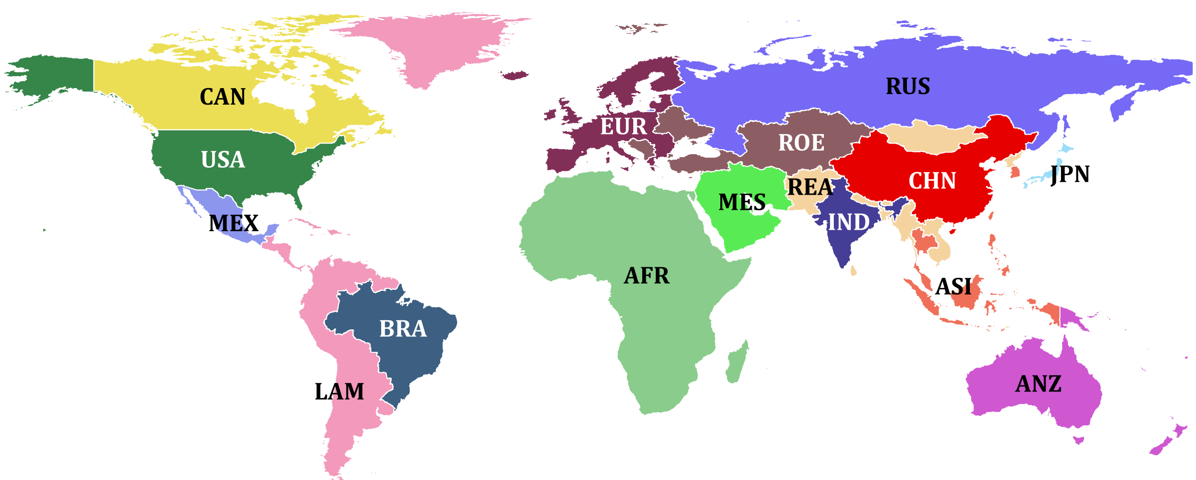
agreement on CO_2, this direction of effect may be more relevant. That is, countries may be more apt to undertake efforts to control conventional pollutants because the benefits of abatement are felt more directly in the country undertaking control, and these efforts may have indirect benefits in reduced carbon pollution.

2. Synergy between pollution control and climate policy

Numerous studies explore air-quality co-benefits of climate mitigation, by recognizing that conventional air pollutants and GHGs are co-generated by fossil-fuel combustion (Smith, 2013). In most cases, ancillary benefits from GHG control are estimated to be substantially large, though central estimates from different studies show a fairly high standard deviation. For example, 10 selected national co-benefit studies, placing emphasis on health benefits from unintended air-quality improvement, present a co-benefits range of \$2 to \$128 (2008 US\$) per ton of CO_2 emissions mitigated (Nemet et al., 2010). In general, co-benefit estimates for developing countries tend to be larger than those for developed countries. From the review of 37 peer-reviewed studies, for example, Nemet et al. (2010) draw the mean and median co-benefits of \$44/tCO_2 and \$31/tCO_2, respectively, for the developed world and those of \$81/tCO_2 and \$43/tCO_2 for developing countries. However, cross-country comparisons of this kind suffer from differences in measures of co-benefits and methods to evaluate them, often considering different sets of air pollutants and GHGs (Bollen et al., 2009a). Apparent cross-country differences may result from different modeling approaches, pollutants considered, valuation methods, or other uncontrolled differences.

Many co-benefit studies (e.g., Bollen et al., 2009b; McCollum et al., 2013; Rafaj et al., 2013) have been motivated to convince the global community that carbon emissions control is less costly than conventionally estimated. The central logic behind this argument is that GHG-reduction policy carries not only long-term benefits from mitigated climate change but also short-term benefits associated with air-quality improvement from the policy-led, reduced-use of fossil energy. However, a large part of the developing world is still skeptical about potential benefits from climate control, taking a conservative attitude toward legally binding GHG mitigation targets (Bodansky, 2010). In this situation, conventional pollution control may be more compelling to developing countries than policies targeting GHG mitigation directly, given that many of them confront imminent pressure to reduce local air pollution. Yet, these efforts may result in carbon reductions as an indirect or ancillary effect.

In contrast to the literature on the air-quality co-benefits of carbon reductions, the literature on the reverse—ancillary carbon benefits from pollution control—is sparse (Morgenstern et al., 2004; Nam et al., 2013; Xu and Masui, 2009). We have found only six studies exploring the latter topic (Table 1). Three of them focus on a particular city or a sector and the others are China's national-level studies without a specific sectoral focus. Despite differences in terms of focus and method, all



EPPA5 REGIONS

AFR	Africa	JPN	Japan
ANZ	Oceania	LAM	Rest of Latin America
ASI	Dynamic Asia	MES	Middle East
BRA	Brazil	MEX	Mexico
CAN	Canada	REA	Rest of East Asia
CHN	China	ROE	Rest of Europe + Central Asia
EUR	Europe	RUS	Russia
IND	India	USA	United States

EPPA5 SECTORS

LIVE	Livestock	SERV	Services
CROP	Crops	ELEC	Electricity
FORS	Forestry	OIL	Crude oil
FOOD	Food production	ROIL	Refined oil
EINT	Energy-intensive industry	COAL	Coal
HTRN	Household transportation	GAS	Natural gas
TRAN	Purchased transportation		
OTHR	Other industry		

Fig. 1. Regional and sectoral aggregation schemes in EPPA5.
Source: Nam et al. (2013), p. 1649.

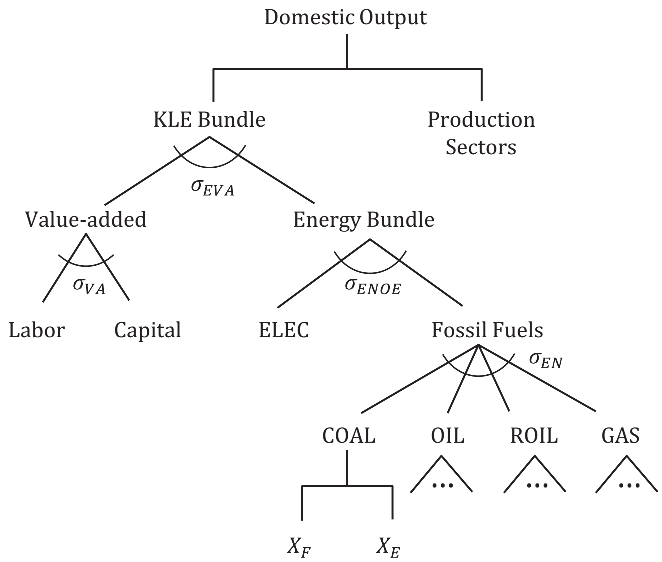


Fig. 2. Fuel-related CO_2 emissions structure in EPPA5.
Source: modified from Paltsev et al. (2005), p. 18.

these studies found substantial carbon-mitigation effects of pollution control, presenting the emissions cross-elasticity of 0.14–0.99. We attempt to generalize these findings and compare the U.S. and China.

3. Current regulations in the U.S. and China

In this section, we briefly review current NO_x, SO_2, and CO_2 regulations in the U.S. and China. In both countries, there is evidence of environmental damages from current pollution levels. These have been estimated at around 4–7% of gross domestic product in China (Matus et al., 2012; Nielsen and Ho, 2007; World Bank and China SEPA, 2007). In the United States the impacts of degraded air quality have been the subject of numerous studies (e.g., Chay and Greenstone, 2003; Matus et al., 2008; U.S. EPA, 2011).

3.1. NO_x and SO_2 emissions control

Both the U.S. and China regulate air pollutant emissions, including both NO_x and SO_2. China's first controls on air pollution were embodied in the Air Pollution Prevention and Control Law China of 1987. Since then, China has regulated air pollution as part of its comprehensive national economic planning, which is set forth and updated through Five-Year Plans. The most recent is the Twelfth Five-Year Plan (FYP12) for the period of 2011–2015, which separately regulates emissions from the electric power sector and mobile sources. For the electric power sector, it calls for a reduction of 8% in SO_2 and of 10% in NO_x (which was regulated under the FYP12 for the first time) (Li, 2011). Longer term, China's stated goal is for ambient air quality in all cities to attain the Chinese national air quality standards and similar guidelines implemented by the World Health Organization. Targets for reducing pollutant emissions include 60% for SO_2, 40% for NO_x, 50% for PM_{10}, and 40% for volatile organic compounds (VOCs) by 2050, relative to 2005 (Wang and Hao, 2012). Efficient and cleaner use of coal and the improvement of vehicle fuel quality are major targets of regulatory efforts. Regulators have also articulated that air quality measures should be harmonized with climate policies. Many climate policy instruments, such as a carbon tax, are considered on the basis of any "green" co-benefits (Tian, 2012).

The U.S. has regulated air pollution from stationary and mobile sources under the Clean Air Act, which was first passed in 1970 and last amended in 1990 (EPA, 2013). Pollution sources are required to implement Maximum Achievable Control Technologies for each polluting activity, which are defined by the U.S. Environmental Protection Agency (EPA) and revisited every eight years. In principle, implementation of control technologies is expected to support the achievement of air quality targets, which are set forth by the U.S. National Ambient Air Quality Standards. These standards set acceptable limits for ambient levels of six "criteria" pollutants: NO_x, SO_2, carbon monoxide (CO), ozone (O_3), particulate matter (PM), and lead. Areas across the U.S. are classified in terms of whether they do or do not meet the standards (attainment or non-attainment areas).

3.2. CO_2 emissions control

In both the U.S. and China there is growing recognition of the need to control GHG emissions, although neither country has adopted controls on the absolute level of such emissions. China has currently pledged to reduce its carbon intensity by 40% in 2020, relative to its 2005 level, as part of its commitment at the Copenhagen climate negotiations in 2009 (NRDC, 2009). As part of the country's FYP12, leaders are targeting a 17% reduction in national carbon intensity, the first explicit target assigned for carbon in national law and designed to be consistent with the country's Copenhagen commitment.

The U.S. committed to reducing carbon emissions by 17% below the 2005 levels by 2020 and suggested a goal of achieving an 83% reduction by 2050 (NRDC, 2009). As of 2013, there was no legislation, executive order, regulation, or published plan explicitly dedicated to achieving these climate goals, but U.S. federal agencies and states have implemented various policies and programs to reduce GHG emissions (Damassa et al., 2012). Examples include federal regulations on vehicle fuel economy and GHG emissions standards and commercial and residential building codes, and state-driven cap-and-trade programs

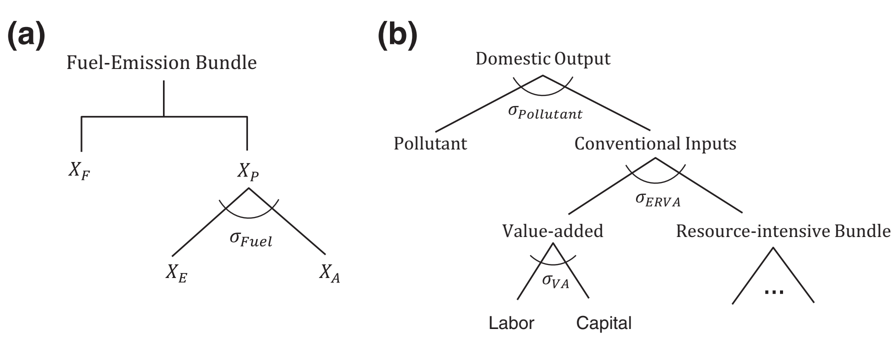


Fig. 3. Pollution abatement structure: (a) fuel-related pollution, (b) non-fuel-related pollution.
Source: adopted from Nam et al. (2013), p. 1650.

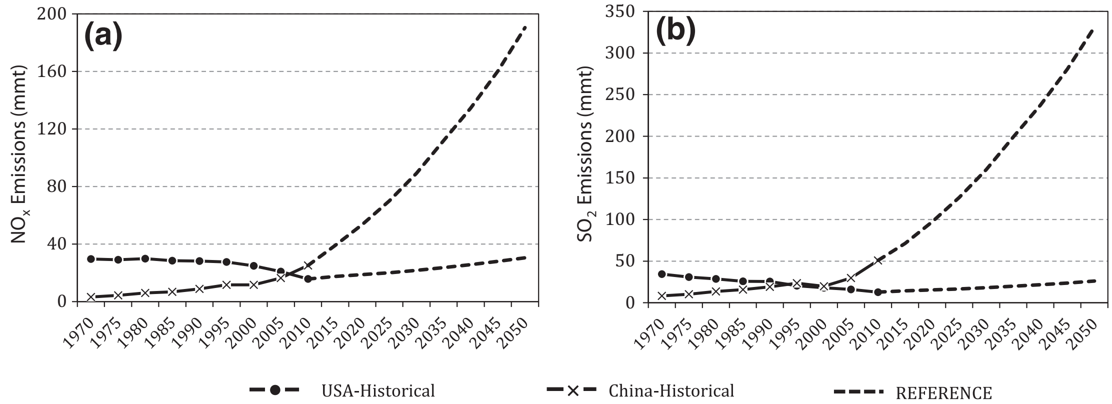


Fig. 4. Baseline emissions schedule: (a) NO_x, (b) SO_2.

implemented in nine northeastern states (RGGI or the Regional Greenhouse Gas Initiative) and California (Damassa et al., 2012). Meanwhile the growing availability of inexpensive, domestically-produced natural gas has displaced coal in the power sector and led to a reduction in total U.S. CO_2 emissions in recent years (NPR, 2012; Paltsev et al., 2011).

4. Method

To explore our research questions, we have extended the MIT Emissions Prediction and Policy Analysis (EPPA5) model. Section 4.1 briefly introduces EPPA5, and Sections 4.2 and 4.3 focus on the model's carbon and pollution abatement structures.

4.1. EPPA5

EPPA5 is a recursive-dynamic computable general equilibrium (CGE) model, built on the Global Trade Analysis Project version 7 (GTAP7) database (Narayanan and Walmsley, 2008). This CGE model of the world economy has 16 global regions and 14 production sectors, as shown in Fig. 1. In addition to economic data, EPPA5 also incorporates data for greenhouse gas (CO_2, CH_4, N_2O, PFCs, HFCs, and SF_6) and urban air pollutant (NO_x, SO_2, CO, NH_3, non-CH_4 VOCs, BC, and OC) emissions, and is capable of projecting their emissions levels, as well as gross domestic product, final demand, and energy consumption.

EPPA5 takes 2004 as the base year, and solves recursively at five-year intervals from 2005 onward. All production and final consumption sectors are modeled using nested constant elasticity of substitution production functions. The model is written in the General Algebraic Modeling System (GAMS) language and solved using the Mathematical Programming System for General Equilibrium Analysis (MPSGE) modeling framework. For further methodological details on EPPA5, refer to Paltsev et al. (2005).

A primary merit of EPPA5 is that it can easily be modified or extended for policy applications. Our modeling work for this study focuses on developing an abatement module for NO_x and SO_2, which corresponds to the CO_2 abatement structure in the standard version of EPPA5. Below we briefly introduce the CO_2 abatement structure of EPPA5 and the pollution abatement structure of the extended model.

4.2. CO_2 abatement structure in EPPA5

EPPA5 supposes three primary channels of CO_2 emissions: fossil-fuel burning, cement production, and deforestation and biomass burning. Among them, it is fossil-fuel burning that is primarily affected by an imposition of carbon caps. Thus, it matters to understand how this channel of CO_2 emissions is structured in the model and how the structure responds to a policy shock.

In the model, CO_2 emissions from the combustion of a fossil energy (X_E) are proportional to the total amount of that energy source used for production (X_F). We consider three kinds of fossil energy—coal, refined oil, and natural gas—and each of them has a constant CO_2 emissions factor with regard to a unit of heat energy that it generates. If a CO_2 emissions cap is imposed under this structure, economic agents within the economy can switch to less CO_2-intensive fossil energy sources or electricity (ELEC) or to substitute capital (or labor) for energy inputs—i.e. adoption of less carbon-intensive technology.

Carbon capture and storage (CCS)—the main *ex-post* carbon-abatement option—comes into play when increased prices of conventional energy inputs under policy constraints justify sizable capital investment for its adoption. CCS is modeled to abate not only CO_2 but also NO_x and SO_2 emissions, as implementation of standard post-combustion CCS technology with an up to 90% CO_2 capture capability requires an additional desulfurization process prior to carbon capture, which removes over 99% of NO_x and SO_2 emissions from the flue gas (Deutch and Moniz, 2007).

Fig. 2 illustrates the model's fuel-related CO_2 emissions structure, explained above.

Table 2
Cross-elasticity (ε_{CO_2,NO_x}) when only NO_x emissions caps are imposed.

	U.S.				China			
	10%	25%	50%	75%	10%	25%	50%	75%
2015	0.12	0.21	0.44	0.59	0.13	0.37	0.73	0.94
2020	0.15	0.25	0.48	0.62	0.12	0.36	0.74	0.94
2025	0.18	0.28	0.52	0.67	0.11	0.35	0.69	0.97
2030	0.19	0.30	0.61	0.61	0.10	0.33	0.64	0.98
2035	0.21	0.32	0.65	0.61	0.09	0.30	0.58	0.99
2040	0.22	0.33	0.67	0.61	0.08	0.28	0.52	1.02
2045	0.23	0.34	0.63	0.61	0.07	0.25	0.47	1.03
2050	0.23	0.34	0.60	0.61	0.06	0.22	0.42	1.03

Table 3
Cross-elasticity (ε_{CO_2,SO_2}) when only SO_2 emissions caps are imposed.

	U.S.				China			
	10%	25%	50%	75%	10%	25%	50%	75%
2015	0.11	0.29	0.34	0.44	0.10	0.33	0.66	0.83
2020	0.13	0.25	0.35	0.47	0.11	0.34	0.63	0.84
2025	0.15	0.33	0.35	0.47	0.11	0.35	0.60	0.87
2030	0.15	0.35	0.39	0.40	0.11	0.35	0.59	0.89
2035	0.14	0.37	0.39	0.40	0.10	0.33	0.54	0.90
2040	0.13	0.39	0.50	0.40	0.10	0.31	0.49	0.92
2045	0.12	0.33	0.48	0.40	0.09	0.28	0.45	0.93
2050	0.11	0.35	0.54	0.40	0.08	0.24	0.41	0.92

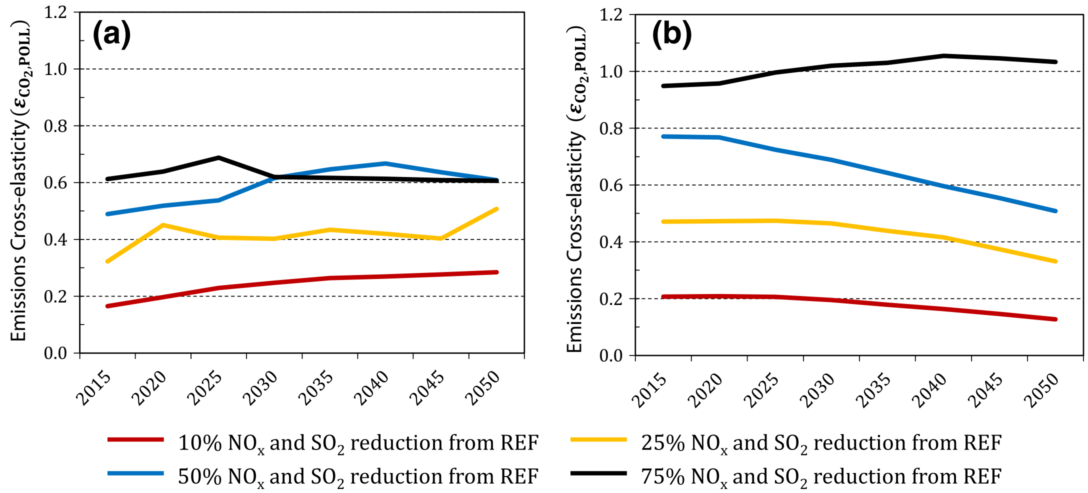


Fig. 5. Cross emissions elasticity ($\varepsilon_{CO_2,POLL}$) by scenario: (a) U.S., (b) China.

4.3. Pollution abatement structure in the extended EPPA5

We consider fuel-related and non-fuel-related pollution separately (Fig. 3). On the one hand, each fuel bundle of the extended model has a fuel-related pollution sub-nest, so that fuel (X_F), precursor emissions (X_E), and pollution abatement (X_A) are considered as direct production inputs. Under the Leontief production structure, each sector requires X_F in a fixed proportion of its total output and each unit of X_F begets a unit of X_E. We then adopt a constant elasticity of substitution (CES) production structure with the elasticity (σ_{Fuel}) between X_E and X_A. As X_A is the capital cost of a unit of abatement, increasing X_A requires additional capital, competing for investment with other capital demands. We estimate σ_{Fuel} from the technology cost and emissions data generated by the baseline scenario of the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model (Nguyen et al., 2011).

In the absence of policy, pollution of X_P is emitted from each activity. With policy, the level of abatement (X_A) is determined by the stringency of pollution control and cost of abatement. In other words, emitting

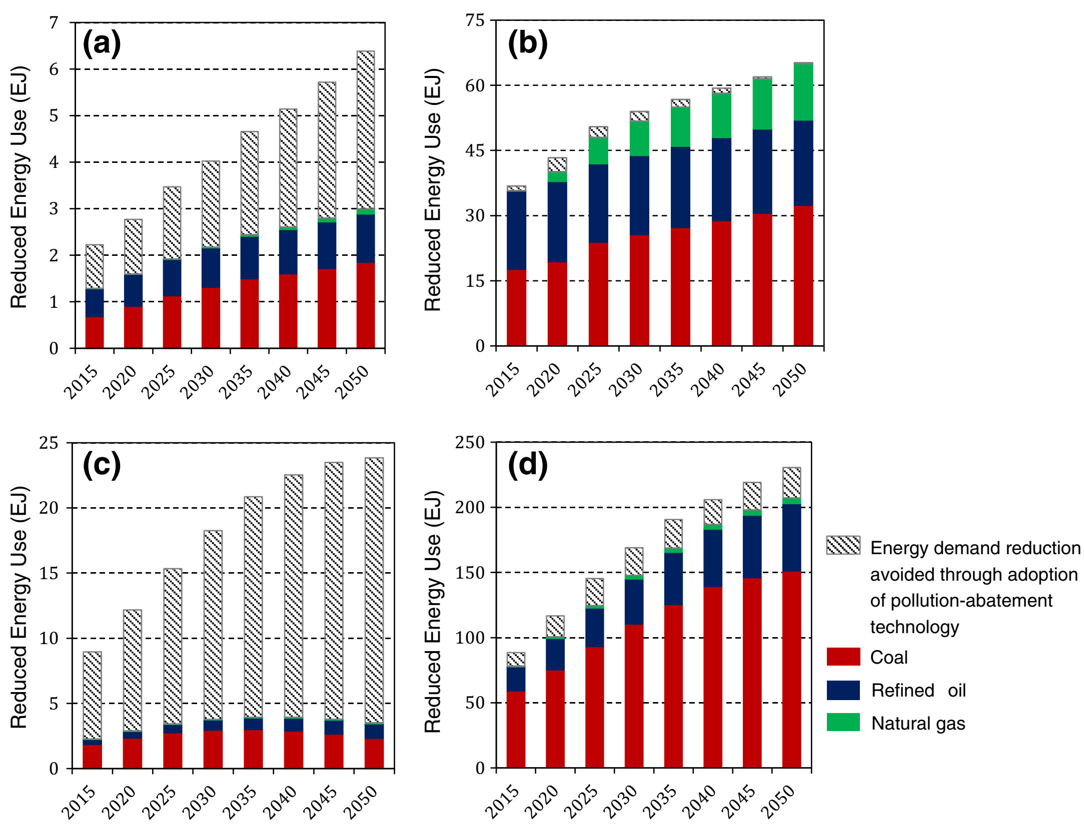


Fig. 6. Reduced demand for primary energy inputs under selected policy scenarios: (a) U.S.: 10%, (b) U.S.: 75%, (c) China: 10%, (d) China: 75%.

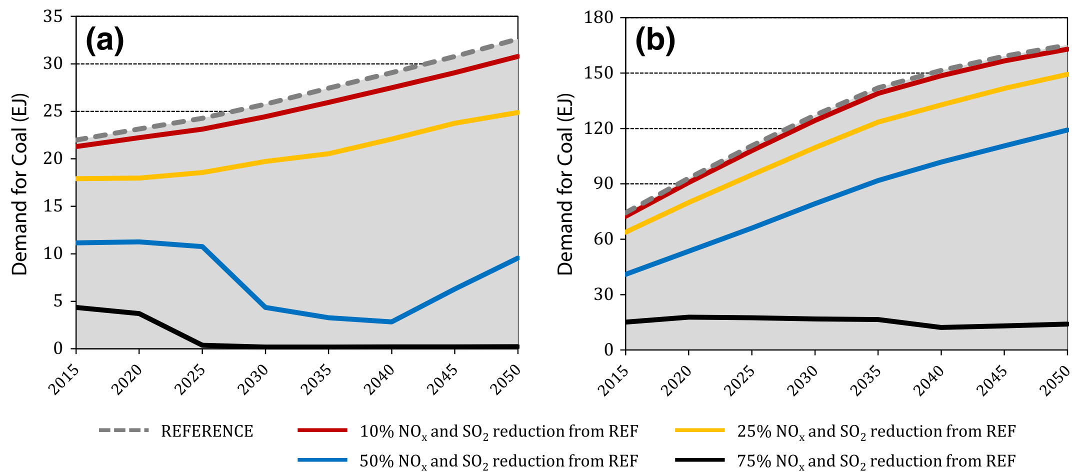


Fig. 7. Demand for coal under policy scenarios: (a) U.S., (b) China.

under pollution control creates an incentive to abate until the marginal price for abating equals the marginal price for emitting. As emitting and abating become overly costly, economic agents will shift toward less pollution-intensive fuels or reduce energy consumption to meet emissions constraints.

Non-fuel-related pollution is represented as a production input, which can be substituted by other conventional inputs, and associated pollution-abatement decisions are determined by $\sigma_{Pollutant}$. In this structure, adoption of abatement inputs results in a proportionally increased use of all other inputs, given all other prices are unchanged. As NO_x and

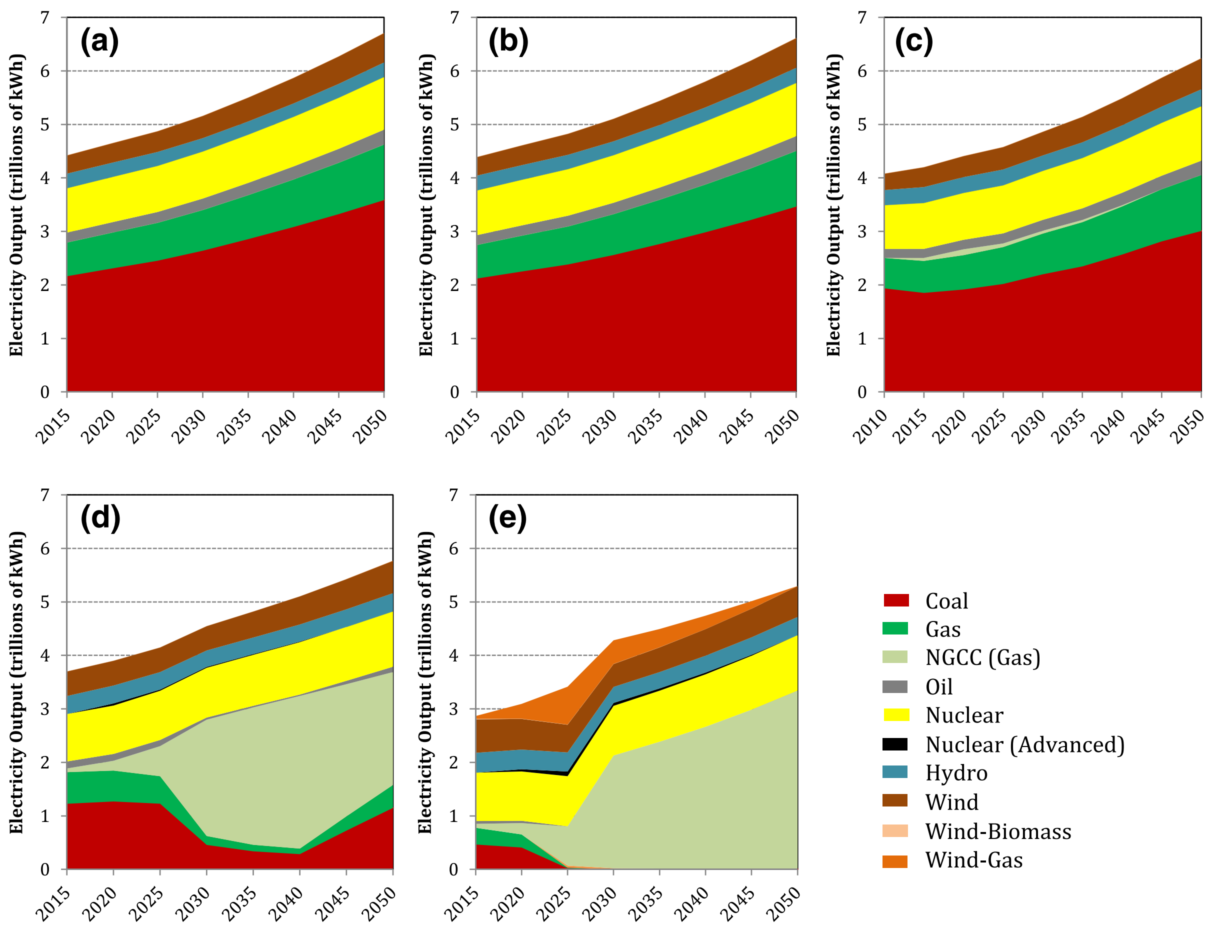


Fig. 8. Electricity output mix in the U.S. under pollution-abatement policy: (a) REF, (b) 10% targets, (c) 25% targets, (d) 50% targets, (e) 75% targets.

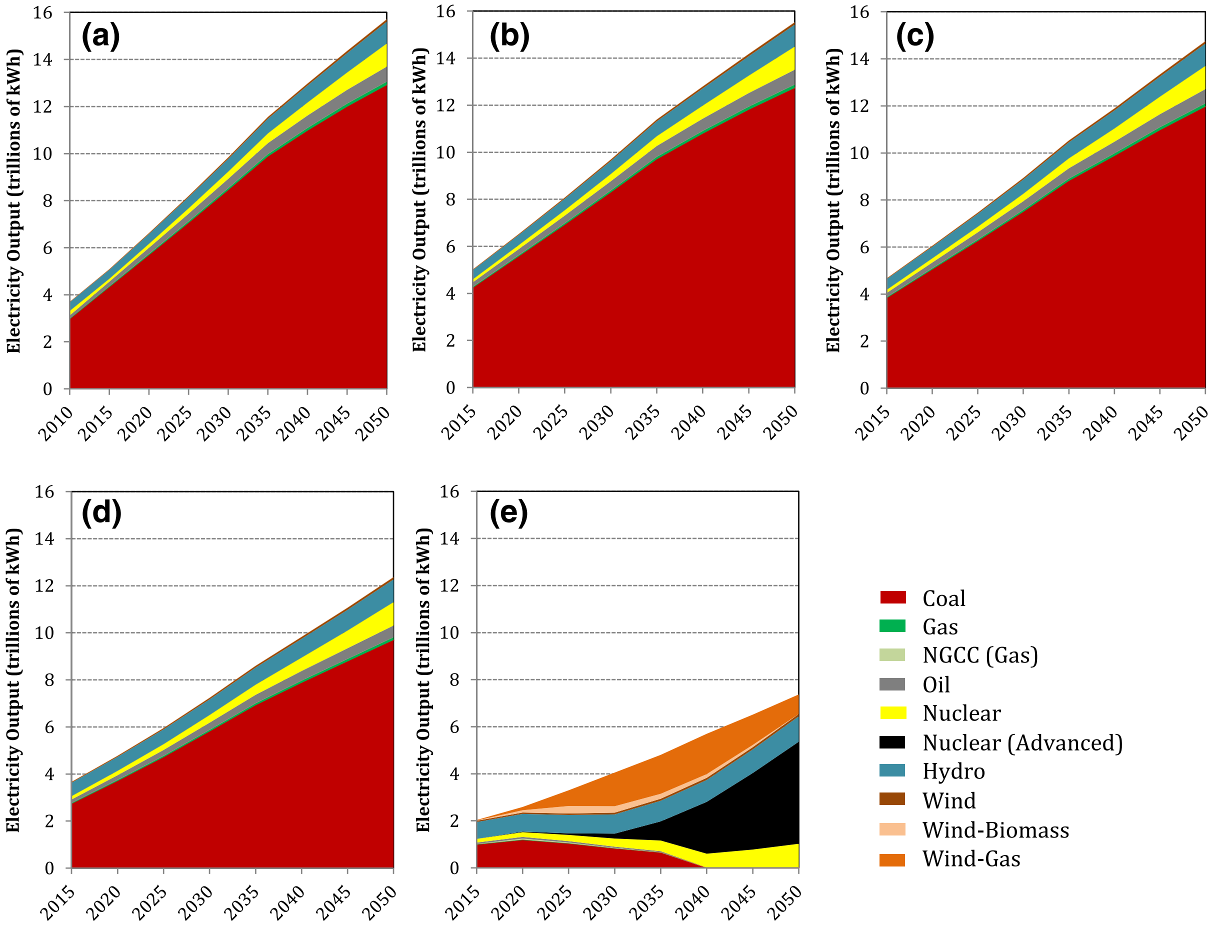


Fig. 9. Electricity output mix in China under pollution-abatement policy: (a) REF, (b) 10% targets, (c) 25% targets, (d) 50% targets, (e) 75% targets.

SO_2 cases are solved separately by sector and by fuel, the initial levels of pollution emissions and marginal abatement costs are unique to the fuel source, sector, and pollutant.

We provide further details on estimating σ_{Fuel} and $\sigma_{Pollutant}$ in Appendix A and the full set of our estimates for the U.S. and China in Appendix B.

5. Results

We simulate the model developed above by imposing progressively tighter levels of nationwide emissions caps. The concept of an emissions cross-elasticity is used to summarize the ancillary reductions in the non-target emissions, *i*, resulting from a policy that targets reductions

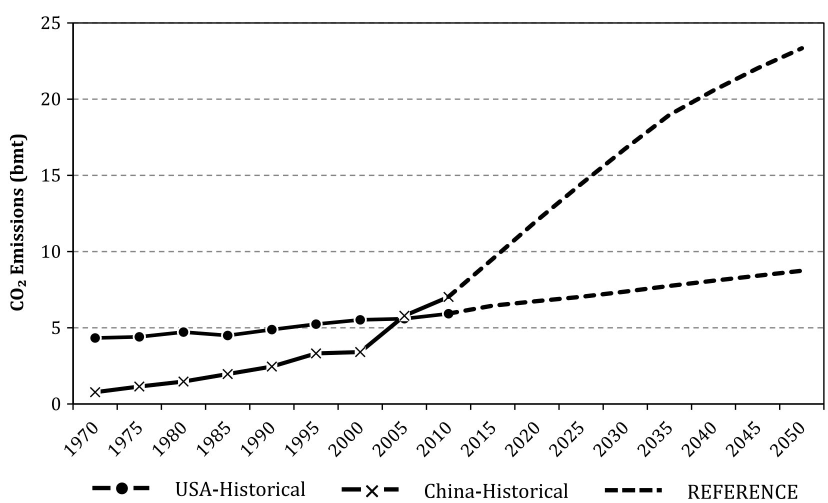


Fig. 10. Baseline CO_2 emissions schedule.

Table 4
Cross-elasticity between NO_x and CO_2 (ε_{NO_x,CO_2}).

	U.S.				China			
	10%	25%	50%	75%	10%	25%	50%	75%
2015	0.78	0.79	0.82	0.85	0.45	0.49	0.55	0.65
2020	0.68	0.73	0.73	0.77	0.40	0.45	0.51	0.61
2025	0.60	0.67	0.68	0.72	0.37	0.42	0.49	0.55
2030	0.54	0.61	0.70	0.68	0.35	0.39	0.47	0.53
2035	0.49	0.56	0.68	0.65	0.33	0.37	0.45	0.50
2040	0.47	0.51	0.66	0.63	0.32	0.36	0.41	0.45
2045	0.45	0.52	0.64	0.61	0.31	0.35	0.39	0.43
2050	0.43	0.48	0.61	0.60	0.29	0.33	0.37	0.41

in pollutant emissions *j*. As shown below, the emissions cross-elasticity ($\varepsilon_{i,j}$) is calculated as the percentage change in emissions of *i* between the reference (*REF*) and policy (*POL*) scenarios divided by the percentage change in emissions of *j*.

$$\varepsilon_{i,j} = \frac{X_i^{REF} - X_i^{POL}}{X_j^{REF} - X_j^{POL}} \cdot \frac{X_j^{REF}}{X_i^{REF}} = \frac{\%\Delta X_i}{\%\Delta X_j}$$

This is a simple arc elasticity comparing the total change from stringent policies with the reference pollution level. We first examine the ancillary benefits of carbon emissions reductions from SO_2 and NO_x policies (ε_{CO_2,SO_2} and ε_{CO_2,NO_x}) and then the reverse (ε_{NO_x,CO_2} and ε_{SO_2,CO_2}).

5.1. Ancillary carbon benefits of SO_2 and NO_x control

We simulate a total of five scenarios. One is a baseline scenario, which we call *REF*. In this scenario, we do not impose any further policy constraint beyond existing NO_x and SO_2 emissions regulations. NO_x and SO_2 emissions schedules for the U.S. and China under the *REF* scenario are displayed in Fig. 4. The other four are policy scenarios imposing progressively tighter reduction targets for NO_x and SO_2 emissions at the national level. We simulate these reductions over the period of 2015–2050. The scenarios cap emissions at 10%, 25%, 50%, or 75% reductions from the baseline NO_x and SO_2 emissions levels. The EPPA model solves every 5 years, and we compute the cross-elasticities for each reduction level and for each solution year. This setup allows us to evaluate (1) how ancillary carbon benefits differ for SO_2 and NO_x control, (2) how they vary over time, and (3) how they change as the stringency of control efforts varies. We set the policy targets relative to the reference emissions levels, instead of imposing constant emissions caps, so that we have comparable reductions in China and the U.S. Emissions of all pollutants are growing rapidly in China and slowly in the U.S., and hence an absolute cap relative to a historic year would imply much greater percentage reductions in China over time than in the U.S., conflating any time trend with changes in the stringency of reduction.

Our results present several common tendencies in each country (Tables 2 and 3). First, ε_{CO_2,NO_x} and ε_{CO_2,SO_2} are comparable, in terms of magnitude, although the former tends to be slightly higher than the latter. ε_{CO_2,NO_x} shows ranges of 0.12–0.67 in the U.S. and 0.06–1.03 in China; similarly, ε_{CO_2,SO_2} shows ranges of 0.11–0.54 in the U.S. and 0.08–0.93 in China. This outcome is primarily because NO_x and SO_2 emissions share similar sources, such as fossil-fuel combustion or energy-intensive production. Both ε_{CO_2,NO_x} and ε_{CO_2,SO_2} tend to be greater under more stringent pollution-control targets. Under the 10% NO_x reduction targets, for example, ε_{CO_2,NO_x} shows ranges of 0.12–0.23 in the U.S. and of 0.06–0.13 in China, but the 75% targets drive up the ranges to 0.59–0.61 for the U.S. and 0.94–1.03 for China. This coincides with our expectation, as stringent pollution-control targets make pollution-abatement options costly and increase the need for cutting energy use—particularly, fossil fuel use.

While the general relationships are similar across countries, China tends to show higher ε_{CO_2,NO_x} and ε_{CO_2,SO_2} than the U.S. under stringent targets. Under the 75% targets, for example, ε_{CO_2,SO_2} in China shows a range of 0.83–0.93, roughly twice as high as that in the U.S. (0.40–0.47). This contrasts the 10% target case, where ε_{CO_2,SO_2} is slightly higher in the U.S. (0.11–0.15) than in China (0.08–0.11). As will be explained in detail, this fact is closely related to China's higher dependency on coal. The time trend of the elasticities in each emissions control scenario also differs by country. In brief, both ε_{CO_2,NO_x} and ε_{CO_2,SO_2} in China present declining tendencies over time, while those in the U.S. show increasing or constant trends. This is primarily because NO_x and SO_2 baseline emissions, which continue to grow over time in China, allow China to have more room to comply with the given policy without reducing energy use in later time periods. In contrast, NO_x and SO_2 baseline emissions in the U.S. grow only marginally over time, leading to relatively constant cross effects over time.

Each simulation run for the results introduced above constrains either NO_x or SO_2, but in reality, China is likely to regulate the two pollutants at the same time. Thus, we developed a new set of policy simulations where limits are set on both pollutants, and this case is denoted as *POLL*. The elasticity denoted as $\varepsilon_{CO_2,POLL}$ refers to the percentage change of CO_2 emissions driven by a unit percent change of NO_x and SO_2 emissions due to targeting reductions in both pollutants together.

As illustrated in Fig. 5, $\varepsilon_{CO_2,POLL}$ presents trends similar to those of ε_{CO_2,NO_x} and ε_{CO_2,SO_2}. The stringency of the policy shock is positively associated with the elasticity in each country, and China tends to show substantially higher $\varepsilon_{CO_2,POLL}$ than the U.S. when targets are stringent.

However, two puzzling aspects are found in the same figure. One is why in the U.S. $\varepsilon_{CO_2,POLL}$ presents lower values under the 75% reduction targets than the 50% case in 2030 and thereafter. As hinted earlier, the answer is closely related to the changed mix of energy demand in the presence of policy shocks. Due to its high emissions factors, coal is affected more greatly by NO_x and SO_2 regulations than other fossil energy sources. We see an increasing role of other energy sources in meeting the given emissions-reduction targets, as energy demand from coal converges to the minimal level that an economy can afford (Fig. 6). Under the 75% targets, for example, the U.S. is expected to remove over 98% of its baseline coal use by 2025 and to comply with the policy by cutting an increased portion of energy demand from refined oil and natural gas since then (Fig. 7). The reduced role of coal and the expanded role of refined oil and natural gas in policy compliance cases lowers cross-elasticities of SO_2 and NO_x control, leading to the relatively sharp decline of $\varepsilon_{CO_2,POLL}$ in 2030, even below the 50% target level. The 50% $\varepsilon_{CO_2,POLL}$ line for the U.S. suddenly rises in 2030 because a large cut in coal use in the electricity sector is achieved through increased substitution of the natural gas combined cycle (NGCC) for conventional coal-fired power-generation technology (Fig. 8).

The other puzzling trend found in Fig. 5 is why $\varepsilon_{CO_2,POLL}$ for China presents an increasing tendency over time under the 75% targets, and a slightly falling trend over time for other reduction targets. This trend is related to the relative magnitude of the policy constraint imposed in each time period. Due to constantly growing baseline emissions levels,

Table 5
Cross-elasticity between SO_2 and CO_2 (ε_{SO_2,CO_2}).

	U.S.				China			
	10%	25%	50%	75%	10%	25%	50%	75%
2015	1.21	1.13	1.10	1.02	0.61	0.64	0.67	0.74
2020	1.10	1.17	1.05	0.97	0.54	0.57	0.61	0.70
2025	0.99	1.12	1.15	0.95	0.48	0.53	0.58	0.65
2030	0.91	1.03	1.30	0.92	0.44	0.48	0.55	0.62
2035	0.84	0.92	1.27	0.90	0.41	0.45	0.53	0.59
2040	0.80	0.80	1.24	0.88	0.39	0.43	0.50	0.55
2045	0.77	0.87	1.21	0.86	0.37	0.42	0.49	0.52
2050	0.74	0.77	1.19	0.85	0.34	0.39	0.47	0.49

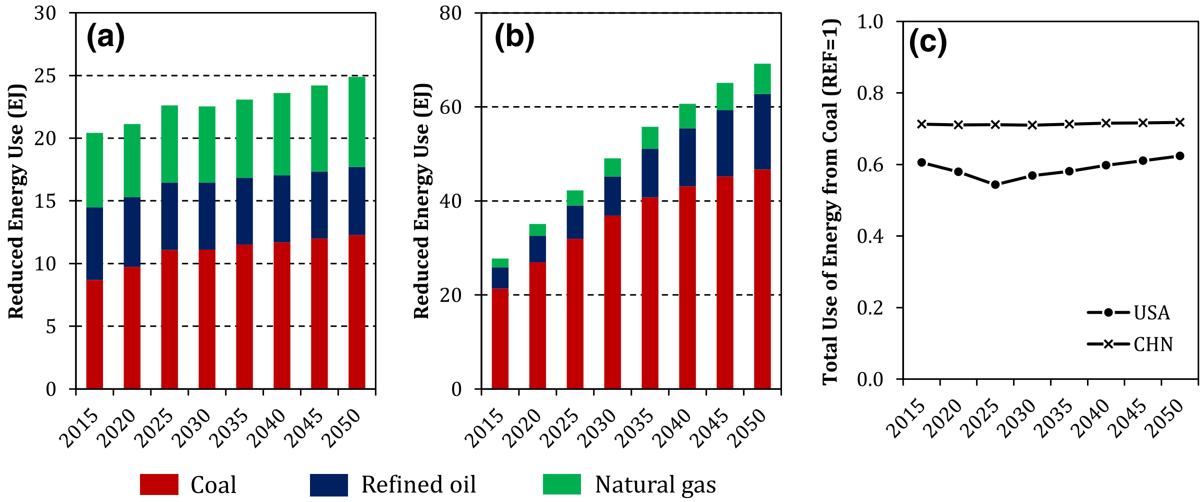


Fig. 11. Reduced energy use under 25% CO_2 reduction scenario: (a) U.S., (b) China, (c) total use of coal-based energy relative to the baseline level.

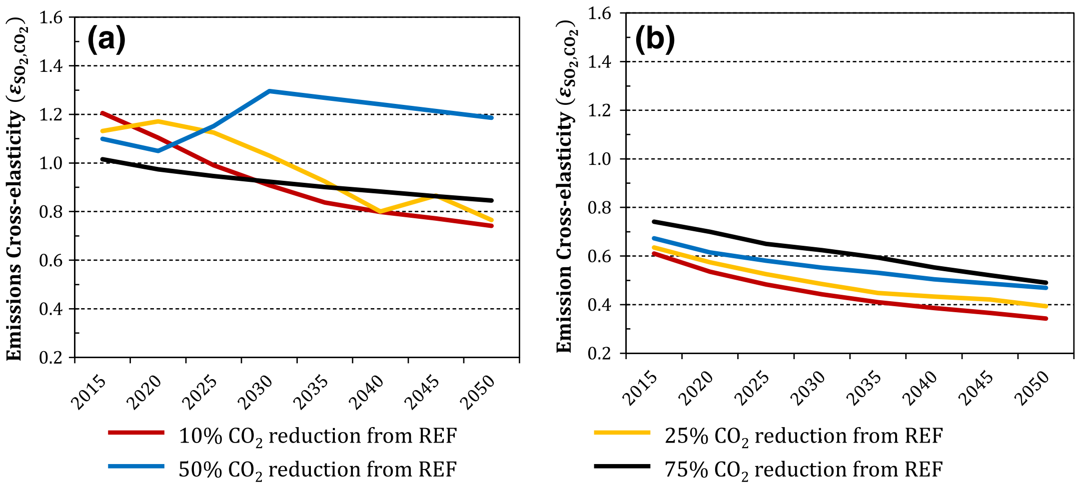


Fig. 12. Emissions cross-elasticity (ε_{SO_2,CO_2}) by scenario: (a) U.S., (b) China. Graph uses data from Table 5.

China tends to have increasing flexibility over time under each policy scenario, in terms of choosing policy-compliance options beyond a cutback of energy use. Under the 10% targets, for example, avoided energy demand reductions through adoption of pollution-abatement technology increase over time from 6.7 EJ in 2015 to 20.3 EJ in 2050 (Fig. 6c). Accordingly, China can comply with the 10% targets without increasing the absolute amount of energy demand reductions in later periods. Due to this increasing flexibility, in terms of response to a given policy shock, $\varepsilon_{CO_2,POLL}$ for China tends to decline over time under relatively moderate targets.

However, this is not the case under the 75% targets, where China confronts increasingly strong pressure for energy demand reductions over time. This is because the increased stringency of policy shock leaves China limited room for other pollution-abatement options and instead energy use itself is reduced (Fig. 6d). China's electricity output mix, shown in Fig. 9, clearly demonstrates our argument: as complying with the 50% or lower reduction targets presents a smooth and gradual coal-use reduction schedule but the 75% reduction targets lead to a more drastic change in output mix, requiring much greater reduction of coal use and more intensive adoption of cleaner technologies, such as advanced nuclear[1] and wind power with back-up capacity from natural gas (wind-gas). In contrast to the corresponding U.S. case, however, China still has capacity to cut its coal use under the 75% targets. The 75% targets completely phase out coal from China's electricity sector by 2040 (Fig. 9), but substantial amounts of coal (12–14 EJ) are still used by non-electricity sectors, most notably energy-intensive industries[2] and households (Fig. 7b). Capacity for further reduction of coal use, as well as increased pressure for fossil-energy use reduction (due to limited opportunities for abatement-technology adoption), contributes to an increasing trend of $\varepsilon_{CO_2,POLL}$ over time under the 75% targets.

[1] *Advanced nuclear* refers to generation 3 + nuclear technologies based on reprocessing or breeder-type fuel cycles.

[2] Energy-intensive industries (EINT) in EPPA5 include the sectors that produce paper products, chemical products, ferrous and non-ferrous metals, metal products, and mineral products.

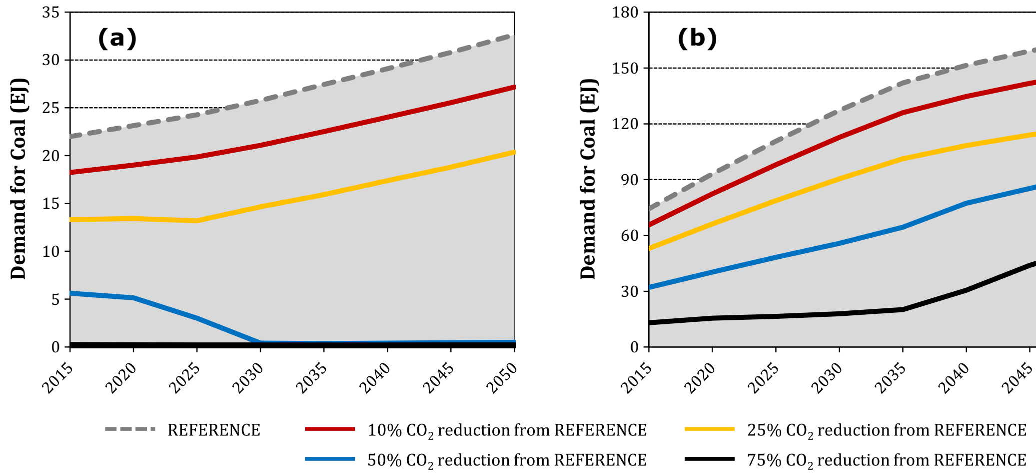


Fig. 13. Reduced demand for coal-based energy: (a) U.S., (b) China.

5.2. Ancillary air quality benefits of CO_2 mitigation

We also simulated a reference and four climate policy scenarios for a cross-country comparison of ancillary NO_x and SO_2 reductions from carbon mitigation. Fig. 10 displays CO_2 emissions schedules for the U.S. and China under the *REF* scenario. We set a range of CO_2 reduction targets—10%, 25%, 50%, or 75% reductions from the baseline levels—and recorded ancillary NO_x and SO_2 reductions to compute emissions cross-elasticities.

In general, ε_{NO_x,CO_2} and ε_{SO_2,CO_2} tend to be much higher than ε_{CO_2,NO_x} and ε_{CO_2,SO_2} at low levels of abatement, but increase more gradually with the level of abatement (Tables 4 and 5). For example, ε_{NO_x,CO_2} shows ranges of 0.43–0.78 in the U.S. and 0.29–0.45 in China under the 10% reduction targets. The ranges go up to 0.60–0.85 and 0.41–0.65, respectively, under the 75% targets. This result can be attributed to the increased stringency of a policy shock leaving little room for fuel switching, placing a greater pressure for energy demand reduction on an economy. In both countries, ε_{SO_2,CO_2} presents slightly higher values than ε_{NO_x,CO_2}.

Both ε_{NO_x,CO_2} and ε_{SO_2,CO_2} are substantially higher in the U.S. than in China under all policy scenarios, presenting a clear contrast to ε_{CO_2,NO_x} and ε_{CO_2,SO_2}. For the given 10–75% CO_2 reduction targets, ε_{NO_x,CO_2}

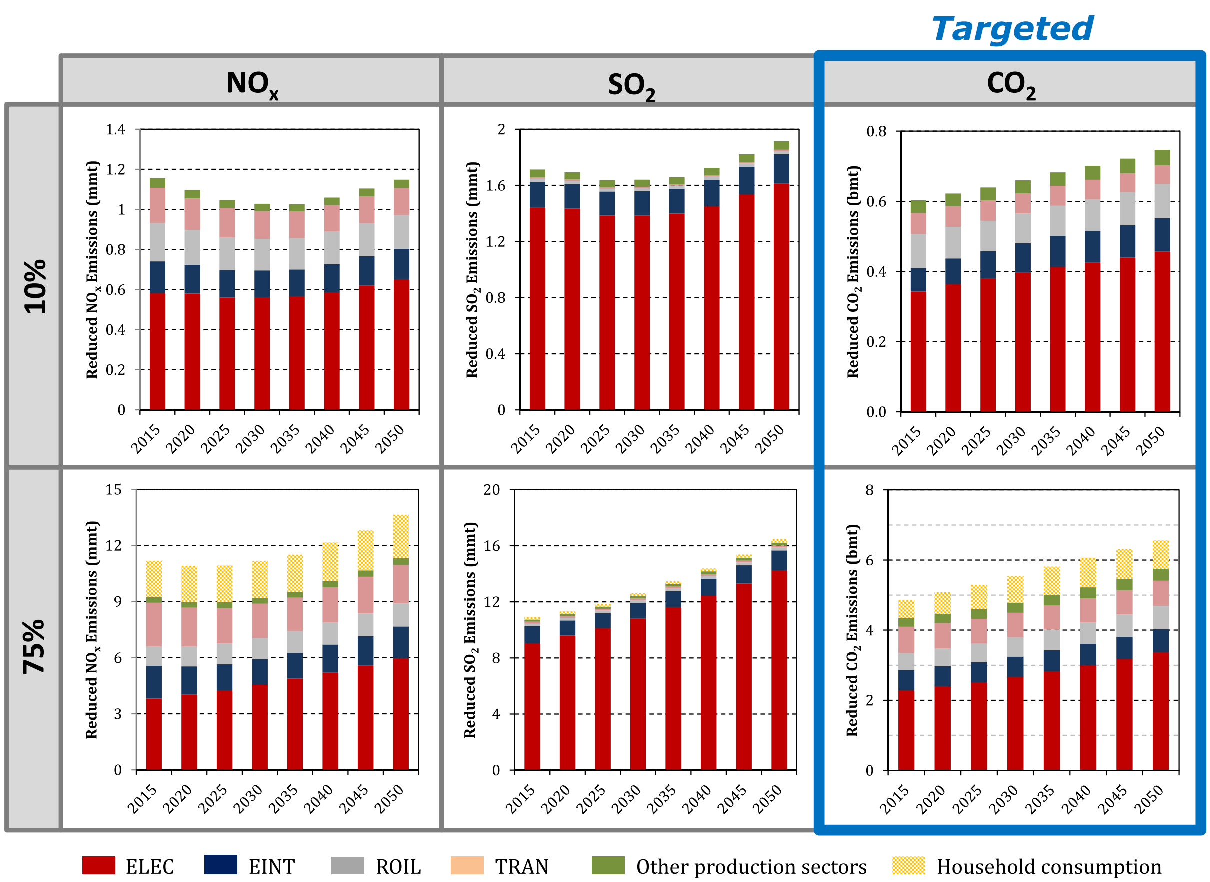


Fig. 14. Reduced emissions in the U.S. by gas and sector under CO_2 control scenarios.

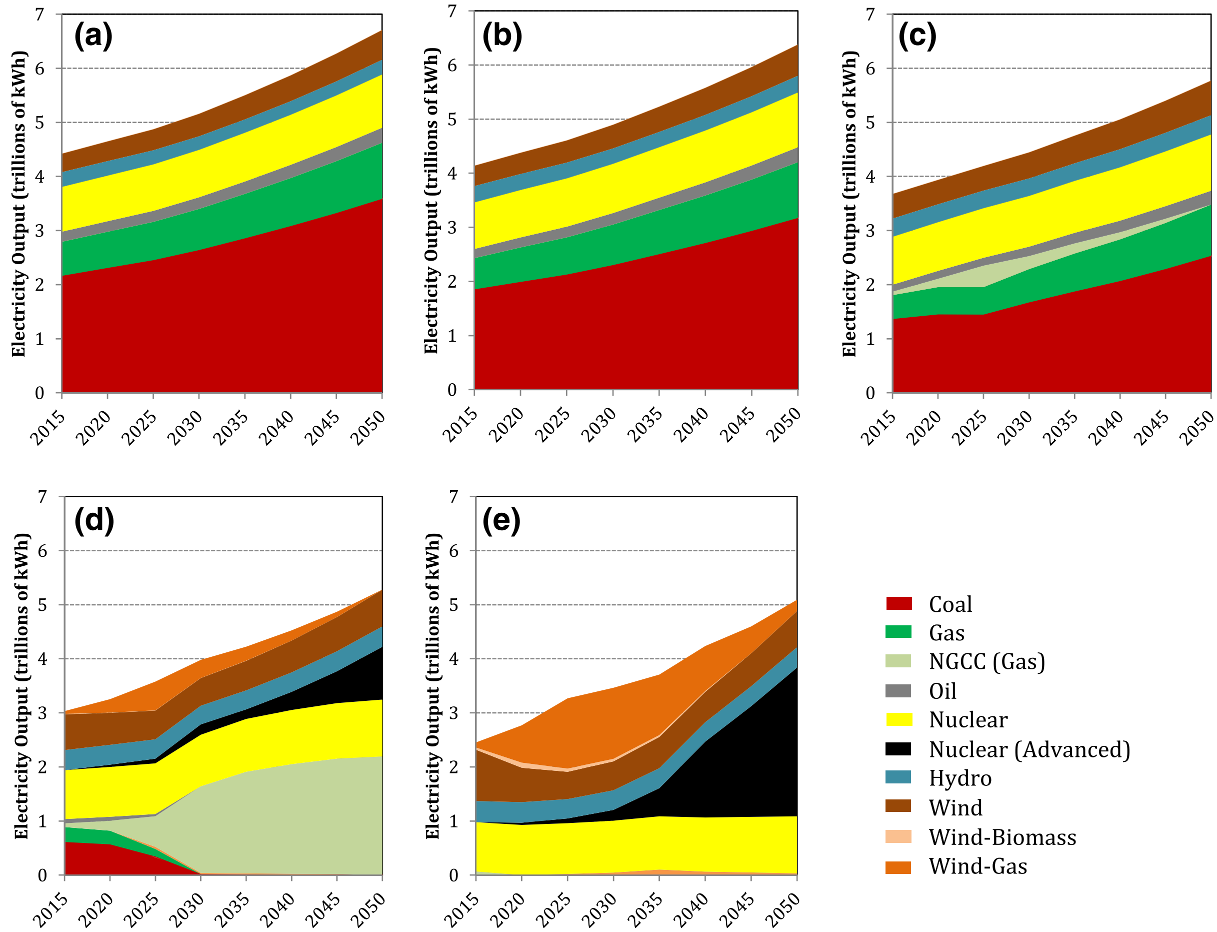


Fig. 15. Electricity output mix in the U.S. under carbon-mitigation policy: (a) REF, (b) 10% targets, (c) 25% targets, (d) 50% targets, (e) 75% targets.

shows ranges of 0.43–0.85 in the U.S. and of 0.29–0.65 in China; ε_{SO_2,CO_2} is distributed between 0.74 and 1.30 in the U.S. and between 0.34 and 0.74 in China. The stronger cross effects in the U.S. are because a policy shock of comparable stringency requires the U.S. to cut a relatively large amount of coal use, as suggested by baseline carbon emissions schedules in Fig. 10. The carbon constraint is met primarily through fuel switching, reduction of energy consumption, and adoption of CCS and non-fossil energy technologies. All these responses entail relatively large reductions in coal use, compared with other fossil energy use, due to coal's higher carbon content. Under the 25% reduction targets, for example, around half the total energy-use reduction in the U.S. is from coal; the corresponding share for China is even higher, ranging from 64.6 to 74.7%, due to China's higher dependence on coal (Fig. 11a and b). In relative terms, however, comparable carbon-mitigation targets induce more drastic cuts in coal use (from the baseline levels) in the U.S. than in China. Under the 25% targets, for example, the U.S. is estimated to reduce 37.6–45.6% of its baseline coal consumption (8.7–12.3 EJ), while China is estimated to reduce 28.3–29.0% (21.4–46.7 EJ) (Fig. 11c). A greater magnitude of coal use reduction in the U.S., in turn, results in higher cross-elasticities for the U.S.

In some cases, the cross effects deviate from the given general trends, as exemplified by ε_{SO_2,CO_2} for the U.S. As illustrated in Fig. 12, a consistent relationship between cross-elasticity and policy stringency does not hold for the U.S., in contrast to the case of China, where the level of ε_{SO_2,CO_2} increases as carbon reduction targets become more stringent. This result is in part explained by policy-driven changes in coal consumption (Fig. 13). The U.S. ε_{SO_2,CO_2} line for the 75% target case is located below that for the 50% case because coal completely exits the market from the initial year of carbon constraint under the 75% targets, while demand for coal remains under the 50% targets until 2025. In other words, a larger share of the total energy demand reduction is from oil and gas under the 75% targets—thus, leading to relatively lower pollution-abatement effects—than under the 50% targets. In contrast, even the 75% carbon reduction policy does not drive coal completely out of China's energy market, causing less drastic changes in the trend of cross-elasticities. Again, this is because under the reference case scenario China's fossil energy use is growing relatively fast while there is limited growth in the U.S.

But the remaining puzzle is why part of the cross-elasticities for the 75% reduction targets in the U.S. remains below the elasticities for the 10% and 25% targets in later periods. A focus on the electricity sector is helpful to understand why this happens, as it is the single most important production sector in complying with carbon-mitigation targets in the U.S. (Fig. 14). First, the 10% targets are not stringent enough to incentivize adoption of low carbon technology, such as NGCC, so the targets are met primarily through fuel switching and less use of energy (Fig. 15). The 25% targets, however, allow NGCC to penetrate the market, and its substitution for coal-fired power generation technology achieves a relatively large reduction of coal use, compared with the reduction under the 10% targets. Therefore, the cross-elasticities for the 25% targets tend to be higher than those for the 10% targets. Under the 50% targets, NGCC and other clean energy technologies,

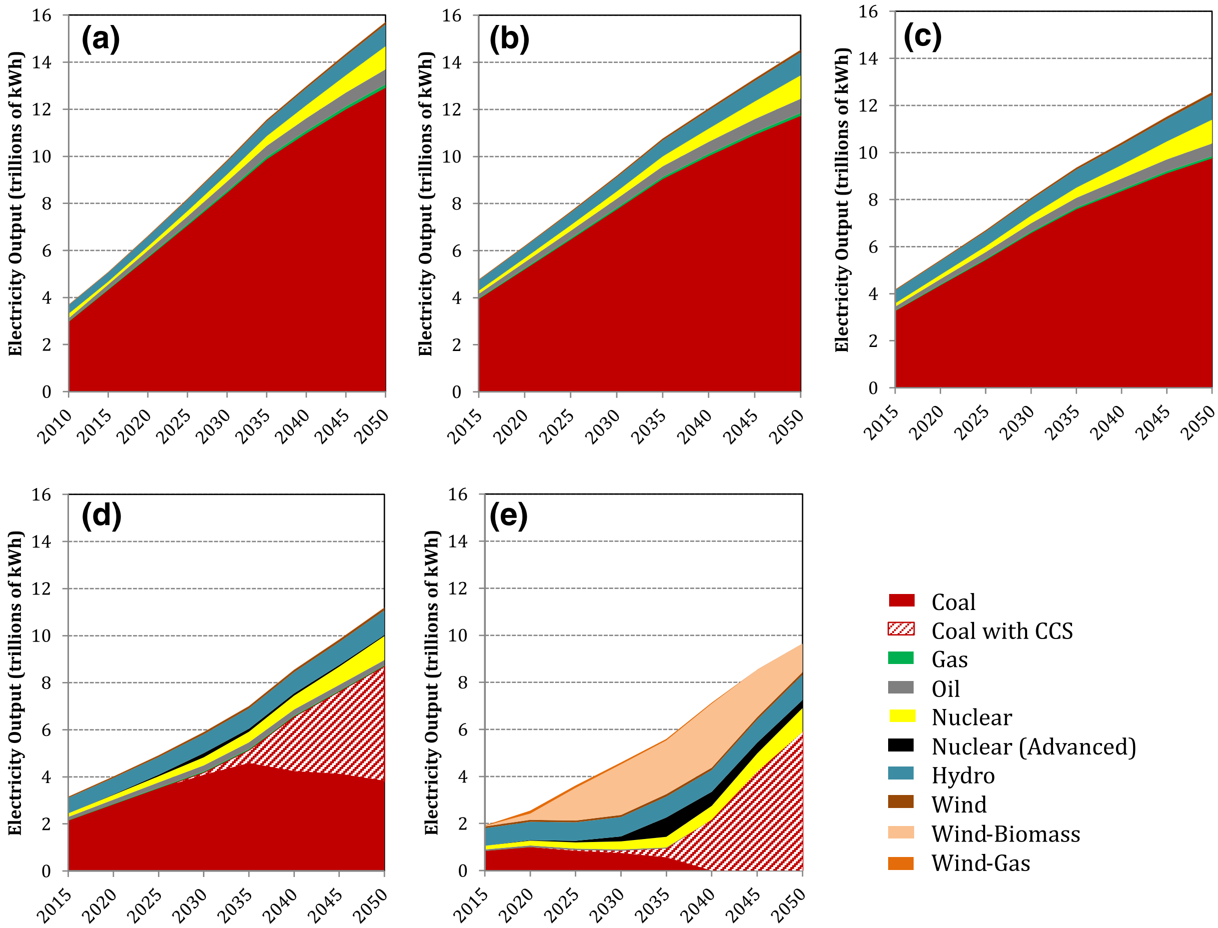


Fig. 16. Electricity output mix in China under carbon-mitigation policy: (a) REF, (b) 10% targets, (c) 25% targets, (d) 50% targets, (e) 75% targets.

such as advanced nuclear and wind-gas, are competitive in the market and crowd out conventional coal at a rapid pace. The cross-elasticities for the 50% targets are greater than those for the 10% and 25% targets in later periods, as the 50% targets drive conventional coal completely out of the market in 2030 and later periods while the 10% and 25% targets allow gradual increase of coal use.

Finally, the 75% targets completely crowd out conventional coal-fired power-generation technology from 2015, allowing expanded roles of advanced nuclear and wind-gas. But reduction of fossil energy use in the electricity sector alone is not enough to comply with the policy; further energy use reduction should come from other sectors, which in general depend on coal less than the electricity sector does. As shown in Fig. 14, the 75% targets in particular require increased energy demand reduction from the household sector, which mainly consumes refined oil and natural gas for vehicle operations and heating. Thus, the cross-elasticities are relatively low under the 75% targets, compared with other cases. However, the elasticities for the 75% targets catch up with those for the 10% and 25% targets in later periods and eventually overtake them, as the 10% and 25% targets allow gradual increase of coal use over time while the 75% targets do not.

Compared to the U.S., China shows a much smoother transition in electricity output mix (Fig. 16). With increased stringency of carbon reduction targets, conventional coal technologies gradually phase out of the electricity sector, and part of the reduced coal-fired power output is increasingly replaced by less emissions-intensive alternatives, such as coal-fired power generation combined with CCS (coal with CCS) and wind power with backup capacity from biomass (wind-biomass). This smoother transition in the electricity sector explains why China displays more consistent trends of ε_{NO_x,CO_2} and ε_{SO_2,CO_2}, in response to increased stringency of policy shock, than the U.S. does.

6. Conclusions

In this study, we first introduce an analytic framework for pollution-climate control synergy and then apply the methodology to the U.S. and China. The primary contributions of this study to the literature and the policy debate include the following three aspects. First, our analysis is based on a new methodological approach, which endogenizes pollution emissions-abatement decisions within a CGE structure, incorporating bottom-up engineering details. This is a substantial improvement on conventional methods assuming fixed emissions factors or exogenous abatement opportunities. Second, our study enriches the literature on ancillary carbon benefits of pollution abatement, which is sparse despite growing attention to the topic. Finally, our results, summarized as emissions cross-elasticities, provide the basis for a parallel comparison of the U.S. and China, in terms of ancillary CO_2 reductions from NO_x and SO_2 targets or of ancillary NO_x and SO_2 reductions from CO_2 targets.

In general, higher stringency of pollution-abatement targets is associated with greater cross-elasticities of pollution control. For ε_{CO_2,NO_x} and ε_{CO_2,SO_2}, we find low values (0.06–0.23) in both countries with the 10% reduction targets, but they rise to 0.40–0.67 in the U.S. and to 0.83–1.03 in China under the 75% targets. The key mechanism underlying this result is that increased costs for abatement-technology adoption and fuel switching under stringent targets incentivize economic agents to shift toward energy-consumption reductions and advanced energy-technology implementation, having greater effects on carbon emissions. That is, this tendency reflects the availability of pollution control to target individual pollutants for smaller reductions but the need for wholesale change toward non-fossil technologies increases when large reductions are required.. The especially high cross-elasticities in China under stringent targets are due to the interplay between increased pressure for energy input reduction and China's high dependence on coal. Meeting stringent targets in both countries requires a massive reduction of energy use, but a larger share of the total energy use reduction in China is from coal. This relatively larger reduction of coal use leads to greater ancillary carbon reductions in China, translating into higher cross-elasticities.

A similar trend is found from the opposite experiment. Both ε_{SO_2,CO_2} and ε_{NO_x,CO_2}, in general, tend to increase with increased stringency of carbon reduction targets. For example, ε_{NO_x,CO_2} presents ranges of 0.43–0.78 in the U.S. and 0.29–0.45 in China under the 10% targets, but the 75% targets drive up the ranges to 0.60–0.85 and 0.41–0.65, respectively. In some cases, however, the cross-elasticities in the U.S. deviate from this general trend, depending on the role of advanced energy technologies. In addition, both ε_{SO_2,CO_2} and ε_{NO_x,CO_2} are much greater in the U.S. than in China, presenting a clear contrast to ε_{CO_2,NO_x} and ε_{CO_2,SO_2}. The magnitude of coal use reductions from the baseline levels is a main source of this result. In general, meeting CO_2 reduction targets of comparable stringency leads to more drastic reduction of coal use in the U.S. (partly through more intensive adoption of low carbon technology), generating greater cross effects in the U.S. than in China.

In sum, our results demonstrate substantial cross effects between the two conventional air pollutants and carbon dioxide in both directions and in both countries. The majority of existing studies have focused on the effect of CO_2 abatement on other pollutants, typically finding strong cross effects, but we also found evidence for similarly strong ancillary carbon-mitigation effects of pollution control. The latter result, in particular, seems to offer some hope that carbon emissions may not increase as much as some forecasts suggest if concerns about conventional pollutants lead to policies to reduce them. Our study of China presents a strong effect on carbon emissions of efforts to reduce SO_2 and NO_x. The U.S. and China are both relatively coal-intensive economies. Given that other economies are less so, we may well see different relationships between control of conventional pollutants and CO_2. It would be interesting to follow up this research for other regions of the world.

Acknowledgments

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Appendix A. Method of Estimating Emission-Abatement Substitution Elasticities[3]

For this study, EPPA5 is extended to capture pollution-abatement opportunities and costs through initial parameterization of cost shares and the relevant elasticities. Since abatement opportunities depend on the specific abatement technologies available in each region and sector, emission-abatement substitution elasticity (σ_{Fuel}) must reflect the technological details unique to these levels of disaggregation. For this purpose, we obtain a price elasticity of supply for abatement from detailed bottom-up engineering studies, and draw σ_{Fuel} from the price elasticity.

First, we estimate region, sector, and fuel-specific marginal abatement cost curves for SO_2 and NO_x from engineering data. With reference to the literature, a log-linear relationship is assumed between pollutant emissions (X_E) and their marginal price (P_E), as shown in Eq. (A1). In this equation, α and β are parameters to be estimated.

$$\log P_E = \log \alpha + \beta \log X_E \tag{A1}$$

Then, the price elasticity of demand for emissions (ε_E) is simply the reciprocal of β. It should be noted that the total quantity of pollution (X_P) is the sum of X_E and pollution abated (X_A), so any reduction in emitting must be made up by abating and vice versa. In other words, the demand curve for emitting equals the supply curve for abating, and the price elasticities are also the same.

$$\varepsilon_E = \frac{\partial \log X_E}{\partial \log P_E} = \frac{1}{\beta} \tag{A2}$$

The relationship between this "own-price" elasticity and the elasticity of substitution can be established from a cost minimization problem (CMP), where the firm seeks to minimize the cost of pollution production (C_P) for a given output subject to the related production technology. The objective function C_P, expressed as a function of X_E and X_A, is shown in Eq. (A3), where P_A denotes the marginal price of abating.

$$C_P = X_E P_E + X_A P_A \tag{A3}$$

We assume that the related pollution-production function takes a CES functional form given as Eq. (A4), where γ, ϕ, and σ refer to the efficiency parameter, value share of emissions, and the elasticity of substitution between abating and emitting, respectively.

$$X_P = \gamma\left(\phi X_E^{\frac{\sigma-1}{\sigma}} + (1-\phi) X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{A4}$$

Solving this CMP, we obtain Eq. (A5), and plugging this equation into Eq. (4) leads to the demand function for emitting shown in Eq. (A6).

$$X_A = \left(\frac{1-\phi}{\phi}\cdot\frac{P_E}{P_A}\right)^{\sigma} X_E \tag{A5}$$

$$X_E = \gamma^{\sigma-1}\phi^{\sigma} X_P{}^{1-\sigma} C_P{}^{\sigma} P_E{}^{-\sigma} \tag{A6}$$

By taking the partial derivative of X_E with regard to P_E, we obtain Eq. (A7).

$$\frac{\partial X_E}{\partial P_E} = -\sigma\frac{X_E}{P_E}\left(1-\frac{P_E}{C_P}\cdot\frac{\partial C_P}{\partial P_E}\right) \tag{A7}$$

Eq. (7) and Shepard's Lemma lead to Eq. (A8).

$$\frac{\partial X_E}{\partial P_E} = -\sigma\frac{X_E}{P_E}\left(1-\frac{X_E P_E}{C_P}\right) \tag{A8}$$

From Eqs. (3) and (8), we obtain the price elasticity of demand shown in Eq. (A9).

$$\varepsilon_E = \frac{\partial X_E}{\partial P_E}\frac{P_E}{X_E} = -\sigma\left(1-\frac{X_E P_E}{X_E P_E + X_A P_A}\right) \tag{A9}$$

[3] The main content of Appendix A is excerpted and modified from Nam *et al.* (2013).

Eq. (9) can be further simplified at equilibrium, as firms in this state will be indifferent between emitting and abating, making P_E equal to P_A. This reduces the relationship to the final form shown in Eq. (A10), where θ_E and θ_A are the emitted and abated shares of total pollution, respectively.

$$\sigma_{Fuel} = \frac{-\varepsilon_E}{1 - \frac{X_E}{X_E + X_A}} = \frac{-\varepsilon_E}{1-\theta_E} = -\frac{\varepsilon_E}{\theta_A} \tag{A10}$$

From this, we see that for fuel-related emissions, the elasticity of substitution can be estimated if the price elasticity of demand for emission and the initial percentage of total pollution abated can be determined. For non-fuel emissions, the relationship is similar except that we substitute between pollution emitted and other conventional inputs, instead of substituting between pollution abated and pollution emitted. Since the cost of conventional inputs is usually much larger than the policy cost for pollution emitted, the value share for emitting for non-fuel related pollution is very small and can be neglected for practical purposes. The elasticity of substitution is therefore just the inverse of the price elasticity of demand for emitting:

$$\sigma_{Pollutant} = -\varepsilon_E \tag{A11}$$

Appendix B. Estimation Results from GAINS Data

In Appendix B, we provide the full list of the parameters estimated from the GAINS data. Application of our method is as explained in Appendix A, but the only difference is that an additional constant term P_0 is introduced in the marginal abatement cost curve (MACC) to capture an initial level of abatement cost. This is because GAINS provides information only on future abatement opportunities beyond the reduction level P_0 that has already been achieved under existing regulations (Fig. B-1). In other words, GAINS does not contain any information on past abatement; thus, the initial price level needs to be estimated independently.

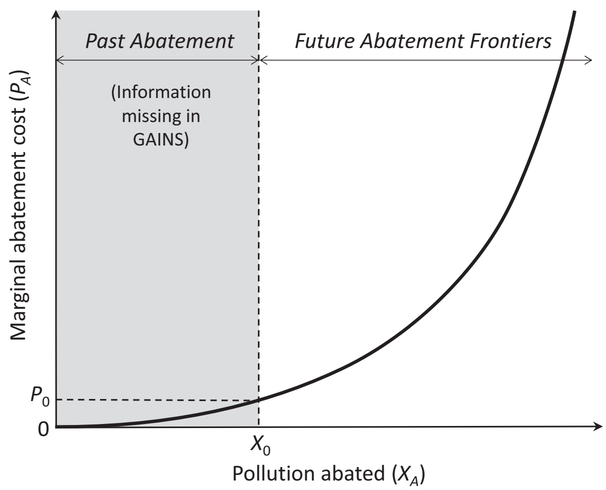

Fig. B-1. Diagram of Marginal Abatement Cost Curve.

For this reason, we transform original MACC shown in Eq. (B1) into Eq. (B2) in the GAINS setting. Here, Eq. (B1) is equivalent to Eq. (A1), as $X_E = X_P - X_A$ by definition and $P_E = P_A$ in equilibrium. The primary purpose of this transformation is to incorporate initial prices of emissions caused by abatement which has already been achieved under existing regulations and to set the limit for further abatement opportunities. Thus, we fit GAINS data points to Eq. (B2), instead of Eq. (B1).

$$P_A = \alpha(X_P - X_A)^{\beta} \tag{B1}$$

$$P_A = P_0 + \alpha\{X_P - (X_A + X_0)\}^{\beta} \tag{B2}$$

Tables B-1 to B-4 display our estimation results. GAINS provides multiple data points for P_A and X_A, and we also compute X_P and X_0 directly from the database. All the other parameters shown in the tables, including P_0, α, and β, are estimated from regression or the equations introduced in Appendix A. Fig. B-2 exemplifies abatement opportunities identified by GAINS for SO_2 emissions from the coal-based power sector in China, and estimated MACC by using this information.

Table B-1
Parameter estimates for SO_2 emissions in China.

Sector	Fuel	X_P (Tg)	X_0 (Tg)	P_0 ($/kg)	α	β	θ_E	ε_E	σ
EINT	COAL	2.03E+01	1.07E+01	0.48	19.68	-2.23	0.47	-0.45	0.85
EINT	OIL	4.34E-01	2.17E-02	3.23	35.93	-7.90	0.95	-0.13	2.53

(continued on next page)

Table B-1 *(continued)*

Sector	Fuel	X_P (Tg)	X_0 (Tg)	P_0 ($/kg)	α	β	θ_E	ε_E	σ
EINT	ROIL	1.19E-01	5.97E-03	1.51	6.38	-1.61	0.95	-0.62	12.42
ELEC	COAL	2.41E+01	8.53E+00	0.40	30.03	-4.01	0.65	-0.25	0.71
ELEC	OIL	3.36E-02	1.68E-03	1.88	11.96	-7.02	0.95	-0.14	2.85
ELEC	ROIL	4.00E-05	2.00E-05	4.48	-36.16	-7.88	0.50	-0.13	0.24
TRAN	ROIL	3.99E-01	3.85E-02	1.96	5.68	-0.85	0.90	-1.18	12.20
FD	COAL	1.63E+00	8.13E-02	0.44	50.91	-7.82	0.95	-0.13	2.56
FORS	PROCESS	1.41E-01	7.04E-03	0.39	11.06	-3.27	0.95	-0.31	0.31
EINT	PROCESS	6.77E+00	3.87E+00	0.22	49.25	-6.88	0.43	-0.15	0.15
OIL	PROCESS	1.96E-01	4.90E-02	0.16	67.23	-17.70	0.75	-0.06	0.06

Note: P_0 is evaluated in 2004 US$.
Source: Created from Waugh (2012).

Table B-2
Parameter estimates for NO_x emissions in China.

Sector	Fuel	X_P (Tg)	X_0 (Tg)	P_0 ($/kg)	α	β	θ_E	ε_E	σ
EINT	COAL	4.61E+00	2.31E-01	0.13	30.11	-3.84	0.95	-0.26	5.21
EINT	OIL	2.27E-01	1.14E-02	0.06	15.75	-3.44	0.95	-0.29	5.81
EINT	ROIL	2.18E-01	1.09E-02	0.15	129.99	-28.23	0.95	-0.04	0.71
EINT	GAS	6.61E-02	3.31E-03	0.09	12.61	-3.71	0.95	-0.27	5.38
ELEC	COAL	5.58E+00	1.07E+00	0.12	21.48	-2.82	0.81	-0.35	1.85
ELEC	OIL	2.07E-02	1.04E-03	0.05	7.30	-3.44	0.95	-0.29	5.82
ELEC	ROIL	2.00E-05	0.00E+00	0.53	-38.29	-7.88	1.00	-0.13	2.54
ELEC	GAS	2.22E-02	1.11E-03	0.55	14.73	-7.88	0.95	-0.13	2.54
FD	ROIL	7.32E-03	3.70E-04	8.84	9.77	-3.92	0.95	-0.26	5.11
FD	GAS	1.22E-02	6.10E-04	4.92	9.36	-3.50	0.95	-0.29	5.71
EINT	PROCESS	2.47E+01	2.22E+01	0.15	48.49	-7.33	0.10	-0.14	0.14
OIL	PROCESS	6.76E-02	3.38E-03	0.35	44.26	-15.17	0.95	-0.07	0.07

Note: P_0 is evaluated in 2004 US$.
Source: Created from Waugh (2012).

Table B-3
Parameter estimates for SO_2 emissions in the U.S.

Sector	Fuel	X_P (Tg)	X_0 (Tg)	P_0 ($/kg)	α	β	θ_E	ε_E	σ
EINT	COAL	6.12E-01	4.26E-02	0.54	68.80	-13.43	0.93	-0.07	1.07
EINT	OIL	6.11E-01	3.48E-02	0.56	12.48	-2.58	0.94	-0.39	6.83
EINT	ROIL	1.50E-01	7.50E-03	1.56	3.35	-0.59	0.95	-1.71	34.18
ELEC	COAL	3.30E+01	2.33E+01	0.44	65.62	-8.90	0.29	-0.11	0.16
ELEC	OIL	2.62E+00	2.10E+00	0.45	50.47	-10.02	0.20	-0.10	0.12
ELEC	ROIL	3.03E-02	1.51E-03	1.75	2.50	-0.58	0.95	-1.73	34.68
TRAN	OIL	7.80E-03	3.90E-04	0.49	2.44	-7.88	0.95	-0.13	2.54
TRAN	ROIL	3.78E+00	3.49E+00	1.61	7.06	-1.16	0.08	-0.86	0.93
FD	COAL	1.23E-01	6.86E-02	0.43	24.01	-7.02	0.44	-0.14	0.26
FD	OIL	2.40E-01	1.57E-01	0.49	27.53	-7.87	0.35	-0.13	0.19
FD	ROIL	3.12E-01	1.56E-02	1.50	7.05	-1.68	0.95	-0.59	11.89
FORS	PROCESS	5.19E-01	2.37E-01	0.41	14.83	-3.28	0.54	-0.30	0.30
EINT	PROCESS	1.77E+00	1.47E+00	0.08	32.53	-6.56	0.17	-0.15	0.15
OIL	PROCESS	1.08E+00	5.66E-01	0.11	19.75	-3.72	0.48	-0.27	0.27

Note: P_0 is evaluated in 2004 US$.
Source: Created from Waugh (2012).

Table B-4
Parameter estimates for NO_x emissions in the U.S.

Sector	Fuel	X_P (Tg)	X_0 (Tg)	P_0 ($/kg)	α	β	θ_E	ε_E	σ
EINT	COAL	1.74E-01	1.08E-02	0.16	13.99	-3.17	0.94	-0.32	5.09
EINT	OIL	1.56E-01	7.78E-03	0.17	10.22	-2.41	0.95	-0.42	8.32
EINT	ROIL	1.07E-01	5.37E-03	0.41	41.98	-10.63	0.95	-0.09	1.88
EINT	GAS	9.73E-01	4.87E-02	0.25	23.92	-4.04	0.95	-0.25	4.95
ELEC	COAL	1.30E+01	9.30E+00	0.21	21.96	-2.86	0.29	-0.35	0.49
ELEC	OIL	1.78E+00	1.60E+00	0.06	21.03	-4.61	0.10	-0.22	0.24
ELEC	ROIL	1.07E-02	5.30E-04	0.43	18.51	-11.10	0.95	-0.09	1.80
ELEC	GAS	2.13E+00	1.02E+00	0.10	25.32	-3.94	0.52	-0.25	0.53
FD	OIL	3.15E-02	1.57E-03	0.65	19.49	-7.88	0.95	-0.13	2.54
FD	ROIL	1.59E-01	7.96E-03	4.04	14.89	-2.69	0.95	-0.37	7.44
FD	GAS	6.40E-01	3.20E-02	1.51	22.03	-3.51	0.95	-0.29	5.71
EINT	PROCESS	4.30E-01	2.15E-02	0.20	18.46	-3.78	0.95	-0.26	0.26
OIL	PROCESS	4.41E-01	2.21E-02	0.36	7.88	-1.47	0.95	-0.68	0.68

Note: P_0 is evaluated in 2004 US$.
Source: Created from Waugh (2012).

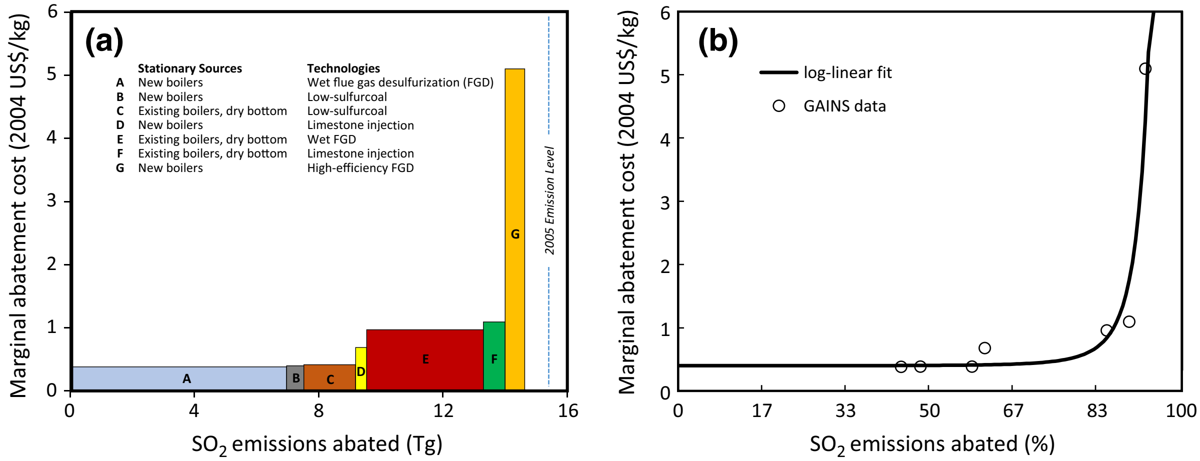

Fig. B-2. MACC for SO_2 emissions from coal-based power generation sector in China, 2005: (a) Abatement opportunities identified by GAINS, (b) MACC estimated from GAINS data. Source: Created from GAINS database.

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